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Modeling of Learning Outcomes, Activities and Profiles in a CSLE

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Abstract. This study explored the relationships between learning outcomes, actions and motivational, learning strategy and social ability profiles in a custom made computer-supported learning environment (CSLE) prototype. The system offered three types of services: 1) Tools that support the use of learning resources; 2) Tools that enable flexible and multifaceted peer-to-peer interaction; 3) Tools that increase awareness of other user's actions. Results showed that all motivational factors were directly or indirectly positively related to learning outcomes. Also self-reported resource management skills and preference for learning by doing were directly positively related to learning outcomes. Both time spent in the CSLE and use of awareness increasing tools were found to be positively related with learning outcomes. Use of social navigation tools in the CSLE was positively strongly related to self-reported group work abilities.

Introduction

This study explores the relationships between *profiles* (learning motivation, learning strategies and social abilities questionnaire), *learning outcomes* (scientific essay and statistical computing exercise) and *actions* (interaction, annotation and social navigation) in a custom made computer-supported learning environment (CSLE) of Finnish educational science adult learners on a university level applied statistics course.

For the specific needs of this study, a CSLE was designed and programmed. The system contains lecture slides (offline), about 50 instructional documents from miscellaneous sources (online), and about 6000 research papers from the conference proceedings on education and educational technology (offline). The system offers following three types of services: 1) Asynchronous tools that support the use of learning resources (annotation, i.e., highlighting and commenting of web pages; searchable scientific article database); 2) Synchronous tools that enable flexible and multifaceted peer-to-peer interaction (chat, email, newsgroups); 3) Synchronous tools that increase awareness of other users actions in the learning environment (social navigation map view). Asynchronous tools enable user to see what others have already done in the system (indirect social navigation, see Munro, Höök & Benyon, 1999), and synchronous tools enable to see what others are currently doing in the system (direct social navigation).

In the beginning of the course, adult learners filled up three questionnaires that provided the profiling information: 1) Initial subject knowledge test (statistics - control variable in the analysis); 2) Information technology knowledge and experience test (computer software, programming and distance learning technology skills – control variable in the analysis); 3) Individual learner profiling information (learning motivation, learning strategies and social abilities – independent variables in the analysis). During the course, learners produced a scientific essay in the system as a distance learning task (first learning outcome). They were expected to use the aforementioned services of the system as their actions were saved into the log file (learner's actions in the system –

dependent and independent variables in the analysis). In the end of the course, a statistical computing exercise was presented to the students (second learning outcome).

This paper answers the following three research questions: 1) Are differences in the learners' profiles statistically related to differences in their learning outcomes? 2) Are the learners' actions in the CSLE during the course related to their learning outcomes? 3) Are the learners' actions in the CSLE related to differences in their profiles?

Theoretical Framework

Students' participatory skills are essential in learning processes. Worldwide scenarios stress the social nature of learning, indicated by concepts such as co-operative learning, collaborative problem-solving, sharing and promotive interaction. Social perspective theories give importance to developing organizational cultures towards more co-operative knowledge creations. The demands of learning, in the future, emphasize teamwork and networking as important tools for getting people closer together. Learning is a social practice, along with its cognitive and emotional nature. (Nokelainen, Niemi & Launonen, 2003.) Encouraging and participatory learning culture is also needed in virtual communication as learning also has a social nature. Knowledge creation is a social project and students need social readiness, for example participatory skills for co-operation and sharing.

Computer-supported collaborative learning (CSCL) has now been the work horse of distance learning courses for well over decade. The traditional interaction tools that generic systems (e.g., Moodle, WebCt, FLE and Blackboard) provide, include, for example, chat, email and news group messaging. Such a limited interaction tool palette easily guide teachers to design structured learning material. Learner’s role in these systems is mainly to interact with the material teacher has prepared for the course.

Naturally, there are some exceptions, for example, when the pedagogical framework relies on problem-based learning (PBL) instead of structured learning. Participants of a PBL course are usually expected to further elaborate ‘raw learning resources’ provided by the teacher and, in addition, link their own materials to the system. However, even PBL courses based on generic platforms usually lack true peer-to-peer interaction. (Nokelainen, 2006.)

However, there are systems that provide more sophisticated tools that enable collaborative knowledge building (KB) or knowledge construction (KB), for example, CSILE/Knowledge Forum (Bereiter & Scardamalia, 2003). Such systems often provide asynchronous (e.g., Kukakuka, see Suthers & Xu, 2002) or synchronous (e.g., EDUCO, see Kurhila, Miettinen, Nokelainen & Tirri, 2002a) visual cues (Mayes & Fowler, 1999).

Social Navigation

The CSLE applied in this study is based on our previous research with EDUCO (Kurhila et al., 2002a), EDUCOSM (Miettinen, Kurhila, Nokelainen, Floréen & Tirri, 2003) and OurWeb

(Miettinen, Kurhila, Nokelainen & Tirri, 2006) systems. The new system features a search engine with a document pool together with annotation, discussion and social navigation tools.

Social navigation is enabled with a semi-transparent graphical view (Figure 1), which floats in the browser window and shows the presence and location of the users in real time. Documents are portrayed as sheets of paper within clusters of related material, and the users appear around the documents as dots. Whenever somebody moves from one document to another, the corresponding dot jumps to the new location. Documents and users can be identified by placing the mouse pointer over the respective icon, which shows the title of the document or the name of the user as a tooltip. Clicking a document icon opens the corresponding page, and clicking a dot opens the instant messaging tool. According to previous research, availability of social navigation tools reduce the learners' self-reported cyber loneliness and encourage them to spontaneous collaboration (Erickson & Kellogg, 2000; Gutwin & Greenberg, 2002; Kurhila et al., 2002a; Kurhila, Miettinen, Nokelainen & Tirri, 2002b).

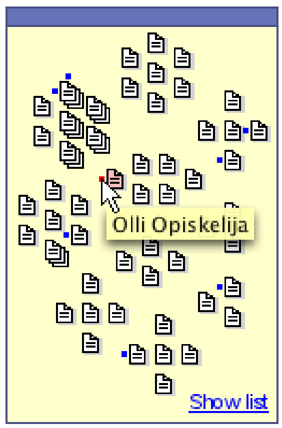

Figure 1: Social navigation map view showing ten document clusters (each consisting of at least two documents) and eight online users (dots around the documents)

Annotation

Several tools for asynchronous communication are also provided in the system. All documents except the lecture slides can be annotated (Figure 2). Two different types of annotations are supported: highlights and comments. Highlights can be applied to marking important parts of the text, analogously to the way people underline text on paper. In practice, adding a highlight involves selecting a fragment of text with the mouse and clicking a button in a small toolbar that appears near the selection. Comments are added the same way, except that the user types the input in a popup window. A comment appears as a tooltip when the mouse pointer is placed on top of the commented text fragment. If several comments are attached to the same text, they appear one after another as a dialogue.

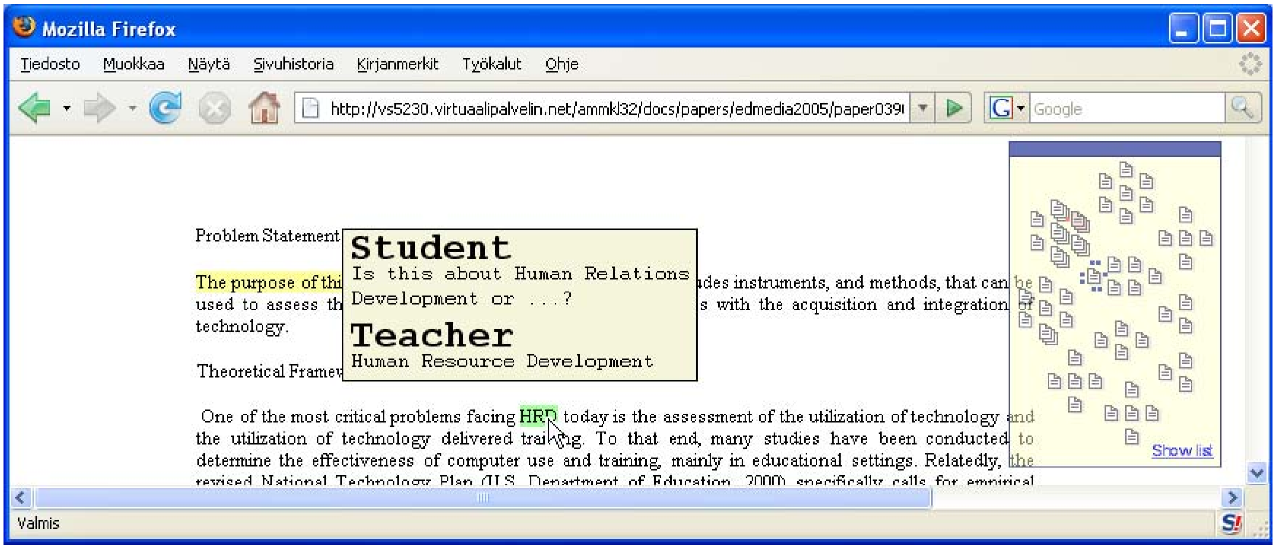

Figure 2: Screen capture of the CSLE showing an annotation (a comment tagged to the highlighted word “HRD”)

Our motivation to include annotation in the CSLE used in this study is based on Marshall’s (1997) finding that underlinings in books are useful to subsequent readers. Further, according to Mayer (2002), deeper learning occurs when key steps in the interactivity are ‘signaled’ rather than non-signaled. Research has shown that combining signaling together with concrete graphical organizers improves various learners learning (Mautone & Mayer, 2007). Signaling is directly related to the first part of annotation, ‘highlighting’ of selected text sequences. Previous research also suggests that an easy-to-use annotation tool promotes asynchronous communication activities and helps to create a constructive learning atmosphere for the course (Nokelainen, Miettinen, Kurhila, Floréen & Tirri, 2005).

Method

Sample

The sample consisting of fourteen adult learners (ten females and four males, age median 43 years) was collected from a university level applied statistics course between October 2007 and March 2008 (http://www.uta.fi/aktkk/ammkl32). During the course, participants had 40 hours face-to-face lectures and exercises, and 120 hours distance learning in the CSLE. Learners previously completed distance learning course numerus ranged from zero to 20. Their self-evaluated computer literacy (web browser, word processor and spreadsheet) was on a good level, but both programming and statistical computing skills were poor.

Instrument

Abilities for Computer Assisted Learning Questionnaire III (ACALQ III) has three parts: 1) Learning motivation (12 items); 2) Learning strategies (10 items); 3) Social abilities (12 items). First two ACALQ III parts are based on the work of Ruohotie and Nokelainen (2000), the third scale is based on the following works: Tirri, K., Komulainen, Nokelainen and Tirri, H. (2002); Nokelainen et al. (2003).

The learning motivation part consists of three sections: 1) Value section; 2) Expectancy section; 3) Affective section. The value section has three subscales: mot_1) Intrinsic goal orientation; mot_2) Extrinsic goal orientation; mot_3) Meaningfulness of study. The expectancy section consists of two subscales: mot_4) Control beliefs; mot_5) Self-efficacy. The affective section includes one component: mot_6) Test anxiety. The learning strategy part consists of four sections: str_1) Metacognition in learning; str_2) Metacognition in practice; str_3) Learning by doing; str_4) Resource management. The social ability part consists of six sections: sa_1) Interpersonal abilities; sa_2) Intrapersonal abilities; sa_3) Self-concept; sa_4) Self-esteem; sa_5) Place oneself (empathy); sa_6) Group work abilities. Theoretical structure and the items of the questionnaire are reported in detail elsewhere (Nokelainen & Ruohotie, 2004).

Procedures

In the beginning of the course, students were profiled with the ACALQ III. In addition, we produced a set of controlling variables by measuring their initial level of statistical knowledge with an online questionnaire and testing their working memory capacity and computer screen (flat panel) text reading speed with a computer-based application. Although the sample size was small, the results pointed out that older participants scored lower in working memory capacity and computer screen reading test than their younger peers, $\chi^2(2, 14) = 4.639$, $p = .098$. Gender was not related to controlling variables.

During the course, students produced two learning outcomes. Firstly, a scientific essay as distance learning task in the CSLE. Secondly, a statistical computing exercise in the last face to face meeting. Both learning outcomes were evaluated on a scale from 1 (poor) to 5 (excellent). The CSLE accumulated fine-grained data on the actions of the students. Several interesting questions can be addressed by analyzing the amount of time invested in various kinds of activities (reviewing lecture slides, skimming and reading instructional material, searching for research papers, skimming and reading research papers, annotating, discussing,...). The system monitored the scrolling of pages in the browser window, and was able to detect periods when the user was not working actively.

Statistical Analyses

Bayesian modeling allows the use of nominal (e.g., gender) and ordinal (e.g., Likert-scale) variables in the analysis. Further, t also analyzes both linear and non-linear dependencies between observed variables and assumes no minimum sample size for technically robust calculations. Most of the aforementioned features are best explained by stating that Bayesian analysis is based on probabilities instead of frequencies. (Nokelainen, Silander, Ruohotie & Tirri, 2007.)

We applied in this study Bayesian Dependency Modeling (BDM), which predicts the most probable statistical dependency structure between the observed variables (Myllymäki, Silander, Tirri & Uronen, 2002). It visualizes the result in a form of a Bayesian network (BN) allowing user to probe the model by adjusting the values of all variables and examining the effects to other variables included in the best model (Heckerman, Geiger & Chickering, 1995).

BN is a viable way to examine dependencies between variables by both their visual representation and probability ratio of each dependency. It is a representation of a probability distribution over a set of random variables, consisting of a Directed Acyclic Graph (DAG), where the nodes correspond to domain variables, and the arcs define a set of independence assumptions which allow the joint probability distribution for a data vector to be factorized as a product of simple conditional probabilities. A graphical visualization of BN contains two components: 1) Observed variables visualized as ellipses; 2) Dependences visualized as lines between nodes. The darker the line, the stronger statistical dependency between the two variables, and more important the dependency is for the model. Variable is considered as independent of all other variables if there is no line attached to it.

Results

In order to answer the three research questions, empirical data from the following three sources was merged into a data matrix: 1) Profiling information (ACALQ III questionnaire); 2) Activities in the CSLE (instant messaging, annotation and social navigation log file data); 3) Learning outcomes (essay and statistical computing test scores).

Research Question 1: Are differences in the learners' profiles statistically related to differences in their learning outcomes?

The first research question investigates if learning motivation (variables “mot_1” – “mot_6”) and learning strategies (variables “str_1” – “str_4”) are related to learning outcomes (variables “lo1_Essay” and “lo2_Computing”). Research literature suggests that higher motivation and learning strategy profile levels are connected to higher learning outcomes (Kettanurak, Ramamurthy & Haseman, 2001). We controlled the analysis with participants age (range from 30 to 54 points; M = 42.8; SD = 7.5) and initial statistics test score (range from 0 to 26 points; M = 15.4; SD = 2.2).

When interpreting the results of BDM presented in Figure 3, it is important to understand that also the directed arches (i.e., arrowhead arches) are interpreted as two-way (recursive) statistical relationships. The obvious reason is that as we have not conducted a true controlled experiment, there is no way to be sure that the relationships between observed variables are causal by nature. For example, variable Lo2_Computing (statistical computing test grade) has an arrow pointing to mot_5 (Self-efficacy), but this dependency should be read as “increasing level of motivation has a positive effect on performance in statistical computation test.”

Results showed that three out of six of the motivational factors (mot_2 ‘Extrinsic goal orientation’, mot_3 ‘Meaningfulness of study’ and mot_5 ‘Self-efficacy’) were positively related to first learning outcome (Lo1_Essay) in our model, a scientific essay that was graded on a scale from 1 (lowest) to 5 (highest). In practice this means that learners who self-reported that they liked to study demanding subjects (despite the possibility of getting low grades), believed in their ability to learn even the most difficult subjects during their studies and expected to get the highest grades from the most demanding courses, did get higher grades from a distance learning task in applied statistics than their peer learners.

Two motivational factors (mot_5 'Self-efficacy' and mot_6 'Test anxiety') were related to the second learning outcome (Lo2_Computing) in the model, a statistical computing task that was graded on a scale from 1 (lowest) to 5 (highest). Self-efficient students believe that they have the ability to learn the most demanding tasks. The computing test was the final examination of the course and had a 40 per cent effect on the final grade. The latter fact explains quite obviously why the last motivational factor, mot_6 'Test anxiety', was related to it.

Further, two motivational factors were directly related to other motivational factors and, thus, indirectly related to learning outcomes: Intrinsic goal orientation (mot_1) was positively related to Meaningfulness of studies (mot_3) and negatively related to Test anxiety (mot_6). Both findings were expected. Firstly, people who tend to study interesting subjects thoroughly, also tend to think that studying is a meaningful task. Secondly, growth of expertise on any subject (due to amount of time and energy put into the studies) decreases fear of test situations and failure, at least to some extent. (Figure 3.)

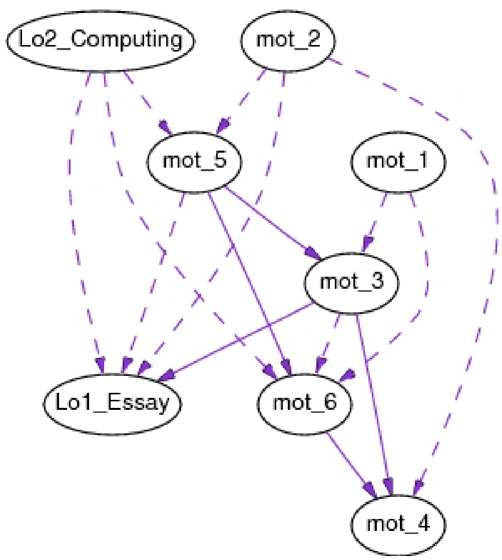

Figure 3: Bayesian network of learning motivation factors (mot_1, … , mot_6) and learning outcomes (Lo1_Essay, Lo2_Computing)

Two dependencies were found between learning strategies and learning outcomes (Figure 4). Self-reported skills in str_4 'Resource management' (i.e., tendency to work hard and prepare well in order to pass both interesting and uninteresting the courses) was related positively to both learning outcomes. Also str_3 'Learning by doing' factor was positively related to both learning outcomes.

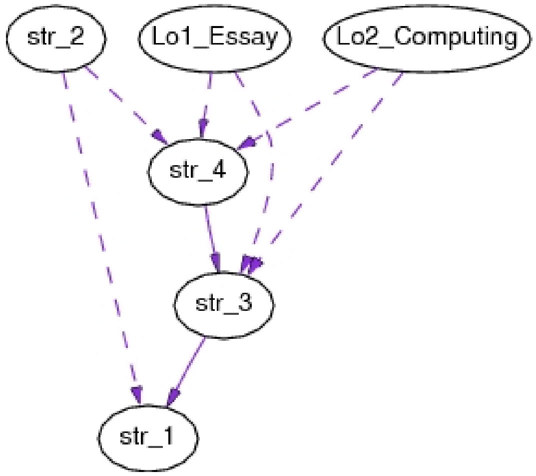

Figure 4: Bayesian network of learning strategy factors (str_1, … , str_4) and learning outcomes (Lo1_Essay, Lo2_Computing)

Neither of the two controlling variables was statistically related to learning outcome variables. However, participant's age was positively connected to 'Learning by doing' factor, that is, older participants preferred practical job-related tasks more than theoretical ones.

Research Question 2: Are the learners' actions in the CSLE during the course related to their learning outcomes?

In order to answer the second research question, learner's actions are further classified into four activity groups according to the previously presented services in the CSLE. *The first activity group* contains the log file about learner's use of annotation tools. Annotation summary variable (activity_1) was calculated from the following variables: 1) Highlightings (range from 0 – 80); 2) Comments (range from 0 – 9); 3) news groups messages (range from 0 – 6). *The second activity group* is represented with a summary variable (activity_2) of chat (range from 0 – 3) and email messages (0 – 1) sent by the learners. *The third activity group* is about social navigation. The log file in this activity group was recorded on two occasions: First, if a user pointed (or clicked) other users "dot" on a map view (i.e., seeking for personal information or instant messaging company, see Figure 1), and second, if a user browsed to a "occupied document" (i.e., document in the map view that one or more other learners are already reading). The summary variables (activity_3) values ranged from 0 to 8. *The fourth activity group* is represented with a summary variable (activity_4) that contains the overall time user has spend reading additional learning material (range from 0 to 159 minutes), scientific articles (range from 49 to 1033 minutes) and lecture slides (range from 0 to 170 minutes) in the system.

We controlled the analysis with two variables (age, initial statistics test score) presented earlier and added a third one that measured participants working memory capacity and reading speed from a computer screen. The values of the third controlling variable range in this sample from 0 (poor) to 8 (excellent), *M* = 3.9, *SD* = 1.7. Analysis showed that the controlling variables were not statistically related to user actions in the CSLE or their learning outcomes.

BN in Figure 5 shows that use of both annotation (activity_1) and instant messaging (activity_2) tools was positively related to use of social navigation (activity_3) tools and, quite naturally, total time spent in the system (activity_4). Results showed that two of the activity groups had a direct positive statistical relationship to learning outcomes: First, an active use of awareness increasing tools (activity_3) predicted high learning outcomes. Second, the most significant predictor for high learning outcomes was the total time spent exploring learning resources in the CSLE (activity_4). Only a weak indirect positive statistical relationship was observed between an active use of annotation tools (activity_1) and learning outcomes.

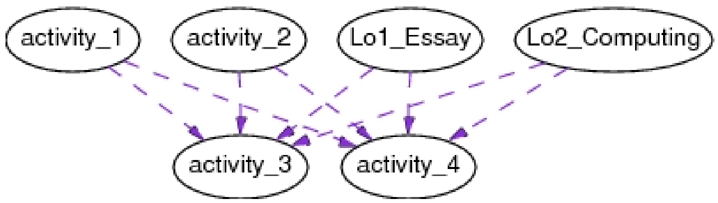

Figure 5: Bayesian network of learner's actions in the CSLE (activity_1, … , activity_4) and learning outcomes (Lo1_Essay, Lo2_Computing)

Research Question 3: Are the learners' actions in the CSLE related to differences in their profiles?

The third research question examined the relationships between learners' self-rated social abilities (variables "sa_1" - "sa_6") and the use of instant messaging (variable "activity_2") and social navigation (variable "activity_3") tools in the CSLE. The same controlling variables were used than in the previous analysis: Age, initial statistics test score and cognitive load and reading speed test score (variables "Age", "StatTest" and "LoadTest", respectively).

BDM showed that the best predictor for the active use of instant messaging tools was the use of social navigation tools. Further, use of social navigation tools in the system was positively strongly related to self-reported group work abilities (sa_6) and positively weakly related to 'Interpersonal abilities' (sa_1) and 'Self-esteem' (sa_4) factors. (Figure 6.)

Controlling variables were not found to be connected with the other variables in the BN.

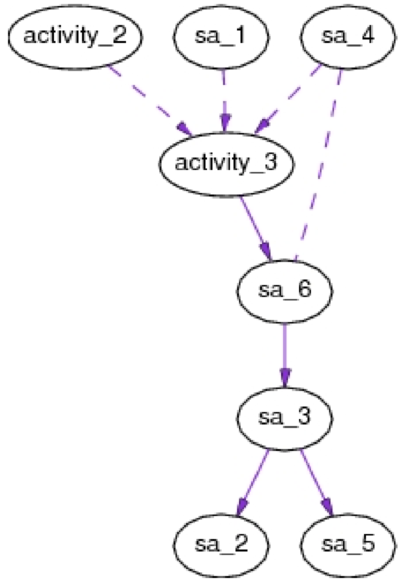

Figure 6: Bayesian network of learner's learning strategy factors (sa_1, … , sa_6), instant messaging actions (activity_2) and social navigation actions (activity_3) in the CSLE

Conclusion

In this study, we explored the relationships between learning outcomes, actions and motivational, learning strategy and social ability profiles in a custom made computer-supported learning environment (CSLE) prototype with an empirical sample of 14 adult learners of a university level applied statistics course.

The research questions were: 1) Are differences in the learners' profiles statistically related to differences in their learning outcomes? 2) Are the learners' actions in the CSLE during the course related to their learning outcomes? 3) Are the learners' actions in the CSLE related to differences in their profiles?

First part of the results showed in parallel with our theoretical framework that learners' motivational profiles were positively connected to learning outcomes. Learner's self-evaluated 'resource management strategies' and willingness to 'learn by doing' were also positively connected to learning outcomes. These findings are similar to those of our previous study with the EDUCOSM prototype (Nokelainen et al., 2005). We conclude that the results of the first research question supported the findings of an earlier study by Kettanurak and his colleagues (2001) suggesting that higher motivation and learning strategy profile levels are connected to higher learning outcomes.

Second part of the results showed that time spent in the CSLE and use of awareness increasing tools (social navigation) correlated positively with learning outcomes. Only a weak positive statistical relationship was observed between an active use of annotation tools (highlighting and commenting documents) and learning outcomes. However, our previous study (Nokelainen et al., 2005) showed a strong positive correlation between quality of annotations in the prototype system and the final grade in the same applied statistics course, $r(50) = .77$, $p < .001$. We recommend on the basis of our current and previous research findings use of annotation tools in CSLE's. However, Marshall's (1997) finding that annotation (she studied underlining of library books, i.e., 'signaling') would be beneficary for peer learners was not supported by the results of neither our current nor previous study (Nokelainen et al., 2005). The results of our previous study indicate that self-made annotations were experienced to be more useful for learning than peer-made annotations. We conclude that this area would benefit from further investigations.

Third part of the study analyzed the statistical relationships between self-reported social abilities and actions in the CSLE. Results showed that those learners, who reported high level of social abilities, were the most active users of the social navigation tools provided by the system. When we connect the results of the second (active use of social navigation tool is positively connected to successful learning outcomes) and third (high social ability level is positively connected to the active use of social navigation tool) part, we notice that high social ability level is indirectly positively connected to successful learning outcomes.

Discussion

Although the sample size in this study was small ($n = 14$), it was too small only for the widely applied frequentistic parametric statistical methods, such as t-test or correlation. Those methods produce robust results when certain assumptions are met: 1) Both phenomena under investigation and its indicators are normally distributed; 2) Statistical relationships under investigation are linear; 3) Measurement level of indicators is at least ordinal; 4) Sample size of the smallest group is more than 30 (Nokelainen, in press). Empirical research projects in the field of educational and computer science quite often violate one or more of these assumptions, for example, if the sample is collected with a Likert-scale (1932) questionnaire.

Assumption free Bayesian probabilistic modeling (Gill, 2002) provides a viable alternative to the traditional frequentistic methods. The good old 'garbage in – garbage out' rule is still working, but is it necessary to label samples with "bad" or "unusable" stickers only because they are 'small'. Actually, it is interesting to ask: Small by *what* standards? Should the scientists of the 21st century obey those standards set in 1930's by frequentistic statisticians (e.g., F-test by Sir Ronald A. Fisher, 1935), or those set by the statisticians of our time (e.g., Self-Organizing Maps by Teuvo Kohonen, 1995)? The issue of sample size should be linked to terms like 'representativeness' or 'generalizability' instead of 'continuous indicators', 'multivariate normality' and so on. It is scientifically meaningful to promote 'all the models are bad, but some are useful' ideology, as even a sample below 30 observations, when analyzed with a technically appropriate method, might have an interesting story to tell!

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