Culture, role and group work: a social network analysis perspective on an online collaborative course

Karen Stepanyan, Richard Mather and Roger Dalrymple

Karen Stepanyan is a Research Fellow at the Intelligent and Adaptive Systems Research Group, University of Warwick, UK. His research interests include social mechanisms of learning, communities and networks, and application of web technologies for learning in general. His recent doctoral work focused on student online engagement and interaction. Address for correspondence: Dr. Karen Stepanyan, Research Fellow, Department of Computer Science, University of Warwick, Coventry, CV4 7AL, United Kingdom. Tel: +44 (0)24 7652 3523. Fax: +44 (0)24 7646 1606. Email: K.Stepanyan@warwick.ac.uk

Richard Mather is a Senior Lecturer at Buckinghamshire New University. His research and publications cover areas that apply computer technology to geospatial/image analysis and to enhancing learning environments. Address for correspondence: Dr. Richard Mather, Design, Media & Management, Buckinghamshire New University, Queen Alexandra Road, High Wycombe, HP11 2JZ, United Kingdom. Tel: +44 (0) 14 9452 2141. Email: Richard.Mather@bucks.ac.uk

Roger Dalrymple is Principal Lecturer in Education at Oxford Brooks University. He gained his MPhil and DPhil and Postgraduate Diploma in Learning and Teaching at the University of Oxford and his PGCE at the University of Reading. He has published books and articles in English studies and Education studies and he is a member of the British Educational Research Association. Address for correspondence: Dr. Roger Dalrymple, School of Education, Oxford Brookes University, Harcourt Hill Campus, Oxford, OX2 9AT, United Kingdom. Tel: +44 (0) 18 6548 8600. Email: rdalrymple@brookes.ac.uk

Abstract
This paper discusses the patterns of network dynamics within a multi-cultural online collaborative learning environment. It analyses the interaction of participants (both students and facilitators) within a discussion board that was established as part of a three-month online collaborative course. The study employs longitudinal probabilistic social network analysis (SNA) to identify the patterns and trends within the network. It conjectures and tests a set of hypotheses concerning the tendencies towards homophily/heterophily and preferential attachment. The paper presents identified interaction network patterns in relation to cultural differences. It also evaluates network dynamics by considering participant roles and group work in the course under study. Results of social network analyses are reported along with measures of statistical confidence in findings. The potential for extending exploratory SNA methods and visualisation techniques in educational research are discussed here.

Introduction

The Higher Education (HE) sector is becoming increasingly multicultural. The impact of globalisation, accelerated by technological progress, is transforming the traditional classroom. HE institutions have considerably increased their intake of international students for both online and campus-based courses (Bhandari & Laughlin, 2009), bringing together increasingly dispersed audiences for targeted education. As a result, cross-cultural interaction within educational institutions occurs more frequently than ever before. Hence, it becomes critical for educators and educational designers to understand the mechanisms of cross-cultural communication and, subsequently, to evaluate and adjust teaching practices in line with the observed cultural diversity. Therefore an improved understanding of learner interaction within multi-cultural environments can provide valuable insight into the design and development of effective learning environments.

This paper reviews earlier research on cultural differences as well as the effects of such differences on learners and learning environments. Highlighting the need for further research into the dynamics of cross-cultural interaction in an educational context, the paper presents results of longitudinal, probabilistic SNA. These reveal patterns of interaction between participants enrolled on a collaborative online course. Study findings are considered in relation to the potential for SNA techniques to be used for monitoring and informing relevant adjustments to teaching and learning approaches in online and multi-cultural environments.

Culture, role and group work in collaborative learning

Much attention has already been devoted to considering how cultural diversity may be accommodated in academic communities and how this may affect course design (Hofstede, 1986; Sweeney, Weaven, & Herington, 2008; Vatrapu & Suthers, 2007). These studies suggest that pedagogical methods and course structure may not be equally effective in multi-cultural learning environments. While learning in culturally heterogeneous groups is often encouraged for developing cross-cultural competence and acquiring culturally diverse knowledge, it remains paramount to the design of educational environments that are effective and beneficial for all the learners, regardless of cultural background. The growing number of courses, offered over the Web and open to a wider population, justifies further research into the effectiveness of multi-cultural learning environments. This paper is particularly concerned with cross-cultural participant interaction within an online collaborative setting.

Online collaborative learning practices (McConnell, 2002, 2006) deviate from traditional lecturing approaches and focus on orchestrating learner interaction. Stimulating, coordinating and encouraging learner interaction is central to collaborative learning. Successful implementation of a collaborative learning environment requires open participation and a diversity of perspectives offered by teachers and learners. However, cultural differences of participants also need to be considered. In the systematic review of earlier research, examining the role of culture on engagement and learning in online environments, Uzuner (2009) reports a broad agreement that cultural variations should be considered in the delivery and design of courses. For instance, Summers and Volet (2008) report that widely used group work approaches should also be modified according to student attitudes and previous multi-cultural experiences.

Facilitators, in an online collaborative learning environment, often appear as consultants or guides for encouraging learner participation and supporting learning (Goold, Coldwell, & Craig, 2010; Reushle & McDonald, 2004). The role of facilitators shifts from that of conventional teachers towards encouraging social interaction and collaborative work across the learner population, where attention to a wide range of cultural norms and expectations is necessary (Thorpe, 2002). Earlier work (Kim & Bonk, 2002) highlights participatory differences between cultural groups of learners that vary in style, behaviour and the level of interaction. Among the most widely studied aspects of group work are issues related to individualist and collectivist cultures (Hofstede, 1986), which may also affect patterns of learner-to-learner and facilitator-to-learner interaction. Although, considerable attention (Bernard *et al.*, 2009) has been given to understanding the contribution of facilitators in participant interaction and its effects, interaction patterns within and across multi-cultural participant role groups of facilitators and learners remain unexplored. In this paper, we seek an answer to the question whether cultural differences and participant roles (as students or facilitators) affect the communication partners.

The pursuit for understanding interaction within and across cultural groups must be contextualised within the studied educational environment. Learning activities and course structure can significantly alter the patterns and the levels of participant interaction. Earlier research concerning multi-cultural group work focuses on the challenges associated with communication skills, group composition, leadership, decision making and conflict management (Popov *et al.*, 2012). The body of research has recently extended to include inquiries into: the mechanisms of developing mutually shared understanding (Van den Bossche, Gijselaers, Segers, & Kirschner, 2006); training and preparation for improving group learning (Sweeney, *et al.*, 2008); and variations in the perspectives of learners on the challenges and potential benefits of group work (Wang, 2007). However, despite recent advances, there remains a gap in understanding the dynamics of multi-cultural group work within a collaborative learning environment.

This paper, therefore, aims to advance understanding of multi-cultural learning environments through the analysis of participant interaction using SNA methods. Part of the study reported here is also concerned with identifying SNA methodologies appropriate to the subject of research.

Social network analysis in educational research

SNA includes a set of methods for analysing human interaction and exploring relationships between individuals, groups and communities (Wasserman & Faust, 1994; Wellman & Berkowitz, 1997). The fundamental concepts of SNA were developed over the last five decades and are now well established (Carrington, Scott, & Wasserman, 2005; Hanneman, 2001; Wasserman & Faust, 1994). The basic constructs of SNA are actors and relational ties. Actors are social entities such as discrete individuals, corporate or collective social units. Relational ties, on the other hand, are the social bonds defining a linkage between a pair of actors. The combination of actors and ties forms a network – the structure of which may be studied in SNA using visual mapping and quantitative techniques for describing network characteristics. SNA has been used to investigate a wide range of subjects such as, the dynamics of community and group development (Monge & Contractor, 2003), understanding the structure of inter-related Web resources (Park, 2003) and the diffusion of information through social networks (Leskovec, 2011). The increasing availability of computer resources and the creation of standardised SNA software packages, such as UCINET, SIENA or ORA, bundled with a variety of graphical visualisation tools, make SNA accessible and valuable for researchers in a number of disciplines, including Education.

The affordances provided by SNA techniques can provide invaluable insight for understanding online teaching and learning (Haythornthwaite, 2005). Evaluation and monitoring of student communication using SNA can reveal, for instance, the level of 'cohesion' (as a measure of network density) within a given group of learners and identify disadvantaged participants (Haythornthwaite, 2005; Reffay & Chanier, 2003). The application of SNA can also reveal otherwise hidden factors that may affect student participation, open collaboration and personal development. Thus, the use of SNA in educational research can become a fundamental resource for understanding student interaction and participation, subsequently leading to improvement of teaching techniques and tools (Martínez, Dimitriadis, Rubia, Gómez, & De la Fuente, 2003). More recently, SNA has drawn the attention of scholars seeking to monitor and analyse learner data to gain insight and improve the process of learning. The analysis of the structure and dynamics of social networks has been featured in studies of informal learning networks (e.g. educational blogs Pham, Derntl, Cao, & Klamma, 2012), as well as in structured and planned formal learning settings (Dawson, 2010; Stepanyan, Borau, & Ullrich, 2010). The use of SNA has led to the development of software tools (e.g. Bakharia & Dawson, 2011; Lambropoulos, Faulkner, & Culwin, 2012) for a range of VLEs. For a fuller account of the potential benefits and uptake of SNA in educational research, the reader is referred to a recent Open University report by Ferguson (2012). However, the use of SNA in educational research is relatively novel and, contrary to the approach adopted in this paper, it has been mainly limited to exploratory methods.

Exploratory methods that include network visualisation and the use of descriptive statistics are not trivial and are often very useful. However, their use is limited when it comes to identifying trends and driving factors of network dynamics with statistical accuracy. The probabilistic techniques, on the other hand, provide the needed affordances for conjecturing and testing hypotheses using network data. The research methodology adopted in this study employs application of probabilistic longitudinal SNA techniques that allow identification of network dynamics and trends, and permit reporting with mathematical precision. A probabilistic analysis of the observed patterns was conducted by formulating and testing a set of hypotheses drawn from the network theory and previous research. Prior to reporting the results of the analysis, the paper elaborates on the context of the study and the process of preparing network data from the messages posted by learners and facilitators on the discussion board.

Context of the study

This study investigates an online course that was jointly designed by a team of Chinese and British educators as part of the Sino-UK eChina project and run purely in distance mode. The course, entitled 'Professional Development of Intercultural E-learning Communities', was targeted at educational professionals and practitioners (i.e. academics, managers, postgraduate students) interested in multi-cultural aspects of online courses and e-learning in general. The course could be positioned under the disciplinary umbrella of social sciences, but it attracted participants with a broad range of backgrounds. It aimed to offer an introduction to the broad subject of collaborative e-learning and encourage a selection of topics for further focused study. The course was structured around reading material, discussions (taking place in pairs and/or larger groups) and group course work on a topic selected by the participants. The data used in this study comprise the discussion board messages communicated by course participants (both students and facilitators) over the three-month duration (October-December 2006) of the course. While the data were accumulated much earlier than the date of this publication, it constitutes a useful dataset due to continued use of discussion boards as part of formal courses as well as less structured online learning environments. The Moodle VLE served as a main platform for running the online course.

The course consisted of six stages organised into three main units an introduction, group work in pairs and in larger groups, and a closing. Groups were formed by assigning students at random, but maintaining a culture balance in terms of participant numbers representing a specific culture. Participants were issued initial reading material then given freedom to select the topics that most interested them, to discuss these and to build knowledge collaboratively. The grouping of students and the assignation of facilitators was imposed without student involvement. The discussion and group work were integrated into the course design as central elements. Participants were able to use chat, participate in conference calls via Skype and to maintain blogs. While online communication and collaborative work was arranged by various means in both synchronous and asynchronous modes, the data considered in this study is limited to public discussions only.

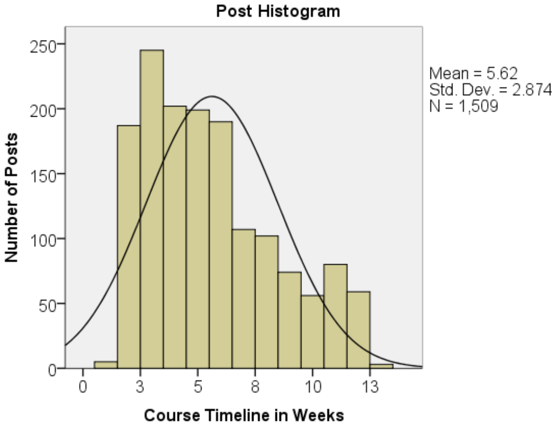

Figure 1: Frequency distribution histogram for discussion board posts throughout the course.

The demographics of course participants comprised 'mainstream' British and Chinese cultures. While 'smaller' cultures were also represented in the cohort, other research discussing this course (McConnell, Banks, & Bowskill, 2008; Zhang & Huang, 2012) categorised the participants using this mainstream dichotomy. This study distinguishes between the two (i.e. Chinese/British) based on the geopolitical location of participants at the time of the course. The numbers of students from two main cultures were nearly equal – 21 from the UK and 23 from China. The seven facilitators, three from China and four from the UK, brought the total number of participants to 51.

Throughout the three months of the course the participants posted 1,509 messages in total. Of these 629 were posted by the facilitators and 880 by learners. The level of engagement, defined by participant contributions to the discussion, varied throughout the course. The frequency of messages posted per day was greatest in the first part of the course and declined considerably in the second part (see Figure 1). The frequency profile of Figure 1 is also consistent with earlier studied pattern of communication for online discussion (Stepanyan, Mather, & Payne, 2007) and is reported here to provide contextual information about the course. Considerable variation was recorded in the number of messages posted by student participants (mean number of posts = 20, standard deviation = 16.4). There was also great variation in the number of messages posted by facilitators (mean number of posts = 89.9, standard deviation = 59.3).

Data preparation

The collected data comprise time-stamped postings either initiating a discussion or responding to another participant. This data, representing the dyadic interaction of participants, was decoded and extracted into a directed social network. The Pajek Arcs/Edges format (de Nooy, Mrvar, & Batagelj, 2005) was considered most suitable for extracting the data due to its laconic format and error prone qualities. At a later stage, this was converted into an adjacency matrix suitable for SIENA/StOCNET software for the statistical analysis of network data.

The directions of the relationships represent the information flow between actors. If actor i replies to a message from actor j, then the direction of relationship is from i to j ($i \rightarrow j$). This may also be represented by a corresponding 'row on column' position in a matrix (Hanneman & Riddle, 2005). Messages posted to initiate a new discussion thread were discarded due to uncertainty as to their relational direction (Gruzd & Haythornthwaite, 2008). As the links between the actors are not always reciprocal the matrix is asymmetric, i.e. the rows and columns are not identical. It should also be noted that despite the availability of reflective links (i.e. ties to oneself) such data was also discarded in this analysis. Thus, the values appearing in the matrix are based on the number of dyadic messages exchanged between pairs of actors. The descriptive network statistic is presented in Table 1. The density and standard deviation demonstrate that the represented interaction network was considerably dense.

Table 1: Descriptive statistic of the studied network. (Notes: [1] Density G is calculated as: the total of all tie values divided by the number of possible ties; [2] the Dichotomised Networks are non-valued reductions of the original network according to the Value).

Networks	*Density (matrix average)*	*Standard Deviation*
Original Valued Network	G=0.47	σ =1.83
Dichotomized Network (Tie present if *Value* > 0)	G=0.15	σ =0.35
Dichotomized Network (Tie present if *Value* > 3)	G=0.04	σ =0.21

Analysis and results

Probabilistic SNA: underlying theory and the formulation of hypotheses

The recent theoretical and technological developments in network analysis catalysed the propagation of empirical research in network theories. Earlier studies of network dynamics enabled development of theoretical models that can be tested and reused in other contexts. Given the accumulated knowledge about the structure and dynamics within certain networks, we can hypothesise whether networks within educational environments resemble the structure and dynamics of networks outside the educational context.

Focusing on the variables of culture, role and group work, we refer to the body of knowledge encompassing established network theories and empirical studies of network dynamics. More specifically, network concepts most useful for addressing issues related to the formation and evolution of social networks were selected. These are: *homophily* (actor level); *reciprocity* (dyadic level); *transitivity* (triadic level) and; *preferential attachment* (global level). The following sections describe these extensively studies concepts, which are already applied in domains outside education, and the formulation of hypotheses to be tested in this study of an online collaborative learning course.

Homophily

Homophily is "the principle that a contact between similar people occurs at a higher rate than among dissimilar people" (McPherson, Smith-Lovin, & Cook, 2001, p. 416). In line with the proverb - 'birds of a feather flock together' - homophily effect is present when contact between similar actors occurs more frequently than among dissimilar actors. This principle structures network ties of friendship, marriage, exchange, advice-giving and other relationships. As a result, homophily affects the formation of personal networks, making them homogeneous with regard to many socio-demographic, behavioural, and intrapersonal characteristics (Louch, 2000; McPherson, *et al.*, 2001; Rogers, 1995). The question is whether this pattern will hold in an educational environment? We elicit two hypotheses for testing the effects of culture and role on network dynamics.

Criteria for encoding participant 'similarity' in this study are restricted to role (dichotomised to learner and facilitator) and culture (attributed to participants representing Britain and China). Do participants prefer to interact with those of same culture? Are there consistent preferences for interacting with peers? Based on the main principle of homophily and similarities between the participants, the following hypotheses (H1 and H2) were formulated:

Hypothesis 1 (H1): Culture affects the creation of new links and interaction among participants.

The structure of the online course rested on a philosophy of collaborative learning and promoted openness for creating favourable conditions for the learners to: share ideas and accept new ones; be intellectually-open and accept the possibility of change; be frank in self- and peer-assessment; and build healthy relationships (McConnell, 2002). The role of a teacher in a collaborative learning environment is less rigid than in more traditional individualistic or cooperative learning environments. In a collaborative learning environment, the differences between teachers (or facilitators as is the case here) and learners are blurred, and less distinct than in more conventional environments. Teachers are regarded to be community members or mentors rather than representing an authoritative body. In contrast, formal structures, such as organisational hierarchies, may hinder interaction across levels and organisational roles. In this collaborative course, given the more active participation of learners and less authoritative attitude of facilitators, it appears reasonable to formulate the following hypothesis:

Hypothesis 2 (H2): Participatory role has little if any effect on the creation of new links and interaction among participants.

Preferential attachment

The concept of preferential attachment refers to the increased attractiveness to actors that already have high degrees of linkage (Barabási & Albert, 1999). In other words, actors accumulate new connections in proportion to the number of connections they already have, and therefore the development of networks resembles the multiplicative process, which is known to give power-law distributions (Barabási & Albert, 1999; Faloutsos, Faloutsos, & Faloutsos, 1999; Newman, 2001). The tendency for preferential attachment in the network leads to the emergence of actors with an extraordinarily high number of connections and is typical for citation networks (Newman, 2001) or Internet topology (Faloutsos, *et al.*, 1999). The effect of preferential attachment is similar to the "rich get richer" phenomenon where some actors in the network become disproportionately well connected while others retain only few connections. Can patterns of preferential attachment be identified in a collaborative online environment? The use of SIENA SNA software allows answering this question and testing for preferential attachment (referred in the system as 'Activity of Alter').

Preferential attachment in an educational setting, particularly in an open discussion space where some participants acquire a dominant position, may not be desirable, making the engagement of less active participants even less likely. However, depending on the philosophy, structure and methodology of the course, this pattern may be interpreted differently. Consequently, the study of preferential attachment and tendencies in educational networks may usefully indicate if course delivery or some other aspect of course design requires modification. Taking into account the open and collaborative design of the course under study, the following hypothesis is proposed:

Hypothesis 3 (H3): There is no tendency towards preferential attachment within the studied network.

Reciprocity and transitivity

Katz and Powell (Katz & Powell, 1955) proposed an index for measuring the tendency of actors to reciprocate initiated contacts more frequently than would occur by chance. This measure is studied on the dyadic level through the process of dyad census. The empirical evidence shows great variation in the reciprocation index depending on the type of network. In a study of friendship networks, where high school students were asked to name their closest friends, the level of reciprocation was 60% (Campbell, Marsden, & Hurlbert, 1986).

The study of physicians' reports, on the other hand, revealed a substantially lower rate in their discussions of cases (37%) and an even lower rate (13%) for the exchange of advice (Coleman, Katz, & Menzel, 1966).

While reciprocity is a structural property studied at the dyadic level, the basis of transitivity lies in triad census analysis. The triple of actors *i, j* and *k* is considered to be transitive if the ties between those actors follow the following pattern: $i \rightarrow j$, $j \rightarrow k$ and $i \rightarrow k$, where the arrow denotes the direction of the tie (Wasserman & Faust, 1994, p. 566). The structural pattern of transitivity, as part of the triad census, has been extensively studied by many social scientists (Davis & Leinhardt, 1967; Holland & Leinhardt, 1971). Networks with a high tendency for transitivity can be beneficial when trust and cooperation are required (Sparrowe & Liden, 1997); nevertheless, transitive relations may not be as useful if actors rely on innovation in a competitive environment (Burt, 1992).

The roots of analysing reciprocity and transitivity go back to the balance theory, propounded by Fritz Heider in 1946 (Wasserman & Faust, 1994). Balance theory explains the emergence of transitive triads, which underlies the clustering effect within the network and the phenomenon of cohesiveness (i.e. higher network density, primarily resulting from reciprocation and transitivity). Thus, the analysis of network dynamics within an educational setting, and particularly the course data used in the current study, can reveal tendencies towards cohesiveness as a result of course activities and structure.

The main activity incorporated within the course studied here is the collaborative work undertaken in the six smaller groups to which participants were affiliated. To test the changes in network dynamics and tendencies at dyadic and triadic levels (at the stage of group work activity) the following hypotheses were formulated:

> *Hypotheses 4 (H4): There is a tendency towards more cohesive interaction within the studied network.*
>
> *Hypotheses 5 (H5): There is a tendency towards more cohesive interaction within smaller groups.*

The hypotheses and the methods selected for testing them are summarised in Table 2. The 'Testing Method, Models and Conditions' column describes the input data (e.g. 6 'waves'; these being the intervals of longitudinal data corresponding to discrete course stages), the effects tested using the SNA software (e.g. homophily effect estimation) and additional parameters considered when testing the effect (e.g. same culture). The network coefficients estimated are the basis for acceptance or rejection of hypotheses adopting a 5% threshold for significance (α=0.05). The 'Measures and Level' demonstrate the use of certain network measures (e.g. network centrality) and the approaches to network analysis associated with each test (e.g. dyadic/triadic level of analysis).

Table 2: Summary of the hypotheses-testing framework. (The definitions of the parameters are given in the corresponding sections of the paper.)

No.	*Hypotheses*	*Testing Method, Models and Conditions*	*Measures and Level*
H1	Culture affects the creation of new links and interaction among participants.	Homophily Effect estimation with SIENA, using 6 waves of longitudinal network data. Parameters: Same Culture, Culture Similarity Null Hypothesis: Estimate coefficient = 0, at α=0.05. Alternative Hypothesis: Estimate ≠ 0, at α=0.05.	Network centrality Actor level
H2	Participatory role has	Homophily Effect estimation with SIENA, using	Network centrality

No.	Hypotheses	Testing Method, Models and Conditions	Measures and Level
	little if any effect on creation of new links and interaction among participants.	6 waves of longitudinal network data. Parameters: Same Role, Role Similarity Null Hypothesis: Estimate coefficient = 0, at α=0.05. Alternative Hypothesis: Estimate ≠ 0, at α=0.05.	Actor level
H3	There is no tendency towards preferential attachment within the studied network.	[a] Pearson Correlation degree centrality and involvement rank. Null Hypothesis: r = 0 Alternative Hypothesis: r ≠ 0 [b] Activity of Alter effect estimation with SIENA, using 6 waves of longitudinal network data. Parameters: Activity of Alter, Betweenness, Null Hypothesis: Estimate coefficient <= 0, at α=0.05. Alternative Hypothesis: Estimate >0, at α=0.05.	Network centrality Global Level
H4	There is a tendency towards more cohesive interaction within the studied network.	Parameters: Reciprocity, Transitivity Null Hypothesis: Estimate coefficients <= 0, at α=0.05. Alternative Hypothesis: Estimate >0, at α=0.05.	Differential mutuality and reciprocation Dyadic and Triadic level
H5	There is a tendency towards more cohesive interaction within smaller groups. [H5a] There is a tendency towards interaction with members of shared small groups. [H5b] Small group members are more likely to have mutual communication ties.	Parameters: Reciprocity, Transitivity, Group Similarity, Group Similarity + Reciprocity Null Hypothesis: Estimate coefficients <= 0, at α=0.05. Alternative Hypothesis: Estimate >0, at α=0.05.	Differential transitivity Dyadic level

Results: hypotheses testing

Stochastic actor-based models were used for analysing the dynamics of the directed networks. This approach enabled studying the factors that influence changes within the network and testing corresponding hypotheses. Further detail, including an introduction to the method adopted (Snijders, Van de Bunt, & Steglich, 2010) and a manual to the software (Snijders, Steglich, Schweinberger, & Huisman, 2006) are available to the interested reader.

Unlike other SNA methods that use a single snapshot of a network (e.g. at the end of the course), the selected approach enables gaining insight into the changes of the studied network. Changes in networks are viewed as a stochastic process, where the probabilities of changes are determined by the characteristics of the actors (e.g. culture or role) or the structural characteristics across actors (i.e. connected or not connected via interaction). Hence, actor-based models are suitable for analysing longitudinal network data. Such models aim to represent network dynamics based on observations and to evaluate these for statistical inference (Snijders, *et al.*, 2010). Analysis was performed using SIENA (v. 3.17) software coupled with the StOCNET graphical interface package (Snijders, 2001; Steglich, Snijders, & West, 2006).

Patterns of homophily and heterophily

To specify the actor-driven model which will be used for testing H1 and H2, a set of objective and rate functions needs to be defined. While the *rate functions* indicate the pace of changes within the interaction network, the *objective functions*, to which random components are added, indicate the change within the interaction network itself (Snijders, 2001). The rate and objective functions, presented below, were estimated with SIENA software (Snijders, *et al.*, 2006), using six waves (stages) of network. The analysis also considered effects of culture and role by treating these as 'constant' actor covariates. A summary of network effects considered by this analysis is presented below.

Outdegree effect:	The interaction may tend to stabilise over time (if a negative value is observed).
Reciprocity effect:	The actors may tend to reciprocate initiated communication.
Culture homophily:	Actors may choose to interact with actors of the same culture, e.g. the British may prefer to communicate with fellow British participants.
Culture ego effect:	Same-culture actors differ in the number of actors they prefer to communicate with, e.g. British students may prefer to communicate with more participants than Chinese.
Culture alter effect:	Same-culture actors differ in 'popularity', e.g. British students may receive fewer initiatives for communication than Chinese.
Role homophily:	Actors tend to choose interaction with actors of the same role, e.g. learner to learner, or facilitator to facilitator.
Role ego effect:	Same-role actors differ in the number of actors they communicate, e.g. facilitators may initiate more contacts with other participants.
Role alter effect:	Actors with the same participatory role may differ in 'popularity', e.g. facilitators may receive more initiatives for communication than students.

The model was run with standard actor-oriented model code, i.e. a multiplication factor of 2, 4 subsequent phases and 1000 of iterations in the third sub-phase, as advocated in the SIENA manual (Snijders, *et al.*, 2006) and described by Steglich et al (2006). All the reported parameters are significant (i.e. parameter > standard error*2) at $\alpha = 0.05$ unless specified otherwise.

The parameters of 'Same Culture' and 'Same Role' correspond to the homophily effect hypothesised in the previous section. The positive (0.98) and significant result for the Same Culture (Model 1) parameter and similar result (0.38) for Culture Similarity (Model 2) indicates that, in this study, interaction between participants of the same culture was more likely. The null H1, therefore, can be rejected.

Unlike the effect of culture, the result of Same Role and Role Similarity parameters are not consistent (positive/negative) and not significant. Had the negative result been significant, this would suggest heterophily (Rogers & Bhowmik, 1970) among actors of the same role. Heterophily, being the opposite of homophily, would indicate a tendency towards interaction across different types of actors, in this case facilitators and students. In other words, having had negative values would imply that student participants of the studied course would be more likely to communicate with facilitators and, vice versa, facilitators would be more likely to communicate with the students. The results however, cannot be elaborated any further due to lack of statistical significance. High value of the standard error prevents the rejection of the null H2.

Table 3: SIENA estimation results. [a]*Coefficient values not significant at α < 0.05*

Sub-model	*Parameter*	*Model 1 Coefficient (s. e.)*	*Model 2 Coefficient (s. e.)*	*Model 3 Coefficient (s. e.)*
Network Dynamics: Structural Effects	*Outdegree Density*	-2.30 *(0.36)*	-1.76 *(0.13)*	-1.54 *(0.13)*
	Reciprocity	0.89 *(0.23)*	0.86 *(0.22)*	0.78 *(0.21)*
	Transitivity	0.12 *(0.05)*	0.13 *(0.05)*	0.10 *(0.04)*
	Distance 2	0.22 *(0.06)*	0.19 *(0.05)*	0.20 *(0.07)*
Network Dynamics: Covariates Effect	*Same Culture*	0.98 *(0.38)*	-	-
	Same Role	*-0.18*[a] *(0.35)*	-	-
	Culture Similarity	-	0.38 *(0.19)*	0.45 *(0.22)*
	Role Similarity	-	*0.14*[a] *(0.21)*	*0.11*[a] *(0.18)*
Behaviour Evolution	*Effect Culture on Rate*	-	-	-0.98 *(0.29)*
	Effect Role on Rate	-	-	1.31 *(0.26)*

The results for the three models, summarised in Table 3, test H1 and H2, as well as reveal further effects that are useful for interpreting the network dynamics. These effects, as discussed below, are the outdegree density, reciprocity, transitivity distance at two, and covariate effects of culture and role.

The value of outdegree density (-2.30) is negative and significant, which is a common observation in many studies. This indicates that the participants are becoming more selective with whom they interact, rather than suggesting a reduction of density over time (Snijders, *et al.*, 2006). In other words, the pattern of interaction stabilizes over time, from the initial stage, when participants initiate communication with many others, to the later stages.

The values of the reciprocity and transitivity parameters are significant and positive, indicating the tendency of participants to: [a] reciprocate ties by responding to initiated communication of others; and [b] towards a shortening of the geodesic distance from one actor to another as cohesiveness increases.

Preferential attachment pattern

The effect of preferential attachment (H3), was tested by [a] calculating the Pearson Correlation Coefficient between the initial and final measures of participant degree centrality; and [b] estimating the preferential attachment (i.e. 'Activity of Alter') effect with a stochastic actor-driven simulation model (Snijders, 1996, 2005). The triangulated results were then used for testing the hypothesis and discussing the identified pattern.

[a] Pearson Correlation Coefficient was calculated on the same set of longitudinal degree centrality five wave data. Course participants were divided into two groups: participants with high and low degree centrality (Figure 2). The correlation calculated for the initial and final stages of the course ($r = 0.91$) demonstrates that participants who were in the group with higher degree centrality in the initial stage of the course were very likely to remain in the same category at the end of the course. Similarly, participants from lower degree centrality group in the beginning of the course were likely to retain their position.

Figure 2 lists participants (Actors) and their degree centrality calculated at six different periods of the course (Waves 1-6). The cells that are not shaded with colour indicate a centrality value that is less than the median for the given wave. The participants whose centrality scores for Waves 1&2 are not coloured in Figure 2 are referred here as a group with low degree centrality. The transition of participants from one group to another becomes visible by consecutively sorting the data for each of the waves in a descending order.

As indicated by correlation analysis, Figure 2 demonstrates that participants generally maintain their positions of centrality over time. However, more pronounced changes of participant degree centrality throughout the course demonstrate that some individuals did move from one category to another. Notably, one participant (the highlighted actor, number 13, in Figure 2), despite the initially low degree centrality, eventually acquired a higher position having a degree centrality greater than the median of the higher-degree group. Others, such as Actor number 17 in Figure 2, moved down the rank during the course. The question as to why some participants acquire greater gain in network centrality than others is of research interest but is beyond the scope of this study.

Higher Degree Centrality | Lower Degree Centrality

Wave 1&2	85	39	20	13	42	17	17	15	17	2	13	23	11	6	11	12	15	19	6	9	6	6	6	15
Wave 3	116	60	28	28	52	20	25	24	28	10	22	25	13	8	18	14	17	24	9	20	11	12	10	16
Wave 4	160	75	42	34	59	29	29	30	34	18	31	32	18	20	20	17	23	28	12	24	18	12	13	19
Wave 5	197	141	69	69	72	68	51	43	48	46	45	43	37	39	38	29	27	31	26	30	28	28	18	22
Wave 6	219	155	82	79	72	71	59	58	55	49	49	45	41	40	40	39	32	31	31	30	29	29	23	22
Actors	30	50	3	8	2	40	10	5	23	13	37	24	31	14	6	22	46	7	25	35	39	26	12	9

Wave 1&2	0	5	7	7	5	3	11	6	0	6	7	3	3	0	0	4	6	7	2	0	2	4	3	0	2	1	1
Wave 3	2	9	11	10	8	8	13	10	4	6	7	5	5	1	1	5	7	7	4	0	2	4	3	1	2	1	1
Wave 4	6	11	14	12	9	8	13	13	10	9	8	9	5	8	7	7	8	7	6	4	4	4	3	3	2	1	1
Wave 5	12	15	15	15	15	11	13	13	13	10	12	11	11	11	10	10	8	7	7	4	5	4	3	3	3	1	1
Wave 6	17	15	15	15	15	14	13	13	13	13	12	12	12	11	11	10	8	7	7	7	5	4	3	3	3	1	1
Actors	41	49	36	19	45	42	17	47	4	1	51	43	27	48	18	21	11	15	20	38	32	44	34	29	33	16	28

Figure 2: Mobility of participants throughout the five phases based on their degree centrality.
Shaded areas indicate members of the group with higher centrality

[b] Activity of Alter Estimation. The results of the analysis are presented in Table 4. Similarly to testing the homophily effect, the rate and objective functions, as shown below, were estimated with SIENA software (Snijders, *et al.*, 2006), using the same six waves of collected network data. In addition to the outdegree and reciprocity functions used in the previous section, the following effects were selected for the model estimation:

Activity of Alter: "the rich get richer" effect (if the value is positive) is present in the network, i.e. more active students become even more involved in discussions over time.

Betweenness: "brokerage" effect, when actors position themselves between not directly connected others, i.e. some individuals may have more control over information flow.

Table 4: Two models for Activity of Alter Estimation. [a]*Coefficient values not significant at α < 0.05*

Sub-model	*Parameter*	*Model 4 Coefficient (s. e.)*	*Model 5 Coefficient (s. e.)*
Network Dynamics: Structural Effects	*Outdegree Density*	-1.67 *(0.68)*	-1.74 *(0.18)*
	Reciprocity	0.73 *(0.29)*	0.59 *(0.19)*
Network Dynamics: Covariates Effect	*Activity of Alter*	9.47 *(2.80)*	6.85 *(3.23)*
	Betweenness	*-0.23* [a] *(0.41)*	*0.02* [a] *(0.03)*
Behaviour Evolution	*Outdegree Effect on Network Rate*	-	0.11 *(0.05)*
	Indegree Effect on Network Rate	-	0.09 *(0.04)*

The results of the estimation show that the Activity of Alter effect is large, positive and significant. This indicates a tendency for participants who are involved in collaborative activities at the beginning of the course to further engage over time. Similar results are produced in estimation of both models (Model 4 and Model 5) with and without consideration of behavioural covariates. Therefore the null H3 can be rejected, supporting the alternative that Activity of Alter in the studied network exists. To ensure that the observed preferential attachment is not the effect of brokerage in the network, betweenness covariate was considered in the model. This was found not to be statistically significant and, therefore, the Activity of Alter effect is unlikely to be the consequence of brokerage within the interaction network.

The existence of an Activity of Alter effect was positive and significant for both parts of the above test. This provides consistent evidence that the observed phenomenon does resemble the pattern of power-law distribution of degree centrality in the studied network. These effects remained independent from both culture proximity and participatory role.

Network cohesion measures

To capture the change in network dynamics (H4 and H5), interaction data was partitioned into three waves. These represented the network during the three major units of the course: [1] pre- group work interaction, [2] group work and [3] group work presentation.

The hypotheses were tested using the same actor-driven simulation model discussed above. Models 6, 7 and 8 summarised in Table 5 were also estimated in SIENA with standard actor-oriented model code, multiplication factor of 2, 4 subsequent phases and 1000 iterations in the third sub-phase (Snijders, *et al.*, 2006).

Table 5: Network cohesion measures. [a]*Coefficient values not significant at α < 0.05*

Sub-model	*Parameter*	*Model 6 Coefficient (s. e.)*	*Model 7 Coefficient (s. e.)*	*Model 8 Coefficient (s. e.)*
Network Dynamics: Structural Effects	*Outdegree Density*	-1.62 *(0.12)*	-1.77 *(0.17)*	-1.71 *(0.16)*
	Reciprocity	1.03 *(0.23)*	0.99 *(0.23)*	1.27 *(0.61)*
	Transitivity	0.13 *(0.05)*	0.13 *(0.05)*	0.10 *(0.04)*
Network Dynamics: Covariates Effect	*Group Similarity*	-	0.60 *(0.30)*	0.51 *(0.25)*
	Same Group x Reciprocity	-	-	*-0.33* [a] *(0.89)*
	Same Group	-	*0.20* [a] *(0.19)*	*0.39* [a] *(0.21)*
Behaviour Evolution	*Reciprocity Effect on Network Rate*	-	-	0.36 *(0.05)*

The estimation of Model 6, which uses only three variables, is, on the whole, consistent with results from Models 1 and 2. The large, positive and significant value of the reciprocity coefficient shows a tendency for an increasing number of mutual ties over time between course participants. The value of the transitivity coefficient is also positive and significant, though not as large as the value of reciprocity. Nevertheless, in addition to reciprocity, the estimation shows a tendency towards an increasing number of transitive ties between participants. Therefore, the null hypothesis under H4 can be rejected, supporting the alternative of increasing cohesiveness within the studied network dynamics.

Models 7 and 8 contain additional objective and rate functions which extend Model 6, so allowing further insight into the dynamics of the observed network. The similarity and identity effects (i.e. Group Similarity and Same Group in Table 5; Same Role/Culture and Role/Culture Similarity in Table 3) included in successive models, were used earlier for testing the homophily effect. A similar approach was adopted for testing H5 with the participant group affiliation attribute used as an independent variable. It may be argued that the existence of groups within the studied network (i.e. affiliation network) may require application of SNA techniques that are suitable for two-mode networks. However, the available software packages, such as SIENA, StOCNET, Statnet and PNet, used for statistical network analysis, do not support the use of two-mode network data when these analyses were undertaken. Nevertheless, due to a static number of participants in each group and, additionally, a single group affiliation policy (defined by the course structure) for each participant, the evaluation technique is valid. If shared-group affiliation effects (i.e. Same Group and Group Similarity) were found to be positive (and significant), this would indicate a tendency for participants to interact with peer group members only rather than with other participants.

Results in Table 5, however, indicate that although coefficients, Same Group and Group Similarity, have positive values in Model 7, only that for Group Similarity was relatively large (0.60) and significant. Further estimation, taking into account additional effects of an interaction (Same Group x Reciprocity) and Reciprocity on Network Rate slightly reduce the value of the Group Similarity coefficient to 0.51, but this nevertheless remains a significant effect. Hence, the null H5a can still be rejected, but only based on the results of a Group Similarity effect, suggesting the 'absence' of a tendency for participants to interact with co-group members *only*.

Furthermore, the coefficient of Same Group and Reciprocity, included in Model 8, is not significant, suggesting that there is no tendency towards reciprocity among participants with shared group attributes (Same Group x Reciprocity = 0.39). However, the positive (0.36) and significant coefficient of Reciprocity Effect on Network Rate (i.e. the effect of the coefficient on the frequency of network change) (Snijders, 2005) suggests a significant effect of reciprocity on network change in general. While, the null H5b cannot be rejected due to lack of significance, the results indicate the existence of a positive effect of reciprocity on network change rate. In general, the tests for H5a and H5b suggest that the cohesiveness of the community improved in terms of the increasing number of mutual ties over time, yet the communication was not limited or focused on interaction with peer group members only.

In summary, this section describes the process of formulating five hypotheses and their testing using probabilistic SNA methods, namely dynamic actor-driven models. The use of the selected method attested to demonstrable dynamic changes, their regularity and tendencies within the studied network, and enabled the reporting of these with statistical accuracy. Results of analysis suggest the presence of: [1] a homophily effect based on participant culture; [2] the absence of heterophily effect based on participant role (i.e. learner/facilitator); and [3] a preferential attachment effect resembling a power-law distribution of centrality measures. Additionally, the evaluation indicated: [4] a positive tendency towards cohesiveness on both dyadic and triadic levels; and [5] no further tendency towards reciprocation within smaller groups.

Discussion and conclusions

In an attempt to understand network dynamics of a multi-cultural collaborative online course, this study applied a method that is new to educational research – probabilistic SNA. Drawing from the existing theoretical work on social networks, this paper elicited a set of hypotheses and tested them in the context of an online collaborative course. Results from this study suggest that many of the common theories may also hold in an educational context. This has pedagogical implications as well as raises further issues concerning the potential benefits and limitations of applying probabilistic SNA to educational research. The key findings of the study are discussed below.

Participants sharing the same culture tend to interact among themselves. The results are consistent with published literature (see earlier) and demonstrate that culture can be a significant factor in shaping participant interaction. The presence of culture homophily and its measurable effect on participant interaction is evident in the studied course. The results are informative given the focus of the study on online collaborative learning and the statistical accuracy of the reported results. The major pedagogical implications of the study are two-fold. Firstly, if greater cross-cultural interaction is desired, it may be necessary to modify facilitation or some other aspect of course design or delivery. Secondly, continuous monitoring of participant interaction and evaluation of changes against the pedagogical interventions may be beneficial for achieving desired improvements in cross-cultural interaction.

Participant role (whether a student or facilitator) does not affect the choice of interaction partner. Neither homophily nor heterophily effects on participant role were apparent in this study. In other words, neither learners nor facilitators exhibited tendencies towards interaction with colleagues or fellow learners only. Perhaps inconsistent with earlier research, which suggests possible differences across individualist and collectivist cultures in choosing interaction partners according to the role (Hofstede, 1986), this result may be viewed as surprising. The phenomenon may, in fact, reflect that emerging social learning environments are characterised by a lowering of boundaries and a greater equality between facilitators and students. Considering the overall interaction pattern, it is evident that role is not definitive in shaping interaction between facilitators and learners. In this instance, where the role of the facilitators was intentionally non-authoritative, the absence of such grouping can be regarded as a positive indicator of open communication between most participants regardless of their role. Additionally, the inference is that it is possible to design a multi-cultural online learning environment where facilitators are not the primary point of contact.

'Popular' participants are likely to become even more 'popular'. The results of this study confirmed the presence of preferential attachment. Commonly referred as 'the rich get richer' effect, preferential attachment suggests that participants who already have high number of responses tend to receive even more. This pattern may not be entirely desirable within a collaborative course. The growing disparity between participants may require facilitator intervention for balancing the interaction. Further investigation of possible reasons for this pattern (which considered 'betweenness'), suggests that preferential attachment is not driven by a network brokerage of participants.

The cohesion of the network increases over time. The study indicates an increasing cohesiveness within the studied network, as participants tend to reciprocate the incoming ties and connect to others in a transitive way. Although patterns stabilise over time, as participants are becoming more selective in their interaction partners, *the choice of interaction partners is not confined to the members of the group* they are assigned to work with. These results indicate that integration of group-work into a collaborative learning environment does not hinder the interaction of individuals with the members of other groups. Monitoring participant interaction across groups, as well as roles and cultures in general, may provide useful information for adjusting facilitation techniques and course design for more effective learning.

More generally, the methodology adopted in this study enables us to argue for introducing precision into the research on collaborative learning environments. As never before, the patterns of network dynamics can be reported with statistical precision and acceptable levels of confidence. This study sets an example for using probabilistic SNA for gaining insight into participant interaction within a collaborative learning environment. As demonstrated in this paper, the use of SNA can enable identification of networks patterns that would otherwise be difficult to detect and quantify. However, the potential of adopting probabilistic SNA stretches beyond the application presented in this paper. The continued theoretical advances and development of SNA tools provide further opportunities for integrating SNA methods into educational research and practice. More specifically, the development of open source software instruments, similar to those used in this study, can be integrated into online educational platforms for monitoring the dynamics and prompting facilitators about developing or existing trends.

Obtaining timely information about emerging trends and patterns within an educational environment can be used by facilitators, tutors, course designers and administrators to act upon and improve the learning environment. For instance, if the observed trend of cultural homophily, as discussed in this study, had been identified earlier during the course, it could have prompted facilitators to intervene and encourage greater level of cross-cultural interaction. Similarly, monitoring participant interaction could have been used for maintaining the desired network dynamics.

Despite the obvious benefits, a word of caution must be issued for adopting SNA techniques. While identification of network patterns is undoubtedly useful, the interpretation of the patterns must be sought in the context of the specific learning environment. Network patterns cannot be equally un/favourable across various courses. Different goals, resources, participant numbers and course structures may lead to diversity in desired network structures and dynamics. Furthermore, not all SNA tools or methods are applicable to study educational environments. For instance, while SIENA allows arbitrary change in the number of actors in the network at any time point, other tools may not be able to accommodate the change in participant numbers of the course. Nevertheless, the adoption of probabilistic SNA methods in educational research can lead to propagation of network dynamics studies that form a foundation for understanding learning processes in general, as well as, developing practitioner applications for automating the process of interpretation and pedagogical intervention.

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