Using Stochastic Actor-Oriented Models to Explain Collaboration Intentionality as a Prerequisite for Peer Feedback and Learning in Networks

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Jasperina Brouwer and Carlos A. de Matos Fernandes

5.1 Introduction

Rooted in social constructivism (Vygotsky, 1978), within the student-centered learning environments students actively co-construct their knowledge in interaction with their peers, which is crucial within learning practices for deep learning (Baeten et al., 2010; O'Donnell, 2006). Next to peer interaction, higher education students discuss the study material, undertake hands-on assignments and provide each other peer feedback. Although peer feedback is often related to assessment, it can also be considered a learning practice within student-centered learning environments (Boud et al., 2001). In the current chapter, we follow Dingyloudi and Strijbos (2018) who go beyond the assessment framework of feedback and task-specific feedback and consider peer feedback more broadly as a process of interpersonal communication contributing to students' learning and performance. Peer feedback is a way in which students share their knowledge, advice, information, and learning experiences. Importantly, peer feedback takes place within the social context of the small group learning environment (i.e., learning communities, see Brouwer et al., 2018, 2022) and is based on the sociocultural perspective

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implying that learning is a social rather than merely a cognitive phenomenon (Vygotsky, 1978). Thus, we define feedback broadly in terms of academic help and advice-seeking in peer networks.

Peer feedback happens among students who are similar in status and educational level (Finn & Garner, 2011) and provide each other with information related to their performance, also informally outside the classroom. The advantage of these informal forms of peer feedback is that it is a safe and convenient way to increase their ability to advance in higher education. Peers are considered as equals and when provided in a non-evaluative way, it is less likely that peer feedback decreases their self-esteem. Moreover, the feedback is often more immediate and timely than feedback provided by the course instructors or teachers (Laydshewsky, 2013). The fact that non-evaluative and informal peer feedback takes place outside the classroom means that students actively need to seek feedback from their peers. Aleven et al. (2003) identified different steps for approaching a peer when he or she needs feedback to get a better understanding of the study material. First, they need to be aware that they need academic support and feedback. Second, they need to know who is an advanced peer who can provide adequate feedback (Sangin et al., 2011). Third, they need to initiate contact and ask for feedback, academic help or advice. Fourth, the other is willing to provide timely and adequate feedback. Fifth, students collaborate, help each other, and provide each other with feedback.

An important means-to-an-end to facilitate feedback processes comprises network relations. That is, network relations are one of the most important sources of support, help, advice, or peer feedback when they are study partners in higher education (Brouwer et al., 2018, 2022; Stadtfeld et al., 2019). For learning, it is crucial that peers do not merely interact, but that students are willing to function as scaffolds by sharing their knowledge from different perspectives (Sangin et al., 2011). However, students seem to prefer to ask for academic support from their friends, who are, in turn, more or less similar to them in terms of background characteristics or attitudes (Brouwer et al., 2018). This is consistent with an important network selection mechanism (i.e., to initiate a network connection), which is the so-called homophily or similarity effect. Homophily, famously known as the social mechanism "birds of a feather flock together" (McPherson et al., 2001), represents the tendency to preferentially connect to similar others. Similarity can be based on individual features such as gender, ethnicity, or achievement (Lomi et al., 2011; McPherson et al., 2001; Stadtfeld et al., 2019), but also on attitudes (McPherson et al., 2001), such as the intention to collaborate and the willingness to provide feedback and support. Another strand of research posits that similarity in individual features is based on influence mechanisms (Snijders et al., 2010; Steglich et al., 2010), stressing that network relations are social conduits through which individuals influence each other to behave similarly. We explain the role of selection and influence mechanisms in what follows as well as in Fig. 5.1.

Peer collaboration intentionality is a selection mechanism that may play a role in feedback seeking. Collaboration intentionality (CI), which is students' willingness to collaborate, seems an important prerequisite for peer feedback. Research within the educational context shows that school principals' and teachers' network

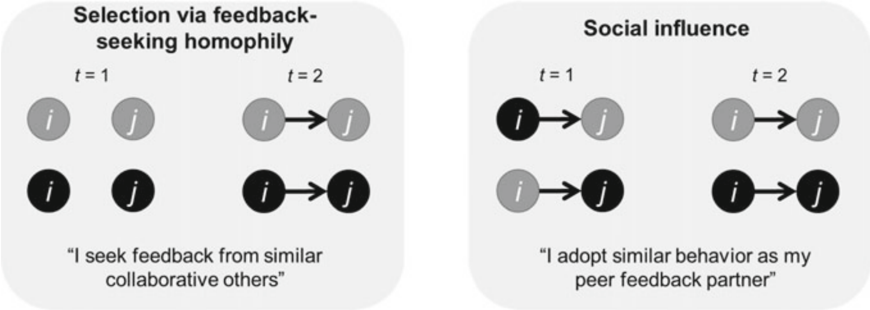


Fig. 5.1 A simple visualization between two individuals. Selection via homophily assumes that individual *i* preferentially nominate a similar other, *j*, for seeking feedback from (similarity is indicated via the color of the node), while influence assumes that a student adjusts his or her collaborative behavior (color of *i*) to behavior shown by peer feedback partners (*j*)

intentionality is associated with social capital formation. Network intentionality refers to the intention of someone to actively connect and interact with other network members (Coleman, 1990; Moolenaar et al., 2014). Van Waes et al. (2015) demonstrate that university teachers who are more *intentional*, actively seek advice and information from their colleagues about teaching. Someone has agency in actively initiating connections when this is of instrumental value, for example, for receiving ideas or feedback. Similarly, peer feedback can only take place within a collaborative learning approach and when students are willing to initiate feedback relationships with their peers (Er et al., 2021). In this respect, social exchange theory (Blau, 1964; Cook & Rise, 2003; Homans, 1961) helps us to understand why someone is willing to help a peer. The social exchange theory posits that someone is willing to do this when a valuable return is expected. Spitzmuller and Dyne (2013) distinguish reactive helping and proactive helping. The former means that others are supported because providing support is the social norm, whereas the latter is beneficial for the helpers contributing to their reputation and self-esteem. Students may also maintain a feedback relationship, for example, when a relationship is assumed to maintain mutually beneficial social exchange relationships (e.g., they obtain both higher grades).

Yet, to understand this complex link between peer feedback relationships and CI, we need to account for selection and influence mechanisms in feedback-seeking networks (Lomi et al., 2011; Snijders et al., 2010). *Selection* comprises whether students preferentially seek feedback from other fellow students because they have similar scores on CI. *Influence* means that students become more similar in CI over time when they provide each other feedback. Influence is an umbrella term for peer influence and social learning (e.g., Bandura, 1977; Steglich et al., 2010). Essentially, influence posits that network relations in place allow connected peers to influence one another in their collaboration, attitudes, opinions, and other behavioral topologies.

In this chapter, selection concerns that someone initiates to form a feedback relation, whereas influence is about the effect of feedback partners on one's CI. The feedback relation is either present (influence) or is under question whether it will be formed or not (selection). Influence and selection are social processes with opposite roles assigned to feedback-seeking relations and collaborative behavior, as indicated in Fig. 5.1. Influence affects CI. Selection, conversely, does not alter CI but only changes the network relation. The striking consequence of homophilous selection and social influence is that the outcome is the same: Connected peers tend to be similar on a certain individual feature (Fig. 5.1).

Not only peer feedback relations may be important for CI, but also gender and personality characteristics play a key role in collaboration and feedback processes (see Noroozi et al., 2020, 2022). Some research, for instance, shows that females tend to express more prosociality than males (Höglinger & Wehrli, 2017) and that this tendency for prosociality is stable over time (de Matos Fernandes et al., 2022). The Five-Factor Model (FFM) of personality consists of a taxonomy of five self-reported traits (McCrae & John, 1992): extraversion (being extravert rather than reserved), agreeableness (altruistic or oriented to cooperate rather than being selfish), openness to new experiences (rather than keeping conventions), conscientiousness (being self-organized rather than disorganized), and neuroticism (being anxious rather than calm). Previous work shows that FFM personality traits, particularly extraversion, agreeableness, and openness, positively affect seeking help or feedback from peers in higher education (Atik & Yalçin, 2011). Moreover, someone who has higher scores on agreeableness seems to be more intended to collaborate (Thielmann et al., 2020). In the current chapter, the main focus is on CI in peer feedback networks, while we control for gender and personality traits.

The interdependence of the social network data and of selection and influence urges researchers to employ a complementary statistical method, namely stochastic actor-orientated models (SAOMs) (Snijders, 2017; Steglich et al., 2010) to dissect underlying mechanisms that give rise to CI—or other individual attributes, such as gender or personality traits—similarity among peers. This approach is necessary because it remains otherwise unclear why students become similar in terms of CI within the feedback network over time. Influence and selection are competing mechanisms but SAOMs allow disentangling one from the other (and vice versa). We introduce this method in our chapter and provide an example using longitudinal feedback-seeking network data of 95 first-year students in higher education.

Although peer feedback takes place within peer networks, to our knowledge, it has been rarely investigated from a network perspective. One of the few examples is Dingyloudi and Strijbos (2018) who investigated peer feedback within learning communities. We want to go beyond Dingyloudi and Strijbos' work by applying the advanced SAOM method to disentangle selection from influence within peer feedback networks regarding CI. These peer networks are collected at two-time points and considered longitudinally in these models (Ripley et al., 2021). Analysis of longitudinally collected social network data informs us about the changes in the relationships and behavior simultaneously (i.e., the network dynamics) and by doing so, the underlying mechanisms of relationship formation within the learning context. This is the so-called co-evolution modeling and allows us to investigate how social networks and attributes, such as characteristics, behavior, or attitudes change over time (Kalish, 2020; Snijders et al., 2010). In this chapter, we will address the following research question: To what extent does homophily of CI plays a role in selecting peers for feedback (selection), and to what extent do peer feedback relationships influence CI (i.e., social influence of CI)? We investigate the co-evolution of peer feedback-seeking network data (i.e., study-related advice or help-seeking) and CI, which is an individual attribute or in SOAM terms a "behavior" variable. We control for the impact of gender, personality traits, and whether feedback providers are friends. SAOM will be further explained in the next section.

The outline of our chapter is as follows. First, we introduce stochastic actor-oriented models and provide examples of the method. Second, we illustrate how this method can be applied to investigate CI within peer feedback networks. Overall, we introduce a new way to investigate peer feedback within longitudinal social network designs, which provides us a better understanding of how students select each other in terms of CI when seeking feedback and to what extent social influence from feedback seeking plays a role regarding CI? By doing so, we can address research questions about social network dynamics and get a better understanding of social mechanisms, such as social selection (e.g., homophily) and social influence. More specifically, do students ask for feedback from a peer who is similar in terms of the intentionality to collaborate, or do students become similar over time in terms of the intentionality to collaborate when they ask each other for feedback?

5.2 Introducing Stochastic Actor-Oriented Models

Stochastic actor-oriented models (SAOMs) represent an important methodological breakthrough in modeling the interdependence of networks and behavior. What do the following terms mean, such as 'stochastic', 'actor-oriented', and 'models'? SAOMs are *stochastic* given that they model changes in network and behavior via an individual decision-making model; SAOMs are *actor-oriented* given that students (i.e., actors) are the locus of modeling (oriented), instead of networks or groups of people. It is assumed that network and behavior changes are due to students' decisions; SAOMs are *models* because the simulation procedure ensures that we control for all possible interdependent network and behavior states between both waves (Kalish, 2020; Snijders, 2017; Snijders et al., 2010; Steglich et al., 2010). The term *behavior* is an umbrella term for individual attributes such as attitudes, opinions, grades, CI, smoking, drinking, bullying, and many more individual characteristics that change over time. *Networks* refer to friendship networks but they also comprise peer feedback-seeking networks, online social networks, acquaintance networks, positive or negative interactions in a network context, workplace networks, and many more other situations in which individuals are linked to one another in a network. Using SAOMs, we can test how behavior and the network co-evolve from one point in time to another. The role of feedback is thus not only assessed theoretically, but it is also an inherent part of the SAOM approach. Namely, SAOMs operate in a feedback loop: behavior affects the network, whereas networks affect changes in behavior. A change in CI spills over to the feedback network, and a change in the network affects CI.

What kind of data do we need for SAOMs? SAOMs enable exploring interdependent longitudinal network and behavioral data (see Steglich et al., 2010), which permits researchers to link antecedents to the consequence of peer feedback-seeking network and CI change. To do so, the data requirements of SAOMs comprise complete (socio-centric) network and behavioral data (i.e., individual attributes) from at least two-time points to estimate co-evolution (Steglich et al., 2010; Veenstra & Steglich, 2012). Complete network data refer to whole networks with a specified boundary, e.g., within a school class, which may vary from 20 to 400 individuals (Niezink, 2018). The advantage of, for example, nominating students within one school class is that it informs us also about non-selection. Not selecting someone as a network partner is a requirement to understand selection (Steglich et al., 2010; Veenstra & Steglich, 2012). To know whether similarity in behavior (i.e., homophily) plays a role in selecting someone as a friend, we need to be informed about whether students who select each other are similar in terms of behavior and when students who do not select each other differ in terms of behavior.

How does the modeling take place within SAOM in the background? Changes in the network and behavior between waves are simulated via mini-steps. Mini-steps follow the actor-oriented paradigm that changes in the network or behavior are driven by individual choices (Ripley et al., 2021; Snijders, 2005; Snijders et al., 2010). In other words, each actor (i.e., individual or student) can make one change in his/her network connection or one change in the behavior variable (here CI) in each step. These steps are simulated based on longitudinal data and then estimated with a probability function based on changes in-between measured data waves. Thus, SAOMs build on the inherent assumption that students have a say over with whom they form network ties and in what way they change the initiative towards collaborative behavior (CI). Within the so-called mini-steps simulation procedure, an actor can decide in each step to form, dissolve, or maintain a network relation or report a higher or lower value on the behavior variable (see Fig. 5.2). A so-called mini-step thus captures a change in network relationships and a behavior change.

How many mini-steps—or, i.e., changes—students can take is modeled via the *rate function*, while which mini-step to take is determined by the *objective function.* The rate function provides a numerical value of how many changes a student can make in network relations or CI. Conversely, the objective function shows how attractive a network state or change in behavior for a student is, thereby controlling for various structural network (e.g., reciprocity, transitivity) parameters. 'Attractiveness' comprises, for example, whether it is attractive to change behavior to 6 instead of 4 (Fig. 5.2). Alternatively, in the network context: whether forming or maintaining no relation (for the blue actor in Fig. 5.2) is more attractive than

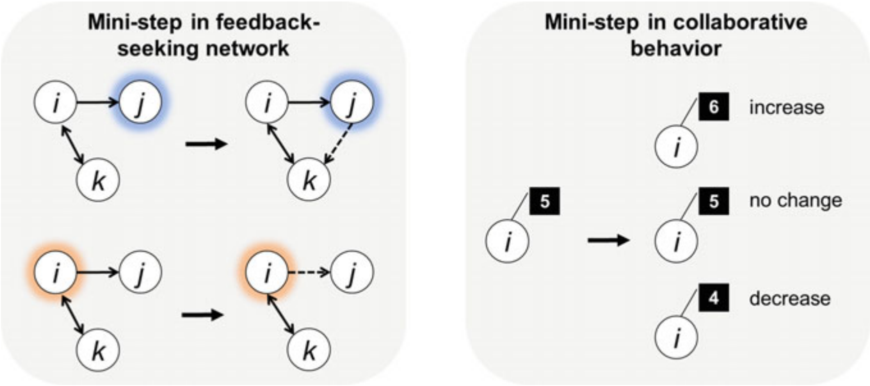


Fig. 5.2 Examples of so-called mini-steps in network selection and behavioral changes. On the left, one actor in blue (top) or orange (bottom) has the opportunity to change one network relationship (dashed arrow). A feedback-seeking relationship may be formed or remain absent for the blue actor, or a feedback-seeking tie may be dissolved or remain to be present for the orange actor. On the right, we see that collaboration scores (in this case 5) may go up, down, or an actor keeps the current score

the other network option (Snijders, 2001, 2005). In other words, the rate function explains the *frequency* of changes are made in the network (i.e., which actor makes a change in either the network relationship or the behavior). The rate function is a single number specifying the number of possible changes each one can make in behavior or the network. Conversely, the objective function determines *which* changes can be made based on the model specification. A model specification within the objective function is based on theory and the related hypotheses, mirroring model specification in more conventional regression analysis, such as logistic or linear regression.

The models are assessed in *R*—a free software system for statistical and graphical computing—using Simulation Investigation for Empirical Network Analysis (*RSiena*) (Ripley et al., 2021). *RSiena* estimates the coevolution of behavior and networks via stochastic actor-oriented models (Snijders et al., 2010). Next to the help function in *R*, potential effects, possibilities, and both in-depth and general information on *RSiena* are available in the free available online manual, written by Ripley et al. (2021). Example *R*-scripts and datasets and more information on the methodology are available on the *RSiena* homepage of Tom Snijders (one of the main developers of *Rsiena*), accessible via the following URLs: https://www.stats.ox.ac.uk/~snijders/siena/ or https://github.com/snlab-nl/rsiena. One can, for instance, find more information concerning the practical side of preparing the dataset, how to run the models in *R*, and other practicalities.

What are the steps a researcher should take when employing a SAOM using *RSiena* can be done via the following four steps (see also Kalish, 2020)?

1. The first step is to prepare the data accordingly to fit the *RSiena* framework. This requires that network data is dichotomized; that is, a feedback nomination is present (1) or not (0). The network data is fitted into an n by n matrix, where n stands for all the students in the network. A network data frame consists of 0's and 1's. A '1' represents a network relation with someone else, whereas a '0' is no network relation. Behavior, or individual characteristics, are included as a common dataset in which rows represent individuals and columns are the variables. Other individual-level data, such as gender, are included as an *RSiena* covariate

For example, we have feedback-seeking network data for waves 1 ($t = 1$) and 2 ($t = 2$). The t is a time point or wave. Longitudinal network and behavioral data (attributes) are separately imported in *RSiena* and in such a way that *RSiena* considers them the dependent variable when modeling selection (dependent variable = feedback network) or influence (dependent variable = collaborative intentionality).

2. The second step is to include effects in the network (selection) and behavioral change (influence) model. Luckily, *RSiena* provides modelers with a documentation file specifically applicable to the dataset at hand. Thus, based on the variables included in the previous step, *RSiena* provides a long list of potential effects to include in the selection and influence function. Some effects are commonly included; think of reciprocity, transitivity, and outdegree (Ripley et al., 2021). Other effects are included based on theoretical considerations. For example, one may include homophily effect regarding an attribute (e.g., CI).
3. The third step is estimating the SAOM using a simulation algorithm specified in *R*. We run the SAOM in *RSiena*, which eventually leads to the results in which selection and influence model-based findings are separated in the output.
4. The final step is to interpret the effects. An estimate can be either positive or negative. The interpretation is similar to the interpretation of a logit/log-odds estimate which can be re-calculated as an odds ratio via measuring the exponential function of the SAOM effect (i.e., e^{x}; with x as the SAOM effect). This means that the estimates can be considered as the likelihood that a connection will be formed or the behavior will be changed. In addition to the estimate of the rate functions (how many changes are made in the network or behavior), an effect in the objective function can be, for example, whether students similar in CI or gender preferentially are more likely to seek feedback from similar others. Such an effect is represented by a positive significant estimate. A negative parameter in the objective function may state, for example, whether reciprocity is unlikely over time in a feedback network or that men are less popular than women in the network. Results from the objective function are usually utilized to test hypotheses. The estimates are divided by the standard error to inspect significance. This is similar to significance testing as in logistic regression. The rate and objective function of both selection and influence operate simultaneously to model coevolution of network or behavior changes respectively (see

Ripley et al., 2021; Snijders, 2001, 2005). We will illustrate the interpretation of the effects in the next sections.

5.3 Illustration of Peer Feedback in Higher Education

We illustrate this method with a longitudinal study conducted in one bachelor's program in higher education among first-year students. We analyze data obtained from 95 first-year sociology students from a large university in the Netherlands. The complete data sample comprises 56 females (64%) and 32 males (36%) with a mean age of 19.5 years old (SD = 1.6). Students answered a 20–30 min computer-based questionnaire across two waves in an academic year (see Brouwer et al., 2018). The current dataset comprises variables on feedback-seeking relations, CI, gender, and personality traits. Wave 1 is often referred to as $t = 1$, and wave 2 is often noted as $t = 2$.

5.3.1 Variables

Peer feedback network. Students could nominate all members in their cohort, i.e., their academic year group, for feedback-seeking in terms of academic help or advice-seeking via a free-recall method. When a respondent started typing, the program automatically provided the respondent with potential names that correspond to the typed text. This eased the network nomination process. Students were allowed to indicate whom they asked for feedback when they do not understand the study material. In other words, students nominated others who they seek for feedback, help, support, or assistance in the academic environment. Students rated per fellow student on a 5-point Likert scale to what extent they agree that they would seek feedback from a certain fellow student (1 = strongly disagree to 5 = strongly agree). To analyze the peer feedback network using *RSiena*, it is necessary to dichotomize feedback nominations. Scores 4 and 5 result in a 1, while other scores resulted in a 0. There are 495 peer feedback nominations at $t = 1$ and 349 at $t = 2$. Using the Hamming statistics (Ripley et al., 2021), we infer 394 changes in feedback nominations between $t = 1$ and $t = 2$. A network generally changes slowly since too much instability and fluctuations pressure the reliability of the *RSiena* analysis (Ripley et al., 2021). The Jaccard index measures changes in tie presence between two waves. A Jaccard index value below 0.30 is deemed unfit for network analysis given too many unstable network relations (Snijders et al., 2010). In this feedback-seeking network, the Jaccard similarity index of 0.36 shows that there is sufficiently high enough stability in peer feedback nominations between both waves. The feedback network is visualized per wave in Fig. 5.3.

Collaboration intentionality (CI). It is difficult to reliably capture collaboration behavior, that is why we asked peers to indicate if they deem others in their year

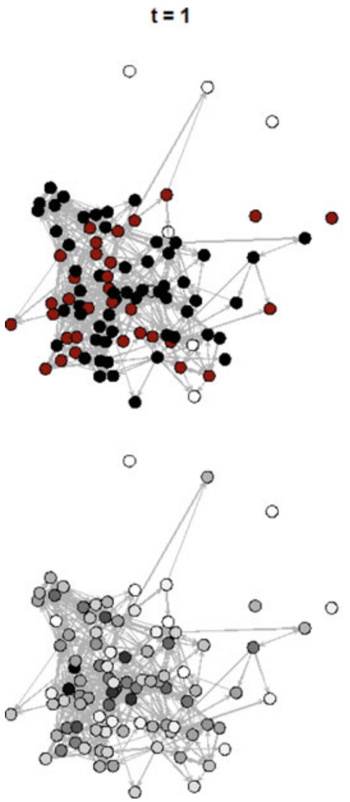


Fig. 5.3 The feedback network is visualized at $t = 1$ and $t = 2$. In the upper row, red nodes are males and black nodes are females (white is missing). The lower two networks show CI as the color of the nodes. The darker the node, the higher one CI score is. Black is score 16, while white is the lowest CI score possible (0)

group collaborative or not. Collaboration intentionality is measured by asking students to nominate others who they deem collaborative. If one is perceived as more collaborative, a student has a higher score. A more collaborative student is then more "popular" as a collaborator. The range of CI is 0–16. A score of 0 represents that a student is never mentioned as a collaborator and a score of 16 means that someone is 16 times nominated. The mean at $t = 1$ is 6.14 (SD = 3.43) and at $t = 2$ it is 5.43 (SD = 3.94). The high standard deviations indicate that there is some variation in CI among students. A combination of the feedback network and CI is presented in the lower row of Fig. 5.3. There is some change in CI scores over time. CI thus captures how collaborative one is via popularity. We assume that a more collaborative student is more popular (i.e., more often nominated as a collaborator).

Gender. Our sample comprises males (0) and females (1). Previous research using SAOMs showed that gender plays an important role in friendship network selection (e.g., Brouwer et al., 2018). A visualization of gender and the feedback network at $t = 1$ and $t = 2$ is provided in the upper row in Fig. 5.3.

Five-Factor Model personality traits. The Five-Factor Model (FFM) measures five personality traits: agreeableness, extraversion, neuroticism, openness, and conscientiousness (McCrae & John, 1992). We relied on the Ten-Item Personality Inventory (Gosling et al., 2003) to assess the five latent traits. The following 10 items are distributed among the students: (1) 'I take time for a talk', (2) 'I try to avoid conflicts', (3) 'I work in a structured manner', (4) 'I am easily enthusiastic', (5) 'I am open to new experiences', (6) 'I ignore adversity quickly', (7) 'I see myself as someone who is generally trusting', (8) 'I can handle stress well', (9) 'I am interested in art', and 10) 'I am self-disciplined'. Students indicated if the statement applies to them on a 5-point Likert scale, ranging from 1 (very inappropriate) to 5 (very appropriate). Extraversion comprises the average of items 1 and 4 ($M = 3.84$, SD = 0.70), agreeableness items 2 and 7 ($M = 4.14$, SD = 0.59), conscientiousness items 3 and 10 ($M = 3.11$, SD = 0.95), neuroticism items 6 and 8 ($M = 3.14$, SD = 0.78), and openness to new experiences items 5 and 9 ($M = 3.56$, SD = 0.77).

5.3.2 Specifying Effects to Be Included in the SAOM

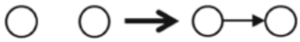
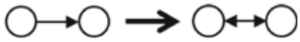
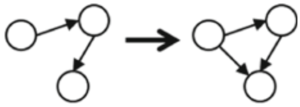
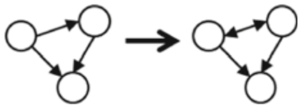
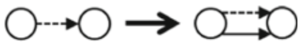
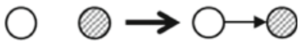
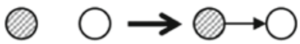
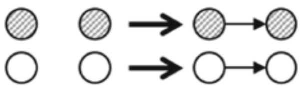
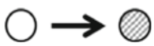
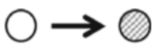
In *RSiena*, the researcher specifies—similar to more conventional regression analysis—the effects included based on theoretical considerations. We describe each included effect in detail and offer an example graphical interpretation of the included effect. We first describe SAOM effects included in the selection model and then discuss the influence model. Table 5.1 provides an explanation and an visualization of the included effects in the model.

5.3.3 *RSiena* Findings

This statistical method allows us to ask the following research question: To what extent does homophily of CI plays a role in selecting peers for feedback (selection), and to what extent do peer feedback relationships influence CI (i.e., social influence of CI)? However, stochastic actor-oriented models permit researchers to control for other factors that may affect the network-CI link: What is the role of gender and Five-Factor Model personality traits in feedback-seeking selection processes and how do these individual features influence individual changes in CI? The findings of the stochastic actor-oriented selection and influence model are presented in Table 5.2. A positive estimate represents that such a state is pursued ('it is more likely that..'), while a negative parameter indicates that such a state tends to be avoided by students if the opportunity comes to alter a feedback-seeking nomination or changes in CI ('it is less likely that…').

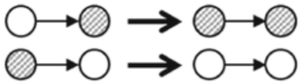
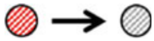
We first start with the selection model presented in Table 5.2 which investigates potential sources of why students seek certain students out for feedback and

Table 5.1 Effects included in the selection and influence SAOMs

Effect ("*RSiena* label")	Description	Simplified visualization
Selection SAOM		
1. Rate ("*rate*")	Rate indicates how many changes students make in their feedback nominations	
2. Outdegree ("*density*")	This effect models the tendency to form feedback relations	
3. Reciprocity ("*recip*")	The tendency towards reciprocal feedback relations	
4. Transitivity ("*transTrip*")	Modeling the tendency to have transitive relations	
5. Interaction reciprocity and transitivity ("*transRecTrip*")	This effect accounts for reciprocity in transitive structures	
6. Friendship ("*X*")	Effect of having a friendship relation (dashed line) on feedback relations	
7. Attribute popularity ("*altX*")	Whether attributes determine feedback popularity (receiving nominations)	
8. Attribute activity ("*egoX*")	Whether attributes determine feedback activity (sending out nominations)	
9. Attribute similarity ("*simX*")	The tendency for similar students to form feedback relations	
Influence SAOM		
10. Rate ("*rate*")	Rate indicates how many changes students make in their CI	
11. Linear shape ("*linear*")	This shape effect captures linear patterns in CI (positive or negative)	
12. Quadratic shape ("*quad*")	Accounting for non-linear distributions of CI	

(continued)

Table 5.1 (continued)

Effect ("*RSiena* label")	Description	Simplified visualization
13. Social influence ("*avSim*")	Adopting a CI similar to the average CI of feedback partners	
14. The effect from attribute ("*effFrom*")	Modeling the effect of an attribute (red) on changes in CI	

Note Attribute refers to an individual feature not related to the network, such as gender, CI, or Five-Factor Model personality traits. Instead of *simX*, we implement *sameX* for categorical variables (gender)

academic support. The dependent variable in the selection model is the feedback seeking network. The rate effect in the rate function shows that students had more than 12 opportunities to alter their feedback-seeking nominations. We are particularly interested in which feature affected feedback-seeking nominations, and we turn to the objective function in the selection model for answers. Students, on the whole, tend to have fewer nominations over time, per the negative outdegree parameter in Table 5.2. We furthermore find that students prefer reciprocated to non-reciprocated relations ('if you seek feedback from me, then I'm more likely to return the favor') and that students are more likely to be embedded in transitive structures ('if I seek feedback from student A and A seeks feedback from student B, then I'm more likely seek feedback from student B'), per the positive and significant reciprocity and transitivity effect in Table 5.2. Yet, the interaction term between reciprocity and transitivity indicates that a reciprocal feedback-seeking relationship is less likely when a student is embedded in a transitive triplet. There are thus multiple social sources for peers to form feedback relations with one another.

Feedback relations are an important source to receive help, support, and feedback from peers. To achieve this, feedback network relations may be utilized to seek others out who most readily can provide qualitative feedback to one another. Notably, we find that students preferentially seek feedback from other students with similar CI scores (estimate = 0.80, SE = 0.36, $p = 0.027$). As such, it is more likely that students seek feedback from students with similar collaboration tendencies.

Yet, CI is not the only defining feature for feedback-seeking selection; that is, gender, friendships, and personality significantly affect underlying features why some students are more likely to be nominated to seek feedback from than others, which in turn may explain why some are more able to provide feedback and receive support than others. Table 5.2 shows that females are less popular (estimate = –0.57, SE = 0.16, $p < 0.001$) for feedback-seeking nominations than their male counterparts. Even so, female-female and male-male feedback relations are more likely than cross-gender relations (estimate = 0.57, SE = 0.15, $p < 0.001$). Thus, similarity in gender is a prerequisite for seeking feedback from one another. Next,

Table 5.2 SAOM findings of *feedback-seeking* selection and influence of *feedback-seekers* on collaboration intentionality (CI), separated by rate and objective function*

Selection model (dep. var. = feedback-seeking nomination)			Influence model (dep. var. = CI)		
Parameter	Est. (SE)	*p*	Parameter	Est. (SE)	*p*
Rate function					
Rate effect	12.57 (1.49)	< 0.001	Rate effect	17.87 (4.29)	< 0.001
Objective function					
Feedback-seeking effects			Effects on CI change		
Outdegree (density)	–3.65 (0.19)	< 0.001	Linear shape	–0.19 (0.06)	0.002
Reciprocity	2.48 (0.25)	< 0.001	Quadratic shape	0.03 (0.01)	0.031
Transitivity	0.54 (0.06)	< 0.001	Influence of peers' CI scores on own CI	7.55 (2.50)	0.003
Reciprocity x transitivity	–0.43 (0.09)	< 0.001	Extraversion	–0.15 (0.08)	0.047
Friendship nominations	0.75 (0.16)	< 0.001			
CI similarity	0.80 (0.36)	0.027			
Gender (1 = female)					
Popularity	–0.57 (0.16)	< 0.001			
Similarity	0.57 (0.15)	< 0.001			
Five-Factor Model traits					
Openness popularity	0.31 (0.10)	0.001			
Openness similarity	0.63 (0.30)	0.033			

Note CI = collaboration intentionality; dep. var. = dependent variable; nom. = nomination; Est. = log-odds estimate; SE = standard error; ref. = reference category; Overall maximum convergence ratio = 0.21, which is below the critical value of good model convergence of 0.25 (Ripley et al., 2021)

*We only show marginally significant effects, meaning $p < 0.10$, to keep table as simple and interpretable as possible

having friendship relationships makes it more likely to seek feedback from one another (estimate = 0.75, SE = 0.16, $p < 0.001$). Relatedly, students higher in openness are perceived as more attractive to seeking feedback, and thus are more likely to receive feedback nominations, than students low in openness (estimate = 0.31, SE = 0.10, $p = 0.001$). Being open to new experiences and willing to try new things are considered attractive features for feedback popularity. Moreover, students similar on openness are more likely to seek feedback from each other than students dissimilar in openness are (estimate = 0.63, SE = 0.30, p = 0.033). These findings suggest that students, who are more willing to embrace new things in higher education, and postulate more readily fresh ideas are also more inclined to select partners for feedback who display similar care for openness.

The influence model, conversely, allows studying whether it is more likely that students become more similar to their feedback partners in CI. Students had in total approximately 18 opportunities to change collaborative intentionality in-between the two waves. We find in the objective function that students tend to have lower scores on CI over time, per the negative linear shape effect (estimate = – 0.19, SE = 0.06, p = 0.002). This effect suggests that there is a linear downward trend in CI. The positive quadratic shape effect stresses that the negative trend is less step for students with higher values on CI (estimate = 0.03, SE = 0.01, p = 0.031).

More importantly, the influence model in Table 5.2 suggests that changes in CI are also driven by social influence (estimate = 7.55, SE = 2.50, p = 0.003). This shows that a student who is nominated to seek feedback from is more likely to adopt a similar value of CI as their peers. Yet, this effect may also exacerbate the problem for non-collaborative students. Namely, students with lower levels of CI tend to have feedback relationships with similar others, and if influence processes are dominant then they may influence each other to take an even lesser collaborative stance. Furthermore, we find that extraversion lowers changes in CI (estimate = – 0.15, SE = 0.08, p = 0.047), meaning that students high on extraversion report lower scores of CI over time.

5.4 Discussion and Outlook

Combining insights from selection and influence, we show that students who are similar in their intention to collaborate are more likely to request each other for feedback. Our network approach elucidates, furthermore, that students are more likely to seek feedback from friends, from students with the same gender, and students who are also open to new experiences. The same-gender effect and similarity in CI is consistent with the homophily principle in selecting peers for feedback (c.f., McPherson et al., 2001).

The novelty of this chapter and the advantage of using stochastic actor-oriented models (SAOMs) is that it allows to unravel social influence from the selection of peers—and vice versa—in feedback-seeking networks. Selection and influence mechanisms are dependent on each other. The major advantage of SAOMs is disentangling influence from selection in a statistically valid way. In our contribution, we show that SAOMs allow us to study the complex interdependence between behavior and network relations. Our methodology builds on an innate feedback loop from selection to influence and influence to selection. In our analysis, we provided a template to analyze and describe selection and influence effects using SAOMs.

Another advantage is that this chapter provides a short introduction to SAOMs but provides, by all means, *not* a full overview of what is possible with SAOMs. If interested, the following references show different applications of SAOMs, providing researchers with more features, possibilities, and information than described here: Snijders (2017), Kalish (2020), Snijders et al. (2010), Steglich et al. (2010), Henneberger et al. (2021), Ripley et al. (2021), Brouwer et al. (2020, 2022), or Veenstra et al. (2013). Here, we illustrated that behavior and networks are two fitting pieces in a puzzle when appropriate statistical methods are utilized. This chapter provides more understanding of the mechanisms underlying peer feedback—utilizing the power that feedback networks provide and SAOMs to monitor selection and influence processes—to advance in higher education.

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