Social interaction of virtual teams, a preference for intrinsic motivation

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Abstract

In recent years, increasing attention has been devoted to virtual learning. In the last decade, a large number of studies in Computer-Supported Collaborative Learning (CSCL) have assessed how social interaction, learning processes and outcomes in virtual settings are intertwined. Although recent research findings indicate that learners differ with respect to the amount and type of discourse contributed in virtual settings, little is known about the causes and consequences of these differences. The research presented here investigates how the motivational orientation (intrinsic/extrinsic) of a learner influences the interaction patterns with other learners.

This study of 100 participants who collaborated together in a virtual setting to remediate deficiencies in economics indicates that three (self-directed) sub-groups were formed within virtual teams. These subgroups were generated by a K-means cluster analysis of academic motivation measured by the AMS-instrument. Afterwards, the different motivational profiles were added to the social network of each virtual team. The research results reveal that the motivational profile influences with whom a learner is interacting. Extrinsically motivated learners have a preference to connect to highly intrinsically motivated learners. However, intrinsically motivated learners prefer to discuss mainly among themselves, implying that extrinsically motivated learners will receive less feedback and discourse possibilities from other members within the virtual team. Our findings might explain why in distance learning large differences in participation are found and why certain learners are more inclined to drop-out in class.

Keywords: K-means cluster analysis, academic motivation, evolution of social networks, Computer-Supported Collaborative Learning, Preferential attachment, Social Network Analysis.

1. Introduction

The attention for virtual collaborative learning in recent years is fuelled by two separate yet mutually enforcing developments: The increasing possibilities of Information Communication Technologies (ICT) to support collaboration (Bromme, Hesse, & Spada, 2005; Resta & Laferrière, 2007; Schellens & Valcke, 2005) and the growing amount of evidence that collaboration can enrich student learning through interaction (Jonassen & Kwon, 2001; Lindblom-Ylänne, Pihlajamäki, & Kotkas, 2003; Van den Bossche, Gijselaers, Segers, & Kirschner, 2006). In general, it can be said that virtual collaborative learning is built on the assumption that ICT has the power to provide a rich learning experience by using a variety of learning methods. ICT-tools like discussion forums, chat or web-videoconferencing “afford” learners to learn in a challenging and interactive manner (Jonassen & Kwon, 2001; Resta & Laferrière, 2007; Yang, Tsai, Kim, Cho, & Laffey, 2006).

Despite the learning possibilities created by ICT-tools, recent findings in Computer-Supported Collaborative Learning (CSCL) indicate that learners who are similar with respect to educational background and prior knowledge nevertheless contribute differently to discourse (Caspi, Chajut, Saporta, & Beyth-Marom, 2006; De Laat, Lally, Lipponen, & Simons, 2007; Rienties, Tempelaar, Van den Bossche, Gijselaers, & Segers, In press). For example, Caspi, Gosky and Chajut (2003) analysed a total of 7706 messages of 47 courses at various faculties of the Open University in Israel and found that the majority (80%) of students contributed only a small amount of messages. A small minority contributed the bulk of the messages. Also differences in the type (cognitive, affective, metacognitive) of contributions have been found (De Laat et al., 2007; Schellens & Valcke, 2005). In other words, these distance learning courses were characterised by largely unequal participation among students.

Furthermore, recent research in CSCL using social network analysis has found that some learners are more central in the social network than other learners (Hurme, Palonen, & Järvelä, 2007; Martinez, Dimitriadis, Rubia, Gomez, & de la Fuente, 2003; Rienties et al., In press). In other words, being central in a social network implies that some learners receive and contribute more messages than others. However, what are the underlying principles why some learners receive a lot of replies to their contributions to discourse while others contribute but get limited reactions from others? To what extent is it a coincidence that some learners become central contributors? In this article, we will investigate what the "invisible" mechanisms in social interaction are that result in learners of virtual teams being central or learners being on the outer fringe of a social network.

2. An invisible hand in social interaction in CSCL: motivation

In CSCL settings where learners are geographically separated, constructing meaning and co-constructing knowledge in a virtual team is not straightforward (Bromme et al., 2005). In particular when learners are interacting using discussion forums, establishing a critical mass of interaction whereby participants contribute actively to cognitive discourse is troublesome (Caspi et al., 2003; Schellens & Valcke, 2005). Some learners are more inclined to start and actively contribute to a discussion than others. Other learners might prefer to wait for a while before contributing to a discussion, in particular when the members of the virtual team are seeking for effective working and learning strategies. Recent research highlights that motivation has a strong influence on how learners contribute to discourse (Järvelä, Järvenoja, & Veermans, 2008; Rienties et al., In press; Veermans & Lallimo, 2007; Yang et al., 2006). For example, Yang et al. (2006) conducted a survey among 250 respondents of eleven online educational psychology courses and found that goal-oriented motivation (Pintrich & De Groot, 1990) positively influences social presence among peers, that is the perception that emotions can be shared using CSCL. Using a cluster analysis among a cohort of 50 psychology students following an online course, Veermans and Lallimo (2007) found that messages contributed by motivated students demonstrate a richer variety of topics. Järvelä et al. (2008) found that students in the face-to-face setting reported more (favourable) learning goals and less performance goals (Pintrich & De Groot, 1990) relative to students in virtual settings. Finally, in our own research we found that intrinsically motivated learners are more inclined to contribute to cognitive discourse than extrinsically motivated learners (Rienties et al., In press).

In this article, we adopt the concept of motivation developed by Deci and Ryan (1985) as the degree of self-determination of learners might explain why some learners contribute more to discourse in CSCL than others. To be motivated means to be moved to do something, while amotivation is a state of lacking any intention to act (Ryan & Deci, 2000). However, focusing only on the level of motivation ignores the underlying attitudes and goals the learner has in order to pursue an action or goal (Deci & Ryan, 1985). Therefore, in Self-Determination Theory (SDT) Ryan and Deci (2000) distinguish between intrinsic motivation, extrinsic motivation and amotivation.

In intrinsically motivated learning, the drive to learn is derived from the satisfaction and pleasure of the activity of learning itself; no external rewards come in play. When an intrinsically motivated learner decides to follow an online course, (s)he is likely to be among the first to contribute to discourse giving the pleasure of learning. In contrast, externally motivated learning refers to learning that is a means to an end, and not engaged for its own sake. SDT proposes that extrinsic motivation is a construct with different facets that vary greatly with the degree to which the learner is autonomous (Deci & Ryan, 1985; Ryan & Deci, 2000). SDT distinguishes four different forms of extrinsic motivation that constitute a motivational continuum reflecting the degree of self-determined behaviour, namely external regulation, introjection, identification and integration. For example, when a learner is forced to join an online course because his parents have told him/her to do so (external regulation), the learner is less likely to be among the first contributors to discourse. In a long series of over 700 studies in classroom settings, the model of Deci and Ryan (1985) has been empirically verified (Ryan & Deci, 2000). For example, more autonomous extrinsic motivation has been found to lead to greater engagement, less dropping out (Legault, Green-Demers, & Pelletier, 2006), higher quality learning and greater psychological well-being (Ryan & Deci, 2000). Greater internalisation yields more behavioural effectiveness as well as greater experienced well-being (Ryan & Deci, 2000). In sum, the type of motivation of individual members of a virtual team might influence social interaction within the virtual team.

Evolution of Social Networks

One method to analyse the interaction patterns among members in virtual teams is visualising the social network interactions. Research in disciplines mainly outside of educational psychology have analysed how social networks develop and evolve over time (e.g. Barabási & Albert, 1999; Katz, Lazer, Arrow, & Contractor, 2004; Newman, 2001, 2003). According to Newman (2003), "[a] social network is a set of people or groups of people with some pattern of contacts or interactions between them". Two important conditions to analyse how networks evolve are first whether the number of participants in a social network increases (e.g. Wikipedia, Facebook) or remains the same. In case the number of participants in a social network continuous grows, being among the first participants in the social network might imply that one is more likely to be connected to others than when one has recently joined a social network. Second, whether nodes (i.e. learners) connect at random to others, or have a specific preference to connect to some type of nodes, influences how networks develop.

In a virtual team (as in most classes), the number of learners is pre-determined and fixed. Therefore, a straightforward assumption would be that the social network of a virtual team will develop and evolve according to random graph theory (Erdős &

Rényi, 1960). In random graph theory, learners connect to other learners in a network with a more or less equal probability. As an explanation how random networks evolve, imagine that you are invited to a party of hundred guests who do not know you or each other (Barabási, 2002; Erdős & Rényi, 1960). As humans are inherently social beings, soon you will start to talk to some guests at the party. After a while you will move on to some other people. After an hour or so, you might have talked to ten or fifteen people, as most others have done. If one would construct a social network of all encounters during the party, the interactions at the party would follow a random pattern. All guests could be connected to each other using the connections of others. In addition, the total number of connections to others guests will very similar among all guests. This brings us to our first research hypothesis.

H1: Learners in a virtual team will have a equal amount of connections to all other learners.

If hypothesis 1 has to be rejected in our setting, then learners in virtual teams do not connect to other learners in line with the random graph theory. A crucial assumption of random graph theory is that people in the social network are perceived by others as equal. However, learners differ with respect to prior knowledge, expertise and motivation when they become member of a virtual team (Järvelä et al., 2008; Rienties et al., In press; Yang et al., 2006). Continuing with the example of the party, when the NBA team winning the finals unexpectedly joins the party, it is likely that the basketball players will receive a lot of attention. As a result, when drawing a social network of all social interactions, the basketball players will have a lot of connections with "ordinary" party guests. In contrast, the ordinary party guests will have limited connections to other ordinary party guests. In a similar vain, when learners in a virtual team become aware that interacting with some learners who have some positive trait (e.g. intrinsic motivation, large knowledge base, expertise) is (perceived to be) beneficial, these learners might be more interesting to interact with.

Given the nature of distance learning, learners will have to base their perceptions of others exclusively on the quantity and quality of discourse activity (Bromme et al., 2005; De Laat et al., 2007). As intrinsically motivated learners are more inclined to contribute to discourse than extrinsically motivated learners, in particular with regard to higher cognitive discourse (Rienties et al., In press), they possess crucial characteristics for distance learning. Superior contributions to discourse at a higher cognitive level might bring them a positive (expert) reputation in the virtual team. Other learners might be more willing to contribute to a learner who is perceived to be motivated and has some expert knowledge. In addition, as extrinsically motivated learners will perceive a lack of external regulation in distance learning, they might direct their attention more towards intrinsically motivated learners. In other words, intrinsically motivated learners lead the discourse development within the virtual team, thereby providing the desired external regulation to extrinsically motivated learners. This will imply that most learners will be connected to intrinsically motivated learners, as phrased in our second and third research hypotheses.

H2: Extrinsically motivated learners are more likely to interact with intrinsically motivated learners than with other extrinsically motivated learners.

H3: Intrinsically motivated learners are more likely to interact with other intrinsically motivated learners than with extrinsically motivated learners.

3. Method

3.1. Setting

The present study took place in an online summer course for prospective bachelor students of an International Business degree programme in the Netherlands. The aim of this course was to bridge the gap in economics prior knowledge for international students starting a bachelor (Rienties, Tempelaar, Waterval, Rehm, & Gijselaers, 2006). The online course was given over a period of six weeks in which students were assumed to work for 10-15 hours per week. The participants never met face-to-face before or during the course and had to learn using the virtual learning environment "on-the-fly". The course was based upon principles of Problem-based learning (PBL), which is an educational method that fosters socio-constructivist learning. PBL focuses student learning on complex situations and on a variety of realistic information (Dochy, Segers, Van den Bossche, & Gijbels, 2003; Van den Bossche et al., 2006). One of the key issues in PBL is that students are actively constructing knowledge together in collaborative groups (Hmelo-Silver, 2004). In our setting, students participated in groups within a collaborative learning environment using discussion forums and announcement boards. During six weeks, students had to collaborate together on solving six tasks through a problem-based learning method.

Given that in virtual teams it is important for tutors to provide rapid feedback on discourse (De Laat et al., 2007; Vonderwell, 2003), each team was coached by two tutors or two tutors and a teaching assistant. For example, in team 1, tutor 1 led the group, while tutor 2 had a more supportive role. In team 2, the roles were the other way around, etc. In this manner, the discourse in each virtual team was monitored and facilitated each day despite the limited availability of staff during the summer holidays period. No obligatory meetings were scheduled. At the end of each week, the "lead tutor" made a suggestion on how to proceed with the next task, thereby focusing on process rather than on content. The results of three interim-tests and a final summative test combined with graded participation in the discussion forums were used to make a pass-fail decision. Students who passed the course received a certificate. Hence, this setting provides a unique opportunity to assess the role of motivation on behaviour of learners in virtual settings as the learners never met each other before and collaborated exclusively in the virtual learning environment.

3.2. Participants

In total 100 non-Dutch participants were randomly assigned in six groups. Data were analysed for those individuals who actually posted at least once a reaction in the discussion forum. This resulted in a total of 82 participants who were selected for analysis. The six groups had an average of 13.66 members (SD= 2.16, range = 11-17) per team. The average age was 19 years and 45% of the learners were female.

3.3. Academic Motivation Scale (AMS)

Individual motivation was measured by the Academic Motivation Scale (AMS), which was developed by Vallerand et al. (1992) for college/university students and measures the contextual motivation for education. Vallerand and colleagues have added further theoretical concepts to the model of Deci and Ryan (1985) as well as adjusting the model for different contexts as the model of Deci and Ryan (1985) was primarily developed to measure motivation among children. Vallerand et al. (1992) acknowledge that the attitudes, values and goals that trigger a learner to become intrinsically motivated can differ. For example, when a learner enters into college or university and voluntarily chooses a study, distinguishing the different intrinsic motives might be important.

The instrument consists of 28 items, in all of which students respond to the question stem "Why are you going to college?". There are seven subscales on the AMS, of which three belong to the intrinsic motivation scale, three to the extrinsic motivation scale and one for amotivation. Intrinsic motivation subscales are intrinsic motivation to know (IMTK): learning for the satisfaction and pleasure to understand something new; intrinsic motivation to accomplish (IMTA): learning for experiencing satisfaction and pleasure to accomplish something; and intrinsic motivation to experience stimulation (IMES): learning to experience stimulating sensations. The three extrinsic motivation subscales are identified regulation (EMID), introjected regulation (EMIN), and external regulation (EMER). The three constitute a motivational continuum reflecting the degree of self-determined behaviour, ranging from identified regulation as the component most adjacent to intrinsic motivation, to externally regulated learning, where learning is steered through external means, such as rewards. The last scale, amotivation (AMOT), constitutes the very extreme of the continuum: the absence of regulation, either externally directed or internally. The reliability and validity of the AMS scale has been established in a variety of studies (Fairchild, Jeanne Horst, Finney, & Barron, 2005; Vallerand & Bissonnette, 1992; Vallerand & Pelletier, 1993). In total 1445 freshmen filled in the questionnaire during the first course of the semester. The response-rate on AMS-questionnaire among the summer course participants was 93% and the Cronbach alpha for the seven items ranged from .760 to .856, which is in line with previous studies (Fairchild et al., 2005; Legault et al., 2006; Vallerand & Pelletier, 1993). In order to align the participants of the online summer course with the 1445 freshmen, the Dutch students were removed from the database as the subjects of the summer course were only foreign students. This leads to 765 students on which a k-means cluster analysis was conducted.

3.4. Statistical analyses

3.4.1. Cluster analysis

At the first step in the statistical analysis, subscale scores for all seven intrinsic motivation, extrinsic motivation, and amotivation variables were calculated for all 765 non-Dutch freshmen. Next, K-means cluster analysis was applied to these subscale scores. It was found that a three cluster solution provides an adequate description of different motivation profiles present in these freshmen. Afterwards, data on cluster membership of all participants of the virtual teams were combined with individual data resulting from the social network analysis. The interrelationships between all measures were assessed through standard T-tests analyses using SPSS 15.0.1.

3.4.2. Positioning of individuals within social network using Social Network Analysis

Social Network Analysis provides us with several tools to analyse interaction patterns among individual learners. Two frequently used measures were employed in order to determine the position of individuals in social networks, namely centrality and ego network density. First, Freeman's degree of Centrality (Freeman, 2000; Wassermann & Faust, 1994) measures whether learners were central in the social network or not. If a learner contributed actively to discourse and most other learners responded to the activities of this learner, he/she became a central learner in the network and therefore had a high degree of centrality. Second, the ego network density of each individual within the network was used, which measures to how many other learners a learner is directly connected. Main indicator for this study is the relative position of each learner within the social network, derived by UCINET version 6.158. In order to assess whether learners with different motivational orientations connect equally to each of the clusters, we will use the (absolute/relative) number of send and received messages per learner to members in each of the (internal/external) clusters as a measurement for equality of interaction between clusters. An innovative feature of this study is that by combining the results of the Social Network Analysis and cluster analysis, we were able to distinguish interaction patterns amongst individual learners based upon their motivation profile.

4. Results

4.1. Virtual teams develop non-random

In order to test hypothesis 1, the average number of connections in the cohort of online summer course participants is compared. On average, a learners has 6.43 (SD= 4.03) connections to other learners and there are substantial differences amongst individual learners with respect to the number of connections as assessed by a Chi-Square test ($\chi 2$ (df= 76) 159.458, $p < .001$). Furthermore, significant differences are found using a Chi-Square test in each of the six virtual teams with the exception of team 3. In other words, in contrast to random graph theory the social networks in our setting do not evolve to a random network with an equal amount of connections per learner, with the exception of team 3. Furthermore, some learners are more central than other learners in the network, as is illustrated by the large standard deviation of the Freeman's degree of centrality (M=26. 6, SD= 24.29), as well as by the Chi-Square test for all participants ($\chi 2$ (df= 80) 1772.74, $p < .001$) and the Chi-Square test for participants within each of the teams. As a result, we need to reject hypothesis 1 that social networks develop and evolve in accordance to the model of the random graph theory for five out of six of our teams.

4.2. Clustering students on Academic Motivation

In order to test hypotheses 2 and 3 and to investigate whether the motivation profile of a learner has an influence on the position within the social network and the neighborhood of a learner, a K-means cluster analysis is applied to obtain three different profiles for motivation, which are further labeled according to the final cluster center position (See Table 1). As can be seen from Figure 1, the three motivation profiles are: cluster 1: low intrinsic motivation (Low In), high extrinsic motivation (High Ex); cluster 2: medium intrinsic motivation (Med In), low to medium extrinsic motivation (Med Ex); cluster 3: high intrinsic motivation (High In), high extrinsic motivation (High Ex).

Table 1 Means and standard deviation of classification measures per cluster (K-means)

	Cluster 1 Low In, High Ex (N=182)	Cluster 2 Med In, Med Ex (N=152)	Cluster 3 High In, High Ex (N=415)
Intrinsic motivation to know	4.68 (0.94)	5.38 (1.02)	6.06 (1.10)
Intrinsic motivation to accomplish	3.95 (0.89)	4.09 (0.89)	5.42 (1.06)
Intrinsic motivation to experience stimulation	3.17 (0.95)	3.81 (0.99)	4.92 (1.18)
Identified regulation	6.04 (1.00)	5.58 (1.20)	6.48 (1.03)
Introjected regulation	4.61 (1.14)	3.24 (1.23)	5.35 (1.22)
External regulation	6.05 (1.03)	4.52 (1.43)	6.12 (1.23)
Amotivation	1.44 (0.73)	1.40 (0.73)	1.32 (0.62)

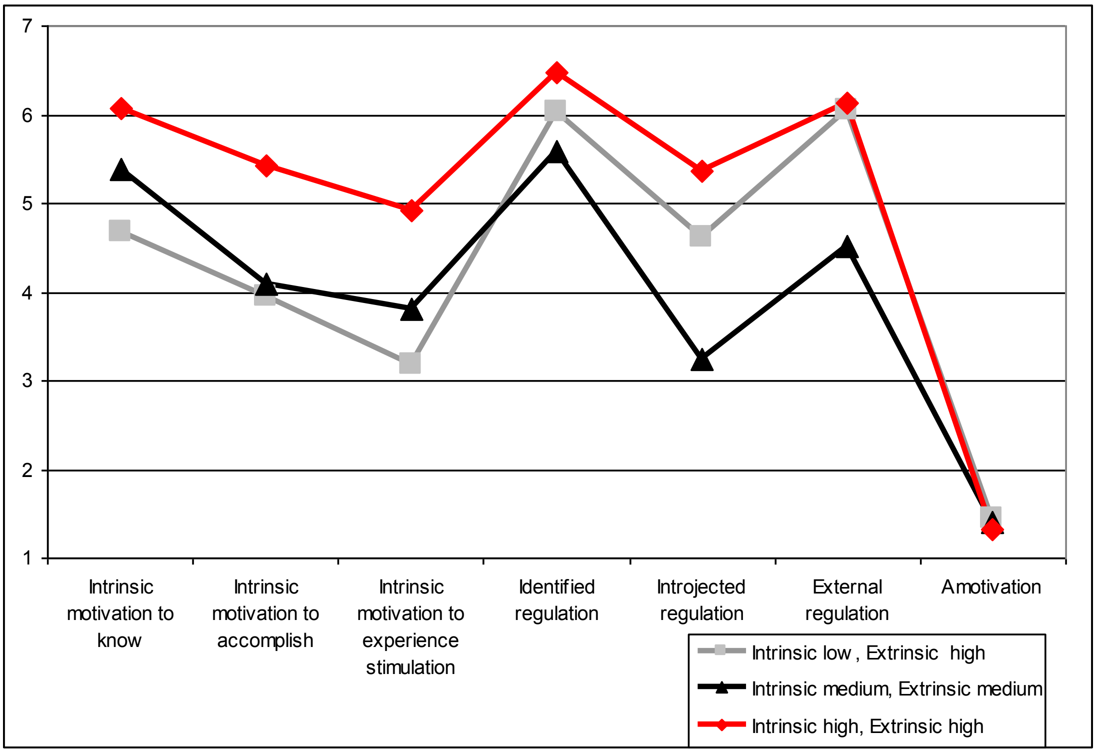

Figure 1 Mean scores of the seven classifications measures per cluster

To assess whether the sub-group of summer course participants differs with respect to motivation profile from the overall group of foreign freshmen on which the cluster analysis was conducted, we compared the number of participants in each of the three clusters. With respect to the first two clusters, no significant differences are found between 82 summer course participants and 683 other foreign students. In cluster 3 (high intrinsic and extrinsic motivation), a significant positive difference is found ($F = 24.883$, $t = 2.030$, p-value = 0.043), implying that the summer course group counts a relatively larger number of cluster 3 students[1]. However, in a formal t-test on differences in means, no significant differences are found between summer course participants and no-participants on any of the AMS variables, except for amotivation. Therefore, we can assume that the summer course participants resemble the overall group of foreign freshmen with respect to type of motivation.

4.3. Relating students' motivation to Social Network Analysis

[1] Given that attendance to the online summer course programme is voluntary, it is reasonable to expect an overrepresentation of high intrinsically motivated learners.

As a third step, the cluster memberships are added as learner attributes to the social networks of each of the six virtual teams. To illustrate the power of SNA in understanding the interaction patterns amongst learners, the social network of team 5 (Figure 2) and team 6 (Figure 3) are presented. Both Team 5 and Team 6 have a mix of learners with different motivation profiles. Learners for which no motivation attributes are available and teachers are represented by a light-coloured circle, while cluster 1 learners (Low In, High In) are represented by a light-coloured square box, cluster 2 learners (Med In, Med Ex) by a dark triangle, and finally cluster 3 learners (High In, High Ex) by a shaded diamond box[2]. In this way, we are able to visualise the position of each learner in the network as well as to whom each learner is connected to depending on his/her motivational profile. Five aspects can be distinguished from these figures.

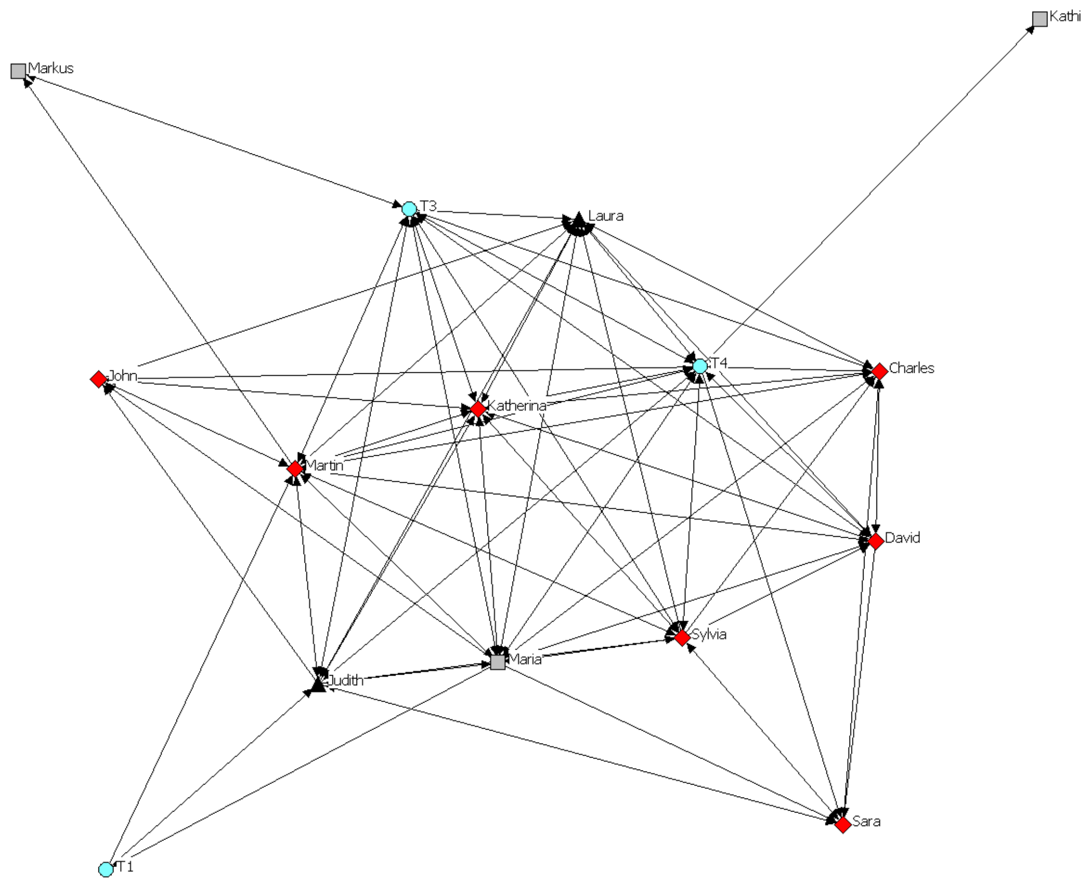

Figure 2. Social Network of team 5

[2] The names of the participants are replaced by fictitious names in order to guarantee privacy of the participants.

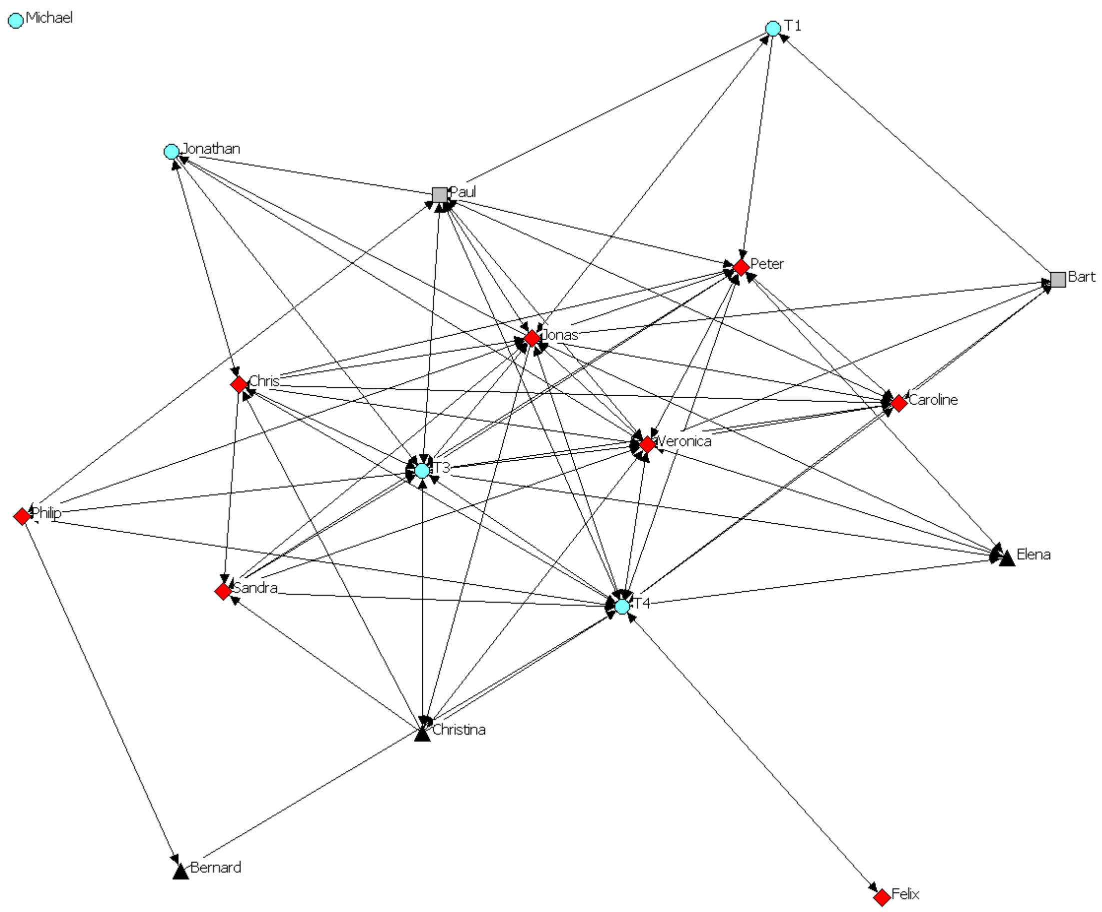

Figure 3. Social Network of team 6

First of all, the social networks illustrate who is communicating with whom and what the direction of communication is (Freeman, 2000). For example, in Figure 2, Tutor 4 replied to a comment of Kathi, which is indicated by the direction of the arrow (Wassermann & Faust, 1994). In addition, Laura and Charles have a so-called "reciprocal link" as they reacted both to each other's contribution and the arrow goes in both directions. Second, some individuals within the network are more central than others (Russo & Koesten, 2005; Wassermann & Faust, 1994). For example, Katherina, Martin, Maria, Sylvia and Tutor 4 are central members in team 5, while Jonas, Veronica and Tutor 3 are central in team 6. Third, some learners are on the outer fringe of the network and are not well-connected. For example, Markus, John and Kathi as well as Bernard and Felix are connected with less than four ties in team 5 and team 6 respectively. Fourth, there are some learners who are connected with most learners but who are still on the outer fringe. For example, Laura, Charles and Judith in team 5 and Christina, Sandra and Paul in team 6 have more than 15 contributions but are still on the outer fringe of the overall network. This means that despite the fact that their number of links to others is high, they do not occupy a central position in the network.

Finally, when looking at the three motivation profiles, it appears that students with high intrinsic motivation are situated closely together. For example, in team 6 most of the connections of Veronica and Jonas (cluster 3) are to students with the same cluster membership. Learners with low and medium motivation are positioned mostly on the outer fringe of the network and are mainly connected to highly intrinsically motivated learners. Furthermore, learners within cluster 1 (Kathi and

Markus of team 5; Paul and Bart of team 6) and learners within cluster 2 (Judith and Laura; Elena, Christina and Bernard) are not well connected to other learners with the same motivation profile. In fact, most cluster 1 and 2 learners are only indirectly linked to each other through cluster 3 learners. For example, in team 6 Bart can only be linked to Paul via Jonas or Caroline. In sum, our learners differ with respect to the number of ties as well as with respect to the position in the network, which has also been found in other research (De Laat et al., 2007; Russo & Koesten, 2005). Furthermore, we find that the position of learners in a social network depends on the type of motivation.

4.4. Internal and External connections in clusters

In Table 2, the contributions to discourse per cluster within each team are provided. For example, in team 6 two tutors and a teaching assistant supported the discourse and contributed 64 messages, whereby tutor 3 had the lead role, tutor 4 the supportive role and tutor 1 assisted when one of other tutors was not available due to taking a day off. Furthermore, one learner in team 6 with no information on academic motivation (Jonathan) has posted 8 messages. The two cluster 1 learners (Bart and Paul) have contributed in total 24 messages. The three cluster 2 learners (Elena, Christina, Bernard) have contributed 22 messages, while the eight cluster 3 learners have contributed 227 messages.

Table 2 Contributions to discourse per cluster within each team

	Teacher		No Info		Cluster 1		Cluster 2		Cluster 3		Total	
	Messages	n	Messages	n	Messages	n	Messages	n	Messages	n	Messages	n
Team 1	38	2	26	3	25	2	110	3	81	5	280	15
Team 2	53	3	3	1	55	2	38	2	366	10	515	18
Team 3	34	2	0	0	85	6	5	1	70	4	194	13
Team 4	68	2	0	0	0	0	10	1	677	16	755	19
Team 5	16	3	0	0	52	3	88	2	290	7	446	15
Team 6	64	3	8	1	24	2	22	3	227	8	345	17
Total	273	15	37	5	241	15	273	12	1711	50	2535	97

In Table 3 we compare the average number of internal and external links of each learner within the three clusters, providing mean scores and standard deviations (in brackets). If we look at the (absolute) discourse per learner of each cluster, the amount of discourse is positively related with the cluster type. Cluster 1 learners contribute the least amount of discourse (13.20 messages per learner), cluster 2 form a middle group (17.42), and finally the most active group is cluster 3 (26.04). When we distinguish internal and external messages with regard to cluster membership, we find that cluster 1 and cluster 2 students send significantly more messages to students outside their cluster than to their own cluster type students. For example, Cluster 1 learners send 2.20 messages on average to learners within cluster 1, while they send 11.00 messages to learners in cluster 2 and 3. As a result, the sent difference in Table 3 for cluster 1 students is negative (-8.80), implying that they send more messages to external cluster students. Furthermore, cluster 1 learners receive more messages from external cluster students. A similar pattern is found for cluster 2 students. In contrast, cluster 3 students send to (18.74) and receive more (20.28) messages from other cluster 3 students. Both sent difference and received difference for cluster 3 students is positive. Using an independent sample T-test, no evidence is found that cluster 1 and 2 differ significantly from each other. In contrast, both cluster 1 and 2 differ significantly from cluster 3. The t-test outcomes of the last column in Table 3 illustrate the differences between the combined first two clusters and cluster 3.

Table 3 Interaction among learners per cluster in absolute numbers

	Cluster 1 Low In, High Ex (N=15)	Cluster 2 Med In, Med Ex (N=12)	Cluster 3 High In, High Ex (N=50)	t-test difference
Sent total	13.20 (12.69)	17.42 (15.22)	26.04 (25.86)	2.048*
Sent to internal cluster	2.20 (2.62)	3.17 (4.32)	18.72 (20.92)	3.96***
Sent to external cluster	11.00 (11.37)	14.25 (11.45)	7.32 (9.36)	-2.13*
Sent difference	-8.80 (10.55)	-11.08 (8.23)	11.40 (19.54)	5.30***
Received total	13.53 (12.94)	18.25 (15.22)	29.82 (25.92)	2.638**
Received from internal cluster	2.20 (2.68)	3.00 (3.64)	20.28 (22.02)	4.15***
Received from external cluster	11.33 (11.30)	15.25 (13.23)	9.54 (8.89)	-1.46
Received difference	-9.13 (10.11)	-12.25 (11.66)	10.74 (21.35)	4.84***

Note: Independent sample T-test (2-sided) (Cluster 1 + 2 vs. Cluster 3)
* Coefficient is significant at the 0.05 level (2-tailed).
** Coefficient is significant at the 0.01 level (2-tailed).
***Coefficient is significant at the 0.001 level (2-tailed).

In Table 4, the relative interactions within and between clusters are illustrated, whereby we correct for the total number of each of the three profiles of motivation within a virtual team. For example, in team 6 there is one learners from cluster 0 (Jonathan), two learners from cluster 1 (Bart and Paul), three from cluster 2 and eight from cluster 3. These 14 students were supported by three tutors. In order to correct for the difference sizes of each cluster, the size of each cluster within each virtual team is compared to the size of the external cluster. Thus, for cluster 1 the number of sent messages to the internal cluster is divided by two, yielding a relative measure for sent to internal cluster for each member within cluster 1. At the same time, the number of sent messages by Bart and Paul to other people is divided by 15. The aggregated results for all clusters in the six teams are illustrated in Table 4.

Table 4 Interaction among learners per cluster corrected by relative cluster size

	Cluster 1 Low In, High Ex (N=15)	Cluster 2 Med In, Med Ex (N=12)	Cluster 3 High In, High Ex (N=50)	t-test difference
Sent total	1.59 (1.50)	2.29 (2.45)	2.74 (2.74)	1.950[†]
Sent to internal cluster	0.62 (0.67)	1.22 (1.54)	1.70 (1.71)	2.790**
Sent to external cluster	0.97 (0.98)	1.06 (0.95)	1.04 (1.18)	0.518
Sent difference	-0.35 (0.76)	0.16 (0.74)	0.66 (1.08)	3.80***
Received total	1.66 (1.64)	2.31 (2.23)	3.25 (2.57)	2.824**
Received from internal cluster	0.62 (0.72)	1.17 (1.34)	1.84 (1.68)	3.356***
Received from external cluster	1.04 (1.09)	1.14 (1.07)	1.41 (1.17)	1.660
Received difference	-0.42 (0.86)	0.025 (0.94)	0.42 (1.10)	3.033**

Note: Independent sample T-test (2-sided) (Cluster 1 + 2 vs. Cluster 3)
[†] Coefficient is significant at the 0.10 level (2-tailed).
* Coefficient is significant at the 0.05 level (2-tailed).
** Coefficient is significant at the 0.01 level (2-tailed).
***Coefficient is significant at the 0.001 level (2-tailed).

For all cluster 1 learners in the six teams, this implies that on average 0.62 messages are sent to each of the cluster 1 learners. At the same time, on average 0.97

messages are sent by cluster 1 learners to each of the external learners. That is, cluster 1 learners send on average 56% more messages outside their cluster and this difference is significant at 10% ($T = -1.768$, $p < 0.10$) in a paired-samples T-test. At the same time, cluster 1 learners received 68% more external messages from outside their cluster than from inside their cluster and this difference is again significant at 10% ($T = -1.883$, $p < 0.10$). Therefore, both sent to and received from measures indicate that cluster 1 learners are mainly focussed on communication with learners outside their own cluster, implying that the motivation profile has an influence on whom cluster 1 learners are connected to. In other words, we find support for hypothesis 2 that extrinsically motivated learners are more likely to interact with intrinsically motivated learners than with extrinsically motivated learners.

Cluster 2 learners (medium intrinsic, low to medium extrinsic motivation) send about an equal amount of messages to both within and outside their cluster. At the same time, they receive an equal amount of messages from within as well as outside their cluster. This implies that cluster 2 learners do not distinguish with whom they communicate. Thus, cluster 2 learners are connected to other learners within the social network as predicted by random graph theory.

Finally, cluster 3 learners contribute most actively to discourse in absolute and relative number. More messages are contributed to learners within the same cluster, namely 1.70 messages per learner in cluster 3. In contrast, only 1.04 messages are sent to each external cluster learner. In other words, cluster 3 learners are almost 40% more likely to send a message to their own cluster and this difference is statistically significant at 1% ($T = 4.326$, $p < 0.01$) in a paired samples T-test. In addition, the majority of the messages received by learners in cluster 3 originate from their own cluster ($T = 2.748$, $p < 0.05$). If we subtract the average number of contributions sent to external clusters (1.04) from those received from external clusters (1.40), we find that the communication of cluster 1 and 2 members is more strongly directed to cluster 3 members than vice-versa, and this difference is significant ($T = -3.879$, $p < 0.01$) in a paired-samples T-test. Hence, the stronger extrinsically motivated learners, and the learners with a less outspoken motivational profile, are connecting primarily to the intrinsically motivated learners, which supports hypothesis 2. In addition, intrinsically motivated learners are the most active contributors to discourse, but, in agreement with hypothesis 3, are contributing mostly with students having similar motivational profile..

5. Discussion

The results of the present study indicate that in our virtual settings learners connect to other learners depending on their motivation profile. We find evidence that learners with high intrinsic motivation receive a relatively large amount of contributions from learners with other motivational profiles. At the same time, intrinsically motivated students themselves are focussing more on discourse with other intrinsically motivated learners. These findings indicate that in distance learning settings interaction patterns amongst participants and evolutions of social networks of virtual teams do not develop randomly. In fact, we find that highly extrinsically motivated learners are more likely to connect to intrinsically motivated learners than vice versa, which contrasts the random graph theory where learners interact irrespective of differences in personal traits.

With respect to the position of the individual learner in the social network, large differences are found amongst learners, which is in line with previous findings

(De Laat et al., 2007; Russo & Koesten, 2005). A new feature is that we are able to link the position of the learner in the social network to his/her motivational profile. The social network graphs indicate that learners with certain motivational profiles are more likely to connect to each other than to learners with other profiles. The majority of the central learners in the social networks are intrinsically motivated learners. In addition, most extrinsically motivated learners seem to be stronger connected to intrinsically motivated students than vice versa. In fact, when we analyse the social networks of all six virtual teams, we find strong support for the idea that most learners have a preference to connect to intrinsically motivated learners. This amongst others implies that intrinsically motivated learners rather prefer to discuss with each other than to connect to learners outside their cluster. Learners with medium intrinsic and low to medium extrinsic motivation interact with other learners with a similar probability. The differences we find between internal and external communication in for students with a less outspoken motivational profile (cluster 2) are not sufficient to produce statistically significant differences, implying that students' motivation profiles do not play such a crucial role in choosing communication partners than for intrinsically and extrinsically motivated students. In contrast, extrinsically motivated learners are more externally focussed than internally focussed, although the effects are marginally significant.

These findings might have important consequences as we find support of the idea that in distance learning settings learners prefer to interact with learners who are highly intrinsically motivated. This implies that learners strong in intrinsic motivation, who due to the nature of distance learning already have an advantage over other students (Rienties et al., In press), will in the duration of the course be further stimulated by extrinsically motivated learners as well as other intrinsically motivated learners that are keen to link to them. By receiving more contributions from others to initiated discourse (in particular from intrinsically motivated students), they can exchange more knowledge and receive more feedback than learners with low intrinsic motivation who receive little contributions from others. In a way, it seems like a self-fulfilling prophesy: active contributors to discourse receive further encouragements from others to continue, while these active contributors at the same time interact mostly with other active contributors rather than students on the outer fringe of the network. Therefore, intrinsically motivated learners appear "well-suited" for our distance learning setting and continuously receive acknowledgements from other learners. In contrast, extrinsically motivated learners contribute less to the discourse and are less successful in inviting responses from other learners. As a result, extrinsically motivated learners receive less feedback and stimuli from others, which might further decrease their integration within the virtual team.

Research by Russo & Koesten (2005) on the position of learners within the network showed that being central is beneficial for learning outcomes. Furthermore, our own longitudinal research of summer course participants in the first year of their bachelor showed that successful summer course participants, who are mainly intrinsically motivated, outperform their peer on study success and study performance (Rienties, Tempelaar, Dijkstra, Rehm, & Gijselaers, 2008). Taking our findings and findings from others together, we find that motivational orientation has a strong influence of the learning interaction processes in collaborative learning, which eventually might lead to large differences in learning outcomes. If our findings are replicated in other distance learning settings, this might imply that due to the nature of preferential attachment to intrinsic motivation extrinsically motivated students will be put at a disadvantage. Given the complex nature of distance learning (Bromme et al., 2005; De Laat et al., 2007; Resta & Laferrière, 2007), this disadvantage might be too large and detrimental for extrinsically motivated learners. This might explain why distance learning courses suffer from large differences in discourse among learners as well as high drop-out rates.

Limitations

The results of this study were based on a k-means cluster analysis on student self-scores for a questionnaire on academic motivation, which was afterwards linked to the social network of each virtual team using Social Network Analysis. This can be viewed as a potential limitation to this study in that no content analysis was conducted on the type of discourse. The aim of content analysis techniques is to reveal evidence about learning and knowledge construction from online discussions. In an extreme case, it might be that extrinsically motivated learners who are not central in the network and contribute to a low degree to discourse might actually contribute mainly to higher cognitive discourse, while intrinsically motivated learners contribute more to non-task related communication or low cognitive discourse, thereby minimizing the negative effects of preferential attachment. However, in our first study (Rienties et al., In press), we showed that extrinsically motivated learners underperform relative to intrinsically motivated learners with respect to contributions to higher cognitive discourse. In fact, we found strong correlations between intrinsic motivation and knowledge construction and hence we expect that a similar pattern will be found as reported in this article if we analyse interaction patterns of higher cognitive discourse.

As a second limitation, the long-term consequences on learning outcomes have not been demonstrated. However, our longitudinal analysis of learning outcomes among summer course participants indicate that active summer course participants outperform others in the first year of their bachelor programme (Rienties et al., 2008). Besides the quantitative measures of learning, implementing qualitative measures of learning like critical event recall (e.g. De Laat et al., 2007) might provide further evidence of how motivational orientation influences learning in virtual settings. We encourage researchers to assess the role of motivation on type of discourse and position in the network in other settings in order to verify our findings.

A third limitation of this study is that no measures were taken to prevent self-selection in the summer course programme. Each novice student who was interested in joining the programme was accepted if his/her prior knowledge was below a pre-defined threshold. Although all students were informed by ordered mail about the opportunities of the summer course, given the voluntary nature of the summer course programme, a reasonable assumption might be that intrinsically motivated students are more inclined to join than extrinsically motivated students. We established that the proportion of cluster 3 students amongst summer course participants is indeed somewhat higher than the proportion in all freshmen, yet cluster 1 and cluster 2 students are not statistically significantly underrepresented in our subsample. So selection effects, if present, are of limited size. In addition, our study does not aim to generalise findings from the summer course participants to the group of all freshmen, so in that sense presented outcomes are immune for selection affects. On top of that: selecting or rejecting students based on motivational orientations rather than prior knowledge leads to ethical issues. For example, preventing externally regulated or amotivated learners to enter a preparatory course, while accepting strongly intrinsically motivated students, leads to obvious ethical problems. Alternatively, composing groups on the motivational orientation of students might also lead to ethical dilemmas. In our setting, which matches the practice teachers in online settings are confronted with (i.e. groups with a mix of various types of motivated students), we did not balance groups based on a pre-determined mix of motivational types.

Future Research and Implications for Education

Based on our findings, we will redesign the learning environment to capitalise on the merits of social interaction, peer-support and planning of learning processes. By increasing social presence in our virtual learning environment by using Web 2.0 tools like wiki's and web-videoconference, we hope to increase the relatedness among learners, which has shown to increase the internalisation of motivation regulation (Ryan & Deci, 2000). Socio-emotional support is an important factor in relational development of groups. In particular in CSCL environments, socio-emotional communication is not an automatic artefact.

These findings are relevant for teachers, managers, admission officers and schedulers as the results imply motivational orientation has a moderately strong influence on the type of discourse and position within the social network. Social Network Analysis tools can be used to assess who is contributing actively to discourse and can be used as a tool for teachers to identify learners on the outer ring of the social network. Appropriate strategies to deal with various types of motivation should be designed to assist each type of learner.

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