Students’ motivations and their contributions to virtual learning

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Abstract: In recent years, increasing attention has been devoted to virtual learning. Individual characteristics are known to play a crucial role in learning processes but only limited research has been conducted in the context of virtual settings. Therefore, we used an integrated multi-method approach in order to examine the impact of types of academic motivation (intrinsic vs. extrinsic) on virtual learning. This study of 100 online summer course participants indicates that the willingness to contribute to discourse depends on the type of motivation. Intrinsically motivated learners became central and prominent contributors to cognitive discourse. In contrast, extrinsically motivated learners contributed less and were positioned on the outer fringe of the social network.

Introduction

The attention for virtual learning is fuelled by two separate yet mutually enforcing developments: The increasing possibilities of Information Communication Technologies (ICT) to support collaboration (Bromme, Hesse, & Spada, 2005; Schellens & Valcke, 2005) and the evidence that collaboration can enrich student learning through interaction (Lindblom-Ylänne, Pihlajamäki, & Kotkas, 2003). Despite the positive possibilities or affordances of ICT-tools (Kirschner, Strijbos, Kreijns, & Beers, 2004), recent findings in Computer-supported Collaborative Learning (CSCL) indicate that learners who seem similar with respect to educational background and prior knowledge nevertheless contribute differently to discourse (De Laat, Lally, Lipponen, & Simons, 2007; Schellens & Valcke, 2005). In particular, Schellens & Valcke (2005) found significant differences amongst individuals with respect to both amount and type of discourse. Although recent research findings indicate that individual learners differ with respect to the amount and type of discourse contributed, little is known about what the causes of these differences in discourse are. This study questions the influence of motivation on the discourse in virtual settings. The nature of distance learning and the limited role of the teacher in collaborative learning constellation (Kirschner, Strijbos, Kreijns, & Beers, 2004) suggest a dominant role for intrinsic motivation, relative to extrinsic motivation. Hence, we will analyse to what extent differences in individual contributions to discourse are explained by differences in motivation. As recommended by recent research (De Laat, Lally, Lipponen, & Simons, 2007; De Wever, Schellens, Valcke, & Van Keer, 2006), we will use a multi-method approach of Content Analysis, which measures the type of discourse activity, as well as Social Network Analysis approach, which measures the interaction processes among learners. Afterwards, we will link the contributions to discourse and the position in the social network of each individual learner to his/her type of motivation.

Individual contributions to discourse

According to two recent reviews of CSCL-literature (De Wever, Schellens, Valcke, & Van Keer, 2006; Rourke, Anderson, Garrison, & Archer, 2001), most researchers use content analysis (CA) schemes to describe discourse in CSCL. According to De Wever et al. (2006), content analysis techniques are used to reveal evidence about learning and knowledge construction from online discussions. In other words, content analysis reveals what participants are talking about. While a large number of researchers in CSCL use content analysis, recently a number of critiques have been raised. First of all, there are several methodological concerns about CA, which are primarily concerns about inter-rated reliability, replicability (De Wever, Schellens, Valcke, & Van Keer, 2006; Schellens & Valcke, 2005) and subjectivity (Rourke & Anderson, 2004; Strijbos & Stahl, 2007). Secondly, and more fundamentally, CA methods fail to depict the interaction and learning processes among individual learners (De Laat, Lally, Lipponen, & Simons, 2007; Jeong, 2003; Rourke & Anderson, 2004). Interaction among learners is known to be an essential trigger for motivation, feedback and co-construction of knowledge (Hmelo-Silver, 2004; Jonassen & Kwon, 2001; Schellens & Valcke, 2005). Focusing on content analysis alone, without taking into consideration interaction processes, restricts our understanding of learning processes in virtual settings (De Laat, Lally, Lipponen, & Simons, 2007; Jeong, 2003). To avoid this, we combined the method of content analysis with insights from social network analysis (SNA).

SNA, a method taken from disciplines like sociology and graph theory (Freeman, 2000; Wassermann & Faust, 1994), provides us with several tools to analyse interaction patterns among individual learners. According to Aviv et al. (2003), a social network is defined as a group of collaborating (and/or competing) entities that are related to each other. Social Network Analysis 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. De Laat et al. (2007) have argued that individuals who are central in the network are in a better position to contribute to discourse than those who are on the outer ring of the network. According to Russo & Koesten (2005), centrality gives a learner the ability to reach others in the network. A learner with a large degree of centrality is in direct contact with many other learners in the social network and therefore might benefit from insights of others. In addition, the more central a learner is in a network, the more power an learner has to influence the direction in which the team is moving (Freeman, 2000). In contrast, other researchers (e.g. Burt, Jannotta, & Mahoney, 1998) see cohesive ties as a source of rigidity that hinders the coordination of complex tasks. In other words, the most favourable position of a learner in a social network is still a matter of debate.

Role of individual motivation

Individual student characteristics are known to play a crucial role in learning processes in face-to-face settings (Vermetten, Lodewijks, & Vermunt, 2001). According to Ryan & Deci (2000), most theories of motivation regard it as a unitary phenomenon, implying that a learner has either a lot or little motivation, also referred to as 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, 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. In particular, the type of motivation (intrinsic/extrinsic) has an important influence on a learner's attitude and learning behaviour (Vallerand et al., 1992). Following the Self-Determination Theory (SDT) of Ryan & Deci (2000), 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. According to Ryan & Deci (2000, p. 56), intrinsic motivation is "… a critical element in cognitive, social, and physical development because it is through acting on one's inherent interests that one grows in knowledge and skills". In a subtheory of SDT, Cognitive Evaluation Theory (CET), social and environmental factors play an important role in determining what facilitates and what hinders intrinsic motivation. A learner's motivation is influenced by the social environment in class (Legault, Green-Demers, & Pelletier, 2006). More specific, in SDT feelings of competence in combination with a sense of autonomy are important facilitators for intrinsic motivation to occur, to maintain and to enhance. Positive feedback on competence have been found to have a positive effect on intrinsic motivation (Ryan & Deci, 2000). The learner's social network (teacher, family, friends) supports his or her feelings of competence (Legault, Green-Demers, & Pelletier, 2006). In fact, when the social network supports and enhances the learner's autonomy and competence, the learner will become more intrinsically motivated (Reeve, Bolt, & Cai, 1999). Also opportunities for self-direction (i.e. more autonomy for the learner) enhance intrinsic motivation, while threats, deadlines and imposed goals diminish intrinsic motivation (Ryan & Deci, 2000).

The research presented here looks into the effects of type of academic motivation of learners on their contribution to virtual learning. Several researchers (Bromme, Hesse, & Spada, 2005; Kirschner, Strijbos, Kreijns, & Beers, 2004) have argued that following a course in an online setting is more demanding than following a course in a face-2-face setting. According to Williams et al. (2006), studying online can be a lonely and frustrating experience, in particular when the social interaction is limited. Bromme, Hesse and Spada argue that also barriers of meaning might hinder effective communication among learners. For example, the intention of one learner posting a message in a discussion-board or chat-box might be interpreted differently by another learner due to a lack of context, body-language or writing-style (Bromme, Hesse, & Spada, 2005). Also the role of the teacher is more complex, whereby providing accurate and timely feedback is notoriously difficult due to barriers in space and time (Bromme, Hesse, & Spada, 2005; De Wever, Schellens, Valcke, & Van Keer, 2006). Hence, the nature of distance learning and the limited role of the teacher in collaborative learning constellation suggest a dominant role for intrinsic motivation, relative to extrinsic motivation. Learners who are intrinsically motivated to learn will depend less on teacher interventions (Reeve, Bolt, & Cai, 1999; Ryan & Deci, 2000). In contrast, students who are triggered extrinsically might find the (delayed) limited support, facilitation, monitoring and tutoring of teachers in virtual settings troublesome. As a consequence, extrinsically motivated students will contribute less to discourse when a teacher is more on the background of the learning process. In the present study we analysed the learning that arose through the contributions of the individual learners from two perspectives: content analysis and social network analysis. Based on the results of the content analysis, the social networks of various content categories were analysed in order to distinguish who were mainly contributing to social and cognitive discourse. We used an integrated multi-method approach whereby we linked the contribution of individual learner to the type of discourse with his/her position in the social network. Afterwards, we combined these measures with motivation in order to assess the impact on learning process.

Method

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 students starting a bachelor. The online course was given over a period of six weeks in which students were assumed to work for 10-15 hours per week.

Subjects

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

Instruments

Individual contribution to discourse using Content Analysis

Content analysis was conducted based on the instrument of Veerman & Veldhuis-Diermanse (2001) that has been used and validated by other researchers (e.g. Schellens & Valcke, 2005). Veerman and Veldhuis-Diermanse make a distinction between non-task related (1 planning; 2 technical; 3 social; 4 non-sense) and task-related discourse activity (5 facts; 6 experience/opinion; 7 theoretical ideas; 8 explication; 9 evaluation). Three independent coders were trained and coded independently all messages. As a unit of analysis, the complete message was chosen, unless the coders considered a message to consist of multiple elements. If two or more coders thought that a message consisted of multiple elements, the message was split. In addition, a message received a code when two or more coders used the same category. Students posted 2307 messages of which 2075 were considered as "codeable" (90%). The Cronbach alpha (α) of these 2075 messages was 0.928. Most studies have set the minimum α at 0.7 and recommend setting $\alpha > 0.8$ in order to assume inter-rater reliability. The Cohen's kappa between Coder 1 – 2, 2 – 3 and 1 – 3 were 0.71, 0.71 and 0.68 respectively. De Wever et al. (2006) argue that values between 0.4 and 0.75 represent fair to good agreement beyond chance.

Position of individual within social network using Social Network Analysis

Two measures were employed in order to determine the position of individuals in social structures. First, Freeman's degree of Centrality (Freeman, 2000; Wassermann & Faust, 1994) was used to measure whether learners were central in the social network or not. If a learner contributes actively to discourse and most other learners respond to the activities of this learner, he/she will become a central learner in the network and therefore have a high degree of centrality. Besides the degree of centralisation of each individual of all communication (Reply Degree), we used the results of the above content analysis and integrated this into communication of only higher cognitive discourse (Reply HC Degree), which implies communication which is labelled as Theoretical Ideas, Explication and Evaluation. In other words, a high Reply HC Degree indicates that a learner actively contributed to higher cognitive discourse and is central in this network (see figure 1). Second, Ego network density of each individual within the network (Size) was used, which measures how many other learners a learner is directly connected to. As with the reply network, we also included a separate measure for higher cognitive discourse (HC Size).

Individual motivation

Individual motivation was measured by the Academic Motivation Scale (AMS), developed by Vallerand et al. (1992). 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 intrinsic motivation scale and three to extrinsic motivation scale. 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. The component most adjacent to intrinsic motivation is identified regulation: the student comes to value learning as important and, therefore, performs it out of choice, but still for extrinsic reasons, as for example achieving personal goals. Regulation is introjected when the formerly external source of motivation has been internalised. Externally regulated learning occurs when 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. Learners who were high on intrinsic motivation in comparison to extrinsic motivation are for simplicity purposes labelled in this paper as "intrinsically motivated learners". In contrast, learners who were relatively high on extrinsic motivation are labelled as "extrinsically motivated learners". In an extreme case, a learner can have both high levels of intrinsic as well as extrinsic motivation. The response-rate on AMS-questionnaire was 93% and the Cronbach alpha for the seven items ranged from .760 to .856.

Analysis

The present study used a methodology of an integrated multi-method approach to identify the effects of differences in individual characteristics on type and amount of discourse. Data were gathered on the individual level as well by means of the relative position of each learner within the social network using UCINET version 6.158. The interrelationships between all measures were assessed through correlation and MANOVA analyses using SPSS 15.0.1.

Results

Individual contributions to discourse

Table 1: Descriptive statistics .

	M	SD	Skewness	Kurtosis	Chi-square	Sign.
Content Analysis						
Non-task related	12.88	15.04	2.77	10.68	1404.63	0.00
Planning (Cat. 1)	1.37	2.03	2.09	4.53	75.33	0.01
Technical (Cat. 2)	1.11	2.12	2.42	6.27	58.22	0.01
Social (Cat. 3)	0.84	1.55	2.51	7.06	38.62	0.09
Nonsense (Cat. 4)	9.53	11.39	3.31	15.58	1065.93	0.00
Task-related	12.77	14.94	2.50	8.25	1037.74	0.00
Facts (Cat. 5)	4.63	5.57	2.36	7.96	355.95	0.00
Experience (Cat. 6)	1.28	2.18	2.52	6.81	88.75	0.00
Theoretical Ideas (Cat. 7)	2.04	2.74	1.91	4.33	101.90	0.00
Explication (Cat. 8)	4.58	5.89	2.29	6.40	376.84	0.00
Evaluation (Cat. 9)	0.22	0.50	2.23	4.33	2.00	1.00
Social Network Analysis						
Reply Degree	26.26	24.30	1.35	1.46	1772.73	0.00
Reply HC Degree	6.82	7.53	1.58	2.56	402.60	0.00
Size	6.44	4.03	0.08	-0.97	159.46	0.00
HC Size	2.38	2.34	0.88	0.08	74.77	0.06

n = 82
HC = higher cognitive communition (cat.7-9)

Table 1 presents the descriptive statistics as well as the chi-squares in order to assess whether individual learners differed from each other with respect to discourse activity as well as position within the network. With respect to the number of posts per individual, there is a significant difference among participants (χ^2 (80) 2258.17, $p < 0.00$). On average, the learners contributed 25.64 messages and there are clear differences amongst individuals with respect to the amount of discourse. In addition, if we distinguish between task- and non-task related communication, again significant differences are found. If we look beyond mean values and take into account standard deviation, Skewness and Kurtosis values, we found large variance in discourse activities. Standard deviations are in all content analysis categories larger than its mean values. In addition, the Skewness in all content analysis categories are positive and around two or higher, implying a distribution with a right tail. Also the Kurtosis values indicate that observations are clustered more and have longer positive tails than a normal distribution. Despite the longer positive tails, the standard errors in Skewness (.267) and Kurtosis (.529) are smaller than two, which implies that we can still assume normality conditions. If we look into the different categories that are discerned by Veerman and Veldhuis-Diermanse (2001), we find evidence of differences in individual contributions to knowledge construction with the exception of category 9 (evaluation). The distribution of the degree of centrality of our social network indicators follows a similar pattern as those of content analysis, although the tail is slightly shorter. With respect to the number of connections (Size) each individual learner has, the differences are still significant yet less pronounced in comparison to the other parameters. In sum, we find large differences among individuals with respect to the amount and type of discourse as well as some differences among individuals with respect to their position in the social network.

To illustrate the power of SNA in understanding the interaction of contributions of individuals, the social network of all discourse activity (left) as well as only higher cognitive discourse (right) of one virtual team is presented in Figure 1(1). Four aspects can be distinguished from these figures. First of all, the figures illustrate who is communicating with whom and what the direction of communication is. For example, in the left figure Tutor 4 has replied to a comment of Irine, which is indicated by the direction of the arrow. In addition, John and Catherina have a so-called reciprocal link when looking at all discourse activities, as they react both to each other's contribution and the arrow goes in both directions, while they do not have any direct link when looking at higher cognitive discourse. Second, some individuals within the network are more central than others. For example, Andre, Mark, Rick, Brigit and Judith are central members in the overall network, while Rick, Maria & Tiffany are central in the higher cognitive network. Third, some learners are on the outer fringe of the network and are not well-connected. For example, Don, Sandra and Irine are connected with less than four ties in the overall network, while they are not taking part in higher cognitive discourse. Finally, there are some learners who are connected with most learners but who are still on the outer fringe. For example, Joe, John, Jonathan and Brenda have more than 15 contributions but are still on the outer fringe of the overall network. This means that despite the fact that their ego-density (i.e. number of links to others) is large, they do not occupy a central position in the network. In the other five teams similar patterns are found. In sum, individuals 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, Lally, Lipponen, & Simons, 2007; Russo & Koesten, 2005). An innovative feature is that by combining the results of CA, a more pronounced picture arises when looking at higher cognitive discourse.

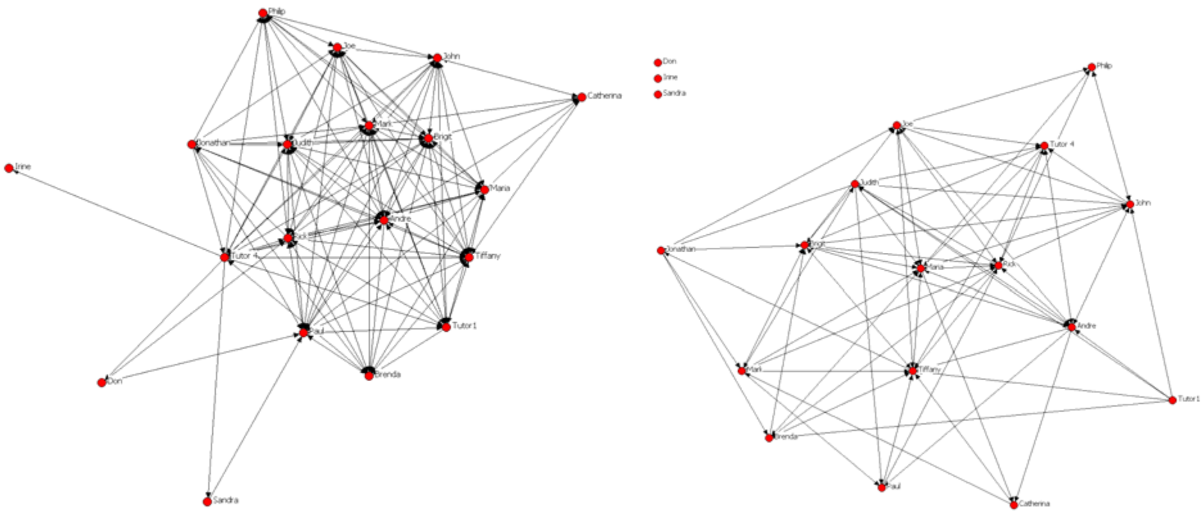

Figure 1. Social Network of all discourse activity (left) and higher cognitive discourse (right)

Relating students' motivations and contributions

Table 2 contains correlations between our selected learning indicators of content analysis and social network analysis with the motivations scales from the AMS instrument (Vallerand et al., 1992). When comparing correlations over the content analysis categories, intrinsically motivated students focus more on task related than on non-task related issues. However, a one-way MANOVA results in an insignificant effect (Lamba (2, 72) = 1.560, $p>0.10$). Although the coefficient of non-task related discourse is positive, it is not significant at 5% confidence interval. Within the non-task related issues, there is an above-average interest in organisational matters, like planning and technical issues. In other words, intrinsically motivated students contribute more to planning and technical issues. Within the task related issues, intrinsically motivated learners contribute more own experiences, theoretical ideas as well as explications. Adding own experiences to a particular problem will help learners to understand the problem as it is perceived and experienced by other individual learners. By sharing new theoretical ideas and comparing these findings with previously mentioned experiences, the mental model of the learner is extended. Finally, the elaboration of these ideas, which in the Veerman et al. (2000) model is labelled explication, will lead to a co-construction of knowledge of the learners in this virtual setting. A MANOVA confirms the results and a significant effect (Lamba (2, 69) = 2.783, $p<0.05$). Follow-up univariate ANOVAs indicated that Theoretical ideas was not significantly affected by intrinsic motivation ($F(2, 69) = 3.096$, $p = .083$), but Experience ($F(2, 69) = 5.273$, $p = .025$) and Explication ($F(2, 69) = 3.859$, $p = .053$) was. The fact that no relationship has been found with respect to evaluation can be contributed to the limited number of messages which have been categorised as evaluation. While intrinsically motivated learners contribute actively to the various types of discourse, extrinsically motivated learners contribute on an average level. Interestingly, the extrinsically motivated learner adds on average significantly less social contributions in our virtual settings. In sum, students who are intrinsically motivated contribute more to cognitive discourse, in particular experience, theoretical ideas and explication. We have been unable to determine what type of motivation has a positive effect on social discourse, although we find a clear negative relationship when learners are extrinsically motivated.

Relating students' motivation to their position in the social network

All three aspects of intrinsic motivation are positively correlated with the learning indicators from our social network analysis. This implies that intrinsically motivated students distinguished themselves much stronger from other students. In other words, individuals who were central contributors to discourse (Reply Degree) seem to be intrinsically motivated students, which is also supported by a MANOVA analysis. In particular, when taking into consideration the type of discourse, students who are central in contributions of higher cognitive discourse are mainly students who are intrinsically motivated. In other words, students like Andre, Mark and Brigit in our example are intrinsically motivated students. If we also take into consideration the number of links an individual learner has, the coefficients for higher cognitive discourse (HC Size) increase and become significant even at 1%. This implies that intrinsically motivated students not necessarily need to be in the centre of the network but can also be on the outer fringe, as long as these learners have sufficient connections to other learners. In other words, students like Joe, Brenda and Jonathan are intrinsically motivated students but are not the most central individuals in their network. Students who are extrinsically motivated are not in the centre of the playground in our virtual setting. The number of links of extrinsically motivated learners is limited and they are most likely to position themselves on the outer fringe of the social network.

Table 2: Learning indicators and student motivation.

	IMTK	IMTA	IMES	EMID	EMIN	EMER	AMOT
Content Analysis							
Non-task related	0.16	0.18	0.18	0.01	0.04	0.01	0.17
Planning (Cat. 1)	0.22	0.25*	0.25*	0.07	0.08	0.04	0.06
Technical (Cat. 2)	0.23*	0.22	0.27*	-0.05	0.07	-0.05	0.07
Social (Cat. 3)	0.18	0.11	0.12	-0.28*	-0.03	-0.29*	-0.13
Nonsense (Cat. 4)	0.09	0.13	0.13	0.02	0.03	0.06	0.22
Task-related	0.28*	0.25*	0.23*	0.03	0.01	-0.05	-0.09
Facts (Cat. 5)	0.25*	0.19	0.19	-0.05	-0.09	-0.13	0.00
Experience (Cat. 6)	0.30**	0.29*	0.29*	0.11	0.03	-0.02	-0.13
Theoretical Ideas (Cat. 7)	0.23*	0.23*	0.26*	0.01	0.12	0.02	-0.04
Explication (Cat. 8)	0.27*	0.26*	0.20	0.07	0.05	-0.01	-0.14
Evaluation (Cat. 9)	-0.09	-0.08	-0.19	0.03	0.02	0.09	-0.08
Social Network Analysis							
Reply Degree	0.24*	0.22	0.19	0.00	0.00	-0.03	0.05
Reply HC Degree	0.28*	0.25*	0.2	0.12	0.06	0.05	-0.16
Size	0.26*	0.23*	0.22	-0.01	0.05	0.05	-0.02
HC Size	0.31**	0.31**	0.25*	0.14	0.06	0.04	-0.12

**Correlation is significant at the 0.01 level (2-tailed).

*Correlation is significant at the 0.05 level (2-tailed).

Discussion

The results of the present study indicate that individuals contribute differently to cognitive and social discourse in virtual settings, depending on their type of motivation. Some learners were active contributors to discourse, while other learners participated but did not contribute actively to discourse. With respect to social discourse contributions of individuals, we found that intrinsically motivated students did not contribute more non-task related messages per se. However, intrinsically motivated students distinguished themselves with respect to contributing to planning and technical issues. In particular planning, activities are important as previous research (e.g. Jehn & Shah, 1997) has shown that effective learning behaviour starts with appropriate planning. In virtual settings, where students work and learn without having received a training before, providing feedback on technical issues might also be considered to be a strong merit and might help other students to overcome their barriers to contribute to discourse (Bromme, Hesse, & Spada, 2005). Extrinsically motivated students contributed less actively to non-task related issues. In particular, they contributed significantly less to social discourse. Social discourse has been found to be a crucial factor for socio-constructivist learning (Schellens & Valcke, 2005; Williams, Duray, & Reddy, 2006). The contribution to cognitive discourse in our setting was positively related to students with intrinsic motivation. Learners high on intrinsic motivation contributed more task-related discourse than other types of learners. In particular, intrinsically motivated students contributed more own experience, new theoretical ideas and explication. By building upon experiences of other students, each learner can construct his/her own mental model of his/her own experience and compare to what extent the experience of other learners differ (Jehn & Shah, 1997; Schellens & Valcke, 2005). Although contributing own experiences to other learners are important to internalise experiences of members of the team, linking these experiences with new theoretical ideas are crucial in academic settings. These contributions are regarded as important elements for collaborative learning settings as they lead to co-construction of knowledge. In contrast, extrinsically motivated students performed "on average" on all task-related categories. Important to note is that other learners might benefit from the co-construction of knowledge of others, even if they are not actively building on the discourse. In other words, by reading and following the discourse as well as constructing one's own mental model literature even "passive" students might learn from discourse activity.

With respect to the position of the individual in the network, large differences were found amongst learners. Central learners in the virtual social network appear to be intrinsically motivated students. Another innovative element in our study is that we integrated the results of content analysis with social network analysis, which we expect to improve our insights of interaction processes as well as the type of interaction. When we take only higher cognitive discourse activities into consideration, central contributors were intrinsically motivated learners. In addition, learners who had more connections in general were intrinsically motivated learners. Quite interestingly, when looking at higher cognitive communication, having more ties to others is an important merit. The coefficients were slightly larger than the coefficients of centrality, implying that having more ties might be more important than being in the centre. In other words, learners who were in between the centre and the outer fringe of the network might also play an important role in (higher) cognitive discourse. Finally, extrinsically motivated learners scored low on both centrality and ego-density measures, implying that these learners were not in the centre of the network and had only a limited number of ties. In other words, extrinsically motivated learners in our setting are learners who were on the outer fringe of the network.

Social Network Analysis (SNA) techniques provided a powerful and useful bridging tool for two fields of research which are commonly separated, namely the focus of cognitive and social discourse of individuals versus team learning behaviour. While Jeong (2003) analyses group interaction from sequential analysis of messages, our research focuses on interaction among individuals rather than messages. By measuring interactivity of discourse activities, we found that individuals take different position in social networks. In particular, by integrating the results of the content analysis and the social network analysis, we were able to distinguish the type of interactivity. Finally, the correlations of the Academic Motivation Scale with the results of the content analysis and social network analysis indicate that the degree and type of activity in virtual learning depends on the type of motivation. Learners who were characterised as intrinsically motivated learners contributed more to (higher cognitive) discourse activity than extrinsically motivated learners and are central in the social network.

Future Research and Practical implications

In future work, we will elaborate on our preliminary findings by incorporating individual as well as group effects. By using a multi-level analysis or clustering individuals in different levels of motivation, we will disentangle any interaction effects. Furthermore, controlled assignment of students to teams based on individual characteristics might create even more attractive learning conditions. In future research, we will also include research on learning styles into our analysis in order to understand what type of learning style is most appropriate in our virtual settings. Afterwards, we intend to construct teams based on our findings, whereby a mix of students with various learning styles and motivation types are combined. These findings are relevant for teachers, managers, admission officers and schedulers as the results imply that arranging teams based on motivations might lead to superior cognitive performance of individuals as well as teams.

Endnotes

(1) The names of the participants are replaced by fictive names in order to guarantee privacy of the participants.

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