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The role of academic motivation in Computer-Supported Collaborative Learning

Recent findings in Computer-Supported Collaborative Learning (CSCL) indicate that learners contribute differently to discourse (Caspi, Chajut, Saporta, & Beyth-Marom, 2006; De Laat & Lally, 2003; Häkkinen & Järvelä, 2006). 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 (20%) of messages. But not only differences in the amount of contributions by students have been found. For example, De Laat and Lally (2003) showed that students in an online E-learning Master's programme also differed with respect to the type (cognitive, affective, metacognitive) of contributions. In a Bachelor's freshman course of educational science, Schellens and Valcke (2005) found significant differences with respect to both amount and type (social, cognitive) 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 of these differences are. Within the field of Computer-Supported Collaborative Learning, researchers try to understand what the underlying reasons for a lack of contributions to cognitive discourse are and how to solve them. For example, Lowry and colleagues (2006) found that informatics learners who in an experimental design collaborated in class and were complemented with ICT established higher levels of communication quality than learners who collaborated only virtually. Hurme and colleagues (2007) analysed the interaction patterns among secondary school children who worked online in pairs on mathematical problems. Metacognitive activity varied among participants, which subsequently influenced the interaction among pairs of learners. Furthermore, by using Social Network Analysis some pairs became central contributors to discourse, while others were less active and were positioned on the outer fringe of the social network (Hurme, Palonen, & Järvelä, 2007).

Recently several researchers have investigated the role of motivation in CSCL. For example, by measuring goal-oriented motivation (Pintrich & De Groot, 1990), Yang and colleagues (2006) found evidence that motivation is positively related with how learners perceive each other's presence in online courses. Järvelä and colleagues (2008) found that students who were working together in groups of 3-5 students reported more (favourable) learning goals and fewer performance goals in the face-to-face setting than students in virtual groups. Besides goal-oriented motivation, several other factors might influence motivation like the degree of self-determination of learners (Ryan & Deci, 2000a, 2000b). For example, in an online setting learners have a large autonomous freedom and can decide their own learning path, which might be beneficial for learners with intrinsic motivation (Ryan & Deci, 2000b; Vallerand & Bissonnette, 1992). In addition, the limited role of the teacher in a distance learning constellation (Kirschner, Strijbos, Kreijns, & Beers, 2004; Vonderwell, 2003) refrains the teacher to interact in a similar manner as in a face-to-face setting. A teacher can directly provide instruction, feedback and coaching in a face-to-face setting, which should help learners who are in need for external regulation (Roth, Assor, Kanat-Maymon, & Kaplan, 2007). In an online setting, the lack of regulation might limit the responses from extrinsically motivated learners.

The research presented here looks into the effects of differences in academic motivation (i.e. intrinsic/extrinsic/a-motivation) of learners on their contribution to discourse. Although recently an increasing number of researchers have analysed the role of motivation in CSCL settings in a qualitative manner, to our knowledge no quantitative study exists that analyses how differently motivated learners behave in an online learning environment. Therefore, we will investigate to what extent differences in individual contributions to discourse are explained by differences in academic 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 composed of Content Analysis, which measures the type of discourse activity, and Social Network Analysis, which measures the interaction processes among learners. Afterwards, we will integrate the type of contributions to discourse with the position of each individual learner in the social network and finally link this to his/her type of motivation. In this way, we attempt to assess to what extent differently motivated learners vary in the type of discourse contributed in online settings.

Importance of motivation for learning

Motivation has an important influence on a learner's attitude and learning behaviour (Deci & Ryan, 1985; Fairchild, Jeanne Horst, Finney, & Barron, 2005; Ryan & Deci, 2000a; Vallerand et al., 1992). "Motivation has been a central and perennial issue in the field of psychology, for it is at the core of biological, cognitive and social regulation" (Ryan & Deci, 2000b, p. 69). As motivation is a multidimensional and multilevel construct (Boekaerts, 1997), 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 "[t]o be motivated means to be moved to do something", as the degree of self-determination of learners might explain why some learners contribute more to discourse in CSCL than others. 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 motivation versus a-motivation. To be motivated means to be moved to do something, while a-motivation 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 a-motivation.

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. According to Ryan and Deci (2000a, 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. More specific, in SDT feelings of competence and social relatedness in combination with a sense of autonomy (defined as basic psychological needs) are important facilitators for intrinsic motivation to occur, to maintain and to enhance.

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). That is, besides intrinsic motivation and a-motivation, SDT distinguishes four different forms of extrinsic motivation that constitute a motivational continuum reflecting an increasing degree of self-determined behaviour, namely external regulation, introjection, identification and integration (Ryan & Deci, 2000a).

As most educational learning settings are externally regulated, a crucial question is how to internalise and to integrate educational activities for learners (Deci & Ryan, 1985). "Internalisation is the process to taking in a value or regulation, and integration is the process by which individuals more fully transform the regulation into their own so that it will emanate from their sense of self" (Ryan & Deci, 2000a, p. 60). When learners internalise their reasons for showing a given behaviour, learners become more self-determined (Legault, Green-Demers, & Pelletier, 2006). Three factors in SDT enhance the internalisation of regulation, namely relatedness, perceived competence and autonomy (Deci & Ryan, 1985). The more a learner perceives a sense of belonging and connectivity to other learners (relatedness), the more willing learners are to show the behaviours that are externally regulated (Legault et al., 2006). In addition, a learner can only adopt an extrinsic goal when the learner feels he or she is competent to achieve this goal. Finally, in order to fully internalise a regulation, a learner must autonomously value its meaning and worth (Ryan & Deci, 2000a).

In a long series of over 700 studies in classroom settings, the model of Deci and Ryan (1985) has been empirically verified (Ryan & Deci, 2000a, 2000b). For example, more autonomous extrinsic motivation has been found to lead to greater engagement, less dropping out (Legault et al., 2006), higher quality learning and greater psychological well-being (Ratelle, Guay, Vallerand, Larose, & Senécal, 2007; Ryan & Deci, 2000a). Greater internalisation yields more behavioural effectiveness as well as greater experienced well-being (Ryan & Deci, 2000a).

Vallerand and colleagues have added further theoretical concepts to the model of Deci and Ryan (1985) by acknowledging that the attitudes, values and goals that trigger a learner to become intrinsically motivated can differ when a learner enters into college or university and voluntarily chooses a study. For example, some students might choose to study economics as they enjoy learning a new science, some might choose economics in order to understand the underlying reasons of an economic crisis, while others might choose economics as playing a manager in a virtual game during a management course seems exciting. Therefore, Vallerand et al. (1992) distinguish between three intrinsic motivation types: intrinsic motivation to know or learning for the satisfaction and pleasure to understand something new; intrinsic motivation to accomplish or learning for experiencing satisfaction and pleasure to accomplish something; and intrinsic motivation to experience stimulation or learning to experience stimulating sensations.

Role of motivation in CSCL

Several researchers have found that learning in CSCL settings is more complex than in face-to-face settings. For example, Schellens and Valcke (2005) found that educational psychologists who worked together online in groups of ten contribute mainly lower level cognitive discourse. Järvelä et al. (2008) found that learners who collaborated online produced less (favourable) learning goals and more performance goals than learners who collaborated in a face-to-face setting. Bromme et al. (2005, p. 4) argue that meaning barriers that obstruct the mutual construction of meaning of information from sender to receiver might hinder effective communication among learners in CSCL settings. For example, the intention of one learner posting a message in a discussion-board might be interpreted differently by another learner due to a lack of context, body-language or writing-style. This might reduce the connectivity and sense of belonging (relatedness) of a learner as well as reduce the perceived competences due to the occurring miscommunications, which in turn might reduce social interaction. According to Williams et al. (2006), working and learning online can be a lonely and frustrating experience, in particular when the social interaction is limited.

Tai (2008) argues that strong motivation is a prerequisite for online learning. Yang et al. (2006) found that the way learners experience and perceive social interaction depends on social presence of peers (i.e. ability of peers to express themselves socially and emotionally in the group) as well as written communication skills. If social interaction is difficult to achieve and maintain in online learning settings, this might have a negative impact on the motivation of learners. In an extreme case, a learner might become amotivated due to the meaning barriers, lack of relatedness and lack of perceived competence and will therefore refrain from contributing to social interaction (Legault et al., 2006; Ratelle et al., 2007).

Recent research in face-to-face settings by Roth, Assor, Kanat-Maymon and Kaplan (2007) and Legault et al. (2006) indicates that the teacher has a strong influence on the type of motivation of students. In online settings, the role of the teacher seems to be more complex (De Laat et al., 2007; Vonderwell, 2003), whereby providing accurate and timely instruction and feedback is notoriously difficult due to barriers in space and time (Bromme, Hesse, & Spada, 2005; De Wever et al., 2006). The limited role of teacher might hamper learners who are triggered mainly by external regulation as the teacher can only provide immediate instruction and feedback when both teacher and student are online simultaneously. At the same time, two potentially opposite effects might occur for intrinsically motivated students. As teacher regulation is limited, this may leave more room for self-directed learning, which is assumed by SDT to be beneficial for intrinsic motivation (Roth et al., 2007). In contrast, the lack of timely positive feedback might hamper intrinsic motivation to be sustained during the entire duration of a course (Ryan & Deci, 2000b).

Three recent studies have analysed the role of motivation in the context of CSCL. Yang et al. (2006) conducted a survey among 250 respondents of eleven online educational psychology courses and found that goal-oriented motivation measured by the Motivated Strategies for Learning Questionnaire (MSLQ) of Pintrich & De Groot (1990) positively influences social presence among peers, that is the perception that emotions can be shared using CSCL. Although the finding that motivation influences perceived social presence among peers is important, the lack of measurement of actual learning processes and learning outcomes and lack of control of 51% non-response requires further research. Therefore, Veermans and Lallimo (2007) used a cluster analysis on eight scales (collaborative learning, interest in learning and technology, controls of learning beliefs and self-efficacy) in an online class of 50 psychology students and conducted a content analysis of discourse activity of three students, each from one of the three identified cluster profiles. The student with the combined highest values on the eight scales produced messages that had more variety of categories within each message, which according to Veermans and Lallimo (2007) is a necessity for genuine knowledge building.

To capture how motivation influences the learning process, Järvelä et al. (2008) have analysed how motivation in collaborative learning settings changed over time (again) using MSLQ (Pintrich & De Groot, 1990). Educational psychology students in groups of 3-5 worked together on three collaborative learning tasks in either face-to-face or virtual settings. Students in the face-to-face setting reported more (favourable) learning goals and less performance goals relative to students in virtual settings. Afterwards, Järvelä et al. (2008) described the relation with motivation and behaviour for two face-to-face groups. Although the two studies of Järvelä et al. (2008) and Veermans and Lallimo (2007) provide important insights in how motivation influences behaviour of learners in CSCL using a qualitative perspective, a quantitative analysis to assess the role of motivation on behaviour of learners in CSCL might increase our understanding why some learners contribute more actively to discourse than others. In addition, by using self-determined motivation rather than goal-oriented motivation, a different perspective on the role of motivation in CSCL is taken.

In this article, we try to unravel the complex dynamics of contributions to discourse in online settings. As some learners are more active than others to contribute to discourse, we need to understand why contributions to discourse and interaction patterns among learners vary. Furthermore, we need to distinguish contributions made by learners solely in cognitive discourse communication, as task-related communication has been found to be positively related to individual knowledge acquisition (Schellens & Valcke, 2005; Weinberger & Fischer, 2006). Therefore, recent research (De Laat et al., 2007; Hurme et al., 2007) has suggested that using a combination of content analysis (type of discourse) with Social Network Analysis (position of learner relative to others) leads to a clearer understanding of interaction patterns in CSCL. 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). In SNA, one can determine the position of a learner within a group relative to other learners. Network centrality, that is the degree to which a learner has a central position in the social network, and ego-density, that is the number of other learners a learner is connected with also called neighbourhood size, are core-concepts within SNA (Hurme et al., 2007; Wassermann & Faust, 1994). For example, in a group of 21 students in a graduate online course genetics regression analysis revealed that network centrality among students who worked in collaborative groups was a robust predictor of cognitive learning outcomes (Russo & Koesten, 2005). Hurme et al. (2006) found that the neighbourhood size was positively related with the number of contributions from and to others.

In particular when SNA is combined with other instruments, SNA provides an powerful instrument to measure dynamics of learning processes (De Laat et al., 2007; Martinez, Dimitriadis, Rubia, Gomez, & de la Fuente, 2003). For example, Martinez et al. (2003) found that by using log data of users and SNA the dominant central role of the teacher in discussion forums could be identified. De Laat et al. (2007) measured the centrality of learners at three distinct phases using SNA in combination with CA, which was afterwards used to as primary input for a critical event recall by the teachers. In this way, the teachers were able to link their own behaviour to the dynamics of the learning processes of the group. Although De Laat et al. (2007) and Hurme et al. (2006) used both Content Analysis (CA) and SNA, they only qualitatively link the methods together. To our knowledge not a single study has (quantitatively) integrated the results of CA into SNA. Our integrated approach distinguishes the various interaction patterns among learners based upon the type of discourse by combining the type of discourse contributed by a learner (e.g. learner 1 has contributed ten messages, of which six that were task-related and four were non-task related) with his/her position relative to others in the social network (e.g. learner 1 has two connections to learner 2 and 5 who also contributed to task-related discourse and three connections to learner 2, 6 and 8 who contributed to non-task related discourse). As a learner can become a central contributor to discourse because of having actively participated in non-task related contributions rather than task-related discourse, distinguishing the type of discourse when using SNA will further improve our understandings of the complex dynamics of discourse within CSCL. Furthermore, by distinguishing the type of task-related discourse contributed by a learner (Schellens & Valcke, 2005; Veerman & Veldhuis-Diermanse, 2001), our integrated approach allows us to distinguish the position of learners within the social network based upon their contributions to cognitive discourse. Schellens and Valcke (2005) argue that learners who contribute mainly to reporting facts or own opinions are primarily contributing to lower cognitive discourse. Learners who mainly contribute to theoretical ideas, elaborate on argumentation of others, or evaluate the argumentations put forward by others are contributing to higher cognitive discourse.

Research questions

We expect that learners who are highly intrinsically motivated to learn contribute more actively to (cognitive) discourse than learners who are low on intrinsic motivation and who may require additional teacher support to participate at levels comparable to intrinsically motivated learners. As a result, learners high on intrinsic motivation will take a more central position relative to other learners, in particular when looking at the (higher) cognitive discourse. In contrast, highly extrinsically motivated learners are expected to contribute less to (cognitive) discourse and will be positioned on the outer fringe of the network. Therefore, we will investigate the following three research questions:

- To what extent do differently motivated students show different non-task related and task-related discourse activity?
- To what extent are differently motivated students different in the degree of centrality in the social network?
- To what extent are differently motivated students different in the degree of centrality in the (higher) cognitive discourse network?

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 (Rienties, Tempelaar, Waterval, Rehm, & Gijselaers, 2006). The online course was given over a period of six weeks in which students were assumed to work for 10-15 hours per week. The participants never met face-to-face before or during the course and had to learn using the virtual learning environment “on-the-fly”. The course was based upon principles of Problem-based learning (PBL), which is an educational method that fosters socio-constructivist learning. PBL focuses student learning on complex situations and on a variety of realistic information (Dochy, Segers, Van den Bossche, & Gijbels, 2003; Van den Bossche, Gijselaers, Segers, & Kirschner, 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. Students who passed the course received a certificate. Hence, this setting provides a unique opportunity to assess the role of motivation on behaviour of learners in virtual settings as the learners never met each other before and collaborated exclusively in the virtual learning environment.

Participants

In total 100 participants were randomly assigned in six groups. Data were analysed for those individuals who actually posted at least once a reaction in the discussion forum. This resulted in a total of 82 participants 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.

Instruments

Individual contribution to discourse using Content Analysis

According to two reviews of CSCL-literature (De Wever et al., 2006; Rourke, Anderson, Garrison, & Archer, 2001), most researchers use Content Analysis (CA) schemes to analyse discourse in CSCL. The aim of content analysis techniques is to reveal evidence about learning and knowledge construction from online discussions. Content analysis for evaluating discourse activities was based on the instrument of Veerman and Veldhuis-Diermanse (2001) that has been used and validated by other researchers (e.g. Schellens & Valcke, 2005). When comparing various content analysis schemes, Schellens and Valcke (2005) conclude that the Veerman et al. (2001) scheme is particularly suited for analysing knowledge construction among novice students. Veerman and Veldhuis-Diermanse (2001) 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). Examples of each of the nine discourse activities are provided in Appendix A. Three independent coders (two economists, one educational psychologist) were trained to use the CA instrument and independently coded all messages. A random sample of 100 messages was used as a test case but the Cronbach alpha was rather low (0.6). Therefore, an additional meeting with the three coders was established and the diverging results were discussed and consensus on the method was arranged. The coding took 80-100 hours per coder, who received a financial compensation in return.

As a unit of analysis, the complete message was chosen, unless the coders considered a message to consist of multiple elements. The message was split when two or more coders thought that a message consisted of multiple elements (see two examples in Appendix B), which occurred for 42 messages. In addition, a message was "codeable" when two or more coders used the same category. When a message was "uncodeable", the message was removed from the analysis (see two examples in Appendix C). Students posted 2307 messages of which 2075 were considered as codeable (90%). The Cronbach alpha (α) for these 2075 messages was 0.928. Most studies have set the minimum α at 0.7 and recommend setting $\alpha > 0.8$. The Cohen's kappa of the coder inter-reliability (coders agreeing with each other) between Coder 1 – 2, 2 – 3 and 1 – 3 was 0.71, 0.71 and 0.68 respectively and Fleiss' kappa of the three coders is 0.66. De Wever et al. (2006) argue that Cohen's kappa values between 0.4 and 0.75 represent fair to good agreement beyond chance, while the Fleiss' kappa indicates substantial agreement among the coders (Lombard, Snyder-Duch, & Campanella Bracken, 2002).

Positioning of individuals within social network using Social Network Analysis

While Content Analysis methods are frequently used in CSCL, focusing on content analysis alone, without taking into consideration interaction processes, restricts our understanding of learning processes in online settings (De Laat et al., 2007; Hurme et al., 2007). While Weinberger & Fischer (2006) solved (part of) this problem by using four separate CA measures for participation, epistemic dimension, argument dimension and social modes of dimension, the "application of the framework is still a challenge due to the enormous work load of analysing discourse corpora on multiple dimensions…" (Weinberger & Fischer, 2006). To avoid this, we integrated the results of the content analysis into our Social Network Analysis (SNA) in order to measure participation, argumentation and social interaction patterns (De Laat et al., 2007; Hurme et al., 2007; Wassermann & Faust, 1994).

Social Network Analysis provides us with several tools to analyse interaction patterns among individual learners. Two frequently used measures were employed in order to determine the position of individuals in the overall, task-related, and higher cognitive social structures, namely centrality and ego network density. First, Freeman's degree of Centrality (Freeman, 2000; Wassermann & Faust, 1994) measures whether learners were central in the social network or not. If a learner contributed actively to discourse and most other learners responded to the activities of this learner, he/she became a central learner in the network and therefore had a high degree of centrality (Reply Degree). Afterwards, all communication identified by CA as facts, experience, theoretical ideas, explication and evaluation was integrated in the SNA in order to measure the degree of centrality of only task-related communication (Reply TR Degree). In this way, we were able to distinguish contributions made by learners solely in task-related communication, as task-related communication has been found to be positively related to individual knowledge acquisition (Schellens & Valcke, 2005; Weinberger & Fischer, 2006). Finally, the degree of centrality with communication restricted to only higher cognitive discourse (Reply HC Degree) was measured, which implies communication labelled by CA as theoretical ideas, explication or evaluation. By building upon theoretical ideas, elaborating on argumentations of others and finally evaluating the arguments raised, learners construct their own mental model about complex problems (Alexander, 2006; Schellens & Valcke, 2005; Weinberger & Fischer, 2006). Second, the ego network density of each individual within the network (Size) was used, which measures to how many other learners a learner is directly connected. As with the centrality measures, we also included a separate measure for task-related discourse (TR Size) and higher cognitive discourse (HC Size).

Individual motivation

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. 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, three to extrinsic motivation scale and one for a-motivation. 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, a-motivation (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 et al., 2005; Vallerand & Bissonnette, 1992;

Vallerand & Pelletier, 1993; Vallerand et al., 1992). The temporal stability of the AMS construct was confirmed by Vallerand and Bissonnette (1992) and Vallerand and Pelletier (1993) with a mean test-retest correlation of .75 and .79 respectively. In addition, the stability of the AMS-instrument after one year (mean test-retest correlation) was .68 and .29 after five years (Guay, Mageau, & Vallerand, 2003). In other words, the AMS instrument measures a relatively stable construct of motivation towards education amongst college and university students.

The AMS questionnaire was distributed one month after the end of the summer course in the regular bachelor programme. The learners were asked to fill in the AMS-questionnaire without taking into consideration a particular course. 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 et al., 2006; Vallerand et al., 1992).

Analysis

We used a methodology of an integrated multi-method approach to identify the effects of differences in academic motivation on the type of discourse as well as on the position of the learner in the social network. Data were gathered on the individual level as well by means of the relative position of each learner within the overall network using UCINET version 6.158. Afterwards, the results of the content analysis were integrated into the Social Network Analysis, whereby we further distinguished the task-related discourse network (cat. 5-9) and the higher cognitive discourse network (cat. 7-9). The interrelationships between all measures were assessed through correlation and MANOVA analyses using SPSS 15.0.1.

Results

Individual contributions to discourse

On average, the learners contributed 25.64 (SD= 28.07) messages and there are substantial differences amongst individuals with respect to the amount of discourse as assessed by a Chi-Square test (χ^2 (df= 81 N=82) 2258.17, $p < .001$). In addition, if we distinguish between task- and non-task related discourse, again significant differences are found (see Table 1). If we look beyond mean values and take into account standard deviation, Skewness and Kurtosis values, we find strong variation in discourse activities. Standard deviations are in all content analysis categories larger than their mean values. In addition, the Skewness in all content analysis categories are positive and around two or higher, implying a distribution with a right-hand tail. Also the Kurtosis values indicate that observations are clustered more and have longer positive tails than the normal distribution, with the exception of the number of ties to others (Size, TR Size, HC Size). Standard errors in Skewness (.267) and Kurtosis (.529) are smaller than two, which implies that normality conditions still satisfy. 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 categories 3 (social) and 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. When discourse becomes more (higher) cognitive, the number of central contributors decreases. With respect to the number of connections (Size) each individual learner has, the differences amongst individuals are significant except for higher cognitive discourse (HC Size). The number of learners that a learner is connected to decreases as we move to (higher) cognitive discourse. In sum, we find large differences among individuals with respect to the amount and type of discourse as well as significant differences among individuals with respect to their position in the social network.

Insert table 1 about here

Table 1: Contributions to discourse and integrated Social Network position

To illustrate the power of SNA in understanding the interaction of contributions of individuals, the social network of all discourse activity (Figure 1) as well as only higher cognitive discourse (Figure 2) of the virtual team with the highest average posts per learner (M=40.41, SD=35.04) is presented[i]. Four aspects can be distinguished from these figures. First of all, the social networks illustrate to whom a learner is communicating with and what the direction of communication is (Freeman, 2000). For example, in Figure 1, Tutor 4 replied to a comment of Irine, which is indicated by the direction of the arrow (Wassermann & Faust, 1994). In addition, John and Catherina have a so-called "reciprocal link" when looking at all discourse activities, as they reacted both to each other's contribution and the arrow goes in both directions. However, John and Catherina do not have any direct link when looking at higher cognitive discourse in Figure 2. Second, some individuals within the network are more central than others (Russo & Koesten, 2005; Wassermann & Faust, 1994). For example, Andre, Mark, Rick, Brigit and Judith are central members in the overall network, while Rick, Maria and Tiffany are central in the higher cognitive network. In other words, not every learner who is central in the overall network (e.g. Andre, Judith) is also central in the higher cognitive network. Other learners who are not central in the overall network might become central contributors to higher cognitive discourse (e.g. Maria and Tiffany). Hence, by integrating CA with SNA, we are able to distinguish dynamic interaction patterns among learners based upon the type of discourse. 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 the higher cognitive discourse network. 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 as the average number of contributions in this team was 40 contributions. In the other five teams similar patterns are found, although the number of messages is lower. 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 et al., 2007; Russo & Koesten, 2005). An innovative feature is that by combining the results of the Social network analysis and the content analysis, we are able to distinguish dynamic interaction patterns at different levels of discourse.

Insert Figure 1 about here

Figure 1. Social Network of all discourse activity

Insert Figure 2 about here

Figure 2. Social Network of higher cognitive discourse

Relating students' motivations and contributions

Table 2 contains correlations between our selected learning indicators of content analysis with the seven motivations scales from the AMS instrument. Focussing first on correlations between the several content analysis categories scores and the scores for the three types of intrinsic motivation, it is evident that being highly intrinsically motivated positively correlates with discourse activity in all categories: all correlations are positive. However, the strongest contribution of being highly intrinsically motivated is in the categories of task-related discourse: correlations in this category are generally higher in value than correlations with non-task related discourse. In order to assess whether the type of motivation has an influence on non-task related as well as task-related discourse, a MANOVA analysis was used. However, a one-way MANOVA results in an insignificant effect (Lambda (2, 72) = 1.560, $p > .10$). Although the coefficient of non-task related discourse is positive, it is not significant at 5% confidence interval. For the aggregate category of all task-related activities, correlations with all three intrinsic motivation scales are moderate in size and statistically significant at the 5% confidence level (IMTK r=0.27; IMTA r=0.24; IMES r=0.23, with $p < .05$). In other words, students high on intrinsic motivation contribute actively to all types of discourse, but most strongly in task-related discourse. Within the categories of non-task related discourse, highly intrinsically motivated students have an above-average interest in organisational matters, like planning (IMTA r=0.24; IMES r=0.24, $p < .05$) and technical issues (IMES r=0.26, $p < .05$).

Insert Table 2 about here

Table 2: Learning indicators and student motivation.

Within the task-related issues, highly intrinsically motivated learners excel most in contributing own experiences, theoretical ideas and explications. The highest correlations are found for experience (IMTK r=0.29; IMTA r=0.28; IMES r=0.28, $p < .05$). The category 'new theoretical ideas' is positively related to intrinsic motivation (IMTA r=0.23; IMES r=0.26, $p < .05$). Finally, a positive correlation with explication has been found for two of the three types of intrinsic motivation (IMTK r=0.26; IMTA r=0.25, $p < .05$). A MANOVA, with three sub-groups of students based on median-splits of intrinsic and extrinsic motivation scores, rendering high-high, high-low and low-high scoring sub-groups, confirms the results and a significant effect (Lambda (2, 69) = 2.783, $p < .05$) was found. Follow-up univariate ANOVAs indicated that learners high on intrinsic motivation did not contribute more theoretical ideas ($F(2, 69) = 3.096$, $p > .05$). However, highly intrinsically motivated learners contributed more Experience ($F(2, 69) = 5.273$, $p < .05$) and Explication ($F(2, 69) = 3.859$, $p < .05$). The fact that no relationship has been found with respect to evaluation may be caused by the limited number of messages that have been categorised as evaluation.

While learners high on intrinsic motivation contribute actively and above average to the various types of discourse, highly extrinsically motivated learners contribute on average. Interestingly, there is one exception to this finding: the extrinsically motivated learner who scores high on identified regulation (EMID) and external regulation (EMER) adds on average significantly less contributions labelled as social (category 3) in our online settings (EMID r=-0.28; EMER r=-0.29, $p < .05$). Learners with high levels of a-motivation (AMOT) do not distinguish themselves, except on non-sense contributions (AMOT r=0.21, $p > .05$), be it marginally significant.

In sum, students who are highly intrinsically motivated contribute more to cognitive discourse, in particular experience, theoretical ideas and explication.

Relating students' motivation to position in social network

While the above analysis captures how differences in levels of the several facets of motivation are related to differences in the intensity to contribute in the different types of discourse, the analysis does not allow us to investigate with whom a learner has interaction. By using an integrated social network analysis, a detailed picture of the role of motivation on learning interaction processes can be established. All three aspects of intrinsic motivation are positively correlated with the three centrality measures from our social network analysis: see Table 3. This implies that highly intrinsically motivated students distinguish themselves (much stronger) from extrinsically and amotivated students also with respect to their position in the network. Especially students with high levels of intrinsic motivation to know are central contributors to overall discourse (Reply Degree) (IMTK $r=0.24$, $p < .05$). Those students are also more central in task-related discourse (IMTK $r=0.27$, $p < .05$) and in contributions of higher cognitive discourse (IMTK $r=0.27$; IMTA $r=0.24$, $p < .05$).

Insert table 3 about here

Table 3: Centrality, ego-density and academic motivation.

If we also take into consideration the number of other learners an individual learner is connected to (Size), again a positive relationship is found for the three types of intrinsic motivation. In addition, when only taking into consideration discourse activity of (higher) cognitive discourse, all intrinsic motivation types are significantly correlated (IMTK $r=0.29$; IMTA $r=0.29$; IMES $r=0.24$, $p < .05$). This implies that highly intrinsically motivated learners both show up in the centre of the network but also on the outer fringe, but then as learners who have above average connections to other learners. Students who are highly extrinsically motivated do not distinguish from the average student in our online setting. The number of links of highly extrinsically motivated learners is on average. A-motivation demonstrates a negative but non-significant relationship with higher cognitive centrality ($r=-0.16$, n.s.) and higher cognitive size ($r=-0.12$, n.s.).

Discussion

The results of the present study indicate that individuals contribute differently to discourse in online settings, depending on their type of motivation. Significant differences are found amongst individuals with respect to the amount and type of discourse activity. Some learners are active contributors to discourse, while other learners contribute only a limited amount to discourse. Although these results have already been found in other studies (e.g. Caspi et al., 2003; De Laat et al., 2007; Järvelä, Järvenoja, & Veermans, 2008; Schellens & Valcke, 2005; Veermans & Lallimo, 2007), this study is the first to empirically demonstrate that motivation is one of the determinants explaining the differences in the amount and quality of contributions to discourse in online settings. We find that highly intrinsically motivated learners contribute more task-related discourse than other types of learners. In addition, highly intrinsically motivated learners do not contribute more non-task related messages per se, but differ with respect to contributing to planning and technical issues. We find that highly extrinsically motivated students contribute less actively to non-task related issues. In particular, they contribute significantly less to discourse labelled by Veerman et al. (2000) as social contributions.

The contribution to cognitive discourse in our setting is positively related to students with the level of intrinsic motivation. Learners high on intrinsic motivation contribute more task-related discourse than other types of learners. In particular, highly intrinsically motivated students contribute more own experience, new theoretical ideas and explication. Extrinsically motivated students "underperform" relative to intrinsically motivated students on all task-related categories. Learners high on a-motivation do not contribute less to discourse, which is contrary to prior expectations. With respect to our first research question, the results indicate that differently motivated student do show different non-task related and task-related discourse activity.

With respect to our second research question, large differences are found amongst learners with respect to their position in the social network, which is in line with previous findings (De Laat et al., 2007; Hurme et al., 2007; Russo & Koesten, 2005). A new feature in this article is that we are able to link the position of the learner in the social network to the type of motivation. Central learners in the social network appear to be highly intrinsically motivated students. In addition, learners who have more connections seem to be highly intrinsically motivated learners. Based upon our correlational analysis, learners with high levels of extrinsic motivation do not differ from average learners in their position in the network.

In order to answer our third research question, we have integrated the results of content analysis with social network analysis, which improves our insights of dynamic interaction processes in CSCL. Centrality within the network decreases as we move to (higher) cognitive discourse. In addition, the number of learners an average learner is connected to (ego-density) decreases when discourse becomes more (higher) cognitive. As is shown by the two visualisations of the social networks, distinguishing the type of discourse leads to additional insights in interactive learning processes. Learners who are central in the overall network are not automatically central in the (higher) cognitive network. When we take only higher cognitive discourse activities into consideration, central contributors seem to be highly intrinsically motivated learners. Quite interestingly, when looking at (higher) cognitive communication, having more ties to others is an important merit for learning. The correlation coefficients of ego-density and scores for intrinsic motivation are somewhat larger than those coefficients of centrality and scores for intrinsic motivation, implying that having more ties might be more important than being in the centre of the social network. In other words, learners who are in between the centre and the outer fringe of the network might also play an important role in contributions to (higher) cognitive discourse. In sum, learners high on intrinsic motivation are more central in social networks of (cognitive) discourse and have more connections to other learners, while highly extrinsically motivated learners and a-motivated learners show no tendency to occupy certain positions in the network more often than other positions.

By distinguishing the type of motivation, we have shown that having strong motivation is not sufficient for contributing to cognitive discourse, it is strong intrinsic motivation that matters. These findings might have important consequences on how we integrate the various motivational types into our learning environment. Students who are extrinsically motivated like Don, Sandra and Irine, appear to be poorly connected in the higher cognitive network (Figure 2). Measures should be taken to let them not be excluded from participating in higher cognitive discourse in groups, as co-construction of knowledge has been shown to be a driving factor for learning. On a positive note, most highly extrinsically motivated students perform on average despite the lack of external teacher regulation in our distance learning setting. We had expected that strongly externally regulated students would find the design of the open collaboration setting less suitable for their motivational type. On a negative note, the fact that there are large differences between (higher) cognitive discourse activities among intrinsic vs. extrinsic students might imply that highly extrinsically motivated students might be difficult to externally regulate to participate in online settings.

Social Network Analysis (SNA) techniques provide a powerful tool to measure the dynamic interaction of learning processes within CSCL. By measuring interactivity of discourse activities at three levels of (cognitive) discourse, we find that individuals take different positions in social networks. In particular, integrating the results of the content analysis with social network analysis, we are able to demonstrate that different patterns of interactivity exist in different types of discourse. 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 online learning depends on the type of motivation.

Limitations

The results of this study are based on a multi-method approach, whereby Content Analysis is used to analyse what learners are contributing, Social Network Analysis is used to determine who is contributing, and finally Academic Motivation Scale for analysing how motivation influences the learner's behaviour. This can be viewed as a potential limitation to this study in that the (long-term) consequences on learning outcomes have not been demonstrated. Russo and Koesten (2005) have found that central contributors to discourse also perform better on learning outcomes. In addition, preliminary findings indicate that active summer course participants outperform others in the first year of the bachelor programme (Rienties, Tempelaar, Dijkstra, Rehm, & Gijselaers, 2008). In a range of studies focussing on learning in a face-to-face problem-based learning programmes in the Netherlands, correlations between these motivational scales and indicators describing learning process and learning outcome aspects typically range between 0.10 and 0.20 (Tempelaar, 2006; Tempelaar, Gijselaers, Schim van der Loeff, & Nijhuis, 2007). Given that the correlations of motivation on discourse activity and position in the social network in our study are larger than in face-to-face settings, we might expect that the type of motivation has an even stronger influence on learning outcomes in online settings. Besides the quantitative measures of learning, implementing qualitative measures of learning like critical event recall (e.g. De Laat et al., 2007; Veermans & Lallimo, 2007) might provide further evidence of how motivation influences learning in online 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 second limitation of this study is that no measures were taken to prevent self-selection in the summer course programme or to introduce a control condition. Selecting or rejecting students based on types of motivation rather than prior knowledge leads to ethical issues. Alternatively, rearranging learners in other groups based on their type of motivation 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. Furthermore, we did not introduce a control condition as our primary research aim was to measure in a real-life realistic CSCL environment how learning processes were influenced by motivation.

Based on our theoretical conceptions, we expected that the more externally regulated a learner was, the less he/she would contribute to discourse given the limited possibilities of teachers to impose external regulation in online settings. Furthermore, we expected that learners high on a-motivation would contribute less to discourse due to their lack of motivation. Although the correlations for extrinsically regulated and a-motivated learners have the expected sign, the coefficients are not significant. Further research should assess whether specific groups of learners can be identified using cluser analysis or by identifying extreme groups in order to assess why no significant negative relationship was found between contributions to discourse and a-motivation. Additionally, the lack of internalisation of the regulation to the self might be explained the short duration of the course. Learners with strong external motivation to education might need more time to internalise the regulation into the self (Guay et al., 2003). Another explanation might be that the limited external benefits in our setting (i.e. credits) might lead extrinsically motivated students to put less effort into the course than others. By increasing the cohorts in the future, we expect that the coefficients will become significant as the sample size increases.

A final limitation was that we did not measure the mutual conception among participants. In groups that have more highly intrinsically motivated learners, one might expect that more (higher) cognitive discourse activities are present than groups with low intrinsically motivated learners. However, as the number of groups (six) was rather small to conduct a group-level analysis and the fact that it is difficult to measure interaction patterns on group level when CA and SNA-measures are combined, further research should assess whether group-level effects also influence behaviour of individual learners in CSCL settings.

Future Research and Implications for Education

Future research should investigate the impact of learner profiles on the behaviours of learners in CSCL, for example by distinguishing various types of learners using cluster analytic methods (Veermans & Lallimo, 2007). In addition, by analysing how learners mutually influence each other in collaborative learning, future research should assess how the type of motivation of one learner influences the behaviour of others in virtual teams. 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. These findings are relevant for teachers, managers, admission officers and schedulers as the results imply the type of motivation has a moderately strong influence on the type of discourse and position within the social network. Appropriate strategies to deal with various types of motivation should be designed to assist each type of learner.

Appendix

Appendix A: Content Analysis scheme (Veerman & Veldhuis-Diermanse, 2001)

Veerman and Veldhuis-Diermanse (2001) distinguish four activities of non-task-related discourse, whereby the examples are taken from the online course economics:

1. Planning: "Shall we first complete Task 1, before we go on with the next one?""
2. Technical: "Does anybody know how to add a graph to my thread?"
3. Social: "I think that a lot of people are very motivated here, which is good"
4. Nonsense: "Have you all made up your mind to start studying at UM in September?"

In the original coding scheme of Veerman and Veldhuis-Diermanse (2001), they consider three basic cognitive processing activities, namely new information (facts, experience, theoretical ideas), explication and evaluation. However, Schellens and Valcke (2005) found that the three new information activities should be distinguished in separate activities. Furthermore, Schellens and Valcke (2005, p. 961) argue that the five task-related discourse activities should be ordered in a hierarchical structure, whereby "[c]onsecutive types of communication represent higher levels of knowledge construction":

5. New fact, that is learners present information that is new in the context of the discussion: "The average rate of inflation in the U.S. for 2004 is 2.7 %."
6. Own Experience/opinions: "I think that VAT-taxes should be reduced to increase demand".
7. Theoretical ideas: "If we take the Circular Flow Model from the book (Parkin/Bade) you are right, because it only takes households into account".
8. Explication. This is a type of communication that reflects a further refining and/or elaboration of earlier ideas: "There are actually quite a lot of different, more specific market forms, the ones you mentioned are the three big ones (monopoly, oligopoly and perfect competition), but some rare ones exist as well. For example a monopsony exists".
9. Evaluation. This type of written messages corresponds to a critical discussion of earlier information or ideas. It goes beyond a simple confirmation or negation and reflects argumentations, reasonings, justifications.

Appendix B: Two examples of messages consisting of multiple elements

The following message was posted by Maria, after a discussion along seven messages on which market types exist. Tiffany had previously explained that there are three market forms (i.e. monopoly, oligopoly and perfect competition). Coders 1-3 coded the first paragraph as an elaboration (category 8), while they coded the second paragraph as social (category 3). Therefore, the message was split.

> "Hey Tiffany!
>
> I would like to add the market of a cartel: a small group of large firms who may agree to work together (there are a type of moopoly), trying to keep their prices and profits high. They only compete on a non-price basis…
>
> I think that a lot of people are very motivated here, which is good. I am of course motivated too but in a little time conflict, but quite confident that I will manage. I don't know how far we are meant to, perhaps the tutors can answer these questions, but I think they just want us to write :-)"

Afterwards, Andre responded to the above message of Maria, whereby coders 1-3 code the first paragraph as social (category 3), while they code the second paragraph as an elaboration (category 8).

> "Hi Maria,
>
> I think it is good as well that we are all that over motivated, because we will get a lot more information if everyone actively contributes something. I don't know if there are any restrictions about how far we want to go, are there?
>
> @ Tiffany
>
> There are actually quite a lot of different, more specific market forms, the ones you mentioned are the three big ones (monopoly, oligopoly and perfect competition), but some rare ones exist as well. For example a monopsony exists, this means there is only one buyer in the market and more than one seller (for example weapons which are only bought by one certain government but could be produced by different companies)."

Appendix C: Two examples of uncodeable messages

The message posted by Rick only includes a reference to a discussion on the difference between nominal Gross Domestic Product (GDP) and real GDP. Coder 1 coded this message as uncodeable, coder 2 as a new fact (category 5), and coder 3 as a new theoretical idea (category 7).

> "Reference: http://en.wikipedia.org/wiki/aggregate_expenditure"

The message posted by Maria after a series of messages discussing the difference between nominal GDP and real GDP was coded by coder 1 as an elaboration (category 8), as it elaborated previous discussions.

Coder 2 coded it as a new fact (category 5), since the GINI coefficient was introduced as new fact without reference to previous ones. Finally, coder 3 coded it as an evaluation (category 9), as the measurement of GDP leads to several problems and Maria provided a possible solution by using the GINI coefficient.

> "I think it is totally true what you said. A big weakness of the GDP is that it does not show the distribution of wealth, but none of you has come up with a solution…
>
> I remember from my geography lessons that there is a gini index (also included in data from CIA worldfact book) that shows the distribution of wealth. As ia wasnt able so far to get this library thing started, I can only give a link ti wikepedia, but perhaps someone else find something...
>
> Another thing I remember from school when talking about development and inequality is that we had data that showed the share of the GDP for the poorest and fro the richest 10% of the population. So if there was a big difference (eg poor 4%, rich 40%) one can assume that there s a very unfais distribution of wealth.
>
> Any additional info?
>
> Has anybody heard of it, too?
>
> Reference: http://en.wikipedia.org/wiki/Gini_index"

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Figure 1

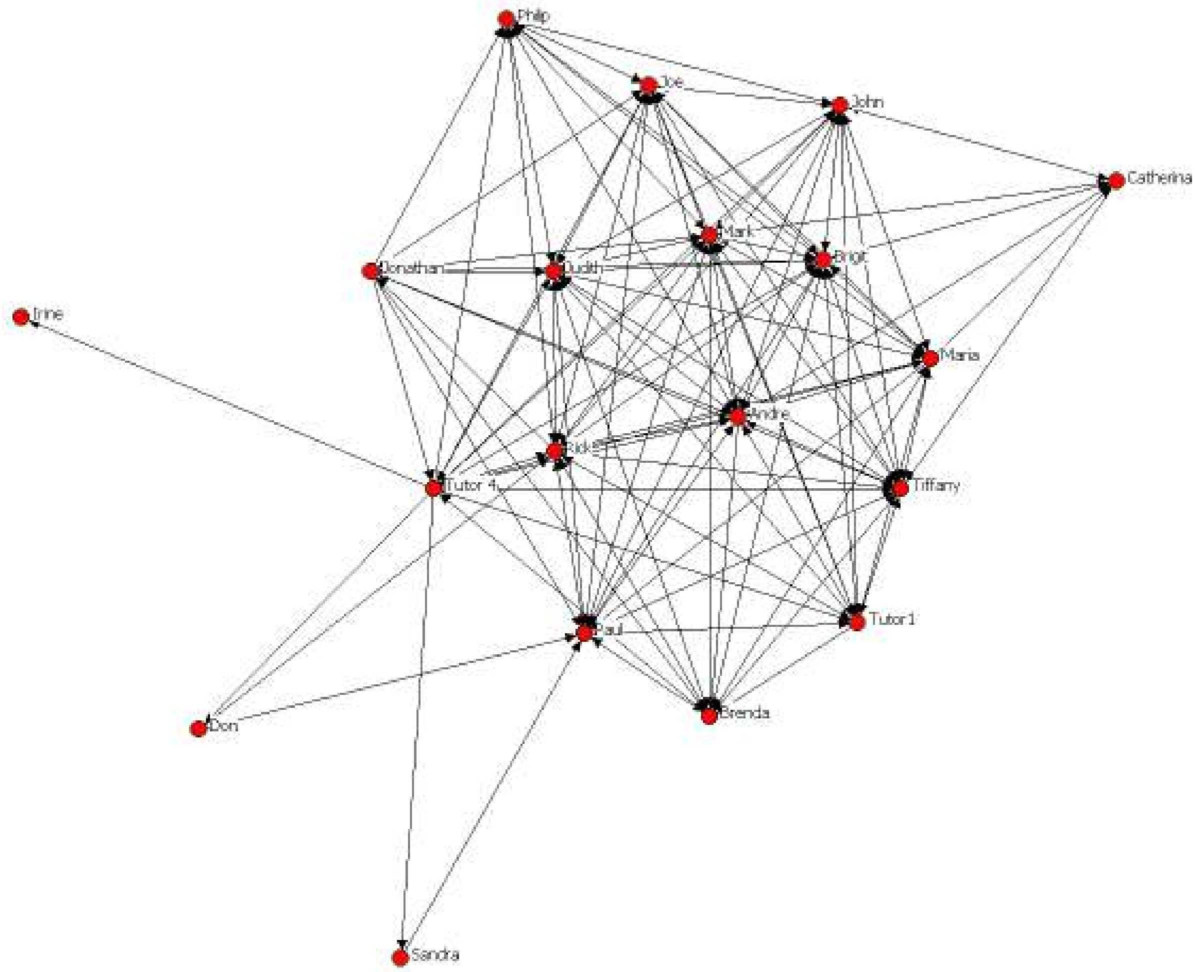
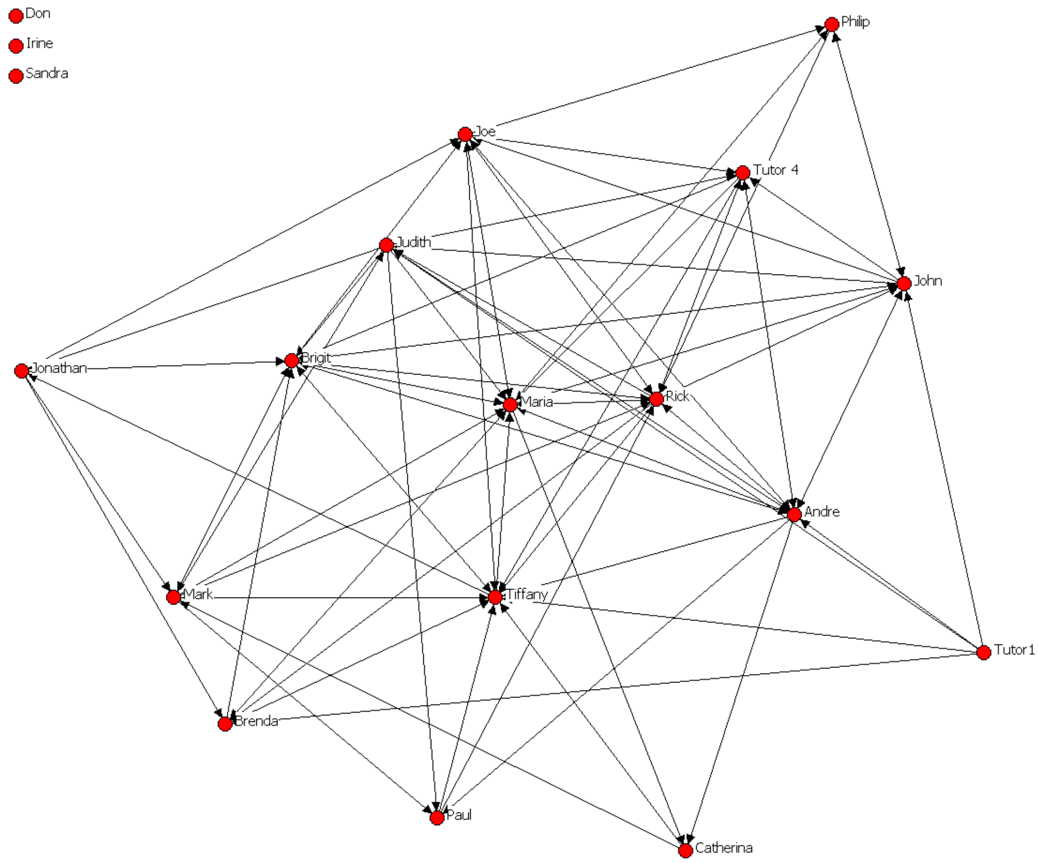


Figure 2


Don
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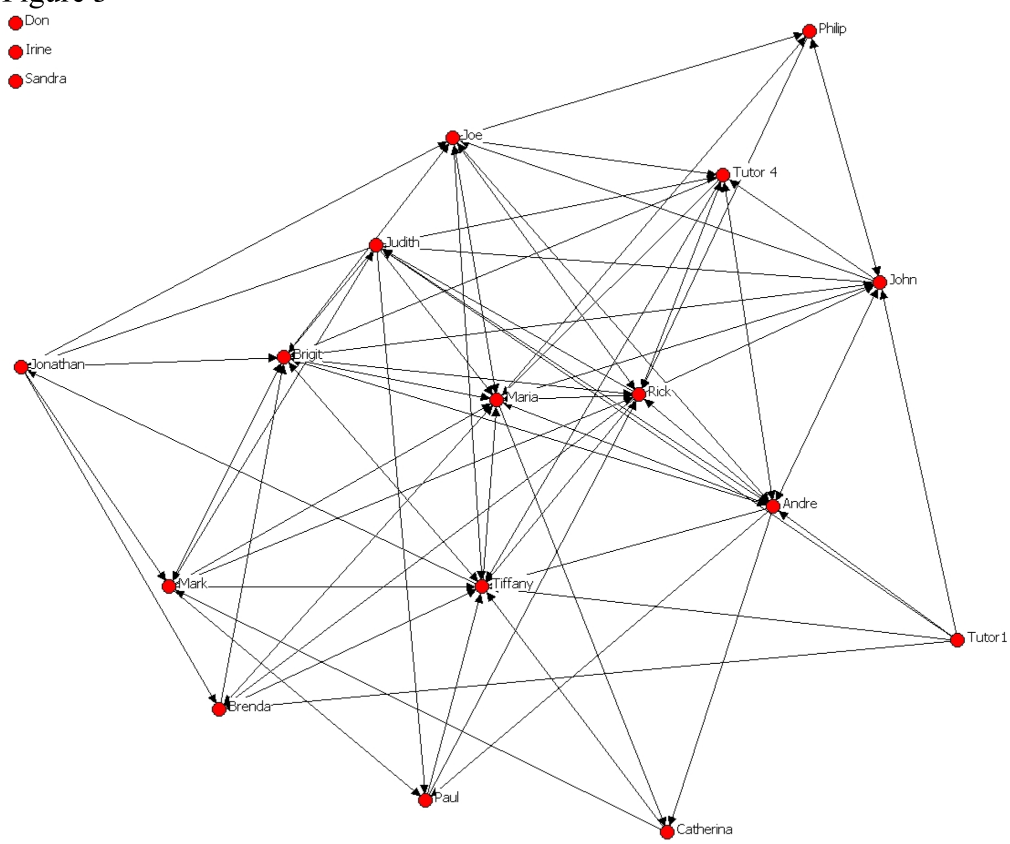
Paul
Catherina

Figure 3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Maria
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Tiffany
Tutor1
Brenda
Paul
Catherina

Table 1

	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 TR Degree	13.36	13.49	1.60	2.72	755.52	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
TR Size	3.73	3.03	0.63	-0.34	113.11	0.00
HC Size	2.38	2.34	0.88	0.08	74.77	0.06

n = 82
TR = Task-Related communition (Content Analysis cat.5-9)
HC = Higher Cognitive communition (Content Analysis cat.7-9)

Table 2

	IMTK	IMTA	IMES	EMID	EMIN	EMER	AMOT
Content Analysis							
Non-task related	0.14	0.17	0.18	-0.02	0.03	0.01	0.17
Planning (Cat. 1)	0.21	0.24*	0.24*	0.07	0.07	0.04	0.06
Technical (Cat. 2)	0.22	0.21	0.26*	-0.06	0.07	-0.05	0.07
Social (Cat. 3)	0.17	0.10	0.12	-0.28*	-0.03	-0.29*	-0.13
Nonsense (Cat. 4)	0.08	0.12	0.12	0.02	0.02	0.06	0.21
Task-related	0.27*	0.24*	0.23*	0.03	0.00	-0.05	-0.09
Facts (Cat. 5)	0.23*	0.18	0.18	-0.05	-0.10	-0.13	0.00
Experience (Cat. 6)	0.29*	0.28*	0.28*	0.10	0.03	-0.02	-0.14
Theoretical Ideas (Cat. 7)	0.22	0.23*	0.26*	0.01	0.11	0.03	-0.05
Explication (Cat. 8)	0.26*	0.25*	0.20	0.07	0.04	-0.01	-0.14
Evaluation (Cat. 9)	-0.10	-0.08	-0.20	0.03	0.01	0.09	-0.08

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

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	IMTK	IMTA	IMES	EMID	EMIN	EMER	AMOT
Social Network Analysis							
Reply Degree	0.23*	0.21	0.18	0.00	0.00	-0.03	0.05
Reply TR Degree	0.27*	0.21	0.18	0.01	-0.04	-0.07	-0.12
Reply HC Degree	0.27*	0.24*	0.20	0.11	0.06	0.05	-0.16
Size	0.24*	0.21	0.22	-0.01	0.04	0.05	-0.02
TR Size	0.29*	0.26*	0.23*	-0.02	0.05	-0.03	-0.08
HC Size	0.29*	0.29*	0.24*	0.13	0.05	0.04	-0.12

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

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