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An dynamic analysis of why learners develop a preference for autonomous learners in CMC

Abstract: A large number of studies in CMC have assessed how social interaction, processes and learning outcomes are intertwined. The present research explores how the degree of self-determination of learners, that is the motivational orientation of a learner, influences the communication and interaction patterns in an online PBL environment. Given the complexity of CMC, we expected that autonomous learners would be more willing to contribute to cognitive discourse. In time, we expected that control-oriented learners would develop a preferential attachment to contribute to discourse from autonomous learners.

Data was gathered from 37 autonomous and 39 control-oriented learners who posted 1669 messages. Using a dynamic multi-method approach of content analysis of cognitive and social discourse, social network analysis, and measures of academic motivation, we find some preliminary evidence that motivational orientation influences communication and social interaction patterns amongst learners. From the beginning, most control-oriented learners develop a preference to connect to and communicate with autonomous learners, although a separate team-analysis indicates that group dynamics also influence how learners develop connections with other learners in time. Our findings further the understanding of differences found in distance learning courses about participation and drop-out.

A common message heard at technology and learning conferences and coffee breaks with faculty staff is that many teachers are puzzled why team dynamics in their courses are often so diverse and complex. Even if teachers provide extensive and explicit structure in their modules, with clear learning objectives and assessment strategies, actively monitor team processes and provide elaborate feedback, many teachers would acknowledge that they have limited control over the social interaction processes within teams.

A large body of research shows that motivation plays a crucial role in learning (Järvelä, Järvenoja, & Veermans, 2008; Mayer, 2011; Ryan & Deci, 2000). Mayer (2011) argues that technology-supported learning environments may promote motivation of learners, as these interactive learning environments facilitate, challenge and stimulate learners to actively engage with tasks and co-construct knowledge with other learners. At the same time, Computer Mediated Communication (CMC) environments may require increased motivation (Chen & Jang, 2010; Chen, Jang, & Branch, 2010; Järvelä, Hurme, & Järvenoja, 2011), as learners are more autonomous deciding what, when and where to learn.

In CMC environments, the degree of self-determination of learners (i.e. the perceived experience that a learner’s behaviour is self-determined, autonomous, or intrinsically motivated) has a strong impact on learning outcomes (Chen & Jang, 2010; Chen et al., 2010; Liu, Horton, Olmanson, & Toprac, 2011; Martens, Gulikers, & Bastiaens, 2004; Rienties, Tempelaar, Van den Bossche, Gijselaers, & Segers, 2009). For example, Lui et al. (2011) showed that students’ intrinsic motivation, that is a drive to learn based on the satisfaction and pleasure of the activity of learning itself rather than external rewards, significantly predicted science knowledge post-test scores in a blended science game. Chen and Jang (2010) found that perceived autonomy of 262 learners was the most significant factor predicting learning outcomes in two distance education programmes.

While an increasing number of studies have indicated that self-determination of learners influences learning outcomes, only a limited number of studies have focussed on the role of self-determination in actual social interaction processes and behaviour of learners in CMC (Järvelä et al., 2011; Martens et al., 2004; Renninger, Cai, Lewis, Adams, & Ernst, 2011; Rienties, 2010). In order to better understand why drop-out rates in CMC are substantial (Nagel, Blignaut, & Cronjé, 2009; Rovai, 2003), and how teachers can design learning environments that continuously motivate learners to actively engage with the task (Järvelä & Häkkinen, 2002; Kirschner, Strijbos, Kreijns, & Beers, 2004; Liu et al., 2011; Nagel et al., 2009), we argue that it is important to understand the complex learning dynamics that occur in CMC and how the degree of self-determination influences behaviour of learners and teams in online settings.

In this explorative study situated in a real-world authentic setting, we investigated how the degree of self-determination of 37 autonomous learners and 39 control-oriented learners in six teams influenced their communication patterns and behaviours in an online Problem Based Learning (PBL) setting, which gave learners a substantial degree of autonomy to decide how to proceed with the task. We will refer to autonomous learners who are primarily intrinsically motivated, and we refer to control-oriented learners who are primarily extrinsically motivated. We used an innovative integrated dynamic multi-method approach composed of Content Analysis, which measured the type of discourse activity, and Social Network Analysis, which measured the interaction processes among autonomous and control-oriented learners. Afterwards, we compared the behaviours of autonomous and control-oriented learners and how their communication and social interaction patterns in the online environment changed in time. Finally, we explored why control-oriented learners strongly prefered to collaborate and interact with autonomous learners.

By bringing together three (separate) research disciplines of motivational science (Järvelä et al., 2011; Ryan & Deci, 2000), CMC for education (Järvelä & Häkkinen, 2002; Luppicini, 2007; Martens et al., 2004), and social network science (Barabási & Albert, 1999; Garton, Haythornthwaite, & Wellman, 1997), we aim to provide a more comprehensive understanding about why participation and contribution to communication in online courses and distance education settings is often unevenly distributed over the participants and teams. Finally, we will address how teachers can improve their instructional design to facilitate learners with different motivational profiles.

The role of Self-Determination in online learning

Several researchers (Järvelä et al., 2011; Martens et al., 2004; Mayer, 2011; Rienties et al., 2009) argue that our understanding of how motivation influences learning behaviour in CMC is not well-understood. Given the openness, flexibility and freedom of most online collaborative settings, learners have (relatively) more autonomy to determine their learning actions in comparison to classroom settings (Chen & Jang, 2010; Chen et al., 2010; Liu et al., 2011). However, not all learners are able to work and learn effectively in a CMC environment where a limited amount of external structure and regulation is provided, thereby requiring a lot of self-determination from learners (Kirschner et al., 2004; Liu et al., 2011; Rienties et al., 2009).

Given the (relative) autonomous nature of CMC in education, in this article we adopt the concept of motivation developed in *Self Determination Theory* (SDT) by Deci and Ryan (1985). SDT distinguishes between intrinsic and extrinsic motivation. According to Deci and Ryan (1985), intrinsically motivated learning can be defined as the drive to learn. This drive is based on the satisfaction and pleasure of the activity of learning itself; no external rewards come into play. Intrinsically motivated learners show autonomous behaviour and have an internal perceived locus of causality (Black & Deci, 2000). Externally motivated learning refers to learning that is a means to an end, and not engaged in for its own sake and behaviours are more controlled.

Why would autonomous and control-oriented learners develop different interactions in time?

The present study considers the way autonomous and control-oriented learners interact together as social network interactions (Garton et al., 1997). According to Newman (2003, p. 174), "[a] social network is a set of people or groups of people with some pattern of contacts or interactions between them". According to network theorists, one important condition that determines how social networks and relationships between learners evolve in time is the (in)equality of characteristics of nodes (i.e. learners) in the network (Barabási, 2002; Barabási & Albert, 1999; Erdős & Rényi, 1960; Newman, 2003). If learners have rather similar characteristics (e.g. preference for autonomous learning, motivation, knowledge, expertise) or personal traits and knowledge in education science jargon, a straightforward assumption from network theory would be that the social network will develop and evolve according to random graph theory (Erdős & Rényi, 1960).

In random graph theory, in time learners connect to other learners within their network at random (i.e. not distinguishing whether learners differ in terms of motivation, knowledge or expertise) with a more or less equal probability. As an explanation how random networks evolve, Barabási (2002) uses the cocktail party example from Erdös and Rényi (1960). Imagine that you are invited to a party of hundred guests who do not know you or each other. Soon you will start to talk to some guests at the party. After a while you will move on to some other people. If one constructs a social network of all encounters during the party, the interactions at the party would follow a random pattern and the total number of connections to others guests will be very similar among all guests.

When two Nobel Prize winners unexpectedly join the party, then it is likely that these scientists will receive a lot of attention. As a result, when drawing a social network of all social interactions, the two Nobel Prize winners will have a lot of connections with "ordinary" party guests. In contrast, the ordinary party guests will have limited connections to other ordinary party guests. Using the metaphor of the cocktail-party, when learners in an online setting become aware that interacting with some learners who have a characteristic (e.g. perceived intrinsic motivation, large knowledge base, expertise) that is beneficial, these learners may become more interesting peers to interact with. Barabási (2002) refers to this phenomenon as *preferential attachment*, whereby nodes (i.e. learners) connect to each other in a random order but in time a preference develops for learners having some positive characteristic(s).

Preliminary evidence indicates that autonomous learners are more inclined to contribute to discourse than control-oriented learners (Martens et al., 2004;

Rienties, 2010; Rienties et al., 2009). In line with Chen and Jang (2010), we expect that autonomous learners possess crucial characteristics for distance learning (i.e. a drive to learn “despite” a lack of structure and regulation in CMC). That is, in time autonomous learners will focus more on cognitive discourse given their academic drive and intrinsic motivation to learn.

As autonomous learners actively contribute to cognitive discourse (i.e. task-related discourse), their experience of perceived competence is enhanced by receiving positive feedback from others on their discussion postings (Liu et al., 2011). In contrast, based upon our previous research published elsewhere (Rienties, Giesbers, et al., 2012; Rienties et al., 2009), we expect that control-oriented learners will perceive a lack of external reinforcements in online settings and therefore in time will contribute less to cognitive discourse.

Hypothesis 1: In time, autonomous learners contribute more actively to cognitive discourse than control-oriented learners.

Hypothesis 2: In time, autonomous learners contribute more to cognitive than non-cognitive discourse.

As we expect that autonomous learners contribute more to cognitive discourse, learners will soon realise that some (autonomous) learners have more positive (motivational) characteristics than other learners. As time passes by, the superior contributions to discourse at a (higher) cognitive level may lead to a positive (cognitive) reputation for autonomous learners. As we expect that autonomous learners contribute more to cognitive discourse, they develop a sense of relatedness amongst each other as autonomous learners continuously challenge each other and provide feedback on each others’ postings. In other words, an incrowd of active, autonomous learners develop in time, whereby these learners benefit from all the positive motivational effects such as cognitive engagement, curiosity and competence as described by Mayer (2011) and Liu et al. (2011). Control-oriented learners may direct their attention more towards autonomous learners given their positive learning characteristics become revealed, thereby strengthening the feelings of competence of autonomous learners. In other words, we expect that autonomous learners will lead the discourse development, thereby providing external regulation to control-oriented learners. In time, this will mean that most learners will be connected to autonomous learners, as phrased in our third and fourth Hypothesis.

Hypothesis 3: In time, control-oriented learners develop a preferential attachment to interact with autonomous learners rather than with other control-oriented learners.

Hypothesis 4: In time, autonomous learners develop a preferential attachment to interact with other autonomous learners rather than with control-oriented learners.

Method

In order to test the four hypotheses, we will explore our triangulated discourse (i.e. who posts and replies to whom?, what do they post?, what motivational profiles do they have?) and social interaction data from three perspectives in order to understand how differences in motivation influence individual learning processes as well as team dynamics. That is, we will first analyse the data from a static perspective (i.e. all messages contributed in the course) using an overall course perspective by aggregating the data for the two summers (see below).

Afterwards, in line with Akyol and Garrison (2008) and Rienties et al. (2013) we will look at a dynamic longitudinal perspective of how autonomous and control-oriented learners interact with each other in time on a week-by-week basis. Finally, we will move from a course to a team-level in order to unravel the complex interplay between different combinations of motivations of learners in teams.

Setting

The present study took place in an online summer course for prospective bachelor students of an International Business degree program at an Institute for Higher Education in the Netherlands (Rienties, Kaper, et al., 2012; Rienties, Tempelaar, Waterval, Rehm, & Gijselaers, 2006). The primary aim of this course was to bridge the gap in economics prior knowledge and the requirements for the degree program (Rienties et al., 2006). Mostly international students participated in the summer course as they did not have economics in their secondary education, whilst most Dutch students followed economics in secondary education and thus did not need a online summer course. In Europe, and in particular in the Netherlands, providing remedial education during the summer period is common (Brants & Struyven, 2009; Rienties, Kaper, et al., 2012).

This online course was given over a period of six weeks in which learners were assumed to work for 10-15 hours per week. The participants were completely unfamiliar with each other before the module started, did not meet 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 PBL, which involves learners working on problems and learning tasks in small teams with the assistance of a tutor. Tasks were constructed to simulate real-world settings but in a semi-structured manner, using a simple-to-complex sequence (Schmidt, Loyens, Van Gog, & Paas, 2007), whereby the learners themselves could decide their learning actions and future directions. That is, problems served as the context for new learning, whereby learners' prior knowledge was activated (Schmidt et al., 2007; Segers, Van den Bossche, & Teunissen, 2003). It resulted in the formulation of learning goals by learners (rather than the tutor), which guided learners to issues that they were unable to solve and therefore requires further investigation (Segers et al., 2003). Their analysis and resolution resulted in the acquisition of knowledge and problem-solving skills. In other words, both collaborative learning and self-determination lie at the heart of PBL. Given space limitations, for an elaborate description of how PBL worked in this context, with specific examples of social interactions, we refer to previous work (Rienties, 2010; Rienties et al., 2013; Rienties et al., 2009).

Learners participated in a total of eight discussion forums. One was a cafe-forum where learners could share non-task related information and get to know each other. In addition, there was a "how does PBL work Task 0?" forum, whereby tutors replicated a discussion to illustrate how PBL worked. The remaining six forums were task-related forums. The first two tasks were introductory and addressed basic terminology to enable students to get a feel for the domain. The tasks were designed to relate to the prior knowledge of students, as recommend by Schmidt et al. (2007). The first task focussed on an international student from North-Korea coming to the institute and realising that the ways markets function in Western Europe are different, while the second task focussed on explaining a graph of longitudinal Gross Domestic Product growth differences between Europe and the U.S. The following four tasks addressed authentic tasks within micro-economics and macro-economics and became increasingly complex.

Longitudinal analysis

Students were grouped into a time-slot of their preference that would start between 1st of July and 1st of August. In this way, students were able to combine their summer plans with following the module at a time that suited them. As the three teams in 2005 and three teams in 2006 started at different periods during the summer, the time stamp of the first student message was regarded as the start of the first week. As the pace of the teams was (in part) determined by the students, some teams were able to finish the six PBL-tasks within five to six weeks. Other teams worked for a longer time period together, while some teams that completed the tasks continued to use the discussion forums for social talk. In order to provide a common benchmark for our longitudinal analysis, we only used messages that were posted within the first six weeks of the module, leading to 1669 student messages.

Participants

In total 82 participants were randomly assigned to six teams in two consecutive summer periods. Only participants that fully completed the Academic Motivation Scale questionnaire (see below) were included in this study, leading to 76 participants (93%). The average age was 19 years and 45% of the learners were female.

Instruments

Academic Motivation Scale

The AMS instrument consists of 28 items whereby learners respond to the question stem "Why are you going to college?" (Vallerand et al., 1992). There are seven subscales on the AMS, of which three belong to the intrinsic motivation scale, three to the extrinsic motivation scale and one for amotivation. Intrinsic motivation subscales are Intrinsic Motivation to Know (IMTK): learning for the satisfaction and pleasure to understand something new; Intrinsic Motivation to Accomplish (IMTA): learning for experiencing satisfaction and pleasure to accomplish something; and Intrinsic Motivation to Experience Stimulation (IMES): learning to experience stimulating sensations. The three Extrinsic Motivation subscales are Identified Regulation (EMID), Introjected Regulation (EMIN), and External Regulation (EMER). The three constitute a motivational continuum reflecting the degree of self-determined behaviour, ranging from identified regulation as the component most adjacent to intrinsic motivation, to externally regulated learning, where learning is steered through external means, such as rewards. The last scale, a-motivation (AMOT), constitutes the very extreme of the continuum: the absence of regulation, either externally directed or internally.

Learners were neither informed about their own motivation scores nor those of other learners until the course was completed. Recent research by Chen et al. (2010) and our own research showed that AMS is an appropriate instrument to distinguish motivational profiles of learners in online learning. The Cronbach alpha reliability for the seven scales ranged from .760 to .856, which is in line with previous studies (Chen & Jang, 2010; Vallerand et al., 1992).

Motivational profiles were determined by first calculating a Relative Autonomy Index (Black & Deci, 2000; Chen & Jang, 2010) based upon the scores of the AMS scales. A median split was conducted, whereby we distinguished between learners relatively low in autonomy (i.e. control-oriented learners) and learners relatively high in autonomy (i.e. autonomous learners). Using a 5% confidence level, significant differences were found between autonomous and control-oriented learners on IMKNOW, IMSTIM, EMINTRO, EMEXT in the expected direction. As is illustrated in Figure 1,, in comparison to control-oriented learners, autonomous learners had higher scores on the intrinsic motivation scales, similar scores on the extrinsic motivation scale closest to intrinsic motivation (EMID), and significantly lower scores on extrinsic motivation scales.

➔ Insert Figure 1 about here

Content Analysis of (non-) cognitive discourse

The aim of content analysis techniques (Chiu & Hsiao, 2010; De Wever, Schellens, Valcke, & Van Keer, 2006) is to reveal evidence about learning and knowledge construction from online discussions. When comparing a range of content analysis schemes, Schellens and Valcke (2005) conclude that the Veerman and Veldhuis-Diermanse (2001) scheme is particularly suited for analysing knowledge construction among novice undergraduate students (as is in this setting). Veerman and Veldhuis-Diermanse (2001) make a distinction between non-task related (1 planning; 2 technical; 3 social; 4 non-sense) and task-related (cognitive) discourse activity (5 facts; 6 experience/opinion; 7 theoretical ideas; 8 explication; 9 evaluation). An elaborate description of the nine discourse activities, the detailed coding procedures and specific examples in our context can be found in Rienties et al. (2010; 2009). 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. The 76 learners posted 1669 messages and the Cronbach alpha (α) was 0.910. The Cohen's kappa of the coder inter-reliability (coders agreeing with each other) between Coder 1 – 2, 2 – 3 and 1 – 3 was 0.64, 0.62 and 0.63 respectively. De Wever et al. (2006) argue that Cohen's kappa values between 0.4 and 0.75 represent fair to good agreement beyond chance.

Positioning of individuals within social network using Social Network Analysis

Social Network Analysis (SNA) provides us with several visualisation tools as well as statistical tools based upon graph theory to analyse interaction patterns among learners (De Laat, Lally, Lipponen, & Simons, 2007; Garton et al., 1997; Hernandez Nanclares, Rienties, & Van den Bossche, 2012; Hommes et al., 2012; Hurme, Palonen, & Järvelä, 2007; Krackhardt & Stern, 1988; Rienties et al., 2009). We integrated the results of the above cognitive discourse content analysis into our SNA in order to measure participation in cognitive discourse, argumentation and social interaction patterns. Afterwards, we determined the amount of connections for each autonomous/control-oriented learner in the cognitive discourse social network with all other autonomous/control-oriented learners within their team (i.e. internal ties) relative to the amount of connections with control-oriented/automous learners (i.e. external ties) using the External – Internal index developed by Krackhardt and Stern (1988), and applied in an education context by Hernandez Nanclares et al. (2012). The resulting index ranges from -1 (i.e. all ties are only with learners with similar motivational profile) to +1 (i.e. all ties are to learners with different motivational profile).

Results

Descriptive statistics of discourse and social interaction (Static perspective)

The division of motivational profiles and number of posts contributed by the six teams are illustrated in Table 1. Autonomous learners contribute 30.97 (SD= 28.76) messages on average, while control-oriented learners contribute 21.87 (SD= 22.10) messages. In four out of six teams, autonomous learners contribute more messages than control-oriented learners. In team 6, autonomous learners contribute below average, while in team 2 autonomous and control-oriented learners contribute equally.

➔ Insert Table 1 about here

In Table 2, we compared the contributions in each of the nine content categories of Veerman and Veldhuis-Diermanse (2001) for autonomous and control-oriented learners. Autonomous learners contribute more to discourse for all nine categories, whereby there are significant differences for Technical (Category 2), Own Experience (Category 6) and Theoretical ideas (Category 7). In other words, when looking at discourse from a static perspective, we find that autonomous learners are more likely to contribute to cognitive discourse than control-oriented learners.

➔ Table 2 about here

With respect to the social interaction patterns within the course, a learner has 6.80 (SD= 3.93) connections to other learners (53%) in the team. In contrast to the postulates of random graph theory, the social networks in our setting does not evolve to a random network with an approximately equal amount of connections per learner as assessed by a Chi-Square test ($\chi 2$ (df= 72) 143.389, $p < .001$). Furthermore, some learners are more inclined to contribute to discourse (in terms of number of posts) than other learners in the network (M= 26.30, SD= 25.80), as is illustrated by the large standard deviation and by the Chi-Square test ($\chi 2$ (df= 72) 1898.139, $p < .001$).

Given that team 3 had only one autonomous learner and ten control-oriented learners, this team was removed from the E-I analysis as all connections of the autonomous learner in this team would be classified as external (Krackhardt & Stern, 1988). Autonomous learners are connected to 4.70 (SD= 3.08) other learners on average for cognitive discourse, while control-oriented learners are connected to 3.34 (SD= 3.06) learners on average during the course. With respect to the number of connections to learners with the same motivational profile (Internal size), an autonomous learner is connected to 3.06 (SD= 2.45) other autonomous learners during the course. A control-oriented learner is connected to 1.31 (SD= 1.17) other control-oriented learners. This indicates that autonomous learners are more likely to connect to learners with the same motivational profile. The overall E-I index from week 1 till week 6 for autonomous learners was -.20 (SD= 0.40), implying that autonomous learners develop a preferential attachment of 20% to autonomous learners rather than to control-oriented learners. The E-I index for control-oriented learners is +.04 (SD= 0.50), implying that control-oriented learners are marginally more likely to communicate and interact with autonomous learners. Finally, when comparing the scores on the E-I index for autonomous and control-oriented learners, a significant difference is found using an independent sample T-test ($t = 2.241$, $df = 63$, p-value < 0.05).

Hypothesis 1: In time, autonomous learners contribute more actively to cognitive discourse than control-oriented learners.

In order to verify hypothesis 1, we compared the contributions to discourse during the six weeks of the course amongst autonomous learners and control-oriented learners, as illustrated in Figure 2. During the first week of the course, autonomous learners contribute on average 1.21 cognitive messages (Category 5-9) and 2.65 non-cognitive messages (Category 1-4), while control-oriented learners contribute 1.43 cognitive messages and 2.12 non-cognitive messages. During the first week no significant differences in any of the nine content categories are found between autonomous and control-oriented learners using independent sample t-testing. In other words, at the start of the course autonomous and control-oriented learners contribute similar to discourse.

➔ Figure 2 about here

As is visually illustrated in Figure 2, the contributions to discourse in time of autonomous and control-oriented learners evolve in different ways. While autonomous learners in the first week start similar to control-oriented learners, there is a notable increase in contributions to cognitive discourse in week 2. That is, when comparing week 1 with week 2 autonomous learners contribute significantly more to all five cognitive discourse categories with the exception of evaluation (not illustrated). After a dip in contributions in week 3, which is exactly the same timing as found by Renninger et al. (2011), autonomous learners pick up the pace and contribute actively to cognitive discourse in week 4 and 6.

As a general trend, autonomous learners contribute more to cognitive discourse in time. In week 6, on average 3.6 contributions per autonomous learner are posted, which is significantly different using a paired T-test comparing week 6 with week 1 ($t = 2.427$, $df = 36$, p-value < 0.05). In particular, autonomous learners contribute significantly more new ideas (p-value < 0.05) and higher cognitive messages (p-value < 0.05) towards the end of the course.

Control-oriented learners contribute less to cognitive discourse in five of six weeks. When comparing control-oriented learners to autonomous learners in week 6, autonomous learners contribute more cognitive messages, in particular significantly more own experience (p-value < 0.01), and higher cognitive discourse (p-value < 0.05). In other words, we find support for Hypothesis 1.

Hypothesis 2: In time, autonomous learners contribute more to cognitive than non-cognitive discourse.

If we compare the contributions of cognitive discourse relative to non-cognitive discourse, in time autonomous learners focus more on cognitive discourse, although this is only marginally significant ($t = 1.928$, $df = 36$, p-value < 0.10). In other words, we find (partial) support for Hypothesis 2.

Hypothesis 3: In time, control-oriented learners develop a preferential attachment to interact with autonomous learners rather than with other control-oriented learners.

➔ Figure 3 about here

As is illustrated in Figure 3, control-oriented learners are more likely to connect to other autonomous learners from the beginning of the course. During the first four weeks of the course, the E-I index for control-oriented learners gradually moves from 0.05 to 0.16 in week 4, which indicates that control-oriented learners are focussing (relatively) more on contributions to social interaction with autonomous learners. Furthermore, a separate analysis at a team-level of how control-oriented learners connected to other learners in Figure 4 illustrates that 15 out of 30 possible relations (5 teams * 6 weeks) between control-oriented and autonomous learners are positive. That is, they are more directed towards autonomous learners than to other control-oriented learners. Seven out of 30 E-I indexes are directed more towards control-oriented learners, whereby three of these originate from team 2, who have almost twice as many control-oriented learners in comparison to autonomous learners. In other words, both from a course perspective and from a team perspective we find some support for Hypothesis 3.

➔ Insert Figure 4 about here

Hypothesis 4: In time, autonomous learners develop a preferential attachment to interact with other autonomous learners rather than with control-oriented learners.

In five out of six weeks, autonomous learners on average are more likely to connect to other autonomous learners, as represented by the negative E-I index score. In particular during week 2 (the most active social interaction phase as illustrated in Figure 3), autonomous learners are actively focussing on communicating with other autonomous learners. Week 3 seems an exception to this overall trend as autonomous learners are not making any distinctions in their willingness to contribute to discourse for learners with either motivational profile. However, in the remaining three weeks autonomous learners are interacting more with other autonomous learners. In Figure 5, 20 out of 30 possible relations were negative, implying that autonomous learners establish more cognitive discourse relations with other autonomous learners than with control-oriented learners. Autonomous learners from team 2 in time establish more relations to control-oriented learners. In contrast to all other teams, autonomous learners from team 6 have more connections to control-oriented learners from week 1 onwards. In other words, we find some support of Hypothesis 4, although team 2 and team 6 illustrate that not every team will develop a preferential attachment towards autonomous learners.

- ➔ Insert Figure 5 about here

Discussion

The results of this explorative study indicate that in our autonomous online PBL-setting learners seem to connect, interact and communicate to other learners depending on their degree of self-determination. We found substantial evidence that autonomous learners receive a relatively large amount of contributions from control-oriented learners. At the same time, most of the autonomous learners themselves are focussing more on cognitive discourse with other autonomous learners. These findings indicate that in online learning settings with a lot of autonomy interaction patterns amongst participants and evolutions of social networks do not develop randomly (Barabási & Albert, 1999; Erdős & Rényi, 1960). In fact, we find that learners seem to develop a preferenial attachment to interact with autonomous learners.

By using an integrated dynamic multi-method approach from a course and team-level, we were able to compare the contributions to cognitive discourse and social network patterns between autonomous and control-oriented learners from both a static and dynamic perspective in a triangulated, innovative manner. When we analysed the contributions to discourse and External-Internal Index for autonomous and control-oriented learners, we found some evidence for our proposition that learners have a preference to connect to autonomous learners in three out of five teams. This amongst others seems to imply that autonomous learners may prefer to discuss with each other rather than to connect to control-oriented learners, in particular when the team division is skewed towards autonomous learners. Control-oriented learners seem to be more externally focussed on connecting to autonomous learners than internally focussed to other control-oriented learners in our setting.

At the same time, the separate analyses at a team-level illustrates that the team dynamics and how autonomous learners and control-oriented learners interact is more complex, which is in line with recent research by Jarvela et al (2011) and Hernandez Nanclares et al. (2012). That is, for team 2 and team 6 the general trend that autonomous learners are more active contributors to discourse did not hold. In team 2, both autonomous and control-oriented learners contributed equally. A possible explanation may be that the majority of learners were control-oriented learners, and after an initial focus on discourse from autonomous learners in week 1-2, control-oriented learners in team 2 picked up the pace after Week 3. It seems that a critical number of autonomous learners is necessary within a team to create a sustainable critical mass of discourse, given the low amount of discourse in team 3 with only one autonomous learner. Finally, in team 6 three autonomous learners contributed less than ten messages, while one control-oriented learner contributed 74 messages. In other words, both individual differences (Nagel et al., 2009) and team dynamics (Hernandez Nanclares et al., 2012; Järvelä & Häkkinen, 2002; Järvelä et al., 2008) seem to influence how learners in online settings co-construct knowledge together.

These findings may have some substantial consequences for CMC research and practice. If these findings are replicated in other settings, this may imply that autonomous learners who, due to the nature of distance learning already have an advantage over other learners due to their preference for autonomy (Chen & Jang, 2010; Martens et al., 2004; Rienties et al., 2009), may over the course become further stimulated by other learners that are keen to link to them.

The careful reader might have noticed that the social interaction patterns amongst autonomous and control-oriented learners seem to be established from the first two weeks onwards for four out of five teams. While we found no significant differences in the amount and type of discourse contributed in week 1 between autonomous and control-oriented learners (see Figure 2), the social interaction patterns (see Figure 3) suggest that autonomous and control-oriented learners prefer to interact with autonomous learners from the first week onwards. That is, by interacting with each other for a limited duration of time, learners in our setting seem to (be able to) form and develop an opinion about the characteristics of their peers and whether it is beneficial to communicate to these learners.

If our findings are replicated in other distance learning settings, this might imply that due to the nature of preferential attachment to autonomous learners, control-oriented learners will be put at a substantial disadvantage from the beginning of the course. For teachers it will be difficult to distinguish behaviour of autonomous and control-oriented learners at the beginning of the course, as both contribute to a similar degree and intensity. However, the results from the E-I index indicates that learners themselves are more aware of potential positive characteristics of their peers, as preferential attachment to autonomous learners is already initiated during the first week. Given the complex nature of distance learning (Bromme, Hesse, & Spada, 2005; De Laat et al., 2007; Wang, 2009), this disadvantage from the beginning of the course might be too large and detrimental for control-oriented learners to overcome. This might explain why distance learning courses suffer from large differences in discourse among learners and teams as well as high drop-out rates.

Limitations

The results of this study were based on a dynamic multi-method approach of content analysis, social network analysis and scores on Academic motivation. Given the robustness of our method of using three independent coders, who each coded all 1669 messages, and the subsequent inter-rated reliability results, a rather unique insight in communication patterns among 76 learners and six teams in an intensive online course was analysed. The AMS instrument can be viewed as a potential limitation to this study as a self-reported measurement of academic motivation was used with obvious limitations. However, the patterns of interaction among the two motivational profiles follow the anticipated direction across two consecutive implementations of the summercourse programme. In addition, research (Chen & Jang, 2010; Chen et al., 2010; Rienties et al., 2009) has found that the AMS instrument is a robust predictor of learning outcomes and academic performance. As a second limitation, our research setting is situated in real-world rather than an experimental setting. The unequal divisions of motivational profiles across the teams seem to illustrate the complexities of team dynamics and individual motivational factors as described by Jarvela et al. (2011; 2008). However, by focussing on the social interaction patterns amongst autonomous and control-oriented learners for a sustained period of time using a dynamic mixed-method approach, as recommend by Akyol & Garrison (2008), a rather unique insight is given how learners in time develop learning relations with other learners in teams with different balances in autonomous and control-oriented motivation.

Implications for instructional design of new media learning environments

These findings are relevant for teachers as the results imply motivational orientation has a substantial influence on the behaviour of learners. By measuring academic motivation before the start of a course, teachers can address the specific learners' needs of autonomous and control-oriented learners. Appropriate strategies to deal with various types of motivation should be designed to assist each type of learner. Although this is relatively unmarked territory, we think that the way forward would be to provide a learning environment that provides sufficient structure and support from the teacher to help control-oriented learners to actively engage, but at the same time allowing for sufficient flexibility and autonomy for autonomous learners (Rienties et al., 2013). This may be realised by providing clear scaffolding of the learning processes at the beginning but to give sufficient freedom to learners to decide how to proceed with solving a particular task as an individual learner or as a team. For example, Jang et al. (2010, p. 598) suggest that learning environments should be designed in an autonomy supportive way, where thestructure provides "clear and detailed expectations and instructions, offering helpful guidance and scaffolding ... and providing feedback to enhance perceptions of competence and perceived personal control during a reflective postperformance period".

Alternatively, providing differentiated (automated) prompts that are dependent on the motivational profile of participants in a similar way as advanced adaptive learning environments may be a relevant way forward, thereby enhancing the perceived competence of learners. Additional work, both on a theoretical and instructional design level, is needed in order to improve our understanding of the complexities of motivation in online learning.

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Figure 1 Scores on Academic Motivation Scale by autonomous and control-oriented learners

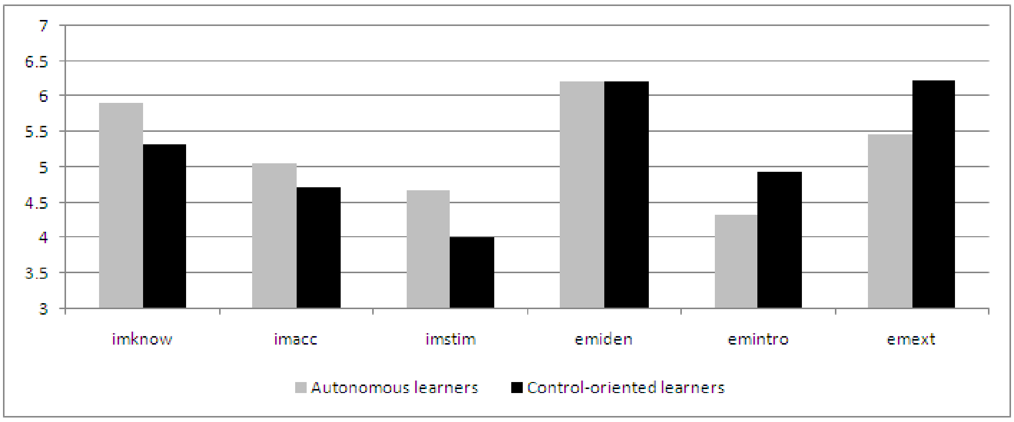

Figure 2 Contributions to cognitive and non-cognitive discourse

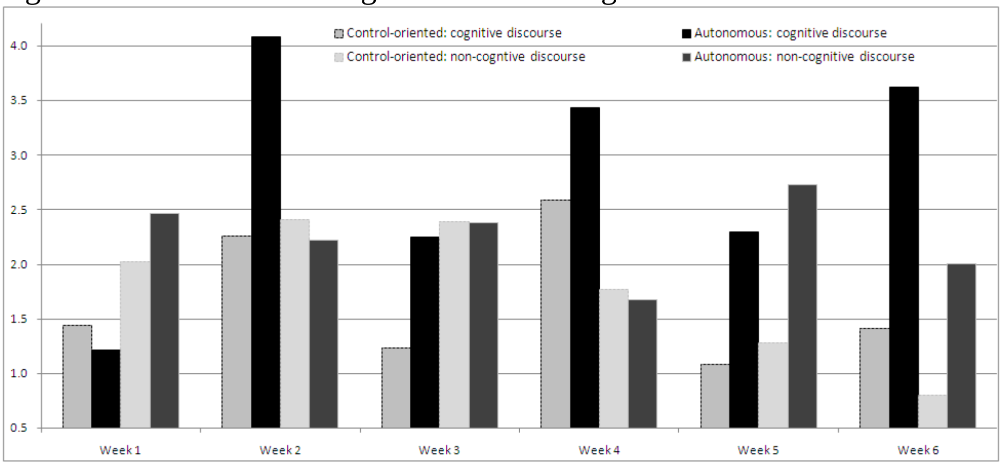

Figure 3 External-Internal index of control-oriented and autonomous learners

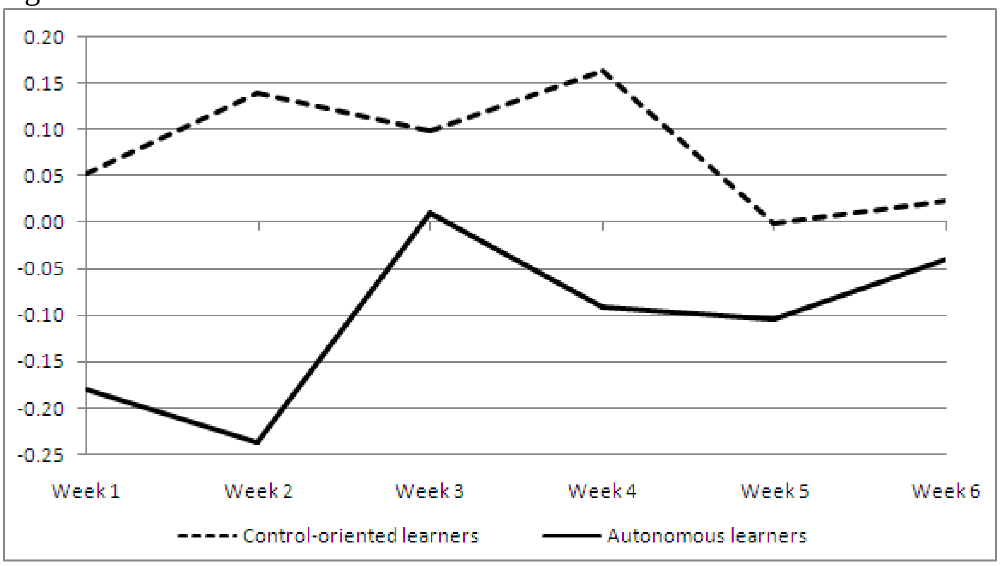

Figure 4 External Index of cognitive discourse for control-oriented learners (per team)

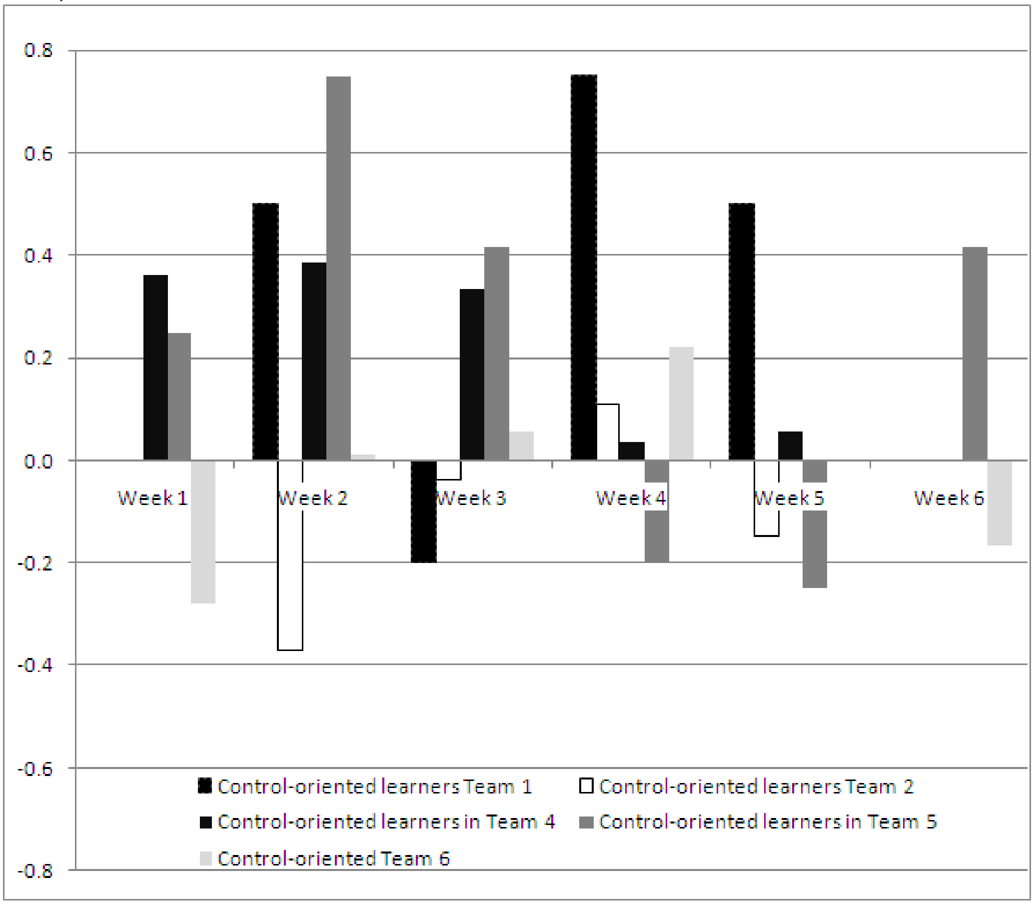

Figure 5 External Index of cognitive discourse for Autonomous learners (per team)

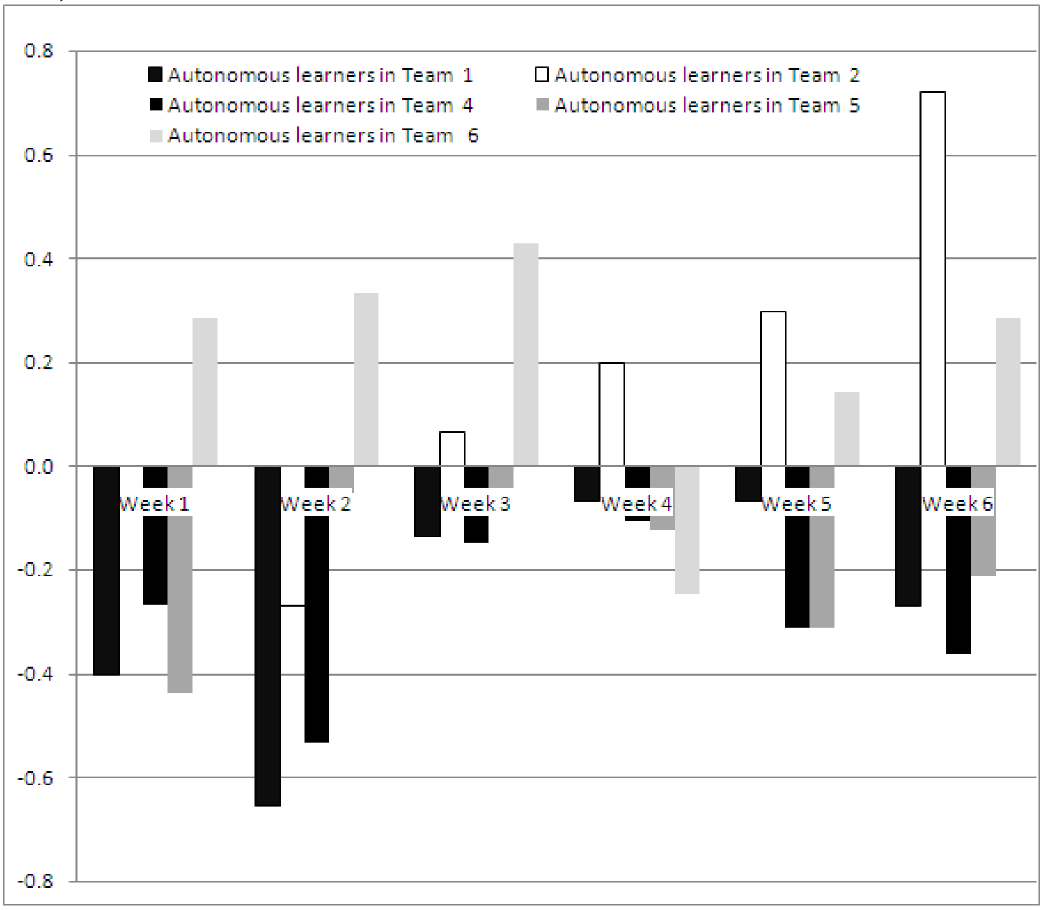

Table 1 Distribution of control-oriented and autonomous learners per team

	Control-oriented learners			Autonomous learners		
	N	# Posts	Post per learner	N	# Post	Post per learner
Team 1	4	57	14.25	5	125	25.00
Team 2	9	244	27.11	5	138	27.60
Team 3	10	125	12.50	1	24	24.00
Team 4	6	171	28.50	11	493	44.82
Team 5	4	103	25.75	8	274	34.25
Team 6	6	153	25.50	7	92	13.14
Total	39	853	21.87	37	1146	30.97

Table 2 Contributions to discourse for autonomous and control-oriented learners (week 1-6).

	Control-oriented Learners		Autonomous learners		T-test
	M	SD	M	SD	
Non-cognitive discourse	11.87	14.30	14.08	14.00	
Planning (Cat. 1)	1.41	1.97	1.97	2.50	
Technical (Cat. 2)	0.59	0.99	1.51	2.68	2.010*
Social (Cat. 3)	0.62	1.25	1.00	1.58	
Nonsense (Cat. 4)	8.05	11.14	8.97	8.81	
Cognitive discourse	10.00	12.89	16.89	18.84	
Facts (Cat. 5)	3.36	4.18	5.46	7.35	
Experience (Cat. 6)	0.92	1.53	2.05	2.99	2.095*
Theoretical Ideas (Cat. 7)	1.46	2.62	3.08	3.48	2.300*
Explication (Cat. 8)	3.87	5.45	6.05	6.59	
Evaluation (Cat. 9)	0.38	0.59	0.24	0.60	

Independent Sample T-test (only significant values reported at $p < 0.05$) for control-oriented learners (n=39) and autonomous learners (n=37).