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A network autocorrelation model to investigate how relations among students affect academic performance

Maria Prosperina Vitale, Giovanni C. Porzio, Patrick Doreian

Abstract The effect of university student networks on their academic performance was assessed. Performance was operationalized as a latent variable and a network effects autocorrelation model was used to estimate the association between student relations and their attainment. A social influence mechanism was hypothesized wherein individuals adjust their own behaviours to those of others with whom they are connected. By using data collected through a questionnaire and administrative archives on a cohort of graduate students enrolled at an Italian university, different types of networks were considered. The results show informal contacts (studying in groups out of classes, friendship, personal support and advice) have a significant impact on performance, while formal relations established by the instructor have no such impact. These findings suggest encouraging higher education institutions to adopt strategies supporting social interactions among students. They can be fruitful for improving student performances.

Key words: Adjacency matrix, Multiplex networks, Network Effects Model, Social influence, Student academic performance.

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1 Introduction

Various contributions have focused identifying determinants of student performance at all stages of education. These include strategies for increasing student retention and academic achievement. Also, many studies have focused on the institutional and individual factors associated with student success at universities in different tracks [39, 32]. Some of the recent work dealt with background variables [5], family support [10], academic and social integration [35], students learning patterns [40], learning approach and time spent studying [28], self-perception of ability [11], teacher influence [21], course scheduling [12] and course resources [24].

Very few studies have considered relations among students as a potential determinant of their academic performance at the university level although a large literature covering this issue at lower levels of education exists (see [29, 34]). Eggens et al. [18] considered the effect of personal networks on student attainment by using the scores measuring to which extent each student is related to the others as predictors in a standard regression model.

An alternative approach is to adopt a social influence mechanism perspective within which the specific links between students in the structure of social relations are considered as relevant, together with the attitudes and behaviors of the actors who compose a network [30]. There is a form of a "contagion effect" among peers. Our basic research hypothesis is simple to state: student performances are related to the performance of the other students belonging to the same network.

Using such a framework, Celant [9] studied the effect of observed relational links among students on university performance using a linear-in-mean model[1]. He introduced a procedure adjusting the methodology of peer effects (for one detailed review see [42]) in a university setting, where courses are not closed and complete systems. As assumed by Celant's model, all actors within subgroups are linked to each other, forming a complete network, but each group has no connection to others outside it. Further, group means were assigned to all individuals within the same group. However, as recognized by the same author, the partition of a network into several disjoint components in which students have no connections with people outside the group, and have relational ties only within the group, is a very strong assumption within a university context. We note also that assigning group mean values to individuals is likely to mask information on how network ties work.

Given these limitations, we used instead a model for the effects of social influence on student performance by adopting a Network Autocorrelation Model (NAM) [14, 15]. NAMs form a class of models discarding the linear-in-mean assumption by taking into account all interpersonal ties within and between groups. More precisely, we used the network effects model [14, 16].

Specifically, we evaluated the effect of interpersonal relations on university student performance assuming students influence each other. We compared the effect on performance of both formal and informal links among students while controlling

[1] These models are mainly used to identify "peer effects" on student outcomes at the elementary, secondary, and post-secondary levels (e.g., [8, 36]).

for other variables. Studying in groups established by the instructor and exchange of learning information are considered as formal relations. In contrast, friendship, personal support and advice plus studying in groups outside of classes are informal relations. The analysis used data from graduate students collected in an Italian university.

This study adds substantial substantive results regarding predictors of university student performance because of the following design features:

- Adopting a NAM approach allows studying the effect of students' relations on performance by taking into account both the interdependence structure of relations while controlling for other student attributes.
- It explored which types of relations have larger impacts on performance.
- Performance was treated as a latent variable, measured by objective (final average score at exams), and subjective indicators (i.e., Dublin's Descriptors, see below).
- A two-step estimation procedure was used to include individual scores of latent variable within a NAM approach. First, factor scores were derived and then a network effects model was estimated.

The paper is organized as follows. Section 2 briefly presents measurement and modeling related issues. Section 3 reports our case study and Section 4 provides a summary of our results along with a discussion of them. Finally, network questionnaire items are offered in the Appendix.

2 Methodological issues

Two main methodological issues were tackled. One dealt with student performance typically being measured by a single objective indicator. The other was the estimation of a NAM model including a latent variable.

2.1 Measurement issues: student performance as a latent variable

Typically, only one objective indicator is considered to measure student performance e.g., the grade point average score (GPA), the percentage of exams passed in a given time, the number of credits obtained, the final grade, etc. Even though these indicators are used most often given their availability in administrative databases, the measurement of performance becomes a challenging task when one wants to take into account the complexities of learning processes. This is a wide open issue. Worthy of note is the recent 2012 feasibility study on the measure of student performance carried out by the OECD "Assessment of Higher Education Learning Outcomes (AHELO)" project[2].

[2] For details visit OECD AHELO project website: www.oecd.org/edu/ahelo.

Our approach combines objective measures of performance with some student self-evaluation measures. For this latter, we used Dublin's Descriptors as "generic statements of typical expectations of achievements and abilities associated with qualifications that represent the end of each Bologna cycle [33, p. 65]". These descriptors consider the perceived quality of the learning activities developed during the field of study after completion of the higher education track as awarded to students. They identify five core competences, or key qualifications, to describe student learning experience (*knowledge and understanding, applying knowledge and understanding, making judgements, communication* and *learning skills*).

This implies considering student performance as a latent variable measured by combining a set of single objective as well as subjective indicators. From the several approaches available in the literature, we adopted Confirmatory Factor Analysis (CFA) [6]. Details on how we obtained individual scores of students' performance in practice through CFA are discussed in the next subsection.

2.2 Model and estimation procedure

Network Autocorrelation Models [14, 15, 16] deal with the presence of interdependent individual units embedded within social structures. Standard linear regression models cannot be adopted because this interdependence violates the assumption of independence among error terms required to obtain unbiased coefficient estimates. As a result, inference for linear regression is compromised, sometimes severely, and the OLS estimation procedure must be abandoned.

In analogy with econometric models for spatial analysis [1], an autocorrelation term is introduced and a maximum-likelihood estimation procedure considered (or some other consistent estimation procedure). The autocorrelation term can be included in either network effects models or network disturbances models. The former permit the estimation of the effect of a network structure on the dependent variable, while the latter take into account the interdependence among units within the disturbance terms.

Of these options, we consider the network effects model because of our interest in the influence of relations among students on their academic performance. The standard network effects model is specified as follows.

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\beta + \varepsilon \tag{1}$$

where $\mathbf{y}$ is an $(N \times 1)$ vector of dependent variable values, $\mathbf{X}$ is an $(N \times p)$ matrix for the p independent variables values (including a unit vector for the intercept term), β is a $(p \times 1)$ vector of regression coefficients, ρ is the autocorrelation parameter measuring the strength of the network effects on $\mathbf{y}$ and $\mathbf{W}$ is a $(N \times N)$ weight matrix whose elements, w_{ij}, measure the influence of subject j on subject i, and N is the total number of observed units.

A key element in these models is the specification of the weight matrix, $\mathbf{W}$, conceptualizing the interdependencies among subjects. Leenders [26] reported several alternative ways for defining weights in $\mathbf{W}$, starting from a scaled adjacency matrix measuring direct connection among units (called cohesion) or deriving (dis)similarity measures for subjects' relational profiles (using structural equivalence, [27, 17]). We used directly scaled adjacency matrices, where rows are normalized to sum to 1, so that w_{ij} is a measure of the relative influence of subject j on i, with values $0 \leq w_{ij} \leq 1$, with diagonal terms w_{ii}= 0.

To incorporate latent variables, we suggest a simple two step estimation procedure for the network effects model. First, individual scores are derived for a latent variable by using CFA[3]. Second, individual scores for latent variables are included in the network effects model, introducing the autocorrelation parameter through the weight matrix $\mathbf{W}$. That is, we consider the model:

$$\hat{\mathbf{F}}_\eta = \rho \mathbf{W} \hat{\mathbf{F}}_\eta + \hat{\mathbf{F}}_\xi \beta + \zeta \tag{2}$$

where $\hat{\mathbf{F}}_\eta$ is a vector containing the individual scores of a latent dependent variable η, $\hat{\mathbf{F}}_\xi$ is a matrix with individual scores for latent independent variables ξ, and ζ denotes a vector of stochastic errors taken to be independent of one another[4].

3 Effects of interpersonal relations among students: a case study

As a result of the two main European higher education policy reform processes (the Bologna Process started in 1999 and the Lisbon Strategy of 2000), the university system in Italy has been subject to numerous changes. This, in turn, yielded a host of studies devoted to the Italian system over the last decades, covering different topics and combining case studies and methodological issues (see e.g. [25, 23, 13, 4, 3, 38], and the contributions in [20, 2]).

Given this large debate, we use data we collected in an attempt to evaluate student relations as determinants of their performance in a graduate track. Our main assumption is that, among others, performance is related to different networks in which individuals interact because of a need for exchanging learning information and of studying together, or because of their friendship or personal support and advice relations.

We state the following hypotheses:

- H1: *Student performance is related to the performance of other students with whom they interact during their academic career*.

[3] Several methods are available to obtain individual scores for latent variables (see e.g. [22]), generally providing different results for each unit. We adopted the Skrondal and Laake [37] revised blockwise factor score regression procedure, that is based on the estimation of individual scores separately for the dependent (Bartlett scores) and independent (Regression scores) latent variables. It produces consistent estimators for all parameters in the case of a latent regression model.

[4] Note that we are using CFA notation from structural equation modeling literature.

- H2: *Not all the networks in which the individuals are embedded during university life have the same effect on performance*.
- H3: *Informal contacts requiring and/or implying deeper relations (such as friendship or personal support) have higher effects on student performance*.

3.1 Data collection

The population for our study was a cohort of 81 students enrolled for the first time in the academic year 2008-09 at a graduate two-year track in an Italian University. Data were collected through a survey exploiting a web platform as well as face-to-face interviews in May-October 2010. Finally, data were validated and integrated by using an administrative archive updated to December 2012.

The survey instrument was designed to collect information about student socio-demographic characteristics, prior educational attainments and their university careers. The variables considered in the present study are provided in Table 1. Furthermore, relational information about different kind of interpersonal relations were collected (as described below).

Different performance indicators were measured: the average grade at exams at the end of their academic career and five subjective perceived learning experience indicators at undergraduate and graduate university level. Learning indicators were defined according to the five core competences of Dublin's Descriptors. For the sake of simplicity, a general item matching each descriptor was adopted. Students were asked to indicate to which degree (on a ten- point scale, 1= Low, 10= High) they:

- have demonstrated knowledge and understanding in their field of study [Descriptor 1];
- can apply their knowledge and understanding in occupational contexts [Descriptor 2];
- have the ability to make autonomous judgements on well-defined problems [Descriptor 3];
- can communicate about their understanding, skills and activities, with peers, supervisors and clients [Descriptor 4];
- have the learning skills to undertake further studies with some autonomy [Descriptor 5].

Relations among students were gathered using a whole-network study design [31] to measure the network configuration of this bounded cohort of students. For whole-network data collection, a roster list of the population was furnished to simplify the reporting task by reminding of the eligible students within each network. We collected *one-mode* network data for multiple types of ties at a single time point.

Students were asked to nominate their contacts for formal relations (exchange of learning information, classmate, and belonging to a working group established by the instructor) as well as informal contacts (studying in groups out of classes, friendship, personal support and advice, enrolled in the same on-line community, attending on-campus student associations, spending spare time in campus activities). The network questionnaire items are shown in the Appendix.

3.2 A first glance at the data

Sixty-six students, out of 81, participated to the survey (an 81% response rate). The students not participating in this study did not substantially differ in terms of age at enrolment and prior scholastic attainment. Furthermore, closer inspection revealed they were barely involved in their university studies or with other students and many (around 90%) of them had not yet graduated four years after enrolment. It is reasonable to exclude such students given their minimal involvement in the academic and social aspects of graduate study. In addition, four participants not yet graduated at the end of 2012 were excluded from our analysis as well. Finally, a very small amount of missing data were imputed using simple linear regression models[5].

The variables selected for our study are presented with their main features in Table 1. About 92% of respondents were female, the average age at enrolment was 26 and average final grade at secondary school is 79 (on a scale ranging from 60 to 100). Father's education years were, on average, around 11 (about the midpoint in the high school track). Performance in terms of average grade at exams (scale: 18=pass; 30=maximum) and of the five Dublin's Descriptors showed high values both at undergraduate and graduate tracks as well. However, a general increase in student attainment is likely when comparing these two higher education levels.

Table 1 ABOUT HERE

Five student networks are considered in this study: exchange of learning information (EI), belonging to working group established by the instructor (WG), studying in group out of classes (SG), friendship (FR), and personal support or advice (AD). The other recorded networks were not considered here mainly because they were very sparse, in such cases "there is little point in estimating autocorrelation models ([16, p. 40])".

Two students out of the sixty-two included were isolates in at least one of the five observed social relations. They were discarded also because their self-exclusion meant they were not part of the social influence process being studied.

The student relational data were binary: the adjacency matrices had cell values of 1 if student i was linked to student j and 0 otherwise. These matrices were symmetrized assuming reciprocated links among subjects for all existent connections. Studying in groups out of classes and belonging to working groups are symmetric

[5] A first model was estimated to predict the graduate average grade of five students from their undergraduate grade. The model was also used to obtain values for five missing undergraduate grades (an inverse regression problem). The same procedure was adopted for the Dublin's Descriptors, where each graduate level descriptor was regressed on the corresponding undergraduate one. In such a case, a total of six missing values were imputed using ten variables.

relations by definition. As for the exchange of learning information, at face value, it is directed according to the direction of the information flows. But, an alternative conceptualization is to think of the relations as the context within which information can flow. It could even be thought of as a minimum level of trust in the sense of feeling safe enough to ask for information and comfortable enough with providing information. For friendship, personal support and advice, we consider the relationship is close enough for this kind of support to be requested and given regardless of the direction of the flow.

Figure 1 provides a visual image of the five social relations we considered, while Table 2 provides a summary of some characteristics of the observed networks. As expected, the highest density and average degrees occur for the exchange of learning information: most of the students shared information with some others during their study at university. In contrast, studying in groups, providing personal support and advice have lower values: asking for support or studying together are more selective processes.

Figure 1 ABOUT HERE

Table 2 ABOUT HERE

Finally, we investigated the extent to which multiple networks can present different characteristics of student relations. The values of correlation for the five adjacency matrices (Table 3) show that all relationships are positively associated[6]. All correlations are significant at or beyond the 5% level.

Table 3 ABOUT HERE

3.3 Model specification and results

Starting from the idea that student performance is influenced by the network surrounding the students, we investigated this relationship while controlling for the effect of the following socio-demographic characteristics: age at enrolment (*EnrAge*), and education years of father (*FathEdu*). Academic background was also controlled by using final grade at secondary school (*HSGrade*), and performance in the undergraduate track (*UndGradPerf*). Gender was dropped because of the very high percentage of females among these students.

According to the discussion in subsection 2.2, individual scores for graduate (*GradPerf*), and undergraduate (*UnderGradPerf*) performance were obtained, and

[6] We used the quadratic assignment procedure (QAP) as implemented in UCINET 6.490 [7].

five network effects models were estimated according to the following general equation:

$$GradPerf = \alpha + \rho \mathbf{W} GradPerf + \beta_1 UnderGradPerf + \beta_2 EnrAge + \\ + \beta_3 FathEdu + \beta_4 HSGrade + \zeta$$

where the parameter ρ measures the magnitude of the network effect of each relation on student performance.

Table 4 shows the results for the five estimated models. There was a significant effect of performance at undergraduate level in all models (a quite natural effect) while the other socio-demographic characteristics are not significant (contrary to what has been observed in other studies in the literature). Considering the social networks, their effects differ according to the kind of relation. Exchange of learning information, and belonging to working groups established by instructors are not significant. On the other hand, studying in groups out of classes, friendship and personal support and advice are positively and significantly correlated with performance.

Table 4 ABOUT HERE

4 Findings and discussion

This contribution represents a novel approach in terms of method by considering performance as a latent variable and adopting a network autocorrelation model to analyze the effect of relations among students on their academic attainment at the graduate level.

Student performance was measured by combining an objective indicator (average grade at exams) with a set of subjective student self-perception indicators of their learning process based on Dublin's Descriptors. Final individual scores were obtained through a Confirmatory Factor Analysis, according to the procedure in Skrondal and Laake [37] for a latent regression model.

A network effects model was adopted. The key issue for these models is the definition of a proper weight matrix to effectively capture the connections among students. We started from the idea that links among students in a learning environment can improve their performance. We used direct connections described by row-scaled dichotomous adjacency matrices. This implies that the performance of a student is related to the average performance of her/his neighbours. Of course, there is room for deeper analyses of the way social influence mechanism among peers works within university settings. This could include a way to take into account that probably students with a *worse* performance can improve if they are connected with better students - but student with *better* performances do not perform less well if they are connected with worse students. In addition, the combined use of multiple autocorrelation network effects in a single model ([16], [41]) of the same group of subjects who are embedded in different networks as a further development of this study can be considered.

Our results suggest that belonging to social networks has a positive effect on student performance - especially if these networks are created by the students rather than be imposed by the instructors. More specifically, by controlling for the effect of socio-demographic characteristics, prior scholastic attainment at secondary school and at undergraduate level, some relations have an effect, while others do not. In particular, informal communications (such as friendship, personal support and advice) are significantly related with graduate student success at university, whereas merely exchanging information and working in groups seems not to have a significant impact on performance.

Given this is one case study limited to a graduate track in a single university, caution is merited. Its generalizability is very limited. However, we note this is one of the first studies of this kind and hope it can set a precedent for further work.

If our findings are confirmed by further analyses in different university contexts, one practical implication follows. It would be beneficial if higher educational institutes encourage social activities among students as potentially effective strategies for learning. In particular, universities can address measures to improve students' interactions so as to facilitate the integration in academic and social life, and thereby contributing in their academic success.

We strongly encourage other researchers to replicate and extend this study in other settings to enhance the generalizability of our findings.

Appendix: Network questionnaire items.

The whole questionnaire was implemented in Italian. The network items is partially depicted in Figure 2. The question says: "A list of the students enrolled in your Master program in the academic year 2008-09 is reported below. Please select the kind of relationship you have with each of them".

Then, for each row, a student name appears and the interviewed must check a box corresponding to the different kind of relations. They are: Exchange of learning information; Studying together out of classes; Working in groups established by instructors; Classmate; Personal support and advice; Friendship; Enrolled in the same on-line community (e.g., yahoo groups, facebook, messanger,...); Attending on-campus student associations; Spending spare time in campus activities (swimming pool, gym, theatre,...); I do not know him/her.

Figure 2 ABOUT HERE

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Table 1 Main characteristics of variables selected for the case study.

Variable	Measurement	Average (St.Dev.)
Gender	categorical	91.9% female
Enrolment Age	continuous	25.8 (*5.4*)
Father years education	discrete	10.6 (*3.4*)
Secondary school final grade	continuous	79.4 (*10.8*)
Undergraduate level		
Average grade at exams	continuous	26.3 (*1.7*)
Dublin descriptor 1	discrete 1-10	7.2 (*1.4*)
Dublin descriptor 2	discrete 1-10	7.3 (*1.2*)
Dublin descriptor 3	discrete 1-10	7.7 (*1.2*)
Dublin descriptor 4	discrete 1-10	7.5 (*1.6*)
Dublin descriptor 5	discrete 1-10	8.1 (*1.4*)
Graduate level		
Average grade at exams	continuous	28.4 (*1.3*)
Dublin descriptor 1	discrete 1-10	7.8 (*1.2*)
Dublin descriptor 2	discrete 1-10	8.0 (*1.1*)
Dublin descriptor 3	discrete 1-10	8.1 (*1.4*)
Dublin descriptor 4	discrete 1-10	8.1 (*1.2*)
Dublin descriptor 5	discrete 1-10	8.5 (*1.3*)

Table 2 Networks characteristics. Their labels are: Exchange of learning information (EI); Belonging to working groups established by instructors (WG); Studying in groups out of classes (SG); Friendship (FR) and Personal support and advice (AD).

Network	Density	Average degree (*St.Dev*)	Degree centralization (%)
EI	0.453	26.733 (*10.542*)	54.822
WG	0.221	13.033 (*7.718*)	33.255
SG	0.132	7.767 (*5.934*)	42.490
FR	0.180	10.600 (*5.386*)	34.015
AD	0.120	7.067 (*4.686*)	22.677

Table 3 QAP correlations among the adjacency matrices. Their labels are: Exchange of learning information (EI); Belonging to working groups established by instructors (WG); Studying in groups out of classes (SG); Friendship (FR) and Personal support and advice (AD).

	EI	**WG**	**SG**	**FR**	**AD**
EI	1.00				
WG	0.46	1.00			
SG	0.39	0.56	1.00		
FR	0.38	0.53	0.58	1.00	
AD	0.37	0.57	0.67	0.63	1.00

Table 4 Estimated network effects models. Estimated coefficients, their standard errors (in italic), R^2, AIC, and BIC for the five estimated models. Response is the individual graduate performance score. The parameter ρ measures the magnitude of the network effect of each relation. Labels are: Age at Enrollment (*EnrAge*); High School Grade (*HSGrade*); Years Education of Father (*FathEdu*); Individual scores for undergraduate performance (*UndGradPerf*). Significant parameters are marked by: * $p < .10$, **$p < .05$, ***$p < .01$.

	EI	**WG**	**SG**	**FR**	**AD**
Const	-0.194	-0.159	-0.186	0.095	-0.236
	0.907	*0.912*	*0.879*	*0.887*	*0.865*
ρ	-0.399	0.099	0.384 *	0.422 *	0.373 **
	0.483	*0.271*	*0.201*	*0.218*	*0.157*
EnrAge	-0.002	-0.004	-0.003	-0.008	-0.002
	0.019	*0.019*	*0.019*	*0.019*	*0.018*
HSGrade	0.003	0.003	0.002	0.000	0.003
	0.008	*0.008*	*0.008*	*0.008*	*0.008*
FathEdu	0.003	0.003	0.006	0.004	0.001
	0.025	*0.026*	*0.025*	*0.025*	*0.024*
UnderGradPerf	0.353 ***	0.358 ***	0.342 ***	0.312 ***	0.308 ***
	0.068	*0.069*	*0.066*	*0.070*	*0.068*
R^2	0.329	0.324	0.329	0.313	0.308
AIC	135.7	136.3	133.1	133.0	131.2
BIC	150.4	150.9	147.7	147.7	145.9

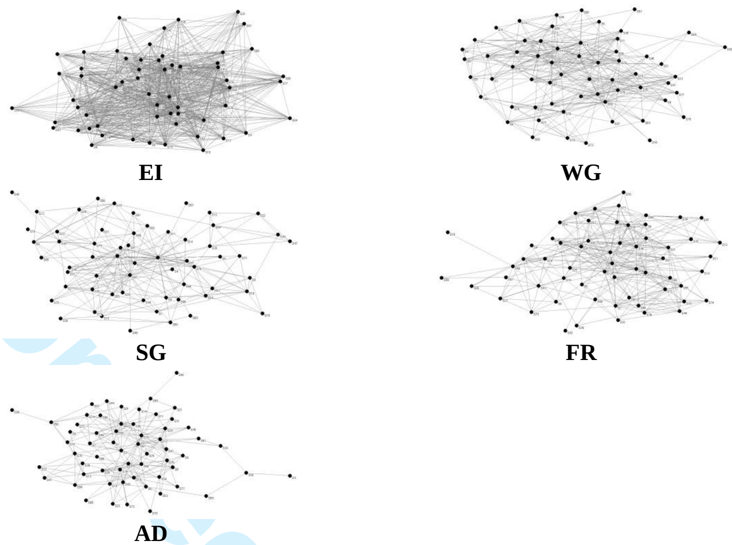

Fig. 1 Graph representations of the five student relations. Their labels are: Exchange of learning information (EI); Belonging to working groups established by instructors (WG); Studying in groups out of classes (SG); Friendship (FR) and Personal support and advice (AD).

Sezione 3: Dinamiche relazionali e Vita universitaria

40. Di seguito è riportata la lista degli studenti che si sono immatricolati come te alla laurea magistrale nell'a.a. 2008-09. Puoi indicare il tipo di legame che intrattieni con ciascuno di loro?

		Scambio di informazioni	*Preparazione esami (aggregazione spontanea)*	*Preparazione esami (tesine, lavori di gruppo previsti dal docente)*	*Frequenza corsi*	*Supporto emotivo/Consigli*	*Amicizia*	*Iscritti a gruppi sul web (es: gruppi yahoo, facebook, messanger,...)*	*Frequenza associazioni studentesche nel campus*	*Frequenza luoghi tempo libero nel campus (piscina, palestra, teatro,...)*	*Non lo conosco*
Cognome	**Nome**										
Studente 1	*Studente 1*	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Studente 2	*Studente 2*	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
...	...	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
...	...	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Studente 81	*Studente 81*	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Fig. 2 An image of the questionnaire network items (in Italian).