Does social software fit for all? Examining students’ profiles and activities in collaborative learning mediated by social software

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Abstract: In this study the dependencies between higher education students’ profiles, activities, and learning outcomes in collaborative learning -- as mediated by social software -- were examined. Although the sample size in this study was small (n=22), Bayesian Dependency Modeling method provided statistically viable insight. The results show that learners who were active reflectors in their blogs, but who were also interested in what others achieved, obtained the best results in knowledge tests. Based on the analysis, two distinct learner profiles that reflect differences in the students’ dependencies can be distinguished: monitor and reflector. Furthermore, an indirect dependencies found in the analysis suggests that both reflectors and monitors are also active wiki editors and participants in face-to-face discussions. Further qualitative analyses are needed in order to get an in-depth view of the complex interactions and dependencies within and between the face-to-face and virtual, but also individual and social, planes of collaboration.

Introduction
Since Mark Weiser (1991) coined the term “ubiquitous computing”, an increasing amount of attention has been given to technologies that provide support to people “on the move” (Laru & Järvelä, 2008a). At the same time, a plethora of digital and networked tools have appeared and been established on the Internet. These digital applications, which enable interaction, collaboration and sharing between users, are frequently referred to as Web 2.0 (Bridsall, 2007) or social software (Kesim and Agaoglu, 2007). The ongoing integration of social software and affordances of wireless technologies into mobile-device-based social networks has created fascinating possibilities for organizing novel learning and working situations (Järvelä, Näykki, Laru, Luokkanen, Järvelä, 2007). In spite of the tremendous popularity of the use of social software in students’ free time, there are very few empirical studies which consider student activities with social software for the purpose of learning.

The general claim has been that when new technologies and software are used in an educational setting, new learning opportunities arise. Many case studies and design experiments using mobile technologies or social software for innovative pedagogical ideas and design studies have been conducted and documented (Laru & Järvelä, 2008a). However, only a few studies provide detailed arguments as to what new opportunities the software offers in terms of learning interaction and collaboration and what the exact processes are that the software addresses. We claim that it is not only the learner being “mobile” or “social” that matters. A stronger argument for applying mobile tools and social software for education is that of increasing students’ opportunities for interactions and sharing ideas and thus, increasing opportunities for an active mind in multiple contexts (Dillenbourg, Järvelä, & Fischer, 2007).

In this paper, social software tools are a part of the socio-technical design for a course in a higher education context. The pedagogical ideas behind the design are grounded on collaborative learning, including the socially shared origin of cognition as well as self-regulated learning theory. Specifically, special effort has been place on enhancing and scaffolding collaborative learning as a cognitive, social, and motivated activity.

Aim
In this study, dependencies between students’ profiles, activities and learning outcomes in collaborative learning – as mediated by social software -- were examined. This paper answers the following three research questions: (1) Are differences in the learners’ profiles related to differences in their learning outcomes; (2) Are the learners’ actions in the Web 2.0 tools and face-to-face sessions related to their learning outcomes; and, (3) Are the learners’ actions in the Web 2.0 tools and face-to-face sessions related to differences in their profiles?

Method and participants
The study participants included 22 adult students (17 females and 5 males, median age 38 years) in a higher education learning sciences and educational technology course for a period of 12 weeks (http://edufeed.wikispaces.com). Groups of 4-5 learners were established for recurrent individual and collective phases (Figure 1) which were facilitated with social software (media sharing, personal weblogs, wiki and syndication services via RSS) as well as mobile phones (media sharing, syndication) and laptop computers (Järvelä & Laru, 2008b). In addition, the students had six group reflection sessions where their task was to
reflect on the content of the lectures. After the group reflection students continued their reflections in their individual blogs. In the middle and at the end of the course, the students participated in collective “meaning-making sessions” where they reviewed all the group members’ weblogs and jointly constructed knowledge into their groups’ wikis. The students’ contributions and course-related information were also available for individual monitoring in an RSS-syndication service.

Instrument
All participants completed a two-part, self-report questionnaire containing 101 items. Each item asked the student how strongly he or she agreed or disagreed with a statement. Responses were based on a 7-point Likert-type scale ranging from “strongly disagree (1)” to “strongly agree (7)”. The first section of the questionnaire was derived from the Motivational Regulation Strategies Questionnaire (Wolters, 2001) and contained items about students’ use of five different motivational regulation strategies including self-consequating (A_SeCo), environment control (A_ECO), performance self-talk (A_PST), mastery self-talk (A_MST), and interest enhancement (A_IntEnh). The second and third sections of the questionnaire were adapted from the Motivated Strategies for Learning Questionnaire (Pintrich, Smith, Garcia & McKeachie, 1993). The second section contained items about students’ five different motivational orientations, including intrinsic goal orientation (B_IGO), extrinsic goal orientation (B_EGO), task-value (B_TV), control of learning beliefs (B_CoLB), and self-efficacy for learning and performance (B_SeEfLe). The third section contained items about students’ use of five different cognitive and metacognitive strategies including rehearsal (C_Reh), elaboration (C_Elab), organization (C_Org), critical thinking (C_CT), metacognitive self-regulation (C_MCSR), and two resource management strategies including time and study environment (C_TSE) and peer learning (C_PeLe). The theoretical structure and items of the questionnaire are reported in detail in Pintrich et al. (1993) and Wolters (2001).

Procedures
At the beginning of the course, the students were profiled with the help of the three-part self-report questionnaire. In addition, a control variable was introduced by measuring the students’ initial level of knowledge (CT_Pre_sum) about the course topics using a paper-and-pencil test. After the course, students were asked to answer the test again in order to measure the level of understanding that they acquired during the course (CT_Gain). Data about the learners’ face-to-face and virtual actions were collected by using video-observations, stimulated recall interviews and log-files. Log-file variables used in the analysis included factors relating to students’ use of mobile phones to upload multimedia to file-sharing communities (Flickr Images, YouTube Videos), personal blogs (WP_Entries, WP_Wordcount), groups’ wikis (WS_Edits, WS_Wordcount, WS_Messages_Written) and RSS-readers (RSS_Read). In addition, each learner’s total participation (F2F_sum) in groups’ face-to-face reflection and meaning-making sessions was calculated from the observation data.

Statistical analyses
Bayesian Dependency Modeling (BDM), which predicts the most probable statistical dependency structure between the observed variables, was used for data analysis (Myllymäki, Silander, Tirri & Uronen, 2002).
Bayesian modeling allows the use of nominal (e.g., gender) and ordinal (e.g., Likert-scale) variables in the analysis and it assumes no minimum sample size for technically robust calculations. A graphical visualization of a Bayesian network (BN) has two components: (1) Observed variables visualized as ellipses; and, (2) Dependencies visualized as lines between nodes.

When interpreting the results of BDM, it is important to understand that the directed arcs (i.e., arrowhead arcs) are interpreted as recursive statistical relationships. The reason for this is because, in this study, controlled experiments were not conducted and there is therefore no way to be sure that relationships between observed variables are causal by nature. For example (Figure 2: Middle), variable B_TV (task-value) has an arrow pointing to CT_Gain (learning outcome), but this dependency should be read “an increasing level of task-value has a positive effect on performance in conceptual knowledge testing.”

**Results**

**Are differences in the learners’ profiles related to differences in their learning outcomes?**

The results showed that none of the five self-regulation factors was related to the learning outcome (Figure 2: Left). A direct causal influence between the motivational variables and learning outcomes (Figure 2: Middle) shows that self-effective (B_SeEfLe) students who were interested in the subject matter of the course (B_TV) achieved the best results in the conceptual knowledge test (CT_Gain). Furthermore, levels of extrinsic goal orientation (B_EGO) and control of learning beliefs (B_CoLB) were also related to level of knowledge acquired during the course. No dependencies were found between learning strategies and learning outcome variables (Figure 2: Right). The controlling variable (CT_Presum) was not statistically related to learning outcome (CT_Gain). However, results show that learners with higher pre-existing knowledge in course subjects were more self-consequated (A_SeCo), had greater self-efficacy (B_SeEfLe) and task-value (B_TV), and were more self-regulative (C_MCSR) when compared with their peers.

![Figure 2. Left: Bayesian network of self-regulation factors (A*) and learning outcome (CT_*); Middle: Bayesian network of motivational factors (B*) and learning outcome (CT_*); Right: Bayesian network of learning strategies factors (C_*) and learning outcome (CT_*).](image)

**Are the learners’ actions in the Web 2.0 tools and face-to-face sessions related to their learning outcomes?**

The second research question aimed to clarify whether the learners’ actions in the Web 2.0 tools and face-to-face sessions were related to their learning outcomes (Figure 3). The relationships between two activity variables (RSS_Read; WP_Entries) and performance in the conceptual knowledge test (CT_Gain) suggests that students who actively monitored peers’ contributions and reflected their own thoughts individually in blogs learned more during the course. Furthermore, six activity factors were directly related to other factors and were thus indirectly related to learning outcome. Based on these dependencies, it is clear that students who were active in following others’ contributions (RSS_Read) were also active blog writers, wiki editors and face-to-face discussion participants. In addition, the controlling variable (CT_Presum) was not statistically related to learning outcome or other variables. However, when the results of the second and third sections are connected, one relationship between latent variables and the controlling variable can be found: learners with pre-existing knowledge were more active in building knowledge (Figure 4) in their group’s wiki (WS_Wordcount).
Are the learners’ actions in the Web 2.0 tools and face-to-face sessions related to differences in their profiles?

The third research question focused on the relationship between learners’ profiles and actions in the Web 2.0 tools and face-to-face sessions. First, from the viewpoint of regulative strategies, the BN analysis (Figure 4: Left) showed that learners who were active users of syndication services (RSS_Read) reported high levels of environmental control and interest-enhancement, as well as performance self-talk as a self-regulation strategy and high levels of elaboration as learning strategy.

Second, the BN analysis from the perspective of motivational factors (Figure 4: Middle) showed that only two motivational factors -- self-efficacy for learning (B_SeEfLe) and control of learning beliefs (B_CoLB) -- were directly related to the active use of blogging tools (WP_Entries) and none was directly related to the active use of syndication services (RSS_Read). Results showed that learners with higher pre-existing knowledge of course subjects were more self-consequated (A_SeCo), had greater self-efficacy (B_SeEfLe), and task-value (B_TV), and were more self-regulative (C_MCSR) when compared to their peers.

Third, from the standpoint of learning strategies (Figure 4: Right) the study reveals that active monitoring of others’ activities (RSS_Read) and reflecting in a personal journal (WP_Entries) were related to elaboration (C_Elab). The latter was also related to rehearsal as a learning strategy. Furthermore, BN modeling reveals that the elaboration factor was directly related to many individual and collective activities, including learners’ individual reflections in their blogs (WP_Entries, WP_Wordcount), monitoring others (RSS_Read), and groups’ reflections in the face-to-face sessions (F2F_Sum). The elaboration factor was also related to peer-learning (C_PeLe), rehearsal (C_Reh) and metacognitive self-regulation factors.
However, results show that learners with higher pre-existing knowledge of course subjects (CT_Prew_sum) had greater self-consequation (A_SeCo) and self-efficacy (B_SeeELe) than learners who used more metacognitive self-regulation skills for learning (C_MCSR). Yet, results show that they were more active in building knowledge in their group’s wiki (WS_Wordcount).

Conclusions
In this study, the relationships between learning outcomes, actions and motivations, learning strategies and regulation profiles were explored in an off-the-self social networking environment with an empirical sample of 22 adult learners of a university-level educational technology course.

The results showed that students who were interested in the subject matter of the course, were self-effective learners, able to control their learning beliefs, and who had an extrinsic goal orientation, achieved the best results in the conceptual knowledge test. An analysis of the dependencies between learning outcome and learners’ activities revealed that learners who were active reflectors in their blogs, but also interested in what others achieved, had the best results in the knowledge test. Based on the analysis, two distinct learner profiles can be distinguished based on differences in students’ dependencies: monitor and reflector. Monitors are active users of syndication services with high levels of environmental control and interest-enhancement, performance self-talk as a self-regulation strategy, and elaboration as learning strategy. Reflectors are active bloggers who reported high levels of control of learning beliefs, self-effectiveness as motivational orientations, and elaboration and rehearsal as their learning strategies. Indirect dependencies between activity variables and learning outcomes suggest that both reflectors and monitors were also active wiki editors and participants in the face-to-face discussions. However, analyses of the role of the controlling variable in the data show that learners with pre-existing knowledge were (for example) more confident about subjects taught in a course, valued the course more, and had better self-regulation skills than peers. Yet, learners with pre-existing knowledge affected the collaborative nature of activities by being active in building knowledge collaboratively in their group’s wiki.

Further qualitative analyses are needed in order to derive an in-depth understanding of these complex interactions and dependencies – not only within and between face-to-face and virtual interactions, but also individual and social planes of collaboration. In order to address this interest, the next step is to focus on conducting a qualitative analysis following the guidelines of “eclectic analysis” established by Suthers et al. (2007).

References