Finding Collaboration Partners in a Scientific Community: The Role of Cognitive Group Awareness, Career Level, and Disciplinary Background Collaboration and integration of newcomers in scientific communities

Julia Eberle, Karsten Stegmann, Frank Fischer, Alain Barrat, Kristine Lund

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Julia Eberle, Ruhr-Universität Bochum, julia.eberle@rub.de
Karsten Stegmann, Ludwig-Maximilians University Munich, karsten.stegmann@psy.lmu.de
Frank Fischer, Ludwig-Maximilians-University Munich, frank.fischer@psy.lmu.de
Alain Barrat, Aix Marseille Univ, Université de Toulon, CNRS, CPT, alain.barrat@cpt.univ-mrs.fr
Kristine Lund, ICAR, CNRS, Ecole Normale Supérieure Lyon, Université de Lyon, kristine.lund@ens-lyon.fr

Abstract: Integrating newcomers and fostering collaboration between researchers with different disciplinary backgrounds is a challenge for scientific communities. Prior research suggests that both network-driven selection patterns (reciprocity and transitivity) and the active selection of specific others are important. Selecting appropriate collaboration partners may moreover require what we call cognitive group awareness, (i.e. knowledge about the knowledge of others). In a field study at two multi-disciplinary scientific events (Alpine Rendez-Vous 2011 and 2013) including N=287 researchers, we investigated selection patterns, looking specifically at career level and disciplinary background, and included a cognitive group awareness intervention. While we could not completely explain how researchers choose with whom they interact, we found that transitivity and interaction duration are relevant for later collaboration. Cognitive group awareness support was beneficial for fostering interdisciplinary collaboration. Career level was a less relevant factor. We discuss measures for supporting newcomer integration and community buildings based on our findings.

Collaboration and integration of newcomers in scientific communities

Communities must constantly integrate new members to stay active and to further develop and cope with changing demands. Scientific communities can be considered to be a special form of communities of practice (Kienle & Wessner, 2006). According to Kienle and Wessner (2005), scientific communities consist of heterogeneous, often interdisciplinary groups of members who are usually geographically distributed. Members of scientific communities also sometimes have backgrounds in different disciplines and scientific cultures, resulting in the use of different methods and theories. What brings them together is a joint field of research interests. Therefore, scientific communities benefit from the integration of new members and their knowledge and ideas. In interdisciplinary scientific communities in particular, successful collaboration among the community members is another important factor for community cohesion and development. Successful interdisciplinary collaboration in a scientific community requires an integration of the contributing disciplines on some level, for example the mutual integration of concepts, theories, methodologies, and epistemological principles (van den Besselaar & Heimeriks, 2001). The development of mutual understanding and the building of shared representations are important for fruitful communication between experts of multiple domains (Fischer, 2000).

Yet many scientific communities struggle in integrating newcomers and developing interdisciplinary collaborations (see for example Kienle & Wessner, 2006, about challenges of the CSCL community) and it is unclear how to improve the situation. The huge body of research on scientific communities is so far mostly based on bibliometric analyses focusing on co-authorship or citation analysis of conference proceedings or journal papers (e.g. Lee, Ye, & Recker, 2012). The publication of articles is affected by many factors and bibliometric analyses so far were not able to identify factors that influence the integration of newcomers. Rather than looking at the results of successful collaborations (i.e. joint publications or references to each other's work), it seems necessary to study the onset of collaborations where newcomers have a chance to be included. Face-to-face meetings in conferences and workshops may provide regular opportunities for newcomers to start collaborations and thereby to become integrated into the scientific community (Kienle & Wessner, 2005).

Potential selection patterns and influential factors on selection processes in scientific communities

To understand the behavior of researchers at scientific events, we should take into account that human interaction in face-to-face settings is based on several robust characteristics (e.g. physical and digital proximity, social support, and community belonging) although there are differences based on the context in which interaction takes place (Isella et al., 2011). Research on interactional linguistics clearly illustrates how human interaction is co-constructed by phenomena such as gaze, prosody of language, gestures and general body movement (e.g. Goodwin, 2000) and this co-construction is viewed by many as a collaboration at the micro-level of communication; it is where any long-term collaboration begins.

Sociological and social network research suggests, furthermore, that the selection of partners for long-term relationships follows several patterns. Selection patterns have been studied in various contexts and the literature provides a variety of observed patterns. Some selection patterns are based on the opportunities provided by the given social network structure surrounding the selecting person, while others focus on personal preferences for specific persons. Reciprocity and transitivity as network-driven patterns and homophily as a person-driven pattern can be described as the three most important selection patterns (Baerveldt, van de Bunt, & de Federico de la Rua, 2010). We will briefly describe them and discuss how they may be relevant for selection processes in scientific communities. Note that network-driven patterns and homophily effects are not mutually exclusive but can co-exist (Aiello, Barrat, Cattuto, Ruffo, & Schifanella).

Reciprocity and transitivity

Network-driven selection patterns assume that the way in which persons choose relations is influenced by the (local) structure of their social network, and in particular that the alters chosen to establish a relation are preferentially chosen among those easily accessible in this network. Reciprocity is one of the simplest such selection patterns: If there is already a connection between two individuals, in which person A has chosen person B, for example as a friend or as someone to ask for advice, while person B does not yet perceive person A likewise, it is very likely that they will balance their relationship in the future. This can either mean that person B also chooses person A or that their relation will dissolve so that reciprocity is reached.

Transitivity is also a selection pattern driven by proximity in the network: Two individuals (A and B) who both are connected to a third person (C) are likely to build a relation as well. In social network terms, they are building a "transitive triple" or "closing a triangle". Reasons for such transitivity patterns are manifold, e.g., person C can easily introduce A and B or A and B may share a common interest or activity which was the initial reason for their connection with C. C might also be interested in setting up a connection between A and B to stabilize the relation to both (Baerveldt et al., 2010).

Selecting specific others

Social capital theory is one of the major approaches that explains person-driven selection patterns (Baerveldt et al., 2010). According to social capital theory (Coleman, 1988; Lin, 2001), people rationally select to engage with others either to maintain their own resources or to get access to resources of others. In the context of a scientific community, a vital resource accessible through social capital is, for instance, information about new developments in the field (Coleman, 1988).

The selection patterns for specific others can be categorized as homophilous or heterophilous. Homophily is a well observed, and probably the oldest and widest studied selection pattern (Baerveldt et al., 2010). Homophily is the tendency of people to be in contact with others who are similar to them (McPherson, Smith-Lovin, & Cook, 2001). Similarity/dissimilarity patterns influencing the selection of contact partners have been studied in regard to very different aspects, such as gender, religion, age, education, occupation and social class, behavior, attitudes, beliefs, abilities and aspirations (McPherson et al., 2001).

According to social capital theory, the selection of specific others is based on the maintenance or gain of resources. Maintaining resources is assumed to be the more dominant motive and leads to expressive actions towards others, meaning that people approach others to claim recognition for their resources or aim at receiving sentiments related to the maintenance of these resources (Lin, 2001). In a scientific community, such actions could include statements to gain recognition for one's own expertise on a topic or sharing feelings about the complicated nature of a certain type of data collection. Such expressive actions require the least effort and bear the lowest risks among peers with similar resources and status, explaining why homophilous selections of interaction partners are most common (Lin, 2001). Researchers from other theoretical perspectives have also provided explanations for the generally observed tendency for homophilous selection patterns, e.g. from a reinforcement perspective, similar others may be more likely to reinforce behavior they show themselves and persons who reward us are preferred (Byrne & Clore, 1970.

Information about others

Perceiving others as similar or dissimilar is likely to be influenced by which information about them is accessible. Some information is usually easily visible, such as gender or ethnicity, while other information is invisible and harder to access (Baerveldt et al., 2010). Invisible information, such as expertise and knowledge of a person, are especially relevant for collaboration and collaborative learning (Cannon-Bowers & Salas, 2001; Wegner, 1987) as they can, for example, simplify grounding processes.

To select appropriate collaboration partners and interact meaningfully with them, knowledge about their knowledge seems to be necessary, i.e. it may require cognitive group awareness (Janssen & Bodemer, 2013). To select collaboration partners in a scientific community, relevant information about other researchers may include their area of expertise, research interest, and knowledge (their personal resources), as well as their professional network and access to other experts (their social resources) (Lin, 2001).

Newcomers usually have only little knowledge about a new community and need to acquire it to become able to contribute more and in a proper way (Levine & Moreland, 2013). Compared to mono-disciplinary communities, this might be even more complicated in multi- and interdisciplinary communities because of the variety of research lines. Although knowledge about researchers seems easy to acquire as most of them present their bios and publications on their websites, it is probably hard for a newcomer to identify the 'important' people in a community or those who could be relevant for their own research in face-to-face settings. In friendship networks, students with little information about their peers are assumed to be less active in initiating new friendships. They seem also more likely to use rather passive selection strategies, such as transitivity (forming new friendships with friends of their friends), instead of initiating new friendships with peers who might be a good fit to them regarding for example, norms and values (Baerveldt et al., 2010). Consequently, newcomers in scientific communities may be disadvantaged in finding new collaboration partners as they may not only use less active strategies for initiating new collaborations with other researchers but they can also benefit less from network-based selection patterns as they are not linked to many other researchers.

Newcomers in scientific communities can be found at all career levels because researchers tend to be involved in several scientific communities at the same time and, therefore, are used to switching roles, often from expert in one scientific community to newcomer in another scientific community (Kienle & Wessner, 2005). However, PhD students are the most common form of newcomers in scientific communities and they can be expected to suffer from the most disadvantages in finding collaboration partners. In contrast to more experienced researchers, PhD students do not only lack group awareness in the new scientific community but also lack knowledge on scientific collaboration in general. They are moreover often seen as having less expertise and being less available to collaborations not involving their supervisor and, therefore, as less attractive collaboration partners for other researchers. Therefore, it seems promising to support PhD students at scientific events. Results from group awareness research in smaller groups suggest that enhancing group awareness may also be a helpful means of support in scientific communities.

Research question

Summing up the previous line of argumentation, it is an open question if certain types of members are more advantaged or disadvantaged in finding interaction and collaboration partners and to what extent the interaction and the initiation of collaborations at meetings of scientific communities follows similar patterns as the development of other forms of relationships. Assuming that PhD students are an especially relevant group of newcomers for scientific communities but disadvantaged in finding collaboration partners, a further question is whether they can benefit from cognitive group awareness support. Finally, the connection between present interaction and later collaboration is still unclear. These research gaps lead to the following question:

To what extent do career level, disciplinary background, and homophily regarding these two attributes, as well as group awareness support, reciprocity and transitivity predict the selection of face-to-face interaction partners and collaboration partners?

Method

Study context and participants

The study was conducted at the Alpine Rendez-Vous' 2011 and 2013 in France, two scientific events that aimed at bringing together researchers from multiple disciplines working on technology-enhanced learning to foster community building and scientific progress in the field.

Both Alpine Rendez-Vous' were structured in a similar way: each event consisted of several workshops on specific topics of technology-enhanced learning, and each workshop lasted one and a half days. Half of the workshops took place in the first part of the event, followed by a community event for all event participants in the evening of the second day. The second group of workshops took place after the community event. Both Alpine Rendez-Vous' were deliberately located in a large hotel at a remote place in the French Alps

to avoid external influences and to provide many opportunities for networking among the participants. Almost all participants stayed in the same hotel.
While each workshop had been selected in a competitive process and was organized independently, there was a general schedule for all workshops at the event to synchronize starting time, breaks, and end time. Between the workshop time slots, all present participants had breakfast, lunch, dinner, and coffee breaks together, as well as a long afternoon break which allowed networking also across workshops in independent social activities.

The Alpine Rendez-Vous 2011 consisted of four workshops in the first half and four workshops in the second half of the event. Additionally, a winter school for doctoral students was held across the whole event. However, winter school data will not be reported in the following analyses because of its unique design and composition compared to other workshops. The Alpine Rendez-Vous 2013 comprised five workshops in the first half and five workshops in the second half of the event. Altogether, 136 persons participated in workshops at the Alpine Rendez-Vous 2011 and 151 individual persons participated in workshops at the Alpine Rendez-Vous 2013, leading to a sample of N = 287 individual participants. The majority of the participants was from European countries.

Study design, data collection, and instruments

The study had an experimental design in which the factor *group awareness support* (with vs. without) was varied across different workshops in a randomized way. Additional quasi-experimental variables *career level* (doctoral student vs. experienced researcher) and disciplinary background (Information Technology vs. Social Sciences) varied naturally among participants within the workshops.

The data collection procedure was the same in both scientific events and for both experimental condition and control group: After being informed about their participation in a study and signing a form of consent during conference registration, participants were equipped with an RFID device, which immediately started tracking their face-to-face proximity with other participants during the conference. Tracking was deactivated when participants checked out of the hotel and returned their RFID device. Additionally, a social network questionnaire was handed out to each participant at the end of each workshop. Participants who had to leave earlier were asked to fill in an online version of the questionnaire. Personal data about the participants (career level and disciplinary background) were collected together with the social network questionnaire and within the registration form for the event.

Independent variables

Group awareness support

In the experimental condition, workshop participants received a brochure with information about other workshop participants. The brochure contained profiles of all workshop participants, which we compiled based on information from participants' personal websites. Each profile included basic information about each person (name, picture, and contact information), information about personal resources (research interests and exemplary publications), and information pointing to their social resources (affiliations and background). We handed the brochure to the participants at the beginning of the workshop without further instructions. The control group did not receive a brochure.

Career level and disciplinary background

Data on both career level and disciplinary background were extracted from a questionnaire. While three different career levels were originally specified on the questionnaire (PhD/doctoral student, Early/Mid career (postdoc), and full professor), we collapsed the two latter categories. This resulted in a variable distinguishing only between PhD/doctoral students and experienced researchers (Early/Mid career and full professors forming a unique category). This allowed us to include career level as a single dummy variable into the model and made the results easier to interpret.

Information about the disciplinary background of the participants was handled similarly, resulting in a variable separating researchers with a background in Information Technology from those with a background in a social science (e.g. psychology, education, learning sciences etc.). This classification was chosen because the Alpine Rendez-Vous' had the specific focus on bringing researchers from those two types of disciplines together and to foster their collaboration.

Data sources and measures of dependent variables

Number of interaction partners and duration of interaction measured by RFID devices for tracking face-to-face proximity

The RFID devices, developed by the SocioPatterns collaboration (http://www.sociopatterns.org) were integrated into the name badge of the participants. The devices engage in bidirectional low-power radio communication. As the human body acts as a shield for the used radio frequency, and as the badges are worn on the chest, badges can exchange radio packets only when the individuals wearing them face each other at close range (about 1 to 1.5 m). The measuring infrastructure captured close face-to-face proximity between two individuals with a temporal resolution of 20 seconds, and therefore gives access to the amount of time that two participants spent together (see Cattuto et al., 2010) for a detailed description of the infrastructure). The RFID devices only tracked face-to-face proximity within the range of antennas, which were located in public spaces of the hotel only, so spare time activities taking place outside of the hotel were not tracked.

In order to exclude noise and very brief, insignificant contacts, we considered only pairs of individuals with a total measured interaction time of at least 100 seconds during the total event. The set of pairs of individuals with such interactions gives us the interaction network of the event. For each participant, we extracted from this network his/her number of distinct interaction partners.

Number of previous and potential new collaboration partners, measured by social network questionnaires

Social network questionnaires were individually adapted to each workshop and contained a list of all workshop participants' names. Participants were asked to indicate with whom they had collaborated already before the event and with whom they had found potential for future collaboration.

We computed the number of previous collaboration partners and potential new collaboration partners using the social network questionnaire data. For each participant, we computed the number of previous collaboration partners ('Freeman degree') as the number of participants in the workshop with whom the participant declared to have had collaborated before the workshop. Likewise, we summed up the number of participants in the workshop with whom the participant had indicated to see potential for future collaboration and this yielded their number of potential new collaboration partners. As many of these include previous collaboration partners, we also consider specifically within these potential future collaboration partners the potential *new* collaboration partners (i.e., the ones who were not declared as previous partners).

Reciprocity, transitivity, and homophily

Reciprocity, transitivity, and homophily in the selection of interaction partners and potential new collaboration partners were computed from both data sources using the analysis tool RSiena. The tool compares the expected number of reciprocal, transitive, and homophile interaction relations and new collaboration relations with the actual numbers (Ripley, Snijders, Boda, Vörös, & Preciado, 2014).

Analyses

Two different analysis methods were used: Linear mixed models were created using the R package lme4 version 1.1 – 11 to predict each person's number of interaction partners / potential new collaboration partners. For each dependent variable, interactions and new collaborations, two models were computed. The first model was computed without interaction effects whereas the second model included interaction effects of career level, disciplinary background, and group awareness support. The models contained random effects for the different workshops and were run on the whole dataset, which included the data from both ARVs. To investigate selection patterns, we used the RSiena package version 1.1-232 in R for simulation investigation for empirical network analysis. We computed a model in which the development from the network of previous collaborations to the network of potential future collaborations was predicted for each workshop. In a meta-analysis of the estimates in the individual workshop models, we calculated the overall estimate across 1) all workshops, 2) all workshops without cognitive group awareness support, and 3) all workshops with cognitive group awareness support.

Results

Table 1 gives an overview of four models aiming at explaining the participants' number of interaction partners during the workshop and their number of potential new collaboration partners at the end of the workshop. Having previous collaboration partners lead to more interaction partners and more potential new collaboration partners. Career level is not a significant predictor in any of the models. Disciplinary background, in contrast, predicts the number of potential new collaboration partners, showing that participants with a background in Information Technology have less potential new collaboration partners at the end of the workshop. We do not see similar effects regarding the number of interaction partners. Moreover, group awareness support does not show an influence on the number of interaction partners nor on the number of potential new collaboration partners. No interaction effect of group awareness support with career level or disciplinary background is observed. The models aimed at predicting the number of interaction partners do not fit well, as they actually create more variance than a model with random effects only. The models explaining the number of potential new collaboration partners, in contrast, explain a large amount of variance.

Table 1: Models for the number of interaction partner and for the number of potential new collaboration partners

	Number of interaction partners		***Number of potential new collaboration partners***	
	Main effects model Estimate (se)	***Interaction effects model Estimate (se)***	***Main effects model Estimate (se)***	***Interaction effects model Estimate (se)***
Fixed Effects				
Intercept	**4.497** (0.939)**	**4.695** (0.984)**	**9.006** (0.669)**	**9.196** (0.774)**
Previous collaboration partners	**0.138* (0.061)**	**0.135* (0.061)**	**0.283** (0.082)**	**0.281** (0.083)**
career level (PhD student)	0.571 (0.486)	0.415 (0.680)	-0.498 (0.720)	-0.759 (1.004)
Discipline (Information Technology)	0.348 (0.505)	0.005 (0.769)	**-1.778* (0.680)**	**-2.044* (0.975)**
Group awareness support	0.965 (1.344)	0.611 (1.449)	-0.387 (0.831)	-0.757 (1.130)
Career level * group awareness support	-	0.256 (0.952)	-	0.484 (1.421)
Discipline * group awareness support	-	0.577 (1.024)	-	0.481 (1.375)
Random Effects				
σ^2	9.338	9.426	21.601	21.791
τ_{00}	7.215	7.069	1.284	1.264
Model fit				
Pseudo-R^2 (variance between workshops explained)	-13%	-10%	73%	74,2%

*p < .05; **p < .01

We now look at the RSiena results that aimed at explaining how dyads that had not previously collaborated identified the potential for a new collaboration after the workshop and which factors are related to this change. Table 2 shows the results of the meta-analyses across the workshops for the different predictors. In the overall model across all workshops, we find that both reciprocity and transitivity seem to be related to the selection of potential new collaboration partners. When the workshops without cognitive group awareness support are contrasted to the workshops with cognitive group awareness support, we find that the reciprocity pattern disappears in both cases, while transitivity is still a significant selection pattern. This highlights the important role of previous collaboration partners, who can introduce different participants to each other. The duration of a face-to-face interaction is also an important positive predictor for selecting a potential new collaboration partner, with a more important role if no cognitive group awareness support is provided.

Regarding the role of career level, we find in the overall model that PhD students reach out to other researchers as potential new collaboration partners to the same extent as experienced researchers. However, PhD students are chosen significantly less than experienced researchers as potential new collaboration partners. In the separated models, we do not find any career level related effects. Finally, we do not find any homophilous selection behavior among career levels. Looking at disciplinary backgrounds of the participants, we find in the overall model and in the workshops without cognitive group awareness support that researchers with an Information Technology background select significantly less potential new collaboration partners. However, this effect cannot be found in the workshops with cognitive group awareness support. We do not find differences between disciplines in being chosen as potential new collaboration partners, nor do we find homophile behavior in relation to disciplines.

Table 2: Models for the selection of potential new collaboration partners

	Overall model		***Without group awareness support***		***With group awareness support***	
	Estimate (sd)	***p***	***Estimate (sd)***	***p***	***Estimate (sd)***	***p***
reciprocity	**0.562 (0.541)**	**.023**	0.397 (0.462)	.212	0.719 (0.534)	.062
transitivity	**0.261 (0.087)**	**< .001**	**0.269 (0.108)**	**.006**	**0.226 (< 0.001)**	**.001**
duration of interaction	**0.0003 (< 0.001)**	**.010**	**0.0004 (< 0.001)**	**.001**	**0.0002 (< 0.001)**	**.014**
ego career level (PhD student)	0.860 (1.1219)	.150	-0.270 (< 0.001)	.654	-1.414 (1.379)	.174
alter career level (PhD student)	**-0.500 (0.479)**	**.028**	-0.412 (< 0.001)	.066	-0.670 (1.074)	.242
homophily career level	-0.194 (0.703)	.452	-0.140 (< 0.001)	.469	-0.358 (1.235)	.552
ego discipline (Information Technology)	**-1.278 (1.344)**	**.036**	**-2.266 (< 0.001)**	**.006**	-0.397 (1.162)	.571
alter discipline (Information Technology)	-0.012 (0.341)	.949	-0.832 (1.173)	.251	0.105 (< 0.001)	.495
homophily discipline	-0.039 (0.258)	.800	-0.220 (.0591)	.547	-0.044 (0.125)	.785

Discussion

Our results have contrasting aspects. On the one hand, we have not been successful in explaining with how many other researchers participants interacted during the scientific events considered. It might be that the variables considered are not the relevant ones for understanding the initiation of face-to-face interaction but others e.g. specific features of the workshop design or personality traits are more relevant. On the other hand, we were more successful in explaining the number of potential new collaboration partners the participants have identified after a workshop and in understanding the patterns that drive the selection process. The number of previous collaboration partners seems to play a major role, which is in line with the finding that transitivity is a constant and relevant selection pattern. Lacking connections to other researchers seem to be the only disadvantage of PhD students, who join a meeting of a scientific community for the first time. The lack of homophily in the interaction patterns is in contrast with the results of Barrat, Cattuto, Szomszor, van den Broeck, and Alani (2010), who found clear signs of homophily with respect to career level in the face-to-face interactions. This discrepancy might be due to the number of participants in the individual workshops, which potentially makes it easier for researchers with different levels of experience to mingle or makes it more difficult for the statistical analysis to uncover such detailed patterns. Moreover, we found that the longer researchers interact with each other, the more likely it is that they will select each other as potential collaboration partners later on. This finding is complementary to the fact, found both here and by Barrat et al. (2010) that previous collaboration partners interacted for longer time on average than pairs of individuals who had not collaborated prior to the workshop. An especially interesting finding for multi- / interdisciplinary scientific communities is that participants' background is a relevant factor for the number of potential new collaboration partners and in the selection patterns and that cognitive group awareness was associated with less differences in selection patterns between disciplines.

However, it has to be noted that this study has several limitations, with the small sample size of workshops being the most important one. Also, the identification of potential new collaboration partners cannot be assumed to equal actual new collaborations and further data about joint publications after the scientific events needs to be analyzed. So far, we can only say that our results indicate that scientific communities seem to share several selection patterns with other kinds of social networks, especially transitivity. However, other expected selection patterns, especially homophily, seem rather to depend on the group setting (larger vs. smaller scientific events).Furthermore, the literature on cognitive group awareness support has been controversial and our findings add new questions about who benefits from this kind of support.

From a practical point of view, the findings indicate that tandems of a new member and an experienced member - as they have been initiated at ICLS 2016 - could be a very valuable endeavor for community building and newcomer integration. Furthermore, supporting cognitive group awareness may be especially helpful when different disciplines come together. However, these findings need further replication and validation to justify these conclusions and can so far only be seen as a first hint in these directions.

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