Longitudinal Peer Network Data in Higher Education

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ABSTRACT

This chapter employs a longitudinal social network approach to research small group teaching in higher education. Longitudinal social network analyses can provide in-depth understanding of the social dynamics in small groups. Specifically, it is possible to investigate and disentangle the processes by which students make or break social connections with peers and are influenced by them, as well as how those processes relate to group compositions and personal attributes, such as achievement level. With advanced methods for modelling longitudinal social networks, researchers can identify social processes affecting small group teaching and learning.

Keywords: Longitudinal peer networks; stochastic actor-based models; RSIENA; small group teaching; achievement; higher education

INTRODUCTION

Small group teaching and learning are common features of higher education nowadays. Based on social constructivism (Vygotsky, 1978), the student-centred small group learning approach gives students the possibility to construct their knowledge by group discussions, joint activities and collaboration on group assignments (O'Donnell, 2006), which is encouraging for deep learning (Baeten, Kyndt, Struyven, & Dochy, 2010). Small groups, such as learning communities, seem especially important in the transition period from secondary education to university, where students have to adjust to their new educational environment (Coertjens, Brahm, Trautwein, & Lindblom-Ylänne, 2017).

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Transition occurs in different stages, such as the encounter, adjustment and stabilisation stages (Nicholson, 1990). When students enter university most students hardly know anyone, because they left their old classmates and friends behind and need to find their way in the university. In addition to meeting the academic requirements, they have to create new networks with fellow students (peers) and teachers. Research shows that relationships with peers and teachers can support dealing with this stressful transition period (Buote et al., 2007; Meeuwisse, Severiens, & Born, 2010; Wilcox, Winn, & Fyvie-Gauld, 2005). Relationships with both teachers and fellow students can importantly affect the outcomes of small group teaching, but especially peer relations are embedded in newly forming and changing social networks within and beyond a learning group (Tao, Dong, Pratt, Hunsberger, & Pancer, 2000). This makes longitudinal social network analysis an important approach for studying the role of peer relations in small group teaching, which is our focus in this chapter.

Social network analysis investigates how the structural patterns of social relations are related to behaviour and characteristics of actors (i.e., individuals) in a network (Wasserman & Faust, 1994). Hitherto there is relatively little research applying social network analysis to the context of small groups in higher education (Brouwer, Flache, Jansen, Hofman, & Steglich, 2018; Hommes et al., 2012; Katz, Lazer, Arrow, & Contractor, 2004; Smith, 2015; Thomas, 2000). One important reason for this may be that it is notoriously difficult to identify the behavioural processes that underlie an observed association between structure and actor characteristics. For example, if students with more friends perform better, is this because they have more friends, or because higher performance attracts friends? An important methodological breakthrough for tackling such questions is the development of methods for analysing longitudinal network data. This allowed for a shift in emphasis, away from merely studying the structure of the network to the processes that form networks and by which networks affect behaviour (e.g., Snijders, 2001, 2005).

As Sweet (2016) notes, advanced methods, such as analysing longitudinal social networks, provide unique insights in social network dynamics over time, including changing peer relationships and their consequences for students' study behaviour and academic achievement in small groups. Therefore, we describe and discuss here longitudinal social network data analysis for higher education research by means of stochastic actor-based models (SABM, Snijders, 2001, 2005). This is a statistical method that investigates the co-evolution of social network structures and student behaviour, taking into account their interdependence. By doing so, it provides the possibility to elaborate on findings in prior studies of network dynamics in higher education classrooms that employ descriptive statistical methods or correlational methods (e.g., Rienties, Héliot, & Jindal-Snape, 2013).

Investigating the underlying mechanisms of the development of peer relationships in small student groups is highly relevant, because it provides insight into how and why a curriculum works. So far, higher education research focused mainly on the outcomes of the implementation of small groups, for example the effects of learning communities on performance (Hotchkiss, Moore, & Pitts,

2006) or engagement (Zhao & Kuh, 2004). A focus on the outcome only, however, does not provide enough insight in how and why small groups might work. Underlying processes are not obvious and vary with the context; the impact can often only be assumed instead of observed (Astbury & Leeuw, 2010). In small groups, though, one of the observed phenomena is that students establish and sustain relationships with their peers and interact during and in-between group meetings.

Self-reports of students have been employed to investigate to what extent students perceive a sense of belonging with their peers and to what extent these perceptions contribute to academic achievement (e.g., Meeuwisse et al., 2010). Although this research has provided valuable insights, the underlying mechanisms of the development of peer relationships in small groups have not been unravelled. Individual perceptions of belonging or attachment to a group as a whole differ from social network data, where the latter provide insights into the structural positions of individual actors in a group, related to their personal characteristics or attributes (Wasserman & Faust, 1994). But to exploit the potential of such more fine-grained data, we need other statistical approaches that allow investigation of how network processes are related to the outcomes of small group teaching.

This chapter will add to the contribution from Birkholz and Shields (2017) in this series regarding the network paradigm, in which they focus on interorganisational relationships among higher education institutions. Rather than institutional networks, we address social network dynamics in small group teaching contexts in higher education. This chapter provides a context for the application of longitudinal social networks, and increased understanding of how research questions, in terms of social dynamics, can be meaningfully addressed with this methodology.

FRIENDSHIPS AND HELP-SEEKING IN SMALL GROUPS OF STUDENTS

Social networks in small group teaching offer ample opportunities for students to get acquainted, to become friends and to seek help when needed. The question is how students build and sustain their peer relationships in small groups. The literature points to several processes and conditions that should be investigated.

A first condition relates to the spatial proximity, which results in the so-called shared propinquity or 'shared foci' effect (Feld, 1981; Wimmer & Lewis, 2010). It is well known that when two employees share the same office, it is highly likely that they develop a certain relationship. When unknown individuals interact frequently and undertake shared activities in a close context, the propinquity or physical proximity effect tends to lead to personal relationships or even friendships, because they expect to interact on a daily basis (Fehr, 1996; Feld, 1981; Van Duijn, Zeggelink, Huisman, Stokman, & Wasseur, 2003; Wimmer & Lewis, 2010). Most first-year students do not know one another at the beginning of the academic year, but through being members of the same small learning group they are aware that they will have joint learning experiences and will need to collaborate during their first semester.

Another pathway of becoming personally connected to others is via the social network itself. When individuals are asked how they became friends, it is likely that they are connected via another friend or family member (e.g., you are introduced to someone or have lunch together; Fehr, 1996), creating a tendency to form closed triads (i.e., transitivity; friends of friends become friends) in networks. However, during our lifetime we meet many persons via third parties, but many of those meetings do not end up in friendship. A further mechanism known to drive friendship selection is homophily. This means that individuals are inclined to select friends who are similar in characteristics, beliefs and behaviour, for example, gender or achievement level or capabilities (Flashman, 2012; Lazarsfeld & Merton, 1954; Lomi, Snijders, Steglich, & Torló, 2011; McPherson, Smith-Lovin, & Cook, 2001).

Asking for study-related help differs from friendship, because this help-seeking and providing information calls upon others' resources (i.e., capability and willingness to provide help) and thus brings in other processes beyond homophily or closure of triads. Suppose you are a student and you realise that you have problems with the assignments for statistics. Then, you need to select a fellow student who can provide the help (Aleven, Stahl, Schworm, Fischer, & Wallace, 2003). This means that you need to ask a student who understands statistics, but also somebody who is most likely willing to explain the material. Borgatti and Cross (2003) show that information-seeking between colleagues more often occurs when they appreciate and have well-timed access to each other's knowledge. Requesting for study-related help in small groups means that students need to know their peers' capabilities and willingness, which is most likely when students are friends (Nebus, 2006). Crucial in this help-seeking process is selecting the fellow students and how the provided help influences the understanding of the help-seeker.

Why would students provide each other support in the small group? Homans (1961) defines social exchange behaviour in terms of pay-offs. Whether at least two persons exchange certain activities depends on whether the consequences of these activities are experienced as relatively rewarding or costly and therefore, not happen or be discontinued. Blau (1964) also emphasises the mutual exchange of a favour while expecting a prospective non-specified return. Based on these principles of social exchange we might expect that students only help when they can expect a valuable return, but what is the valuable return for the capable peers when they help the less capable peers? Capable peers might either decide not to help the less capable peer because it is too time-consuming or decide to help because the less capable peer can pay-off in the future in other valuable returns, such as friendship support. The question that arises is to what extent and how study-related help-seeking relationships are established and continued between students who differ in terms of capabilities. Longitudinal social network analysis provides insight into how students select their partners and how they are influenced by them over time when they seek academic help within the small groups.

SELECTION AND INFLUENCE EFFECTS IN PEER NETWORKS

Individuals in a network can select each other based on similarity or homophily in characteristics (Lazarsfeld & Merton, 1954; McPherson et al., 2001), or influence each other (Friedkin, 1998), implying that individuals become more similar over time. Several theoretical perspectives that consider human behaviour in relation to its surrounding social constellations underscore the role of these social constellations in individuals' selection and influence. Indicative examples of such theoretical perspectives relevant for the small group teaching context are the social comparison theory (Festinger, 1954) and the social cognitive theory (see Bandura, 1977a, 1977b).

According to the social cognitive theory (Bandura, 1977a, 1977b, 1997), fellow students in small groups may function as role models. First-year students may feel unsecure about their own capabilities (Christie, Tett, Cree, Hounsell, & McCune, 2008) and look at how other students study in order to get good results (i.e., social comparison; Festinger, 1954). For example, when a fellow student succeeds during the examinations, the focal student may feel that he or she can succeed as well. The student may ask the fellow student how they studied and, in turn, the focal student can try to mirror this study behaviour. They select their role models based on similar grades and adjust their behaviour according to the behaviour of their role model. Over time, students may also influence each other in their study behaviour and get similar grades. Whether selection or influence plays a more important role in small groups, and under which conditions, is unclear, but it can be relevant for the curriculum design of small groups. The underlying mechanism of the empirical association between relationships, characteristics and beliefs or behaviours can be investigated with the analysis of longitudinally collected social network data (see Steglich, Snijders, & Pearson, 2010).

INVESTIGATION OF LONGITUDINAL SOCIAL NETWORKS IN SMALL GROUPS

Thus far, a remarkable number of models have been proposed for the statistical analysis of longitudinal social network data (see, e.g., Frank, 1991; Wasserman, 1987). Snijders (2005) shows a vast number of methods that have been proposed for the analysis of social networks in which changes are implied to occur in discrete time points (e.g., Banks & Carley, 1996; Katz & Proctor, 1959; Robins & Pattison, 2001; Wasserman, 1987). However, in all these models, the evolution of networks is not considered to occur in a time continuum and they cannot disentangle selection from influence mechanisms in small groups. Therefore, the study of the dynamics of individual outcomes and network structures as well as the way in which they affect each other constitutes a pre-requisite for understanding the underlying social mechanisms in small groups (cf. Steglich et al., 2010). Before we elaborate on the statistical model that is used for analysing longitudinally collected data (SABM), we address other methodological aspects, such as research questions and data collection.

Research Questions

The research questions addressed with longitudinally collected social network data differ from research questions addressed with cross-sectional social network data. The overarching research question addressed with longitudinally collected social network data is how *change* is created in the social network, for example 'What kinds of individual and network variables explain changes over time within a friendship network?' or 'At what stages, and why, are these variables important?' (Van Duijn et al., 2003, p. 155). More specifically, longitudinally collected data about social relations in a group can be used to address questions about selection or influence of individuals over time. For example, recently Brouwer et al. (2018, p. 485) focused on how students select each other and formulated the following research questions: 'With whom do first-year students connect when they need academic support or advice during their first year?'; 'Do they ask a higher-achieving student who is not a friend, or do they ask a similar-achieving friend who is not an "expert" but is willing to help?' Another example of a research question about school networks, focusing on selection and influence, is: 'To what degree can influence and selection mechanisms account for the observed co-evolution of substance use and friendship ties (connections)?' (Steglich et al., 2010, p. 363). Research questions like these are addressed by applying SABM (Snijders, Van de Bunt, & Steglich, 2010).

Boundary Specification

When referring to 'small groups' in network research, two meanings can be implied, namely: (1) a structural feature of a network (e.g., cliques) or (2) an exogenously defined or imposed category (e.g., pre-determined group boundary) (Katz et al., 2004). In this chapter, we use the latter meaning, relating groups to their exogenously defined category, i.e., student members in small group teaching classrooms. This relates, in turn, to the challenge of deciding which actors should be included in the sample. The boundary of a set of actors allows a researcher to investigate the population of interest. This is the so-called boundary specification for which two approaches can be distinguished (Laumann, Marsden, & Prensky, 1983). First, according to the nominalist approach the researcher defines the social group, often based on frequency or intensity of contact among the members compared to non-members, or the researcher's interest, such as first-year students who dropped out at the end of the academic year. Second, according to the realist approach, the participants or actors define the social group, for example, the actors define who belongs to a gang. Many social network studies focus on small settings with clearly defined boundaries, such as a classroom (Wasserman & Faust, 1994).

To investigate selection and influence patterns in small groups, complete or sociometric network data are preferred. For investigation of selection patterns, information about non-selected group members is necessary and this is only available when complete social network data are collected (Steglich et al., 2010). This refers to measurements of the complete network structure in a certain group instead of personal (ego-centred) networks. In ego-centred networks, the focal actor nominates others (i.e., alters) and the ego provides information about alters, such as background characteristic or alter–alter relationships (Wasserman & Faust, 1994).

Data Collection and Format

In social network research qualitative and quantitative data collection methods are used, such as archival records, interviews and observations. For longitudinal studies about relationship changes among people surveys or interviews are often used. In these studies, the relationships over time are measured at fixed intervals, for example, whom respondents nominate for asking advice or prefer to collaborate with. There are several formats for network questionnaires discussed in the literature (see Wasserman & Faust, 1994).

Longitudinal data measure a network at least two, but preferably more, points not too far apart in time. However, the time gap between the measurements must be large enough to provide insight in the network dynamics (Snijders, 2009). This implies that network data are collected over time, but also individual characteristics, attitudes and motivation, among others, as personal attributes and depending on the focus of the research.

One of the challenges in data collection is to prevent missing data. Missing data can be the result of missing cases (i.e., actors), which influence the network composition or random missingness. The former can be partly solved by indication of the 'leavers' and the 'joiners' during simulation, whereas in the latter case the missing variables should be considered as missing at random, although it is likely that missing data are not totally the result of random processes (Huisman & Steglich, 2008; Ripley, Snijders, Boda, Vörös, & Preciado, 2016). Ripley et al. (2016) suggest that missing data at random of more than 20% is too much for SABM, because the model might not converge and the estimations may be biased. Missing data of 10% might be acceptable.

Data Analysis

Network relations cannot be considered as mutually independent observations, like in classical regression analysis. Network ties and actors' characteristics are both dependent and independent variables at the same time in modelling their change. This requires modelling the interdependencies between network ties with specifically designed models, rather than assuming their independence. Thus, social network methods differ from conventional statistical inferential techniques, such as regression analysis, in the data structure, but also in the violation of the assumption of independent observations (Snijders et al., 2010; Sweet, 2016).

Statistical social network modelling approaches such as Exponential Random Graph Models (ERGM, also called p*models) for cross-sectional social network data (see, for an overview, Snijders, 2011) allow investigation of the dependencies among ties, as well as how ties depend on characteristics of the actors they connect. Modelling social network dynamics in longitudinal data is particularly challenging because the network effects can change the dynamics. The models should be able to represent these process interdependencies, but should be also parsimonious to remain empirically relevant and interpretable (Snijders, 2009). Since we focus on the analysis of longitudinally collected data, we try to summarise the most important aspects of SABM (for more details, see Ripley et al., 2016; Snijders, 2005, 2009; Steglich et al., 2010).

Stochastic Actor-Based Models

SABM is applied for testing hypotheses about change of network composition and actor attributes simultaneously (Snijders et al., 2010). Stochastic refers to the presence or absence of a tie being determined probabilistically or randomly (Sweet, 2016). SABM or stochastic actor−oriented (based) models (SAO(B)M) are terms that can be used interchangeably and have underlying assumptions as outlined by Snijders (2005, 2009) and Snijders et al. (2010). One assumption relates to 'actor-based', which refers to modelling network change from an *actor perspective* and implies that an actor (i.e., students) can 'decide' about creating, maintaining or dissolving a tie. The decision refers to the fact that the changes are initiated by the actor in the model, but not to a decision by definition (Ripley et al., 2016).

One further element is that changes only occur when actors get a chance to modify their network or behaviour at some point in time. The frequency with which this is assumed to happen is captured by the change rate in the model which is estimated from the data, and used to model a rate function (specifying the moment and frequency of change). The change itself that occurs in the network structure is driven by the objective or evaluation function. The elementary time unit for change is a so-called *ministep*, in which at most one tie or one behavioural variable of one actor can change. Changes of more than one tie or behaviour are decomposed in ministeps and based on a probabilistic function. The more attractive the resulting network after the change – given the evaluation function specified by the modeller – the more likely this change will happen according to the model. How attractive particular changes are at a given moment depends on the current configuration of relationships and actor characteristics in a network (Snijders, 2005). For example, if the modeller assumes that actors prefer to initiate help-request ties to high-performing rather than low-performing students, the probability of selecting a specific fellow student for a help request increases with the performance level of the student at the given moment.

Network evolution models include the social network as a dependent variable while simultaneously taking into account the structural network effects, explanatory actor independent variables or covariates (e.g., gender, achievement), and explanatory dyadic independent variables or covariates (e.g., similarity among friends). Structural effects mean that the existence of a tie depends on the existence of other ties or tie configurations in the network. The simplest example is a reciprocity effect. If the formation of network relations is governed to some extent by reciprocity, a reciprocity effect should be found such that the formation of a tie from ego to alter becomes more likely, when there is already a tie from alter to ego (Snijders et al., 2010; Wasserman & Faust, 1994). Transitivity is another common structural effect referring to the tendency that a friend of a friend becomes a friend (Davis, 1970; Holland & Leinhardt, 1971; Veenstra & Steglich, 2012).

In a network-behaviour co-evolution model, the network is not only the dependent variable, but it is also the independent variable and the same holds for the behaviour, for example, in the co-evolution of friendships and alcohol consumption. The change in the networks and in the behaviour is modelled simultaneously. This can be useful for investigating network and behaviour dynamics simultaneously and, by doing so, for disentangling selection and influence effects (Steglich et al., 2010). Behaviour does not always refer to behaviour as such but can also refer to attitudes, motivation and even changing characteristics, such as academic achievement. Variables referring to behaviour should be measured at a nominal (dichotomous) or discrete (ordinal) level. However, recently extensions of the model have been developed that allow including continuously measured actor attributes (Niezink, 2018). The model can indicate to what extent the behaviour changes over time. The exogenous variables or covariates do not change themselves, and are therefore not modelled as such, but these are used as an explanation for change in the network or behaviour. Covariates can be included as dummy or continuous variables. We can distinguish between covariates referring to actor attributes or dyadic attributes (Ripley et al., 2016; Snijders, 2005; Steglich et al., 2010).

These models apply simulation methods combined with statistical model fitting and are estimated by using the data-analysis package RSIENA (Simulation Investigation for Empirical Network Analysis in R; Ripley et al., 2016), which is applicable for dichotomous social network data. The network data should be formatted in a so-called adjacency matrix, which is a square matrix with zeros for no ties, self-ties on the diagonal and ones for a tie (Snijders, 2001). Based on the model, we can estimate actors' preferences for certain changes of network and behaviour that optimally explain observed changes in the network in terms of relationships and actor characteristics. In turn, this allows the researcher to assess whether the assumptions specified in the model (e.g., that network change is driven by reciprocity, or by homophily in achievement levels) are sufficiently supported by the data. To estimate this, a simulation algorithm is applied. In each of the iterations, a randomly chosen actor can decide between maintaining, creating or dissolving a tie. This decision is based on the current network configuration, actor's characteristics and position in the network and the characteristics of potential helpers or friends (see Snijders, 2005).

The simulation algorithm is related to the statistical testing of the model as follows. A researcher specifies in advance which network processes are of theoretical interest in explaining the observed dynamics, such as reciprocation of ties, or a tendency to form closed triads in friendships, or a tendency to select peers with higher achievement for help request. Then, the model algorithm generates with simulation methods the expected changes of network and behaviour that follow for different combinations of parameters which specify how strongly each of these processes governs the simulated change. Finally, the set of parameters is chosen that yields the most optimal fit with the simulated and the observed data across all measurements used in the analysis. This model result, accompanied with estimated standard errors for the parameter estimation, can be used to interpret the model outcome (Snijders, 2005; Snijders et al., 2010; Stark & Flache, 2012). With *t*-ratios the significance level of the model effects are assessed. This is calculated as the parameter estimate divided by its standard error (Snijders, 2005).

EXAMPLE

As an empirical example of modelling a selection process in peer help-seeking networks, we describe a longitudinal social network study among first-year students in learning communities (see Brouwer et al., 2018). Learning communities are in this case small groups of about 12 students who follow together all the courses during the first semester. Since students meet each other frequently, students get to know each other easily, but have also the possibility to share their knowledge when they collaborate and undertake group assignments. The main research questions addressed in this study are: Do students prefer to relate to higher achieving peers or to more similar achieving peers when they need academic help? Do friendships make the help requests more likely and vice versa?

The data were collected from 95 first-year bachelor students in a degree programme with learning communities. They filled out an online survey, including background characteristics and nomination questions. For this study, we used the data collection of two time points, i.e., after the first and second semester. Among others, students responded to the following nomination questions. First, 'I ask this fellow student for help when I don't understand the study material?' with answering categories on a five-point Likert scale from 1 = 'strongly disagree' to 5 = 'strongly agree'. Second, 'What kind of friendship you have with your fellow students?', i.e., 'best friend', 'friend', 'friendly relationship'/'possible friendship', 'neutral relationship', 'unknown relationship' (you know his name or face), 'I don't know who this is' (i.e., 'you don't know his/her face'). In a roster format, they answered these nomination questions for each of their fellow students of their learning community, and students could add other fellow students of their study programme with whom they have contact on a regular basis.

For the analysis, we dichotomised the data. For help-seeking, the answering categories 'agree' and 'strongly agree' were recoded as 1 = 'relationship' and the others as 0 = 'no relationship'. For friendship, the categories 'best friend', 'friend' and 'friendly relationship' were recoded as 1 = 'friendship' and the others as 0 = 'no friendship'. In the model specification, we addressed the research questions by including achievement ego, achievement alter, achievement similarity effects and cross-network effects by including connection in one network on connections in another network i.e., help-seeking, friendship. We controlled for structural network effects (endogenous effects, such as reciprocity, transitivity) and gender as non-essential covariate effects. See Table 1 for more details and explanation of the effects.

The stochastic actor-based modeling of our data shows that students are more likely to direct help requests to friends (positive effect of friendship on help-seeking) and peers with similar achievement (positive effect of achievement similarity). We also find that higher achieving students are more likely to initiate help requests (positive effect of achievement ego). We do not find support for the assumption that higher achieving peers are selected more often for help requests (non-significant alter effect). One of the possible emerging phenomena that was revealed by employing SABM was the risk of achievement segregation despite the small groups: higher achieving students tend be more often connected with each other than with lower achieving students. Therefore, special attention should be paid to this risk, which could undo the advantage that students can use the diversity of capabilities in the small groups.

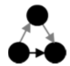
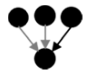
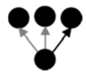
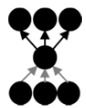
Our example shows how SABM is essential for testing these types of hypotheses due to the separation of simultaneous and competing network processes. For example, our analysis showed that higher achieving students are not chosen more often for help requests because they are high achievers (one possible explanation for their higher connectedness in the network), but because they are more active initiating help requests themselves, in combination with a general tendency to reciprocate help requests and to direct them to students with similar achievement levels. The method allows disentangling whether it is similarity in achievement levels or a general tendency to prefer higher achieving peers as friends that creates an association between student's grades and their likelihood to receive friendship nominations. Also, the study shows how the effect of having a friendship on creating a helping relation can be separated from the reverse effect, where both effects could be a potential explanation for an observed correlation between friendship and study-related helping.

DISCUSSION AND CONCLUSION

Small group teaching can be considered as an institutional answer to facilitate the transition to university, where peer relations are essential when students enter university (Exley & Dennick, 2004). The question addressed in this chapter is: What is the added value of a longitudinal social network approach for small group research in higher education?

Social network analysis is a analysis method for getting insight into the social network structure and how it relates to actor attributes in different peer networks. With the development of approaches for modelling longitudinally collected social network data, research moved from merely describing network structures to modelling social network dynamics over time, including disentangling influence (e.g., friends influence study behaviour, beliefs or performance)

Table 1. Help-seeking and Friendship in Learning Communities: Parameter Estimates and Standard Errors (SE) of SIENA Models.

Effect[a]	Explanation[b]	Graphical Representation[c]	Help-seeking	Friendship
Rate period	The frequency of opportunities for changing connections		11.54* (1.98)	11.83 (1.80)
Endogenous effects				
Outdegree (density)	Outgoing nominations		−2.97* (0.32)	−2.80* (0.30)
Reciprocity	Mutual connection		2.76* (0.27)	2.78* (0.41)
Transitivity	'A friend of a friend is a friend'		0.65* (0.08)	0.55* (0.09)
Transitive reciprocated triplets	Interaction of transitivity and reciprocity		−0.44* (0.11)	−0.34* (0.09)
Indegree popularity	Individuals who are already popular (i.e., more incoming nominations) become even more popular		−0.03 (0.04)	−0.02 (0.03)
Outdegree activity	Individuals who are active in nominating others, become even more active		−0.01 (0.02)	0.04 (0.02)
Indegree activity	Individuals who are popular (i.e., many incoming nominations) are more active in nominating others.		−0.28* (0.08)	−0.26* (0.11)

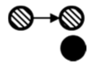
Exogenous effects				
Friendship			0.93* (0.22)	
Pref. collaboration			0.42 (0.22)	0.50* (0.19)
Help-seeking				0.33 (0.21)
Covariate effects				
Gender (F) alter	Females are nominated more often by others (Female = 1 (striated in the configuration); male =0)		−0.65* (0.20)	−0.22 (0.16)
Gender (F) ego	Females nominate others more often (initiate more connections).		0.09 (0.20)	−0.19 (0.14)
Same gender (F)	Connections between two individuals of same gender are more likely (homophily effect).		0.62* (0.13)	0.61* (0.14)
Achievement alter	The higher someone achieves, the more often he or she is nominated by others		0.13 (0.09)	−0.01 (0.07)
Achievement ego	The higher someone achieves, the more often he or she nominates others		0.41* (0.12)	0.34* (0.11)
Achievement similarity	It is more likely that connections exist between two similar achieving individuals (homophily).		2.10* (0.60)	2.14* (0.53)
Achievement higher			−0.25 (0.23)	−0.19 (0.20)
Self-efficacy alter			0.13 (0.42)	0.14 (0.36)
Self-efficacy ego			0.40 (0.41)	0.33 (0.34)
Self-efficacy similarity			0.04 (0.53)	−0.30 (0.49)

Table 1. (*Continued*)

Effect[a]	Explanation[b]	Graphical Representation[c]	Help-seeking	Friendship
Self-efficacy higher			0.02 (0.45)	0.03 (0.40)
Same FLC	It is more likely that connections exist between two students of the same learning community (homophily effect).		−0.34 (0.18)	−0.07 (0.15)
Achievement ego*same FLC			−0.02 (0.13)	−0.04 (0.10)

Note. We only explain the most important results (depicted in black) of the final models of help-seeking and friendship as an example (derived from Brouwer et al., 2018).
*$p \leq .05$; unrounded estimate value/ (SE) ≥ 2.
[a]Ego = sender (nominating others); alter = receiver (nominated by others).
[b]The explanations are valid for positive effects.
[c]Graphical configuration: grey indicates the present connection(s); black arrows represent the connection that likely arises.

from selection effects (e.g., individuals select each other as friends) (Snijders, 2001, 2009; Steglich et al., 2010; Veenstra & Steglich, 2012). With SABM it is possible to investigate a sample with a fixed boundary instead of investigating subsamples based on the presence or absence of influencing factors. This technique allows us to investigate groups where the assumption of independent observations is violated, because dependencies among actors are explicitly modelled. The advantages of these models are that unobserved changes between measurement points are modelled, while controlling for structural network effects and dependencies among observations. However, there are also limitations. The model assumptions are not always valid for how processes take place in reality. The assumption that actors decide about their relationships independently from each other implies that collective group phenomena cannot be modelled (see Veenstra & Steglich, 2012).

Although the statistical approaches were already developed a few decades ago as outlined in Snijders (2005), the application of these approaches is still rather limited in a small group teaching context in higher education. So far, the example we described in this chapter (Brouwer et al., 2018) is one of the few exceptions and, therefore, we want to encourage other researchers in the field to consider this approach. We argued that longitudinal social network analysis can contribute to a better understanding of the underlying mechanisms of peer networks during the transition period from secondary education to university, in particular selection and influence mechanisms in friendships and help-seeking networks. Our example illustrates the important added value of longitudinal social network analysis beyond individual perceptions of social belongingness. Analysis of longitudinal social network data provides insight into the structural positions of individual actors in a group, related to their personal characteristics or attributes (Wasserman & Faust, 1994). This approach is not only of importance for enhancing or hindering a smooth transition to the new university environment and thereby to first-year study success but can also be applied in other contexts. For example, how university teachers collaborate within professional learning communities over time, how institutional networks change over time and how this influences their performance, how educational managers are socially influenced in their decision-making over time and the role of changes in collaboration and feedback networks among employees in workplace learning.

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