

An invisible preference for intrinsic motivation in Computer-Mediated Communication

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Abstract: A large number of studies in CMC have assessed how social interaction, learning processes and outcomes 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 underlying causes and its consequences explaining differences between participants' contributions to discourse. The present research investigates how motivational orientation of a learner influences the interaction patterns with other learners in a virtual network.

Our research among 100 participants in six virtual teams indicates that three sub-groups were formed within each virtual network. These subgroups were generated by a K-means cluster analysis of academic motivation measured by AMS. Extrinsically motivated learners prefer to connect to intrinsically motivated learners. 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 network.

Introduction

In recent years, the attention for virtual collaborative learning seems to be fuelled by two separate, yet mutually enforcing developments: First, the availability of increasing possibilities of Information Communication Technologies (ICT) provide enhanced support for collaboration (Bromme, Hesse, & Spada, 2005; Resta & Laferrière, 2007; Schellens & Valcke, 2005). Second, growing amounts of evidence have become available showing that collaboration can enrich student learning through interaction (Jonassen & Kwon, 2001; Lindblom-Ylänne, Pihlajamäki, & Kotkas, 2003; Van den Bossche, Gijsselaers, 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 (Beers, Boshuizen, Kirschner, & Gijsselaers, 2007; Giesbers, Rienties, Gijsselaers, Segers, & Tempelaar, 2009; Jonassen & Kwon, 2001; Resta & Laferrière, 2007).

Despite the learning possibilities created by ICT-tools, recent findings in research on computer-mediated communication (CMC) indicate that interaction and contributions made to interaction depend on a variety of factors. Not every learner contributes equally to others. It has been found 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; Martens, Gulikers, & Bastiaens, 2004; Rienties, Tempelaar, Van den Bossche, Gijsselaers, & Segers, 2009). An overall finding in research is that the majority of interactions and contributions within online courses can be attributed to a small number of learners. While this research has demonstrated the existence of this phenomenon, the obvious question is how these differential patterns between learners can be explained.

Several studies have examined this phenomenon by using social network analysis to explain interaction patterns in CMC. Social network analysis (SNA) provides powerful tools to analyze how people interact over a given period of time (Hurme, Palonen, & Järvelä, 2007; Martinez, Dimitriadis, Rubia, Gomez, & de la Fuente, 2003; Rienties et al., 2009). It considers whether certain individuals are central in networks or at the peripheries, and how interactions between individuals may change over time. Research findings have indeed revealed that some learners are more central in the social network than other learners (Hurme et al., 2007; Russo & Koesten, 2005). It has been found that learners who were central in a social network received and also contributed more messages than other learners. In addition, Russo and Koesten (2005) found that learners who were central in the social network had better cognitive learning outcomes.

Although recently several researchers have identified that some participants are more likely than others to be in the centre of networks, they could not explain the underlying mechanisms of these social interaction patterns. The present study aims to fill in this gap, by examining the underlying causes that explain differential contributions to social networks. We address the question why some learners receive relatively more replies to their contributions in discourse while others do contribute but get only limited response from others. So the issue is 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 networks being central or learners being on the outer fringe of a social network.

An invisible hand in social interaction in CMC: motivation

In most virtual networks learners are geographically separated and dispersed over many settings. In collaborative settings, learners have to construct meaning and co-construct knowledge in a virtual setting. However, participation and making contributions to discourse in collaborative settings cannot be taken for granted (Bromme et al., 2005; Kirschner, Beers, Boshuizen, & Gijssels, 2008). In particular when learners are interacting using lean ICT-tools like discussion forums or WIKIs, establishing a critical mass of interaction whereby participants contribute actively to cognitive discourse is troublesome (Caspi, Gorsky, & Chajut, 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 network are seeking for effective working and learning strategies (Beers et al., 2007; Kirschner et al., 2008).

Within CMC, several researchers have tried to influence the interaction patterns among learners by (re)scaffolding the learning process by designing scripts (Weinberger & Fischer, 2006), adjusting the degree of social presence of ICT tools (Giesbers et al., 2009; Jonassen & Kwon, 2001; Tu & McIsaac, 2002) or regulating the interaction processes (Kirschner et al., 2008). For example, by increasing the regulation of interaction processes, Beers et al. (2005) found that interaction among participants could be enhanced. By establishing argumentative scripts, learners contributed more argumentative discourse than when other scripts were used (Weinberger & Fischer, 2006). Nonetheless, individual differences to contributions to discourse still persist when redesigning the learning environment. Limited research has been conducted how differences in individual traits influence the interaction patterns of learners in networks.

One of the explanations for these individual differences lies in the motivation of learners to contribute to the virtual network. Recent research highlights indeed that motivation has a strong influence on how learners contribute to discourse in online settings (Järvelä, Järvenoja, & Veermans, 2008; Martens et al., 2004; Rienties et al., 2009; Veermans & Lallimo, 2007; Yang, Tsai, Kim, Cho, & Laffey, 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 positively influences social presence among peers, that is the perception that emotions can be shared using CMC. 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 relative to students in virtual settings.

The present research builds further on these findings by examining how motivation affects the creation, development and evolution of links between learners in virtual networks. As motivation is a multidimensional and multilevel construct (Boekaerts & Minnaert, 2006), a wide variety of definitions and instruments are discussed and used in educational psychology research. We adopt the concept of motivation developed by Deci and Ryan (1985), where to be motivated means to be moved to do something. The degree of self-determination of learners might explain why some learners contribute more to discourse in CMC than others. As a consequence, it is expected that some learners contribute more to discourse in CMC than others, given their motivation. 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).

Evolution of Social Networks

The present study considers the way learners interact in virtual networks as social network interactions. 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”. Within educational psychology, limited research has been conducted to understand dynamic social network interactions. According to network theorists, there are two important conditions that determine how social networks evolve: 1) the stability of the number of nodes (i.e. participants in virtual network); 2) the (in)equality of characteristics of nodes in the network (Barabási & Albert, 1999; Erdős & Rényi, 1960; Newman, 2003). In case the number of participants in a social network grows continuously (e.g. Wikipedia, Facebook), 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. In contrast, in an online course (as in most classes), the number of learners is mostly pre-determined and relatively stable. Therefore, a straightforward assumption from network theory would be that the social network of an online course will develop and evolve according to random graph theory (Barabási, 2002; Erdős & Rényi, 1960). In random graph theory, learners connect to other learners in a network with a more or less equal probability. *H1: Learners in a virtual network will have an equal amount of connections to all other learners.*

If hypothesis 1 has to be rejected in our setting, then learners in virtual networks 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 (Erdős & Rényi, 1960; Newman, 2003). However, in line with the second condition when nodes (i.e. learners) have a specific preference to connect to some type of nodes, the network will not develop according to random graph theory (Barabási & Albert, 1999; Newman,

2003). Several researchers have indicated that learners in online settings differ with respect to prior knowledge, expertise and motivation when they become member of a virtual network (Järvelä et al., 2008; Martens et al., 2004; Rienties et al., 2009; Yang et al., 2006). When learners in a virtual network become aware that interacting with some learners who have a trait (e.g. intrinsic motivation, large knowledge base, expertise) that is (perceived to be) beneficial, these learners might be more interesting to interact with (Martens et al., 2004).

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., 2009), 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 network. 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 network, 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.*

Method

Setting

The present study took place in an online summer course for prospective bachelor students of an International Business degree program at an Institute for Higher Education in the Netherlands (Rienties, Tempelaar, Waterval, Rehm, & Gijssels, 2006). This online course was given over a period of six weeks in which learners 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”. In our setting, learners participated in virtual networks within a collaborative learning environment using discussion forums and announcement boards. During six weeks, learners had to collaborate together on solving six tasks through a problem-based learning method. No obligatory meetings were scheduled. 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. Learners who passed the course received a certificate.

Participants

In total 100 non-Dutch participants were randomly assigned in six networks. Data were analysed for those individuals who actually posted at least once a reaction in the discussion forum. We found that 18 learners, although registered for this course, never posted a contribution to the discussion forums. The 82 participants who posted at least once a reaction in the discussion forum were selected for our analysis. The six networks had an average of 13.66 members (SD = 2.16, range = 11-17) per network. The average age was 19 years and 45% of the learners were female.

Academic Motivation Scale (AMS)

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 SDT was primarily developed to measure motivation among children. Individual motivation was measured by the Academic Motivation Scale (AMS), which was developed by Vallerand et al. (1992) for college/university learners and measures the contextual motivation for education. The instrument consists of 28 items, in all of which learners 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. The response-rate on AMS-questionnaire among the summer course participants was 93%. The Cronbach alpha reliability for the seven scales ranged from .760 to .856. The 82 students who participated in our setting were unaware of the scores of the AMS and those of their peers with whom they worked and learned together in their virtual team.

Statistical analyses

Cluster analysis

The 82 students in the experiment are part of the inflow of 765 international freshmen. Motivational profiles were determined of all international students by applying k-means cluster analysis to subscale scores of the AMS-instrument. It was decided to base motivational profiles on the complete sample of international freshmen. First of all, this will lead to a more stable outcome of the cluster analysis. Second, in this way we are able to express the motivational patterns found amongst participants relative to the motivational profiles present

amongst all international students. Since participation in the experiment is voluntarily, motivation scores of participating freshmen might be different from motivation scores of all freshmen. In this situation, profiles found amongst all international students were regarded as more relevant benchmarks than profiles found in the restricted group of participants of the experiment. It was found that a three cluster solution provides the best fit for different motivation profiles present in these freshmen. Afterwards, data on cluster membership of all participants of the virtual networks 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.

Positioning of individuals within social network using SNA

Two SNA measures were used, namely ego network density, which measures to how many other learners a learner is directly connected, and Freeman's degree of Centrality, which measures whether learners were central in the social network or not (Freeman, 2000; Wassemann & Faust, 1994). 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 (send to own/outside) clusters as a measurement for equality of interaction between clusters. An innovative feature of this study is that by combining the results of the SNA and cluster analysis, we were able to distinguish interaction patterns amongst individual learners based upon their motivation profile.

Results

In order to test hypothesis 1, the average number of connections in the cohort of online summer course participants is compared. On average, a learner 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 (χ^2 (df = 76) 159.46, $p < .001$). Furthermore, significant differences are found using a Chi-Square test in each of the six virtual networks with the exception of network 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 approximately equal amount of connections per learner, with the exception of network 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 ($M = 26.60$, $SD = 24.29$), as well as by the Chi-Square test for all participants (χ^2 (df = 80) 1772.74, $p < .001$) and the Chi-Square test for participants within each of the networks. 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 networks.

In order to test hypotheses 2 and 3 and to investigate whether the motivation profile of a learner has an influence on the formation of links to other learners within the social network, 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). 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 duster (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 (IMTK)	4.68 (0.94)	5.38 (1.02)	6.06 (1.10)
Intrinsic motivation to accomplish (IMTA)	3.95 (0.89)	4.09 (0.89)	5.42 (1.06)
Intrinsic motivation to experience stimulation (IMES)	3.17 (0.95)	3.81 (0.99)	4.92 (1.18)
Identified regulation (EMID)	6.04 (1.00)	5.58 (1.20)	6.48 (1.03)
Introjected regulation (EMIN)	4.61 (1.14)	3.24 (1.23)	5.35 (1.22)
External regulation (EMIR)	6.05 (1.03)	4.52 (1.43)	6.12 (1.23)
Amotivation (AMOT)	1.44 (0.73)	1.40 (0.73)	1.32 (0.62)

As a third step, the cluster memberships are added as learner attributes to the social networks of each of the six virtual networks. Based upon the division of motivational profiles, network 5 (Figure 2) and network 6 (Figure 3) can be categorised as prototypical networks. 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 box¹. In this way, we are able to visualise the position of each learner

¹ The names of the participants are replaced by fictitious names in order to guarantee privacy of the participants.

in the network as well as to whom each learner is connected to depending on his/her motivational profile. When looking at the three motivation profiles, it appears that learners with high intrinsic motivation are situated closely together. For example, in network 6 most of the connections of Veronica and Jonas (cluster 3) are to learners 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 network 5; Paul and Bart of network 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 network 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. Furthermore, we find that the position of learners in a social network depends on the type of motivation. Cluster 3 learners form the center core of the network, while the other learners are mostly situated on the outer fringe.

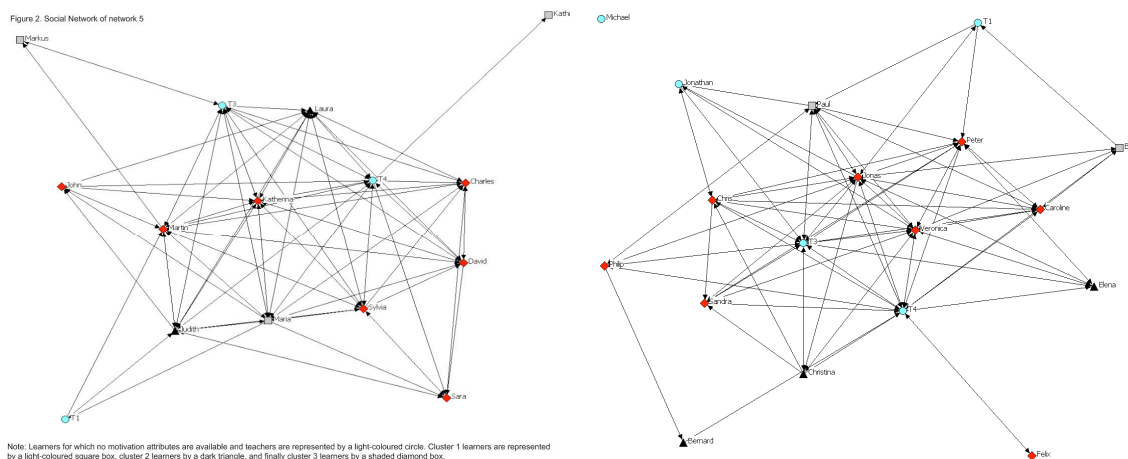


Figure 2. Social Network of network 5 Figure 3. Social Network of network 6

Table 2 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	1.60 (1.50)	2.30 (2.45)	2.74 (2.74)	1.950 [†]
Sent to own cluster	0.62 (0.67)	1.22 (1.54)	1.70 (1.71)	2.790**
Sent outside own cluster	0.97 (0.98)	1.07 (0.95)	1.04 (1.18)	0.518
Sent difference	-0.35 (0.76)	0.15 (0.75)	0.66 (1.08)	3.80***
Received total	1.67 (1.64)	2.32 (2.23)	3.25 (2.57)	2.824**
Received from own cluster	0.62 (0.72)	1.17 (1.34)	1.84 (1.68)	3.356***
Received from outside own cluster	1.04 (1.09)	1.15 (1.07)	1.41 (1.17)	1.660
Received difference	-0.42 (0.86)	0.02 (0.95)	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).

In Table 2, 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 network. Both cluster 1 and 2 differ significantly from cluster 3 using an independent sample T-test with the exception of sent outside own cluster and received from outside own cluster. For all cluster 1 learners in the six networks, 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 learner outside their own cluster. 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 receive 68% more external messages from outside their cluster than from inside their cluster and this difference is again significant at 10% ($T = -1.883$, $p < 0.10$) in a paired-samples T-test. 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 (Barabási, 2002; Barabási & Albert, 1999; Erdős & Rényi, 1960).

Finally, cluster 3 learners contribute most actively to discourse in absolute and relative numbers. 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 learner outside their own cluster. 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. Last but not least, intrinsically motivated learners are the most active contributors to discourse, but, in agreement with hypothesis 3, are contributing mostly with learners having similar motivational profile.

Discussion

The results of the present study indicate that in our settings learners connect to other learners in their virtual network 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 learners 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 networks 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. A new feature is that we are able to link the position of the learner in the virtual network to his/her motivational profile. Most extrinsically motivated learners seem to be stronger connected to intrinsically motivated learners than vice versa.

These findings might have important consequences for instructional designer and online teachers (Mishra & Koehler, 2006; Wang, 2009) as we find support of the idea that in distance learning settings learners prefer to interact with learners who are highly intrinsically motivated (Martens et al., 2004; Rienties et al., 2009). This implies that learners strong in intrinsic motivation, who due to the nature of distance learning already have an advantage over other learners (Rienties et al., 2009), 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 learners), 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 learners 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 (Martens et al., 2004). Given that many educational psychologists have found that learners who are actively co-constructing knowledge eventually have a deeper learning experience (Hmelo-Silver, 2004; Järvelä et al., 2008; Van den Bossche et al., 2006), receiving a lack of reply on contributions might have a negative impact on learning for extrinsically motivated learners. As a result, extrinsically motivated learners receive less feedback and stimuli from others, which might further decrease their integration within the virtual network.

The role of the teacher in designing a challenging and interactive learning environment (Mishra & Koehler, 2006; Wang, 2009) for all types of learners seems to be a prerequisite for interactive learning for all learners. Furthermore, a helpful tool for teachers to understand the complex dynamics of social interaction is to use the insights from motivational science to enhance learning. We suggest that teachers ask their students to fill in a motivation questionnaire before the beginning of the course. This can for example be the Academic Motivation Scale developed by Vallerand and colleagues (1992) or the Quality of Working in Groups Instruments developed by Boekaerts and Minnaert (2006). The results can be used to assess what type of motivated learners teachers have in their course and to actively stimulate students who are less active in discourse.

Limitations

The results of this study were based on a k-means cluster analysis on learner self-scores for a questionnaire on academic motivation, which was afterwards linked to the social network of each virtual network using Social Network Analysis. This can be viewed as a potential limitation to this study as a self-reported measurement of

academic motivation was used with obvious limitations. However, the patterns of interaction among the three identified motivational profiles follow the anticipated direction. In addition, research by Vallerand and colleagues has found that the AMS instrument is a robust predictor of learning outcomes and academic performance. 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, Tempelaar, Dijkstra, Rehm, & Gijsselaers, 2008). A third limitation of this study is that no measures were taken to prevent self-selection in the summer course programme. In our setting, which matches the practice teachers in online settings are confronted with (i.e. networks with a mix of various types of motivated learners), we did not balance networks based on a pre-determined mix of motivational types. We established that the proportion of cluster 3 learners amongst summer course participants is indeed somewhat higher than the proportion in all freshmen, yet cluster 1 and cluster 2 learners are not statistically significantly underrepresented in our subsample. So selection effects, if present, are of limited size.

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 networks. In particular in CMC 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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