A Qualitative Evaluation of Evolution of a Learning Analytics Tool

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ABSTRACT

New systems are designed with improved quality or features. However, not every new system lives to its pre-development expectations when tested with end-users. The evaluation of the first version of our LOCO-Analyst tool for providing teachers with feedback on students learning activities and performance led to the enhancing the visualization features of the tool. The second evaluation of the improved tool allowed us to see how the improvements affect the user perceptions of the tool. Here, we present the qualitative results of our two evaluations. The results show that educators find the kinds of feedback implemented in the tool informative and they value the mix of textual and graphical representations of different kinds of feedback provided by the tool.

Keywords

Learning analytics, visualization, Semantic Web, qualitative evaluation, content analysis

1. Introduction

Today’s web-based learning systems are built under the promise to make the ‘anywhere, anytime’ learning vision possible by transcending the time and space boundaries inherent to the traditional classroom-based teaching and learning. A typical form of web-based learning is through Learning Content Management Systems (LCMSs), such as WebCT¹ or Moodle². These LCMSs require teachers to constantly adapt their courses (both structure and content) to assure comprehensibility, high performance and learning efficiency of their students [Gasevic et al, 2007]. Educators’ awareness of how students engage in the learning process, how they perform on the assigned learning and assessment tasks, and where they experience difficulties is the imperative for this adaptation. For this reason, educators need comprehensive and informative feedback about their online courses. A comprehensive feedback is based on semantically interlinked data about all the major elements of a learning process, including: learning activities (e.g. reading and discussing), learning content, learning outcomes, and students [Jovanovic et al, 2008]. An informative feedback provides an educator with a quick and easy-to-understand insight into a certain aspect of the learning process. Contemporary LCMSs, however, provide rather basic analytics such as simple statistics on technology usage or low-level data on a student’s interaction with learning content (e.g. page view).

Recognizing the importance of analysis of learner activities in learning environments, a new research area of learning analytics has emerged. Learning analytics is defined as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs”³. In our research, we have been specifically interested in investigating the use of semantic technologies for learning analytics. Our motivation for the use of semantic technologies lies in the fact that these technologies can enable meaningful linking of students’ learning activities as well as their mutual interactions and interactions with learning content. To be able to develop such a learning analytics tool, we initially developed an ontology framework, named LOCO, for modeling learning contexts [Jovanovic et al, 2007b]. The key notion of LOCO is learning context, which is defined as an interplay of a learning activity, learning content, and participants (e.g., learners and/or educators); thus, LOCO enables us to collect and meaningfully interlink learning context data from different learning environments, or from different services (e.g., chat rooms and discussion forums) inside the same learning environment. On top of the LOCO framework and by leveraging principles of text mining and semantic annotation [Popov et al, 2003], we developed a learning analytics tool LOCO-Analyst⁴.

¹ www.webct.com
² http://moodle.org/
³ https://tekri.athabascau.ca/analytics/
⁴ http://www.jelenajovanovic.net/LOCO-Analyst
Our research in learning analytics followed the standard design-based educational research method [Reeves et al., 2005] in which we assumed the use of an iterative approach. In the end of our first iteration, our research prototype – LOCO-Analyst – was capable of providing educators with a basic set of feedback interlinking learning contexts about students’ interactions with learning content, their discussions in forums and chat rooms, and performances on quizzes (Sect. 2). In the end of this iteration (November 2006), we conducted an empirical study with a group of educators aiming to identify the perceived value of individual elements of learning analytics implemented in the tool. As reported in [Jovanovic et al, 2008], the participants’ responses were highly positive. However, the participants also indicated a need for enhancing the way in which the feedback was presented; they explicitly suggested higher usage of visual representations of feedback. We found this demand for other ways of feedback presentation consistent with the cognitive and educational psychology studies [Cassidy & Eachus, 2000; Dunn, 1983; Harrison, Andrews, & Saklofske, 2003; Mayer and Massa, 2003]. Responding to the outcomes of our first study, we improved LOCO-Analyst by introducing advanced visualizations (Sect. 4). In 2009, we conducted the evaluation of this new version of LOCO-Analyst to find out how the educators valued the enhancements.

Having in mind the abovementioned research activities, the objective of this paper is to report on the results of the evaluation of LOCO-Analyst with the specific goal to analyze systematically the qualitative data collected in the both studies through open-ended questionnaires with a focus on effect of feedback visualization. While the results of the first (2006) evaluation are to some extent reported in [Jovanovic et al, 2008], our analysis was rather focused on the quantitative (Likert-scale) data; also, the data were not systematically coded. To be able to better understand the emerging trends and compare the results of the two studies (2006 and 2009), we needed to study the evaluation results in a more systematic manner. In order to be able to analyze the qualitative data collected in the both evaluations systematically, we performed a content analysis. In this paper, we report on the results of this content analysis (Sections 3 and 5). Furthermore, we compare the results of the two qualitative evaluations (Sect. 6) as well as compare them with the results of our analysis of quantitative data, which were also collected in our evaluations and reported on in [Asadi et al, 2011]. In Sect. 7 we discuss some threats to the validity of our findings, next we compare our work with the related work (Sect. 8) and conclude the paper in Sect. 9.

2. **First Version of LOCO-Analyst**

LOCO-Analyst is an educational tool aimed at providing educators with feedback on the relevant aspects of the learning process taking place in a web-based learning environment, and thus helps them improve the content and the structure of their web-based courses. It provides educators with feedback regarding: (1) all kinds of activities their students performed and/or took part in during the learning process; (2) the usage and the comprehensibility of the learning content they had prepared and deployed in the LCMS; and (3) contextualized social interactions among students (i.e., social networking) in the virtual learning environment.

The generation of feedback in LOCO-Analyst is based on analysis of the user tracking data. These analyses are grounded in the notion of learning context which is about a student (or a group of students) interacting with a learning content by performing a certain activity (e.g. reading, quizzing, chatting) with a particular purpose in mind [Jovanovic et al, 2007b]. The purpose of learning object context is to facilitate abstraction of relevant concepts from user-tracking data of various e-learning systems and tools.

As a Semantic Web application, LOCO-Analyst is built on top of the LOCO (Learning Object Context Ontologies) ontological framework, which we developed to enable formal representation of the learning context data [Jovanovic et al, 2008]. Furthermore, it exploits semantic annotation to interrelate diverse kinds of learning artifacts such as lessons, tests, and messages exchanged during online interactions. Finally, it employs reasoning to derive meaningful information from the learning object context data.

LOCO-Analyst provides different kinds of feedback to educators thus enabling them to get insight into most relevant information. The feedback includes: single lesson feedback; topic level feedback; module level feedback; feedback about different types of learning objects (e.g., lessons and tests); and feedback on individual student – i.e. student’s interactions with the learning content as well as with other students. In Table 1, we outline the main types of feedback supported in the LOCO-Analyst tool, along with the indicators about their presence in the first version of the tool, and applied improvement in the second version of the tool.
<table>
<thead>
<tr>
<th>Feedback type</th>
<th>Provided feedback</th>
<th>Present in the 2006 version</th>
<th>Improvement in the 2009 version</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1 Individual lesson</td>
<td>Basic statistical indicators related to the lesson (re-)visits and dwell time; estimated difficulty level of the lesson and how it compares w.r.t. other related lessons; students’ messages discussing the topics of the lesson; tags attached to the lesson by students.</td>
<td>All the elements of the feedback except students' tags</td>
<td>Students collaborative tags were added; Visualization of lessons difficulty levels was introduced; Reduction of the amount of data provided upfront with option of getting more information upon request ('Learn More')</td>
</tr>
<tr>
<td>F2 A group of (related) lessons</td>
<td>The same kind of data as for an individual lesson but on a more coarse grained level, i.e., the level of a lessons (topically-related) group.</td>
<td>All the elements of the feedback were present</td>
<td>The same data were presented but with more visual elements</td>
</tr>
<tr>
<td>F3 A learning module as a whole</td>
<td>The same as for the previous two but on an even higher generality level, referring to a learning module(^5) as a whole.</td>
<td>All the elements of the feedback were present</td>
<td>Completely redesigned; feedback data presented using visualizations (charts and graphs)</td>
</tr>
<tr>
<td>F4 Students’ performance on a quiz</td>
<td>Overview of the quiz (test) results, including, besides the basic statistics also the list of the most difficult question and comparison with students performance on quizzes in other learning modules (both on individual and group level).</td>
<td>All the elements of the feedback were present</td>
<td>Visual representation of the feedback data; one view is given in Figure 4.</td>
</tr>
<tr>
<td>F5 Student’s activities in discussion forums and chat rooms</td>
<td>Number of sent/received messages across different forums and chat rooms; an insight into the social network established through the students’ online communications, e.g., the most frequent communication partners.</td>
<td>All the elements of the feedback were present</td>
<td>Feedback presented in the tabular form only.</td>
</tr>
<tr>
<td>F6 Student’s interaction with the learning content (lessons)</td>
<td>Student’s engagement with the different lessons of different learning modules</td>
<td>Feedback presented in the tabular form only.</td>
<td>Visual representation of the feedback data; one view is given in Figure 4.</td>
</tr>
<tr>
<td>F7 Student’s comprehension of the studied topics (based on his/her annotations)</td>
<td>Different kinds of annotations the student used to annotate the lessons of the learning module, including tags (presented within the tag cloud of the entire class), notes/comments, and highlights.</td>
<td>Not present</td>
<td>An entirely new kind of feedback, introduced in 2009 version</td>
</tr>
</tbody>
</table>

LOCO-Analyst is implemented as an extension of Reload Content Packaging Editor\(^6\), an open-source tool for creating courses compliant with the IMS Content Packaging (IMS CP)\(^7\) specification. Having extended Reload editor with the functionalities of LOCO-Analyst, we effectively enabled educators to use the same tool for creating courses, viewing the feedback on those courses, and modifying the courses accordingly. Figure 1\(^8\) illustrates the 2006 version of the LOCO-Analyst tool. It shows a quiz feedback on “Programming Process” learning module. User interface window of the LOCO-Analyst tool is divided into two parts. The left hand side (LHS) part is allocated to the Reload editor and displays course structure (Fig. 1 M) using the Reload editor’s functionality as well as some IMS CP specific attributes of the selected course item (Fig. 1 D). The right hand side (RHS) part of the Window is reserved for LOCO-Analyst’s functionalities, i.e., the feedback the tool generates.

\(^5\) Learning module is considered here as a relatively independent unit of a course which focuses on one specific subject area taught within the course (often correspond to one chapter of the course’s textbook).

\(^6\) http://www.reload.ac.uk/editor.html

\(^7\) http://www.imsglobal.org/content/packaging/

\(^8\) For Additional details (regarding the both versions as discussed here in Sect. 2 and later in Sect. 5) about the tool, we refer interested readers to the website of the tool where we provided a number of demo videos outlining the tool and its features [http://jelenajovanovic.net/LOCO-Analyst/videos.html](http://jelenajovanovic.net/LOCO-Analyst/videos.html). The tool is also available as open source at [http://www.semwebcentral.org/projects/locoanalyst](http://www.semwebcentral.org/projects/locoanalyst).
The LOCO-Analyst feedback section (i.e. RHS) is further divided into three panels: top, middle and bottom, marked as A, B, and C in Figure 1 respectively. The information presented in each part depends on the feedback type (Table 1). The top panel is generally reserved for displaying meta-statistics for the selected feedback type. In Figure 1, the top panel shows statistics related to the time students spent on the quiz. The middle panel presents the summary statistics which directly measure the given feedback type, such as the students’ performance on the quiz. In addition, the educator can learn more about the students’ scores. The lower panel generally presents more details at granular level for selected items. For instance, for the quiz scenario in Figure 1 it shows students’ performance at the questions level. In particular, it shows the average number of incorrect answers per question, as well as a list of questions that were identified as the most difficult for students. For each ‘difficult’ question, the panel shows the question text and the number of students who answered it incorrectly.


3.1 Study Design

3.1.1 Design

We conducted an evaluation study to determine whether and to what extent educators find LOCO-Analyst useful for their everyday practice. The user observations were obtained through a questionnaire, which was completed after a session with the tool. Once the data were collected, we used qualitative methods (content analysis) for data analysis.

3.1.2 Participants

We recruited 18 participants from University of Belgrade, Simon Fraser University, and the University of Saskatchewan for our study in 2006. The participants had prior teaching experience and exposure to online learning systems. Five of the participants had previous exposure to similar feedback provisioning systems. We gave minimal instructions to the participants on how to use LOCO-Analyst as we wanted to estimate how intuitive the feedback provision functionalities were. All the participants successfully completed all the steps of the experiment.

The participants were also asked to express their role, which would best describe their experience in online education. We distinguished between the following three roles:

- **Instructors** – had independently instructed at least one entire course. There were six participants in this group and they had on average 4.75 years of experience (SD=4.90, n=6);
- **Teaching assistants** - had teaching experience in an assisting role only. There were eight participants in this group and they
had on average 1.88 years of experience with (SD = 1.13, n=8); and
• Research students/practitioners – had done research related to online education, or practiced online education in industry through software and content development and delivery. There were four participants in this group and they had on average 3.0 years of experience (SD=2.0, n=4).
The average experience of all participants in their role was 3.09 years (SD = 3.12, n=18).

3.1.3 Materials
The study used the LOCO-Analyst tool and a questionnaire to evaluate all the features of the tool. The questionnaire consisted of 16 items (i.e., questions): first three items asked participants to specify their role and experience; nine of the items were related to the tool’s feedback features and functionality; and remaining four items focused on the GUI and intuitiveness features. Eight of the items (listed in Table 2) had two parts: nominal scale responses (i.e., quantitative) and open-ended (i.e., qualitative) part for putting observation in a free text form. All of the nominal scale responses used the scale 1-yes, 2-partially yes, 3-no, and 4-have no opinion, but one that used the scale with items 1-no, 2-have no opinion, and 3-yes. The open-ended (qualitative) observations are analyzed in this paper. For the sake of more complete coverage of the problem under study, we also report on the descriptive statistics of the quantitative data, but the detailed analysis of those data is given in [Asadi et al, 2011].

3.1.4 Procedures
We emailed the participants the guidelines on how to perform the evaluation of the tool’s features. The guidelines explained the purpose of the evaluation and outlined the evaluation steps. The participants were asked to download the tool and try all the feedback types available in the 2006 version of the tool (c.f. Table 1). They were supplied with written guidelines describing how to use the tool and each individual feedback type. The participants were also encouraged to send any further clarification questions to the researchers. Once finished, the participants were expected to send the completed evaluation questionnaire back within a week from the time of their initial acceptance to participate in the study. Finally, having received completed questionnaires, we entered all the participants’ answers and observations into an Excel spreadsheet for the further analysis.

Table 2. The table with the open-ended questions asked in both surveys: the first column of the table is the category of the questions; the second column shows the content of the questions; third and fourth indicate if a question was included in the 2006 and 2009 surveys, respectively (i.e., + question was asked and – question was not asked). The following signs indicate that (†) – a question in the 2006 study had 4-point scale. (‡)– a question in the 2006 study had 3-point scale

<table>
<thead>
<tr>
<th>Category</th>
<th>Question Description in the questionnaire</th>
<th>Asked in 2006</th>
<th>Asked in 2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived usefulness of the tool for improving the course content and instruction</td>
<td>Q1†: The tool enables me to get an insight into the students’ interactions with the learning content</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Q2†: The information the tool provides helps me identify what needs to be improved in the learning content</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Q3†: The tool provides relevant information regarding the students’ interactions within the online learning environment.</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Q4†: The information provided by the tool helps me determine how to improve the students’ online interactions.</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Q5: The tool helps me identify the domain topics the students were having difficulties with.</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Perceived value of the tool’s GUI</td>
<td>Q6: LOCO-Analyst’s GUI (Graphical User Interface) is intuitive enough</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Q7‡: LOCO-Analyst’s GUI is overburdened with information</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Q8: My general opinion about the GUI</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>General perception of the tool</td>
<td>Q9: I would like to be able to use LOCO-Analyst in my teaching practice</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Q10: LOCO-Analyst provides me with more useful feedback than other similar tool(s) I have used/ tried</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Q11: LOCO-Analyst is more intuitive than the other tools capable of for feedback provisioning I have used/ tried</td>
<td>-</td>
<td>+</td>
</tr>
</tbody>
</table>

3.1.5 Content Analysis
The survey collected both the quantitative and qualitative data. However, as mentioned earlier, this paper is focused primarily on the interpretative inquiry of the qualitative data. Content analysis, which is generally used for systematically studying large amounts of communication content such as articles, discussion forum messages, or blogs, was used for
making the interpretative inquiry. Each answer was analyzed to identify the keywords associated with the participants’ feedback and user interface (such as intuitive interface, helpful statistics, etc.) and to understand its context.

The key characteristic of content analysis is that the analyzed contents are categorized by researchers. Based on the participants’ answers, we developed a coding scheme which consisted of three general categories: (1) **Positive comment** – expressing positive opinion without any concerns; (2) **Positive comment with some observations** – expressing positive opinion, but also has some observations that question some decisions or suggest some improvements; and (3) **Negative comment** - expressing either negative observations or some concerns questioning the decisions made in the design. These categories were further sub-categorized into 3 subcategories, namely: (1) **Feedback feature** – observations about specific feedback mechanisms supported by the user interface of LOCO-Analyst; (2) **Intuitiveness** – observations about the intuitiveness of the user interface; and (3) **General comment** - conceptual comments not only applicable to the user interface and implementation of LOCO-Analyst. Each subcategory was assigned a numerical identifier (1-9). Some participants provided observations which did not directly address the posed question and did not show any obvious relatedness to the context of the question. We treated these observations as suggestions and comments and coded them differently.

A slightly different coding scheme was applied to one of the question items, which sought suggestions for improving the tool’s GUI. Each response was broadly recognized as either a **suggestion** or a **compliment**. Both of these categories were further subdivided as: (1) **mainly related to improving data visualization/graphics**; (2) **mainly related to improving interface design**; (3) **mainly related to improving annotations**; and (4) **other**.

The validity of qualitative analysis is gauged through the notions of trustworthiness and credibility. To assure validity of codes, two raters applied the coding scheme independently to rate the answers. The agreement between the raters was computed using Cohen’s Kappa. The values for Cohen’s Kappa for the two coding schemes used were 0.84 (based on Table 3) and 0.81 (based on Table 4), which can be interpreted as a **nearly perfect agreement** according to the conventional interpretation of kappa [Landis & Koch, 1977] for both coding schemes respectively. In the final step all the differences were resolved through the discussion during the meeting of the two raters.

### 3.2 Results

The questions which elicited open-ended responses from participants (in addition to the 4-point Likert scale responses) are summarized in Table 2. Within the text, descriptive statistics (i.e. M=Mean, SD=Standard Deviation, and N=Frequency) from the quantitative study are included to show how our qualitative results fare with the quantitative analysis for each question.

#### 3.2.1 Perceived Value for Improving Course Content/Instruction

Questions Q1 to Q4 sought participants’ views on the value of the feedback provided by the LOCO-Analyst tool. The percentages of the observations based on the first coding scheme described in Section 3.1.5 are presented in Table 3. Please note that not every participant provided answers to all open-end parts of the questions, as these were optional.

Table 3. Percentages of the observations of the participants according to the codes assigned after the content analysis. The percentages were calculated with respect to the overall number (N=18) of the participants in the study; however, not all of them responded to all the questions and we were not able to assign an appropriate code to all the responses. This is the reason why the sums of percentages per columns are not equal to 100%.

<table>
<thead>
<tr>
<th>Category</th>
<th>Sub-category</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive Comments</td>
<td>Feedback</td>
<td>27.78%</td>
<td>27.78%</td>
<td>16.67%</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Intuitiveness</td>
<td>5.56%</td>
<td>-</td>
<td>5.56%</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>General comments</td>
<td>-</td>
<td>22.24%</td>
<td>16.67%</td>
<td>5.56%</td>
</tr>
<tr>
<td>Positive Comments</td>
<td>Feedback</td>
<td>16.67%</td>
<td>5.56%</td>
<td>-</td>
<td>5.56%</td>
</tr>
<tr>
<td>with Some Observations</td>
<td>Intuitiveness</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>General comments</td>
<td>-</td>
<td>5.56%</td>
<td>16.67%</td>
<td>16.67%</td>
</tr>
<tr>
<td>Negative Comments</td>
<td>Feedback</td>
<td>5.56%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Intuitiveness</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>General comments</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>22.24%</td>
</tr>
</tbody>
</table>
Questions Q1 and Q2 sought the participants’ views on the tool’s feedback on domain topics and contents. Overall 55.57% participants provided their observations in response to Q1 and 61.14% to Q2. The responses to these questions are predominantly grouped in the first two coding categories i.e. Positive comments and Positive comments with some observation. Of those who responded to the open-ended part of Q1 (M=3.71, SD=0.47, N=17), the majority overwhelmingly liked the feedback (50%) and thought that the tool’s feedback “provides solid insight into the knowledge of learners” encompassing many aspects of the students’ level of understanding including their interactions. Of these, 33.3% participants gave positive comments on the value of the tool’s feedback in developing teacher’s awareness of student’s level of understanding the studied domain topics. One respondent summed it nicely stating “The system gives all relevant information I need to get insight into the students understanding of domain topic”. Another participant echoed the positive views, saying “Yes, the feedback does provide important information on a student’s learning behavior. An instructor can use the information to help students who need help the most”. Other three participants gave positive comments but had some observations which questioned some design decisions or gave suggestions for enhancement of the feedback features. One participant strongly acknowledged the feedback but suggested more analysis, saying “I think that the system [LOCO-Analyst] offers a solid insight into the knowledge of learners. But, this could be complemented with some additional types of analyses such as those reflecting on students’ level of knowledge of the studied curriculum; how often did the student return back to already studied lessons or how often did the student ask for some help from the system.” One participant, who disagreed with the question, thought that the feedback on performance and interactions alone is insufficient to gauge student’s comprehension of domain content. And to measure the level of comprehension, feedback on the students’ behavior is needed too. This participant, however, agreed that feedback on student’s performance and interactions can provide some insight. One of the participants who gave the positive feedback commented the potency of the tool’s feedback in understanding the learner’s behavior: “Yes, the feedback does provide important information on a student’s learning behavior. An instructor can use the information to help students who need help the most.” Three of the participants only gave suggestions or comments which lacked an obvious connection to the context of the question. For instance, one participant noted: “You may consider divide chapter lessons into theoretical part and examples.”

Question Q2 (M=3.50, SD=0.70, N=18) asked users if the feedback enabled them to identify what should be changed in the learning content. We received responses from 11 participants. From these, 9 participants wrote positive comments, while the remaining two gave positive comments with some observations. Positive comments showed a unanimous agreement that feedback was helpful in identifying the difficult topics. These comments suggested that feedback enabled teachers and content authors to “identify students’ learning difficulties.” Participants were able to “see the difficulties students” were having “with specific topics.” They got enough information to determine if the “contents need to be changed” and could then put “more resources to enhance such topics.” One participant commended the feedback on difficultly levels by reflecting on previous experience as a teaching assistant “...I remember TAing [i.e. working as Teaching Assistant] a class in which the instructor would ask the students to write the vague points (muddy points as he had called them) in a wiki to review and then provide feedback for the students. The LOCO-system in a way helps with finding the muddy points without forcing students to do that.” Of the two participants who gave positive comments with some observations, one noted that frequent visit to the domain topic might indicate that student found the topic useful rather than difficult. Thus, the algorithm that computes difficulty level should differentiate between the two events. The second participant agreed that the feedback identified the topics that need to be improved but wanted the LOCO-Analyst to pinpoint what exactly was wrong “... I can get enough information if some content needs to be changed. That is, I can see if the content is not good enough. However, I do think that there is not enough information about what exactly is not alright with the content.” The participants who gave positive comments, however, noted that we can pinpoint the areas of difficulty by “viewing discussions of the students”. One participant, however, suggested that the quiz results and discussions in the forums should be tied to the concepts in the learning content to enable an automatic identification of the troublesome parts.

The focus of questions Q3 and Q4 was the feedback on students’ interactions. Overall 10 (55.57%) participants responded to Q3 (M=3.72, SD=0.46, N=18). From those who responded, the majority found the feedback relevant (eight out of 10). Seven of them gave positive comments, and the remaining three gave positive comments with some observations. None of the participants gave negative comments. Positive comments generally highlighted the usefulness of the feedback in understanding students’ behavioral and learning patterns, such as “[feedback] reveals how students acquire their knowledge through the online system”. Through the quiz feedback participants could see “which posts a student read, and in which activity he involved.” Besides commenting on the usefulness and relevancy of the interaction feedback, the participants were eager to give suggestion for further enhancement: “The Discussed Topics Info panel is very useful, but could be even better if it would show the most discussed lessons”; and “the purpose of the student interaction types (i.e. read, chat etc.) could be identified automatically”. The participants also acknowledged additional features of the tool, particularly the annotations and the intuitive interface “I found automatic topic annotation especially useful while analyzing student interaction. Besides that,
the interface for interaction browsing is very intuitive.” One participant found the information on number of posts in relation with quiz score valuable. Another participant observed that the chat messages were not relevant to the domain topic, and it hindered his or her ability to answer the question sufficiently.

Through question Q4 (M=3.33, SD=0.76, N=18), we wanted to know if the tool’s feedback helped the participants in identifying what needs to be done to improve students’ communication and collaboration. Only 9 (50%) participants answered this question (nine out of 18). The response rate was relatively low primarily because the question assumed higher expectations from the feedback. Many of the respondents interpreted the question as if the feedback should explicitly tell them how to improve the students’ communication and collaboration. One participant categorically agreed that the tool helped in identifying what needed to be done to improve interaction. Four participants (22.24%) gave positive comments with some observations, and other four (22.24%) disagreed by giving negative comments. One of the comments represented the overall impression quite comprehensively “Improvement of students’ collaboration depends on many factors that are independent from collected feedback.” Another participant put it this way “No program and no hard indicator can help determine the definite causes of bad interaction, which itself is a soft element”.

3.2.2 Perceived Value of GUI

Questions Q6 and Q7 enquired participants about the tool’s GUI. Both questions attracted the least responses of all the open-ended questions. Q6 (M=3.11, SD=0.58, N=18) asked if the GUI was intuitive enough. Only one participant responded noting that it was highly intuitive, but could be enhanced with graphics. While we wanted to provide extensive feedback about students’ performance, we did not want the tool’s interface to look overburdened with information. Through Q7 (M=1.94, SD=0.55, N=17 on 3-value Likert scale 1-yes, 2-no opinion, and 3-no) we sought participants’ responses on the overburdened aspect of the GUI. The number of responses to Q7 was slightly better as two participants responded to it. One agreed that the GUI was overburdened while the other disagreed. Massive number of participants, more precisely, 94.44% and 88.89% of them did not reply to Q6 and Q7 respectively. This high percentage of non-response indicated that the question was either sensitive or required more cognitive effort to answer it [Shoemaker et al. 2002]. A sensitive question usually inquires about some socially undesirable behaviors or the personal issues which the respondent may not wish to talk about. Using this concept of sensitivity, we do not categorize Q6 and Q7 as sensitive. Instead, we conclude that the participants found these questions more difficult.

The response to question Q8 (M=4, SD=0.84, N=18) was however 100% present as all the participants gave their comments on the general perception of the tool’s GUI. The majority of the suggestions (77.8%) were for improving either the tool’s data visualization or the GUI in general, as shown in Table 4. Of this, 44.4% participants emphasized the need for improved data visualization which is easy to understand. There was an impression that the display was overburdened with information: “…In this (i.e. current) solution there is plenty of information on a window.” One participant though did not say that the current information is overburdening but was apprehensive that without insightful visualizations the data analysis would become tiresome once the data grow. The rest of the participants explicitly asked for the improvements in the GUI.

They generally asked for a simpler interface design with more panels and windows “Use simpler interface, divide information into panels.”, or “Divide Content Package GUI into 3 independent windows, because a user may open two of three, or one of three windows”. One participant was wary of the non-technical users who might find the current interface difficult to use and thus wanted the information to be divided into panels. The participants also reported several GUI issues. One participant complained that with the current display settings on his/her my laptop, some of the text was truncated and there was no way to adjust it. Another participant noted that three icons had similar colors and wanted more differentiating color coding scheme.

Table 4. Percentages of suggestions for improving GUI. The percentages were calculated with respect to the overall number (N=18) of the participants in the study; however, not all of them responded to all the questions and we were not able to assign an appropriate code to all the responses. This is the reason why the sums of percentages per columns are not equal to 100%.

<table>
<thead>
<tr>
<th>Category</th>
<th>Sub-category</th>
<th>Q8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suggestions for improving</td>
<td>Visualization/GUI</td>
<td>77.8%</td>
</tr>
<tr>
<td></td>
<td>Annotations</td>
<td>5.66%</td>
</tr>
<tr>
<td></td>
<td>Other Features</td>
<td>11.11%</td>
</tr>
<tr>
<td>No suggestions but liked</td>
<td>Data Visualization</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Interface Design</td>
<td>5.56%</td>
</tr>
</tbody>
</table>
3.2.3 General Perception of the Tool

When asked to compare LOCO-Analyst to other relevant tools in question Q10, four of those with previous experience described advantages, while one participant mentioned disadvantages. Advantages highlighted the qualitative value and comprehensiveness of the provided feedback: “analysis results are displayed without too many unnecessary details”. LOCO-Analyst’s provision of qualitative difficulty estimation was considered as another important advantage over similar systems. One participant observed that “LOCO-analyst was strongly focused on raw data analysis”. The feedback provided in the tool was mostly presented in a tabular form. This presentation of feedback was termed as simple by one participant asking for additional means of visual data representation: “Very simple style, use some colour graphics…” Another comment was about the feedback presentation on the RHS of the tool’s window (Figure 1, RHS), which was deemed inconsistent: “…the RHS keeps changing constantly, try to keep it constant…sometimes statistical overview is scrolling up and down and sometimes all are visible. Similarly, all the items of difficult lessons are all visible sometime and sometime you have to click on Learn More to get that same info. Try to keep the structure same throughout. If you need more same, open the feedback page in a new window.” We used the RHS of the window to display different kinds of feedbacks. Some feedbacks, for instance, were students specific while others were course specific. The feedback presentation format was consistent for each feedback type. There was, however, some presentational variation across the feedback types. This variation was due to the inherent characteristics of the feedback, such as using the scrolling feature to handle large data.

3.3 A Summary of the Results and Suggestions

We grouped the participants’ suggestions in the preceding section into three broad categories: (S1) Data Visualization - suggestions for enhancing the way feedback is presented to the users; (S2) GUI - suggestions for enhancing the user interface; and (S3) Feedback - suggestions related to the feedback or functionalities provided by the tool. Using these three categories we summarized the notable suggestions from all the responses in Table 5.

Table 5. A summary of suggestions participants gave in the 2006 survey for enhancing LOCO-Analyst’s features.

<table>
<thead>
<tr>
<th>No.</th>
<th>Suggestion</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Improve the data visualization.</td>
</tr>
<tr>
<td>S1.1</td>
<td>Use graphics [for feedback presentation].</td>
</tr>
<tr>
<td>S1.2</td>
<td>Allow instructors to get insights by using different graphical chart, bar, XY diagrams etc.</td>
</tr>
<tr>
<td>S1.3</td>
<td>Improve the visualization of analysis results [i.e. feedback]</td>
</tr>
<tr>
<td>S1.4</td>
<td>Use more colors for representing data.</td>
</tr>
<tr>
<td>S2</td>
<td>Improve the Graphical User Interface.</td>
</tr>
<tr>
<td>S2.1</td>
<td>Keep the structure on the right hand side (RHS) of the tool window same, throughout. [The RHS part of the tool’s user interface is used to display the feedback.]</td>
</tr>
<tr>
<td>S2.2</td>
<td>Organize the contents in a way that the interface does not look overburdened. Try using more panels, windows, drop-down list, if needed.</td>
</tr>
<tr>
<td>S2.3</td>
<td>Use color codes and tool tips which pop up on hovers (such as on the hyperlinks) to give further idea of the feature or functionality available on clicking.</td>
</tr>
<tr>
<td>S3</td>
<td>Further enhance the feedback.</td>
</tr>
</tbody>
</table>

4. Improvements in the Second Version of LOCO-Analyst

Improvements in the second version of LOCO-Analyst were largely made in the light of suggestions received from the 2006 study participants, as summarized in Table 4. The great majority of the participants suggested improvements to the way the data is presented and communicated back to the educators. The participants wanted the use of graphical data representation techniques (i.e. data visualization) which are capable of boosting understanding and facilitating insights. Card et al. define visualization as “the use of computer-supported, interactive, visual representations of data to amplify cognition,” [Card et al., 1999] where cognition is the acquisition or use of knowledge. The use of multiple external representations (such as data visualization or pictorials) to boost conceptual and procedural knowledge has been investigated in the field of educational psychology. The study of Zapalska and Dabb shows that acquisition and retention of information depends largely on the person’s preferred learning modality [Zapalska & Dabb, 2002]. The study of Mayer and Massa also mentions that learners
with ‘Visualizer’ cognitive style use visual modes of thinking, while ‘Verbalizer’ learners use verbal modes of thinking [Mayer & Massa, 2003].

There were also some suggestions for improving the existing graphical user interface and adding new kinds of feedbacks. In general, all the changes could be split into two categories: (a) changes done with the aim to improve presentation of the existing kinds of feedback offered by the tool; and (b) changes done to introduce new kinds of functionality. The changes in the category (a) include: visual representation of the data (suggestions set S1); refining of Graphical User Interface to better organize data, presented in individual panels and dialog boxes, to address the information overload issue that many participants reported in the 2006 study (suggestion set S2).

Accordingly, we developed a new version of the tool by enhancing the presentation features, user-interface, and by adding new kind of feedback. In this report we have analyzed the impacts of presentation and GUI features only. The purpose of this analysis is to understand how the use of additional (visual) representation of data and enhancement of GUI impact (increases or decreases) the overall value of the tool and tool’s feedback.

The new version of the tool maintained the vertical divisions of the user interface window to display the Reload editor (RHS) and the LOCO-Analyst functionalities (LHS) as in the previous version. We, however, allocated the lower left section of the window (Fig. 2A) for displaying annotation feedback. Previously this section was used by the Reload Editor to display the attributes of the course-tree nodes. These attributes displayed the values which were more of technical nature and were not meant for the broader audience of the tool. This reallocation of the space allowed for a better organization of the feedback relevant contents on the screen.

![Figure 2](image-url)

**Figure 2.** A screenshot of the revised version of LOCO-Analyst showing Reload Editor and other feedback panels which typically display lesson feedback⁹.

The feedback about individual students (RHS) in the new version of the tool was divided into four tab panels: Forums, Chats, Learning, and Annotation. Forums and Chats panels show student's online interactions with other students during the course of learning. Learning panel presents information on student's interaction with the learning contents. Finally, the

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⁹ Please, see details given in footnote 8
Annotations panel provides feedback associated with the annotations (notes, comments, tags) created or used by a student during the learning process. We discuss the parts of the RHS (S, E, D) in Sect. 6.

![Student Interactions]

Figure 3. A screenshot of LOCO-Analyst showing a student’s interactions in a discussion forum.

The major improvement in the new version was the way we present and communicate feedback to the educators (i.e., data visualization). For example, we can see this improvement in Figure 3. This figure shows all the interactions of a selected student in Discussion Forums. The feedback is represented in both tabular and visual forms. Recall that in the previous version we used the tabular form only. We now use bar charts to represent the number of posts in each instance of a discussion forum. The color codes are used to differentiate between the read posts (red bar), submitted posts (blue bar), and initiated threads (green bar). These visual cues in Figure 3 assist a reader to notice at a glance that this particular student submitted only two posts and initiated none.

Similarly, Figure 4 gives a visual overview of statistical information about student’s interaction with the content of a learning module (JavaScript Concepts in the given example). The figure shows three statistics, namely Total Time Spent, Average Time Spent, and Page Revisits, presented in two different charts for each lesson of the module. The table below the charts shows the same statistics, but for the entire module. If the ‘Show statistical data’ checkbox is checked, average values for the entire module (i.e., Average Time Spent and Average Revisits) are presented on the charts, so that educators can easily spot the lessons that deviate from the module’s average values.


We conducted an evaluative study of the improved version of LOCO-Analyst in 2009 to reassess the perceived usefulness of the enhanced features of the tool.

5.1 Study Design

5.1.1 Design

As in 2006, we obtained user observations through a questionnaire. In the 2009 study, however, participants saw the video clips of the tool’s new features (functionalities and visualizations) before recording their observations. They also had access to the software as in the first study. The process and consideration for selection of participants remained the same. We used the same quantitative and qualitative (coding and content analysis) methods for data analysis as we did for the 2006 study.
5.1.2 Participants
In October 2009, we recruited 22 participants from the University of Belgrade, Simon Fraser University, Athabasca University, and a private Canada-based company developing and offering technology and content for professional training. Seven of the participants were the same as in the 2006 study. The average experience of the participants in their role was 6.45 years (SD = 5.58, N=22). There were six Instructors with average 10.67 years of experience (SD = 7.09, N=6); eight Teaching assistants with average 3 years of experience (SD = 1.06, N=8); and eight Research students/practitioners who had on average 6.75 years of experience (SD=5.23, N=8) in the area of e-learning.

Figure 4. A visualization giving a statistical overview of a student’s interactions with JavaScript Concepts learning module.

5.1.3 Materials
The major material change in 2009 study was the use of video clips in addition to the improved version of LOCO-Analyst introduced in Section 4. To demonstrate implemented features of the LOCO-Analyst tool, we created video clips describing each individual feature in detail. These clips also served as guidance on how to use the implemented functionality and made sure that its interpretation is clearly carried to the participants of the study. The participants were asked to use the tool and try its functionalities. They were further asked to watch the relevant video(s) before responding to specific part of the questionnaire. We uploaded demo videos in a high-resolution onto Dropbox. We also uploaded stream versions of the videos on Athabasca University’s vShare server supporting video streaming. The quality of these videos was not as good as those hosted on Dropbox, but we wanted to make sure that participants with preference of streamed videos are adequately supported. Both versions of these videos are available on the website of LOCO-Analyst.

The instrument consisted of 21 items – of these only 11 items had the associated qualitative parts. The first three items asked participants to specify their role and experience. Six of the items were related to tool’s feedback features and functionality; and four items focused on the GUI and intuitiveness related features. Most of the feedback and GUI related questions had two parts: (1) a five level Likert scale (1-Strongly Disagree to 5-Strongly Agree); and (2) open ended part allowing participants to further reflect on the asked questions in the free text form. As before, our study focus in this report is the open-ended i.e. qualitative part of the questions.

10 http://www.jelenajovanovic.net/LOCO-Analyst/videos.html
5.1.4 Procedures

The study procedure was the same as in the 2006 (Section 3.1.4), except instead of the written guidelines, used in the 2006 study, we created video clips explaining the functionalities of the tool. The demo videos were uploaded on one of the on-line repositories\(^{11}\) and we also uploaded stream version of the demos on the Athabasca University server. It was explicitly mentioned to the participants that all the videos referenced from the questionnaire could be either downloaded or directly streamed from the given links. All the other parts of the procedures defined in Section 3.1.4 applied here as well.

5.1.5 Content Analysis

We analyzed the qualitative data of 2009 study in the same manner we did for the 2006 study. We used the same coding scheme as used before and described in Section 4.1.4. Two raters applied the coding scheme independently to rate the answers. The agreement between raters was computed using Cohen’s Kappa. The result of 0.88 for Cohen’s kappa can be interpreted as a *nearly perfect agreement* according to the conventional interpretation of kappa [Landis & Koch, 1977].

5.2 Results

In Table 5, we summarize the percentages of responses for each of 11 qualitative items asked in the 2009 study. The following subsections discuss the three many categories of the questions asked.

5.2.1 Perceived Value for Improving the Course Content/Instruction

Through question Q1 (Table 2), we wanted to know to what extent the tool provides insights into students’ interactions with the learning content. Overall, 20 participants (90.90%) responded to the open-ended part of question Q1 (M=4.45, SD=0.67, N=22\(^{12}\)). From those who responded, 72.72% highly appreciated the improved features of feedback provisioning in general (17 out of 20). Of this, 59.09% participants gave overwhelmingly *positive comments* and 13.64% gave *positive comments with some observations*. Majority of the participants (54.55%) explicitly appreciated the feedback on students’ interactions “The tool provides a lot of useful statistical information about the students’ interaction”. Some participants attributed the effectiveness of the feedback to the way it was presented (i.e. to the intuitiveness) “Graphical presentation of information makes it very easy to understand it.” Many participants noted that the interaction feedback (statistics) also enabled them to understand student’s experience with the contents (i.e. difficulty level): “The tool slices the data very well allowing (us) understand particular aspects of students’ understanding and the lack thereof. It provides quick insight into most difficult content.” The overall response affirms that tool provides insightful interaction feedback.

Table 6. The percentages of interaction-feedback observations of the participants according to the codes assigned after the content analysis. The percentages with respect to the overall number (N=22) of the participants in the study among; however, not all of them responded to all the questions and we were not able to assign an appropriate code to all the responses. This is the reason why the sums of percentages per columns are not equal to 100%.

<table>
<thead>
<tr>
<th>Category</th>
<th>Sub-category</th>
<th>Perceived usefulness of the tool for improving the course content/instruction</th>
<th>Perceived value of the tool’s GUI</th>
<th>General perception of the tool</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Q1</td>
<td>Q2</td>
<td>Q3</td>
</tr>
<tr>
<td>Positive Comments</td>
<td>Feedback</td>
<td>36.36%</td>
<td>31.82%</td>
<td>13.64%</td>
</tr>
<tr>
<td></td>
<td>Intuitiveness</td>
<td>9.09%</td>
<td>9.09%</td>
<td>9.09%</td>
</tr>
<tr>
<td></td>
<td>General comments</td>
<td>13.64%</td>
<td>27.27%</td>
<td>22.73%</td>
</tr>
<tr>
<td>Positive Comments with</td>
<td>Feedback</td>
<td>13.64%</td>
<td>4.55%</td>
<td>-</td>
</tr>
<tr>
<td>some observations</td>
<td>Intuitiveness</td>
<td>-</td>
<td>4.55%</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>General comments</td>
<td>-</td>
<td>-</td>
<td>9.09%</td>
</tr>
<tr>
<td>Negative Comments</td>
<td>Feedback</td>
<td>-</td>
<td>4.55%</td>
<td>4.55%</td>
</tr>
<tr>
<td></td>
<td>Intuitiveness</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>General comments</td>
<td>4.55%</td>
<td>-</td>
<td>4.55%</td>
</tr>
</tbody>
</table>

\(^{11}\) Dropbox - https://www.dropbox.com/

\(^{12}\) Quantitative results in 2009 study are based on the participants’ responses to the 5-value Likert scale. The number of responses to the Likert scale differs from the number of responses to the open ended questions, as qualitative questions were optional (i.e., not all the participants responded to them). Details of the qualitative evaluation can be found in [Asadi et al, 2011].
In the 2006 study, some participants reported that they were overburden with information, so through question Q7 we found that the teacher should be able to turn some frames on and off, according to his/her needs. One worry was that for the instructor, “mislabeled or missing, and some areas of the screen need more labeling.” These complaints are reflected in the statement, “tips may be required to explain certain interactions, like the drag and drop.” A couple of participants noted that some of the students’ interaction information is passive, but how is this finding useful?”

LOCO-analyst is not capable of giving suggestion on how to improve things. Question Q4 aimed at “provoking” the participants to give us their views on the tool’s capacity to help them decide how to improve online interactions. Overall, 77.29% (i.e., 17) participants responded the open-ended part of Q4 (M=4.41, SD=0.80, N=22). As anticipated, a very large majority of participants (12 out of 14) agreed that the tool provided relevant interaction information, and that the teacher can easily track how active a student has been. This tool gives “quite a bit of statistics” and provides “interesting information to the teacher.” Many have also said that the social graphs clearly show the student’s participation and are effective. However, the purpose of this tool was questioned by one participant “you can determine that these students are passive, but how is this finding useful?”.

In question Q3, we wanted to assess the relevancy of the tool’s feedback on students’ (mutual) interactions within a learning environment. Fourteen participants (63.63%) responded the open-ended part of Q3 (M=4.41, SD=0.80, N=22). From those who responded, a large majority of participants (12 out of 14) agreed that the tool provided relevant interaction information, and that the teacher can easily track how active a student has been. This tool gives “quite a bit of statistics” and provides “interesting information to the teacher.” Many have also said that the social graphs clearly show the student’s participation and are effective. However, the purpose of this tool was questioned by one participant “you can determine that these students are passive, but how is this finding useful?”.

LOCO-analyst is not capable of giving suggestion on how to improve things. Question Q4 aimed at “provoking” the participants to give us their views on the tool’s capacity to help them decide how to improve online interactions. Overall, 77.29% (i.e., 17) participants responded the open-ended part of Q4 (M=3.54, SD=1.01, N=22). As anticipated, a very large majority of participants (12 out of 14) agreed that the tool does not provide enough information on how to improve students’ online interactions. It appears that the wording of Q4, in particular the use of “how”, created more confusion than eliciting any notable suggestions from the participants. Just having statistical data is not enough to “know how to improve the student’s online interactions.” This tool does “show [a] lot of information but it does not explicitly show how I can improve students’ interaction.” Also, the quality of the interactions cannot be measured so the tool is not completely accurate. Nevertheless, like in Q1 and Q2, there is a consistent appreciation of the value of interaction feedback provided in LOCAnalyst “this tool gives me excellent overview of the interactions”.

Question Q5 sought the participants’ perception of the tool’s ability to identify difficult domain topics (i.e. not just individual lessons). Overall, 15 participants (68.18%) responded the open-ended part of Q5 (M=4.57, SD=0.68, N=21). The vast majority of participants (14 out of 15) believed that this tool helps them to identify domain topics where students are encountering difficulties. Of these, 12 participants gave overwhelmingly positive comments and two gave positive comments with some observations. However, some participants criticized the type of information LOCO-Analyst gives. According to one participant, “it would be more realistic if the algorithm calculates the degree of the topic’s difficulty rather than deduces if the topic is difficult or not.” There was also doubt on ease-of-use for non-computer science teachers, and that there might be too much data being presented, but they were quite happy with the explained feedback itself. One participant saw “a lot of numerical data and don’t know what the data means.” Another felt “that analysis of quiz data vs. time spent on a page” was more important. Despite this, most of the participants felt that the interface was clear and the information relevant.

5.2.2 Perceived Value of GUI

The participants repeatedly praised the improved GUI features of LOCO-Analyst in their responses to the previously discussed questions (Q1-Q5). In question Q6 (M=4.5, SD=0.80, N=22), we wanted the participants to explicitly comment on the intuitiveness of the GUI-related features. We got response from 17 participants (77.28%) to the open-ended part of Q6. Most of the participants felt that the GUI was intuitive and well organized (15 out of 17). Some participants have noted that tips may be required to explain certain interactions, like the drag and drop. A couple of participants noted that some of the information needs to be explained better and simplified for the novice. One participant pointed out that many options are mislabeled or missing, and some areas of the screen need more labeling. These complaints are reflected in the statement, “the statistical data is still too complicated to the teacher to find the useful and straightforward information out.” However, most of the participants agreed that the GUI was easy to use.

In the 2006 study, some participants reported that they were overburden with information, so through question Q7 we wanted to check if that was still the case. Overall, 13 participants (59.09%) responded to the open-ended part of Q7 (M=2.5, SD=1.34, N=22). Generally, the participants found the GUI not at all overburdened (45.45%). A few participants suggest that the teacher should be able to turn some frames on and off, according to his/her needs. One worry was that for the instructor, “who most likely doesn’t have much background in knowledge engineering, the amount of information and
available functionalities might be overwhelming.” However, for “someone with enough prior experience or knowledge the amount of information on the GUI is not a problem”.

Twelve participants responded to the open-ended part of question Q8 (M=3.25, SD=0.55, N=22) and all gave Positive Comments on GUI while two of them gave Positive Comments with Some Observations. The general opinion is that GUI is easy to use and get acquainted with. Participants appreciated that it was similar to other tools they were used to. They also liked some parts of the GUI, such as the tree-like representation of the lessons and resizable frames. This tree-like structure was inherited from the Reload tool we discussed earlier. However, there were some remarks on the look of the GUI, as well. Some participants did not like the color scheme. They said it looked outdated or non-commercial-like. All in all, almost all participants felt the GUI was simple, well organized, and presented a lot of useful data.

5.2.3 General Perception of the Tool

Through the question Q9 (M=4.04, SD=0.90, N=22), we wanted to learn about the participants’ global impression if they would be willing to use the tool in their teaching practices. Out of 22, 11 participants responded to the open-ended part of this question. Many of the participants felt that LOCO-Analyst can be used for any science or technology related courses, or any course that has a modular structure. Another train of thought was “that courses that are based on social activities could mostly benefit from this tool,” with one participant further explaining this as “any course that includes a small group of students. Otherwise, their collaboration and interaction is questionable.”

Through Q10 (M=3.33, SD=0.86, N=21), we aimed at a comparative analysis of our tool with other tools offering similar features. Many participants had no previous experience with similar tools and did not reply to the question. Of the participants who answered the open-ended part of this question, most of them (five out of six) complimented LOCO-Analyst as comprehensive and detailed, as well as user friendly. The tool seems to be well integrated, as it includes “both interaction statistics, and ontology + tags enhanced learning topic statistics,” making it helpful. Participants compared it to Moodle, which “lacks support for capturing and visualizing students’ social activities in a form of the social graphs and forum posts distribution charts, which I find very useful in the LOCO-Analyst system.” On the other hand, one participant claimed that LOCO-Analyst is too complicated for a non-computer science teacher. Another complaint is that teachers can not view results for particular questions in the quizzes.

In question Q11 (M=4.50, SD=0.60, N=22), we sought some comparisons of the intuitiveness of LOCO-Analyst compared to other tools. We got response from 15 participants to the open-ended part of the question. Of those 15, only two had prior experience with other similar tools. Remaining 13 participants said they could not reply. Of the two participants who answered, neither found LOCO-Analyst more intuitive than other tools capable of feedback. Both agreed that the other tools they tried presented less information. One participant also wrote that the other tools he used were simpler and intuitive. The participant did not mention name of any of the tools used previously.

6. Discussion

In this section, we discuss the results of our content analysis reported in the previous section with the primary aim to further cover the effects of the introduced visual interventions in the LOCO-Analyst tool. As reported in Section 3, the results of our 2006 study of LOCO-Analyst showed that the participants wanted us to supplement the textual (tabular) feedback with the visual representations. In the new version of LOCO-Analyst, we made major enhancements by adding the data visualization techniques for presenting feedback types, as described in Section 4. In Table 7, we give a comparative summary of the results of the three major categories used for coding the data of the both studies.

In the 2009 study, we obviously obtained a substantially higher number of open-ended responses compared to the 2006 study. Having a follow-up discussions with the returning participants (seven of them), the participant indicated that with the new visualizations and interfaces, they had been able to better grasp the value of the tool, situate the type of feedback to the real situations, and consequently, they had more ideas to provide constructive responses in the 2009 study.

Concerning the first group of questions which addressed the perceived usefulness of different feedback types, a more than an apparent increase in the number of responses was recorded in the 2009 study. Overall, responses to this group of questions were dominantly positive and much higher than in the 2006 study. This very high percentage of positive views on the tool’s feedback reflected that the participants found the feedback representations informative. While some negative observations were obtained in the 2009 study, as well, there was not a single negative observation about the data visualizations used to represent feedback in the new version of the tool. This finding supported our expectations that visual representation of feedback would better enable educators to quickly and easily get an overall insight into a certain aspect of the learning process. Some participants explicitly attributed the effectiveness of the feedback to the way it was represented in the new version. The data visualization in LOCO-Analyst is reported as the distinguishing feature which is lacking in the popular
contemporary systems: “Moodle lacks support for capturing and visualizing students’ social activities in a form of the social graphs and forum posts distribution charts, which I find very useful in the LOCO-Analyst system” (2009, participant #11).

Table 7. Summative analysis of all the responses based on the three groups of questions, as indicated in Table 2. The table reports: NR – number of responses; OF – frequency of responses with respect to the overall number of the participants (18 in 2006 and 22 in 2009); and RR – frequency of responses relative to the number of the received responses.

<table>
<thead>
<tr>
<th>Question group</th>
<th>Response category</th>
<th>2009</th>
<th>2006</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>NR</td>
<td>OF</td>
</tr>
<tr>
<td>Perceived usefulness of the tool’s feedback</td>
<td>Positive</td>
<td>50</td>
<td>56.82%</td>
</tr>
<tr>
<td></td>
<td>Positive w/ concern</td>
<td>9</td>
<td>10.23%</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>5</td>
<td>5.68%</td>
</tr>
<tr>
<td>Perceived value of the tool’s GUI</td>
<td>Positive</td>
<td>26</td>
<td>39.39%</td>
</tr>
<tr>
<td></td>
<td>Positive w/ concern</td>
<td>5</td>
<td>7.58%</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>12</td>
<td>16.67%</td>
</tr>
<tr>
<td>General perceived value of the tool</td>
<td>Positive</td>
<td>14</td>
<td>21.21%</td>
</tr>
<tr>
<td></td>
<td>Positive w/ concern</td>
<td>3</td>
<td>4.55%</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>3</td>
<td>4.55%</td>
</tr>
</tbody>
</table>

1Includes questions Q1, Q2, and Q3. Question Q4 was also not included in the table, as it did cover a feedback type (i.e., what) but guidance (i.e., how). Question Q5 was not asked in the 2006 study (c.f. Table 2). That is, a total of 18*3=54 (2006) and 22*4=88 (2009) of possible answers.

2Includes questions Q6, Q7, and Q8. For results (NR, OF, RF) from the 2006 study, we did not consider responses to question Q8 in this table, given that they are coded with a different coding scheme (c.f. Table 4). That is, total of 18*2=36 (2006) and 22*3=66 (2009) of possible answers.

3Includes questions Q9, Q10, and Q11. Questions Q9 and Q11 were not asked in the 2006 study (c.f. Table 2). That is, total of 18 (2006) and 22*3=66 (2009) of possible answers.

Analyzing the negative responses, we refer to the two participants who questioned the usefulness of the statistics. For instance, “you can determine that these students are passive, but how is this finding useful?” The statistics in isolation represent only one aspect of any real-world situation. To make more meaningful interpretations, we often need to look at the two or more statistics together. For instance, interaction statistics report on the time spent and the activities performed by a student – which is only one dimension of the feedback on the student’s learning process. Combined with other statistics, such as scores on tests, these statistics can provide educators with broader picture of the student’s overall performance. Poor interaction with high grades reflect probably reclusive but successful student, whereas poor interaction with low grades is a sign for the educator to intervene.

There were also a few observations about the feedback on lessons difficulty (Q4 and Q5). One participant wanted to see the degree of lesson difficulty as well as how the difficulty was computed. In the 2006 version of the tool, we provided users with single information whether a lesson was considered difficult or not. In the 2009 version, however, we provided both the summative measurements of the difficulty level of a lesson (Figure 2. S and E) and a relative degree of difficulty of a lesson compared to other lessons in the module. In particular, there is a "Learn More" button (Figure 2, D), which after being pressed, shows more information on the lesson’s difficulty in a new window (Figure 5). The difficulty of a lesson is estimated by taking into account some basic usage metrics (average revisits, average reading time, scores etc.) of all the lessons in the same module. It is very similar to how grades are defined for students in most North American schools and universities. However, students can find a lesson difficult for various reasons.

Another participant wanted the tool to show the reasons why a lesson was difficult. The current version of the tool generates its feedback by using the interaction and quiz data. Students, however, might share their perceptions of the lesson difficulty via chat and discussion forums, or through email communication. The tool allows educators to track the discussions (chats and forums) to better understand the difficulties that their students might have. However, it does not do text analysis of the exchanged messages to automatically identify potential signs of students’ dissatisfaction with the learning content. It does also not explicitly ask users to rate the lessons on a difficulty scale or to specify the reasons. From these observations it is evident that the educators would like to see even more information on the lesson’s difficulty. This is also a connection with
the recent research trends in learning analytics, where embedding of formative evaluations is proposed as a method to collect more data about difficulties students are experiencing [Richards & DeVries, 2011]. It is our plan to investigate if the combination of this formative evaluation embedding can improve the value of this feedback type.

Figure 5. “Learn More” window for lesson’s difficulty.

Another observation pointed out that in some instances chat messages were not relevant to the domain topic. We used an automatic semantic annotation and indexing tool KIM (Knowledge and Information Management) [Popov et al., 2003] for relating students’ posts with the domain topics. Thus, using an imperfect automatic annotation tool might result in such observations of educators. Nevertheless, we understand such a discrepancy, no matter how small it is, might lead to reduced trust. There is a need to further improve the accuracy of automatic semantic annotation processes and we plan to investigate the use of other contemporary semantic annotation tools [Nešić et al., 2010].

We further analyzed mutual relations among the perceived values of the evaluated aspects of the feedback types in LOCO-Analyst. We found, by using Cramer’s V, a standard symmetric coefficient of relationship between categorical variables, that there is a statistically significant relationship (V = .710, p = .011) between the perceived utility of the tool to enable educators to get an insight into the students interactions with the content (Q1) and the perceived utility of the tool to help identify the domain topics the students were having difficulties with (Q5). This further emphasizes the need for accurate semantic annotators, as an important enabler for analysis of students’ interactions with the learning content and domain topics they experience difficulties with.

In Table 7, we did not include results of responses to question Q4, as that question did not actually asked about feedback utility, but it rather asked about the utility of the tool to provide guidance how to improve students’ interactions. We anticipated a low positive response to this question due to the already stated fact that LOCO-Analyst has not been designed to provide suggestion on how to improve things, but it was rather designed to provide insights into what could be improved. By including question Q4 into our studies, we wanted to “provok” the participants to give us their views on what could be done in our future work when the guidance features are to be developed.

Concerning the second group of questions, which asked the GUI related questions, we can see in Table 7 that there was a substantial increase in the overall number of responses to the GUI-related questions. This increase (from 88% to 23%) is an indication that the GUI features were more obvious in the new version of the tool, and served as a better stimulus for participants to constructively comment on the tool’s GUI. This higher participation affected the number of both negative and positive comments, as already reported in Section 5.2. We believe that those comments are particularly valuable for further improvement of similar types of analytics tools.
Regarding the intuitiveness of the tool’s GUI, we found that there is a significant relationship between the perceived utility of the tool to help identify what needs to be improved in the learning content (Q2) and the perceived intuitiveness of the tool (Cramer’s $V = .598$, $p = .03$). In the individual responses we found that the participants considered LOCO-Analyst more intuitive compared to other tools (e.g., “I think both [Moodle and LOCO-Analyst] are intuitive but Moodle presents far less information.”) as well as more informative, without sacrificing its intuitiveness (e.g., “What I can compare it with is feedback tools integrated within existing LMS systems. Comparing to those, I found that LOCO-Analyst provides much more comprehensive and detailed information. However, this information is very intuitive and presented at user-friendly way.”). In fact, comparing the two versions of the tool, we can see that the 2009 version contains much more information. However, our results showed that the improved version of the tool, in spite of the amount of information, was not found to be overburden with information. While the increase of responses in all the three categories was evident, our analysis of the data of two questions related to GUI (Q6-7) with Pearson’s $\chi^2$ test showed that there was no significant difference between the two groups (2006 and 2009). This corroborates the results of our analysis of the quantitative data for the Q6 and Q7 variables regarding the intuitiveness and information overload of the tool [Asadi et al, 2011]. These findings provide some evidence that an extensive use of visualizations does not necessarily improve the intuitiveness of a learning analytics tool (which we also anticipated). However, the visualizations can be an effective mean to deal with larger amounts of data in order not to increase the cognitive load of educators. As data of question Q8 were differently coded in different studies, it was not meaningful to compare the two groups. Yet, our analysis of quantitative data for the same question (i.e., Likert-scale) showed that there was a statistically significant preference of the study participants for the GUI of the tool used in the 2009 study [Asadi et al, 2011]. This provided an additional important indication that educators prefer the use of visualizations in the learning analytics tasks.

Concerning the third group of questions about the general impressions of the tool, we were able only to compare the results of question Q10, which asked the participants of the both studies to compare the tool with other related ones. As the area of learning analytics is rather immature, the participants were not aware of many tools, and thus very few provided some observations. We expect that with the progress in the area and availability of more tools, we will be able to more accurately compare similar learning analytics tools to each other.

Given the dominant positive response of the participants to question Q9 in the 2009 study, which asked if the participants would like to use this tool in their teaching practice, we wanted to check if the role (i.e., instructor, teaching assistant, and research students/practitioners) of the participants had any relationship with the responses to this question. Our analysis with Pearson’s $\chi^2$ test revealed that this relation is significant ($\chi^2 (2) = 11.00, p = .004$). Looking at the distribution of the data per different roles, we can see that all the teaching assistants (four) and instructors (five) who responded to this question expressed fully positive preference to use the tool, while a smaller number (two) of research students/practitioners expressed a wish to use the tool in their practice, but they had some concerns on that matter. This finding complements the result of our (t-test) analysis of the quantitative data of the 2009 study [Asadi et al, 2011], which showed that instructors significantly valued the feedback provisioning mechanisms that the other two roles of the participants involved in our evaluation. This outcome also provides additional evidence for our earlier interpretation, given in [Asadi et al, 2011], that details and sophistication of the feedback types used in the new version of LOCO-Analyst is primarily appreciated by the instructors who comprehend the entire learning process in much more details than other roles.

### 7. Threats to Validity

In this section, we discuss the two main types of threats to validity commonly analyzed in empirical research – internal and external validity. With respect to internal validity of our experiment, we are interested in checking if some confounding factors significantly influence the analysis of the collected data [Chin, 2001]. In our studies, the two main confounding factors are difference in experience with using similar tools and motivation. In both of our studies very few participants were familiar with any other similar tool expect some learning analytics functionality offered by mainstream LMCSs. As shown in this paper and also in our analysis of the quantitative data [Asadi et al, 2010], we could not find any significant differences between the participants who were and those who were not familiar with this kind of tools. Motivation as a confounding factor is also eliminated as the responses to open-ended questions analyzed in this paper were optional. Thus, all those who responded, already demonstrated a high motivation level.

It is also important to note that we have no information about the extent to which the participants used the tool before completing their evaluations, as the evaluation was not conducted in a controlled laboratory setting. As it can be seen from the thorough observations of the participants, reported in this paper, in which we have found no inaccurate interpretations of any of the tool’s functionality, we can conclude that the participants very carefully studied and tried the tool before completing our questionnaires.
With respect to external validity, we are concerned to what extent the results of our study can be generalized. More specifically, regarding the evaluations presented in this paper, we are interested to know if and to what extent we can generalize our findings to a class of similar systems in the learning analytics domain. According to [Chin, 2001], the two main confounding factors to be considered are population and ecology.

In the case of our evaluations, the population consisted of university instructors, teaching assistants and research students/practitioners as representatives of the target users of the LOCO-Analyst tool. While it can be questioned if teaching assistants and research students are appropriate participants, a counter argument is that they have already participated in online education and gained some practical insights in working under such circumstances. According to our findings (Sect. 6), there were no significant differences in the observations of the three groups. We only found that research students/practitioners were more reserved in their willingness to use the tool in their immediate practice (c.f. the analysis of question Q9), which can likely be attributed to their lower-level involvement in the course instruction, and higher familiarity with instructional design, content authoring, and data analysis. This is also consistent with our findings of the Likert-scale data analyzed in [Asadi et al, 2011] in which we observed that instructors typically expressed the highest level of perceived value of the tool. Of course, a replicated experiment should further investigate the validity of this analysis.

We should also indicate that in both our studies, we had the participants with Computer Science or Information Systems background: 16 out of 18 in 2006, and 21 out of 22 in 2009. This certainly calls for a replicated experiment with different populations of educators to validate the general applicability of our results. Our previous empirical experience in evaluating Semantic Web-based learning tools indicates that educators with computer science background are significantly more critical than those with non-computer science background [Hatala et al., 2009].

Finally, we should also restate that our empirical findings are only validated in the context of university education, as that was our original target when started working on LOCO-Analyst [Jovanovic et al., 2007b]. However, we had two participants from industry involved in workplace learning; their responses did not diverge from the rest of the participants. This gives us some encouraging evidence that the findings of our studies could be transferred to workplace learning, but another replicated study should confirm this claim.

8. Related Work

As already stated in the introduction, the community around the newly-established International Conference on Learning Analytics has emerged as a response to the rapidly growing needs to improve the present state of learning analytics in order to allow educators to make better informed decisions on their instructional strategies. This goal is to be accomplished through a holistic approach that combines principles of different computing areas (data and text mining, visual analytics and data visualization) with those of social sciences, pedagogy and psychology. Traditionally, log data analysis and visualization applied for the analysis of students’ behavior and activities have been one of the main research topics in the research communities around venues such as AIED (Artificial Intelligence in Education)13 and EDM (Educational Data Mining)14. The research outcomes of these communities are significant, especially in the domain of generating student-centered feedback by leveraging user tracking data from learning systems such as ITTs (Intelligent Tutoring Systems) [Domínguez et al, 2010] [Roll et al, 2010] [Kazi et al, 2010]). To the best of our knowledge, much less research has been dedicated to educator-centered feedback provisioning and analytics. In fact, this is a bit surprising given the fact that there is a strong need and very loud calls for such tools by learning technology practitioners15. Moreover, there have been very limited attempts to evaluate such systems with educators, especially by using qualitative evaluation methods, as we have presented in this paper.

Generally speaking, both student- and educator-centered feedback types provided by learning analytics tools can be divided into the two main groups [Melis and Ullrich, 2003]: local and global. Typically, local feedback is an immediate response to some students’ activities (e.g., answering the questions of quizzes) in e-learning systems. On the other hand, global feedback is not necessarily immediate and is used to inform students and/or educators about a learning process as a whole or some of its subprocesses. Given this division of feedback provisioning, we can classify our approach into the group of global learning feedback types. This is also the case for most of other educator-centered feedback types supported by other systems (e.g., [Mazza & Dimitrova, 2003] [Zinn & Scheuer, 2006]). In the reminder of this section, we discuss some research related to our work presented in this paper. This discussion is primarily focused on the tools that support educator-centered feedback provisioning through analysis of log data and visualization of the outcomes of such analyzes.

13 http://iaied.org/
14 http://educationaldatamining.org/
15 http://janeknight.typepad.com/socialmedia/2010/05/using-google-analytics-as-an-lms.html
The *Teacher ADVisor* (TADV) framework uses LCMS tracking data to extract student, group, or class models [Kosba et al, 2005]. TADV relies on a set of predefined conditions to identify situations that require teachers’ intervention. When such conditions are satisfied, TADV informs teachers and provides them with advice on how to assist the students. Unlike LOCO-Analyst, which is developed to inform educators about the quality of the used learning content and design, TADV focuses on day-to-day activities of teachers.

The *Student Inspector* tool analyzes and visualizes the log data of student activities in online learning environments in order to assist educators to learn more about their students [Zinn & Scheuer, 2007]. The tool provides a number of important feedback types with information about students, such as the lowest performance or frequent errors. These feedback types are based on an earlier user study which elicited from educators the types of feedback they would like to have as well as the types that could be automatically generated based on the log data [Zinn & Scheuer, 2006]. While Student Inspector was developed to work exclusively with ActiveMath16 (learning tool for studying mathematics) and iClass17 (an intelligent collaborative learning system), LOCO-Analyst is independent of any learning system or tool due to the use of the LOCO ontology framework [Jovanovic et al, 2008].

The area of Educational Data Mining has looked at developing methods and tools that would be used as effective pedagogical support for different types of learning contexts [Baker & Yacef, 2010]. For example, Zaine & Luo (2001) made use of novel data mining techniques for the analysis of access logs of an LCMS aiming at extracting and visualizing patterns that might be valuable for evaluating and interpreting learning activities in on-line courses. Similarly, *TADA-Ed* (Tool for Advanced Data Analysis in Education) combines different data visualization and mining methods in order to assist educators in detecting pedagogically important patterns in students’ assignments [Merceron & Yacef, 2005]. While these systems focus exclusively on one type of learning activities (e.g., reading and exercises), LOCO-Analyst can analyze different kinds of learning activities that commonly take place in modern LCMSs. Moreover, our study showed a very promising perceived usability of LOCO-Analyst, while we are not aware of any similar studies with the aforementioned educational data mining tools.

The use of sequential data mining has been employed in [Romero et al, 2008] for analysis of students’ navigation activities in an on-line learning system. The extracted patterns from students’ click-streams are shown to the educators in the form of a graph-based visualization. While the usability of this visualization is still to be empirically validated, the overall idea of discovering and consequently sharing successful learning paths would be an important research direction for our future work on LOCO-Analyst and similar learning analytics systems.

The work presented in [Ben-Naim et al, 2009] aimed to develop a system that will assist educators to improve their feedback for students in adaptive tutorials, in cases when students encounter known “error-states” or when new “error-states” emerge. The outcome of this research is two tools: one which makes use of the graph-based visualization of the students’ activities, so that educators can discover important patterns; and the second one which provides educators with a list of important issues. While this solution is very valuable for learning systems in which problems that students need to solve are well-structured and precisely defined (e.g., Intelligent Tutoring Systems), LOCO-Analyst is designed for feedback generation in learning contexts where problems that students need to solve and space of possible states they may end up into are either unstructured or only partially structured.

In another group of research work, the focus was primarily on novel visual representations of raw usage data in which educators are those who are to detect the patterns rather than sophisticated data mining algorithms. For example, CourseViz is developed to work with WebCT to visualize student tracking data [Mazza & Dimitrova, 2007]; GISMO follows a similar approach for Moodle [Mazza & Milani, 2005]. Both of these tools try to assist educators in exploring social, cognitive, and behavioral insights of student activities in Web-based learning systems. Whereas user studies of these systems showed some promising results, LOCO-Analyst uses a more advanced analysis of log data in order to provide educators with more qualitative feedback types.

With the widespread adoption of social software in learning and education, the topics of social network analysis and visual analytics have been attracting more and more attention [de Laat et al, 2007]. For example, SNAPP (Social Networks Adapting Pedagogical Practice)18 visualizes a network of interactions among users by leveraging data from a discussion forum. There is also a number of general purpose visualization tools, which are commonly used in social software. For example, Wordle19 has been identified as valuable tool for quick analysis and visualization of students’ texts and

16 http://www.activemath.org
17 http://www.iclass.info
18 http://research.uow.edu.au/learningnetworks/seeing/snapp/
19 http://www.wordle.net/
collaborative tags [Johnson et al, 2010]. This is also quite in line with LOCO-Analyst’s feedback based on collaborative tags, which was detected as one of the main predictors of the perceived utility of a learning analytics tool in our quantitative analysis of the LOCO-Analyst evaluation [Asadi et al, 2011]. With this empirical finding in mind, the future research on learning analytics tools certainly needs to pay a lot of attention to these aspects.

In line with the above relevant observation for the future research in learning analytics tools, the final part of this section is dedicated to the recent research that can be very valuable for the improvement of existing and introduction of new types of feedback provided by LOCO-Analyst. For example, Macfadyen & Dawson [2010] conducted an analysis of usage tracking data collected by a LCMS in order to determine the best predictors of students’ academic performance based on their activities in Web-based learning systems. Total number of posted discussion messages, sent email messages, and completed assessments are identified as the variables that can best predict (i.e., explain most of the variability of) the final grade of students. This empirical result is very important for LOCO-Analyst, as it can be directly applied to the feedback types listed in Table 1, and especially to those related to analysis of social interactions.

Learning analytics has been recognized as an important research topic for workplace learning, as well. However, in that context, common assessment approaches (e.g., formal exams) are not easily applicable [Murray & Efendioglu, 2007]. A very important work in this domain is presented in [Macfadyen & Sorenson, 2010] who proposed Learner Interaction Monitoring System (LiMS) which collects fine-grained data about learners’ activities in learning environments. Through the analysis of those data, the system then generates learner profiles that are used by learners to self-reflect on their learning performance and by managers to get information about learning activities of their employees. This work is highly important for our ongoing work20 in which aim at adapting and extending feedback types explored in LOCO-Analyst in the workplace learning context.

9. Conclusion

In this paper, we have analyzed the results of two qualitative studies conducted in 2006 and 2009 to evaluate the two versions of LOCO-Analyst, a learning analytics tool. Following the suggestions of the 2006 study participants, we improved the initial feedback to provide additional information by representing the feedback data using data visualization techniques and enhanced the tool’s GUI. Our results showed that multiple ways of visualizing data increase the perceived value of the feedback types. It is very important to recapitulate our finding that the improved version of the tool, although showed to the participants a much larger amount of data, did not increase the perceived information overload of the learning analytics tool. With this in mind, we can conclude that the significance of this research is in providing clear evidence that a great care has to be given to the human-computer interaction (HCI) aspect of the systems for supporting educational processes. Although this conclusion seems rather intuitive, in the technology-enhanced learning domain the focus over the last decade was predominantly on pedagogical, adaptive and responsive aspects of the systems. We argue that further research is warranted on how we can utilize existing knowledge from the HCI and visual analytics fields to improve the effectiveness of learning analytics (for different both educators and learners) and study which particular HCI and visualization techniques work best for learning and education. This need is especially emphasized with growing support for personal learning environments which imply the use of even larger amounts of (distributed) data.

10. References


20 http://www.intelleo.eu


