Virtual teams and preferential attachment 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 sub-groups were formed within virtual teams. These sub-groups are based on motivation profiles and differ with respect to the amount and the direction of discourse activity. The research results reveal that the motivation profile influences with whom a learner is interacting. Extrinsically motivated learners have a preferential attachment 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, Social Network Analysis, Computer Supported Collaborative Learning.

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 evidence that collaboration can enrich student learning through interaction (Jonassen & Kwon, 2001; Lindblom-Ylänne, Pihlajamäki, & Kotkas, 2003; Van den Bossche, Gijselaers, Segers, & Kirschner, 2006). A common assumption is that ICT has the power to provide a rich learning experience by using a variety of learning methods. ICT-tools like discussion forums and chat “afford” learners to learn in a challenging and interactive manner (Jonassen & Kwon, 2001; Kirschner, Strijbos, Kreijns, & Beers, 2004; Resta & Laferrière, 2007; Yang, Tsai, Kim, Cho, & Laffey, 2006).

Despite the possibilities or affordances of 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, 2003; Nussbaum & Bendixen, 2003). 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. Thus, these distance learning courses are characterised by largely unequal participation among students. But not only differences in contributions by students have been found. For example, De Laat and Lally (2003) and Schellens and Valcke (2005) showed that students also differed with respect to the type (cognitive, affective, metacognitive) of contributions. In general, it seems there is mounting evidence showing that learners in virtual settings contribute substantially different in terms of amount of messages as well as type of discourse.

Although recent research findings indicate that learners differ with respect to the amount and type of discourse contributed, little is known about what the causes and consequences of these differences are. Previous research has shown that the type of motivation has a strong influence on the amount and type of discourse when looking at bachelor students economics who worked together in virtual teams. In addition, intrinsically motivated students were found to be more central in the social network than extrinsically motivated students (Rienties, Tempelaar, Van den Bossche, Gijselaers, & Segers, Submitted). Motivation plays such an important role as the nature of distance learning and the limited role of the teacher in a collaborative learning constellation (Kirschner et al., 2004; Vonderwell, 2003) refrains the teacher to interact in a similar manner as in a face-to-face setting. In addition, learners are given a large autonomous freedom to decide their own learning path in virtual settings, which is beneficial for learners with intrinsic motivation. Hence, the nature of distance learning suggests a dominant role for intrinsic motivation (Ryan & Deci, 2000a), relative to extrinsic motivation.

In this follow-up study, we investigate whether the motivational orientation has an influence on whom a learner is interacting with. As we previously found a large difference in discourse due to differences in the motivational orientation of learners (Rienties et al., Submitted), in this paper we will explore whether learners perceive and act upon these differences in motivation. One method to draw inferences from interaction patterns among individuals is Social Network Analysis (Wassermann & Faust, 1994). Within educational psychology, a limited amount of research is conducted on how learners are connecting to other learners within in groups using Social Network Analysis (Otte & Rousseau, 2002). In contrast, in disciplines like economics and sociology Social Network Analysis techniques are used more often (Cowan & Jonard, 1998; Otte & Rousseau, 2002). Within these fields, developments of linkages between individuals in networks can be described based on random graph theory or by networks having preferential attachment (Barabasi, 2002). In networks that develop according to random graph theory (Barabasi, 2002; Cowan & Jonard, 1998), learners connect to other learners on an equal basis, irrespective of personality traits like motivational orientation. In contrast, in networks with preferential attachment (Barabasi, 2002), learners are mainly connecting to other learners with some perceived "positive" trait (e.g. large knowledge-base, large network of peers).

For example, a student who is highly intrinsically motivated to learn a particular subject might develop a deeper insight into this subject than an extrinsically motivated learner (Ryan & Deci, 2000b). Hence, the intrinsically motivated learner might be perceived by others to be an attractive learner to connect to in collaborative learning settings in order to exchange knowledge and feedback.

If virtual teams develop like networks with preferential attachment, this will imply that the existence of variation in motivational orientation of the members of a virtual team can have an impact on the interaction patterns of learners. To verify which network is more likely to develop, we will use a cluster analysis of motivational variables in combination with Social Network Analysis to assess how the profiles of motivation influence to whom an individual learner is connected to. Based upon the results of our first study, that demonstrated that intrinsically motivated learners distinguish themselves from extrinsically motivated learners with respect to the number of higher cognitive contributions to the discourse, we expect that all learners have a preference to connect to intrinsically motivated learners. Furthermore, we expect that intrinsically motivated learners are mainly connecting amongst themselves in order to elaborate their insights into a particular subject.

2. Preferential attachment to intrinsically motivated learners

In order to assess whether learners are interacting differently based on their motivational orientation, we first elaborate on the concept of motivation. Afterwards, we analyse whether certain profiles of motivation are more favourable in distance learning settings than others in order to assess whether learners have a preference to attach to particular profiles of motivation. According to Ryan and Deci (2000a; 2000b), most theories of motivation regard motivation as a unitary phenomenon, implying that a learner has either a lot or little motivation, also referred to as states of motivation versus amotivation. To be motivated means to be moved to do something, while amotivation is a state of lacking any intention to act (Ryan & Deci, 2000a). 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). In Self-Determination Theory (SDT), Ryan and Deci (2000a; 2000b) 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. Externally motivated learning refers to learning that is a means to an end, and not engaged for its own sake. In contrast to classical theories of motivation that regard extrinsic motivation as a single construct, 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, 2000a). 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. External regulation depicts behaviour that is performed to satisfy external demand without that it is integrated into the self. For example, homework provided by the teacher is made by the learner without that the learner integrates the activity into the self. Introjected motivation represents a form of regulation by contingent self-esteem, which implies that although the regulation is internal to the learner, the behaviour is not fully part of the self (Ryan & Deci, 2000a).

For example, when parents indicate that making homework is important, the learner will integrate (parts of) the regulation when making homework in order to prevent guilt. In identification, the learner has identified the importance of a behaviour and has accepted its regulation as his or her own. For example, making mathematics homework will enable the learner to be mathematically skilled, which will increase his career chances in the future and hence the learner will consciously value this regulation (Ryan & Deci, 2000b). Finally, the most autonomous form of extrinsic motivation is integrated regulation, where a learner fully values the activity and integrates the regulation into the self.

Given the complex 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, Lally, Lipponen, & Simons, 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., Submitted), they possess crucial characteristics for distance learning. Superior contributions to discourse at 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, who lead the discourse development within the virtual team, thereby providing the desired external regulation to extrinsically motivated learners. As a result, we expect that extrinsically motivated learners will have a preferential attachment to intrinsically motivated learners. At the same time, given the attractiveness to establish discourse with intrinsically motivated learners, intrinsically motivated learners are expected to establish connections primarily within their own sub-group.

In conclusion, the complex nature of social interaction in distance learning suggests a dominant role for intrinsic motivation, relative to extrinsic motivation. Hence, we expect that learners will have preferential attachments to learners with high intrinsic motivation as they can gain more knowledge, feedback and learning regulation. This then will imply our hypothesis that low extrinsically motivated learners send more (external) messages to high intrinsically motivated learners, while intrinsically motivated learners will send more (internal) messages to high intrinsically motivated learners.

3. Method

3.1. Setting

This study is part of a large European research programme on the effectiveness of virtual team learning in remedial education[i]. 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 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 used principles of Problem-based learning (PBL), which is a typical application 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). Students participated in groups within a collaborative learning environment using discussion forums and announcement boards. Within six weeks, students had to collaborate together on solving six tasks through a problem-based learning method. The group, together with the tutor, could decide upon the pace in which content and context were dealt with. No obligatory meetings were scheduled. At the end of each week, the 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. A non-recognised certificate and a drink at a graduation ceremony were the only external rewards. 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. Subjects

In total 100 participants were randomly assigned into 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 that 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, to 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 (Cokley, Bernard, Cunningham, & Motoike, 2001; Fairchild, Jeanne Horst, Finney, & Barron, 2005; Vallerand & Bissonnette, 1992; Vallerand & Pelletier, 1993; Vallerand et al., 1992). In total 1445 freshmen filled in the questionnaire during the first course of the semester. The response-rate on AMS-questionnaire 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, Green-Demers, & Pelletier, 2006; Vallerand et al., 1992). As the subjects of the summer course were foreign students, the Dutch students were removed from the database, leading to 765 students on which a k-means cluster analysis was conducted.

3.4. Statistical analyses

3.4.1. Cluster analysis

As 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

According to Aviv, Erlich, Ravid and Geva (2003), a social network is defined as a group of collaborating (and/or competing) entities that are related to each other. Social Network Analysis (SNA) can be considered as a wide-ranging strategy to explore social structures to uncover the existence of social positions of individuals within the network (Aviv, Erlich, Ravid, & Geva, 2003). According to Russo and Koesten (2005), SNA can provide a better understanding of patterns of interaction of individuals in virtual settings. 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.

4. Results

4.1. Clustering students on Academic Motivation

In order 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 algorithm was applied to obtain three different profiles for motivation, which were further labeled according to the final cluster center position (See Table 1). As can be seen from Figure 1, the three motivation profiles are: (1) cluster one: low intrinsic motivation, high extrinsic motivation; (2) cluster two: medium intrinsic motivation, low to medium extrinsic motivation; (3) cluster three: high intrinsic motivation, high extrinsic motivation.

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)

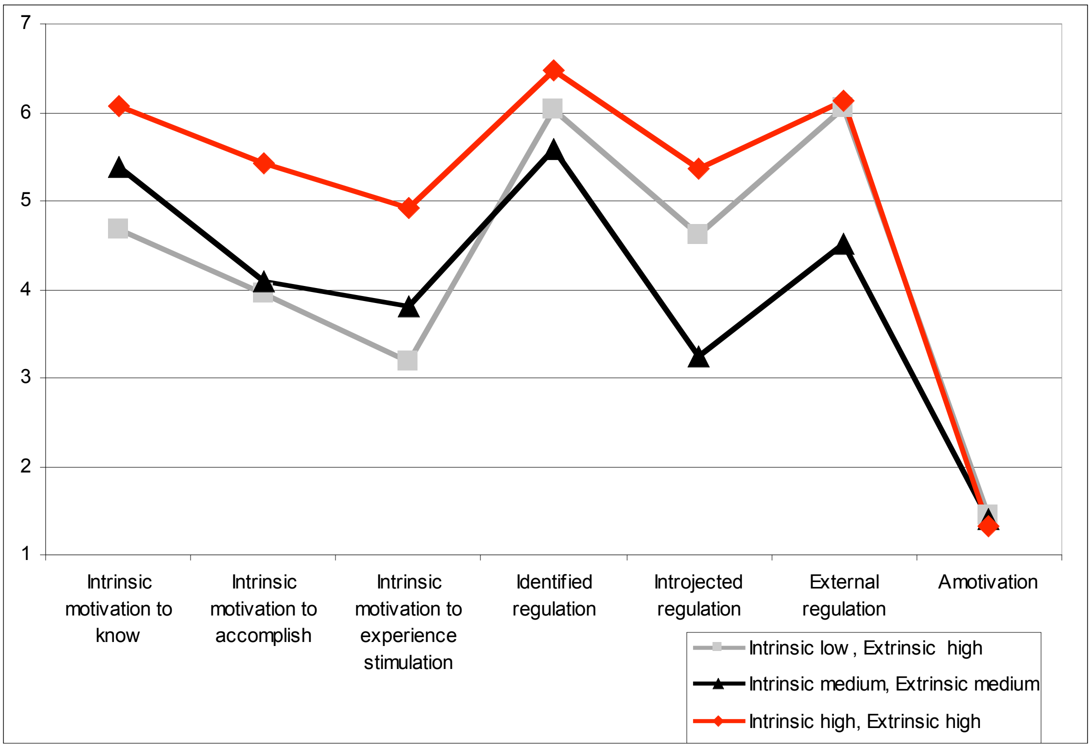

Figure 1 Mean scores of the 7 classifications measures per cluster

To assess whether the sub-group of summercourse 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 difference was found between summercourse and no summercourse participants. In cluster 3 (high intrinsic and extrinsic motivation), a significant positive difference was found ($F = 24.883$, $t = 2.030$, p-value = 0.043), implying that the summercourse group counts a relatively larger number of cluster 3 students[1]. However, in a formal t-test on differences in means, no significant differences were found between summercourse participants and no-participants on any of the AMS variables, except for amotivation. Therefore, we can assume that the summercourse participants resemble the overall group of foreign freshmen with respect to type of motivation.

4.2. Relating students' motivation to Social Network Analysis

As a second step, the cluster memberships were 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 intrinsic, high extrinsic) are represented by a light-coloured square box, cluster 2 learners (medium intrinsic, low to medium extrinsic) by a dark triangle, and finally cluster 3 learners (high intrinsic and extrinsic) by a shaded diamond box[ii]. In this way, we were able to visualise the position of each learner in the network as well as to whom each learner was connected to depending on his/her motivational profile. Five aspects can be distinguished from these figures.

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 motivation profiles, it appears that students with high intrinsic motivation are clustered in subgroups. 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 high intrinsically motivated

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

learners, which is in line with the hypothesis of networks with preferential attachment. 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; Rienties et al., Submitted; Russo & Koesten, 2005). 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.

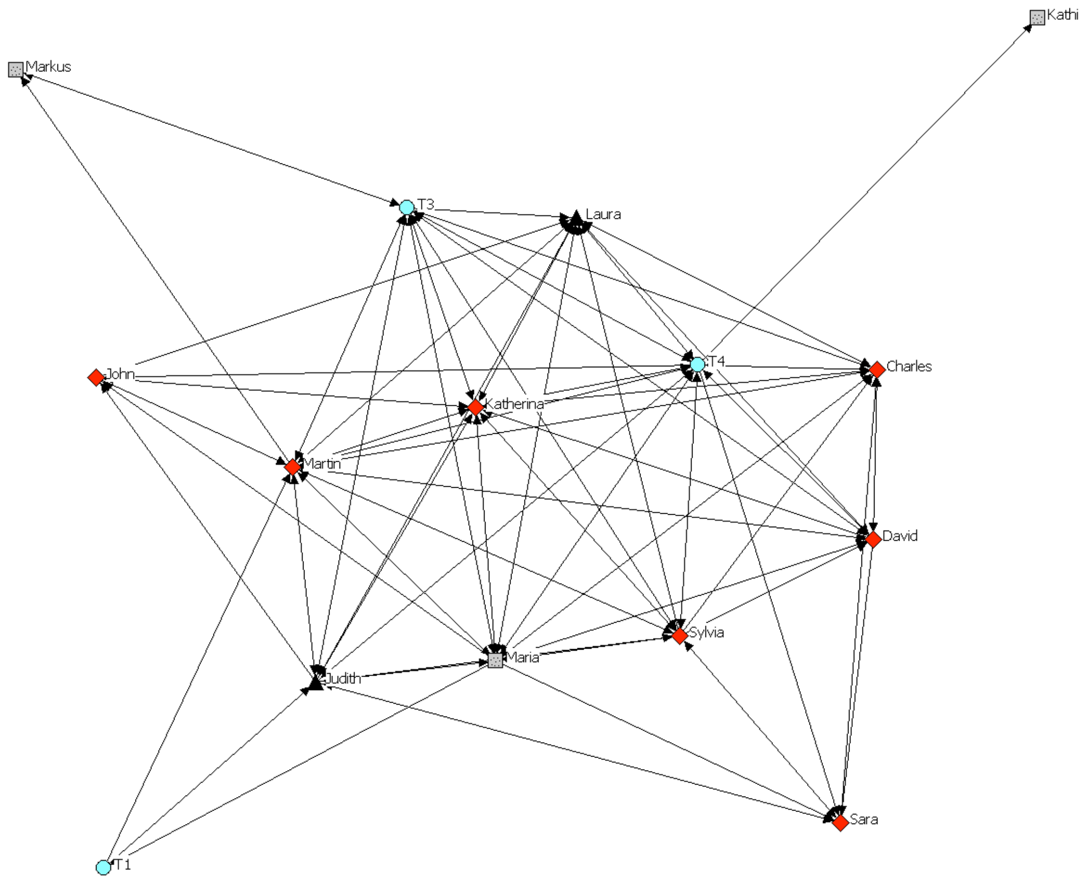

Figure 2. Social Network of team 5

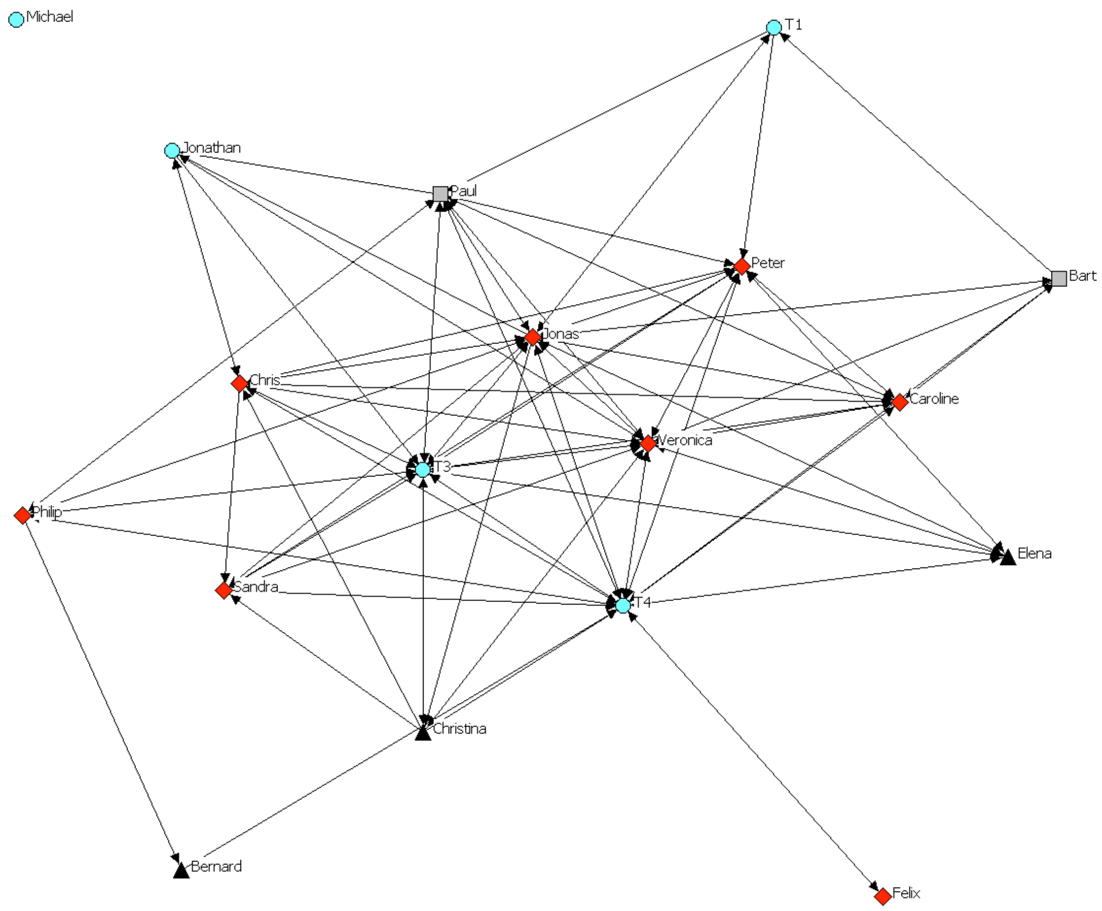

Figure 3. Social Network of team 6

4.3. Internal and External connections in clusters

Although the social network graphs of team 5, 6 and the other four teams (not illustrated) indicate some degree of preferential attachment to high intrinsically motivated learners, it is unclear whether this phenomenon is statistically significant in all six teams. Therefore, we first look at the overall distribution of each cluster type (Table 2) and afterwards assess whether particular profiles contribute more/less internal/external messages. In Table 2, the contributions to discourse per cluster within each team are provided. For example, in team 6 the two cluster 1 learners have contributed in total 24 messages. The two cluster 2 learners have contributed 22 messages, while the eight cluster 3 learners have contributed 227 messages.

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 (total) discourse per learner of each cluster, the amount of discourse is positively related with the cluster type, as cluster 1 learners contribute the least amount of discourse (13.20 messages per learner), cluster 2 form a middle group (17.42 messages per learner), and finally the most active group is cluster 3 (26.04 messages per leaner). In almost all discourse intensities, the standard deviations are approximately equal to the mean scores. This implies that within each cluster there exist large differences amongst individual learners in the amount of discourse; see also Rienties et al. (submitted).

Table 2 Contributions to discourse per cluster within each team

	Cluster 1		Cluster 2		Cluster 3	
	Messages	n	Messages	n	Messages	n
Team 1	25	2	110	3	81	5
Team 2	55	2	38	2	366	10
Team 3	85	6	5	1	70	4
Team 4	0	0	10	1	677	16
Team 5	52	3	88	2	290	7
Team 6	24	2	22	3	227	8
Total	241	15	273	12	1711	50

Table 3 Interaction among learners per cluster

	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
Absolute				
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 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***
Relative				
Sent to internal cluster	0.62 (0.67)	1.22 (1.54)	1.70 (1.71)	2.21*
Sent to external cluster	0.97 (0.98)	1.06 (0.95)	1.04 (1.18)	0.11
Sent difference	-0.35 (0.76)	0.16 (0.74)	0.66 (1.08)	3.32**
Received from internal cluster	0.62 (0.72)	1.17 (1.34)	1.83 (1.67)	2.73**
Received from external cluster	1.04 (1.09)	1.14 (1.07)	1.40 (1.16)	1.119
Received difference	-0.42 (0.86)	0.025 (0.94)	0.42 (1.10)	2.62**

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 the second part of Table 3, 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 are five learners from cluster 0, two learners from cluster 1, three from cluster 2 and nine from cluster 3. For cluster 1 the number of sent messages to internal cluster is divided by two, yielding a relative measure for sent to internal cluster for each member within cluster 1. For all cluster 1 learners, this implies that on average 0.62 (0.67) messages are sent to each of the cluster 1 learners. At the same time, the number of sent messages to external clusters is divided by 17, implying that on average 0.97 (0.98) messages are sent by cluster 1 learners to each of the external learners. In this way, we correct for the relative size of each cluster type within each virtual team. Finally, 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.

Cluster 1 learners (low intrinsic, high extrinsic) send 2.20 messages on average to learners within cluster 1, while they send 11.00 messages to learners in cluster 2 and 3. If we use the relative numbers, whereby we correct for the number of learners within each cluster, learners in cluster 1 remain stronger externally focussed. 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-value = 0.09) 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-value = 0.08). 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. Hence, we find (weakly significant) evidence that cluster 1 learners have a preferential attachment for higher intrinsically motivated learners.

After correction for the relative group size of each cluster, cluster 2 learners (medium intrinsic, low to medium extrinsic) 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 when we cluster based upon the motivation profile. Thus, cluster 2 learners are connected to all other learners within the social network as predicted by random graph theory.

The last cluster (high intrinsic and extrinsic motivation) contributes the highest absolute number of messages, namely 26.04 messages on average per learner. After correction for differences in size between the clusters, it appears that learners in cluster 3 contribute larger amounts of messages to its own cluster, namely 1.70 message per learner in cluster 3, while only 1.04 messages are sent to each learner in cluster 1 and 2. In other words, cluster 3 learners were almost 40% more likely to send a message to their own cluster and this difference is statistically highly significant at 1% ($T = 4.326$, p-value < 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-value = 0.01). If we subtract the average number of contributions sent to external clusters (1.04) from those the received from external clusters (1.40), more learners from cluster 1 and 2 are connected to cluster 3 than vice-versa and this difference is again highly significant ($T = -3.879$, p-value = 0.00), in a paired-samples T-test. Hence, intrinsically motivated learners are the most active contributors to discourse but at the same time are contributing most within their own sub-group. In addition, the learners of cluster 1 and cluster 2 are connecting more to cluster 3 learners, implying support for the preferential attachment model.

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 motivation profiles. At the same time, intrinsically motivated students themselves are focussing more on discourse within their own cluster than outside their cluster. These findings indicate that in distance learning settings interaction patterns amongst participants of virtual teams do not develop randomly. In fact, we find that extrinsically motivated learners are more likely to connect to intrinsically motivated learners than vice versa, which corroborates the preferential attachment model.

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 motivation profile. The social network graphs indicate that learners with certain motivation profiles are more likely to connect to each other than to learners with other profiles. The majority of the central learners in the social network are intrinsically motivated learners. In addition, most of the cluster 1 and 2 learners seem to be stronger connected to cluster 3 students than vice versa. In fact, when we analyse the social networks of all six virtual teams, we find strong support of 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. Communication patterns in cluster 2 do not provide additional support to the preferential attachment model. The differences we find between internal and external communication in cluster 2 are not that strong to produce statistically significant differences, implying that students' motivation profiles do not play such a crucial role in choosing communication partners than in other clusters.
In contrast, learners in cluster 1 are more externally focussed than internally focussed. Although the effects are marginally significant, most likely due to the relatively small sample size, we find some proof for the preferential attachment model for cluster 1 learners.

These findings might have important consequences as we find support of the idea of preferential attachment based on students' motivation profiles in distance learning. This implies that students strong in intrinsic motivation, who due to the nature of distance learning already have an advantage over other students (Rienties et al., Submitted), will in the duration of the course be further stimulated by extrinsically motivated students as well as other intrinsically motivated students 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. Intrinsically motivated learners are "well-suited" for our distance learning setting and continuously receive acknowledgements from other learners, while extrinsically motivated learners both contribute less to the discourse and, when they do contribute, are less successful in inviting responses from other students. 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 with the network showed that being central is beneficial for learning outcomes. Furthermore, our own longitudinal research of summercourse participants in the first year of their bachelor showed that successful summercourse participants, who are mainly intrinsically motivated, outperform their peer on study success and study performance (Rienties, Tempelaar, Dijkstra, Rehm, & Gijselaers, In press). Taken our findings and findings from others together, we find that motivational orientation has a strong influence of 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.

6. Limitations

The results of this study were based on a k-means cluster analysis of student self-scores of 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., Submitted), 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. The longitudinal effects of the motivational orientation on type of discourse and position within the network need to be assessed in future research. Preliminary findings indicate that active summer course participants outperform others in the first year of their bachelor programme (Rienties et al., In press). 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 Summercourse 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 summercourse 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.

7. 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 blogs, wiki's and webconference, we hope to increase the relatedness among learners, which has shown to increase the internalisation of a regulation (Ryan & Deci, 2000b). 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 motivation 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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[ii] The names of the participants are replaced by fictitious names in order to guarantee privacy of the participants.