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Factors Influencing Beliefs for Adoption of a Learning Analytics Tool: An Empirical Study

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Abstract. Present research and development offer various learning analytics tools providing insights into different aspects of learning processes. Adoption of a specific tool for practice is based on how its learning analytics are perceived by educators to support their pedagogical and organizational goals. In this paper, we propose and empirically validate a Learning Analytics Acceptance Model (LAAM) of factors influencing the beliefs of educators concerning the adoption a learning analytics tool. In particular, our model explains how the usage beliefs (i.e., *ease-of-use* and *usefulness* perceptions) about the learning analytics of a tool are associated with the intention to adopt the tool. In our study, we considered several factors that could potentially affect the adoption beliefs: i) pedagogical knowledge and information design skills of educators; ii) educators' perceived utility of a learning analytics tool; and iii) educators' perceived ease-of-use of a learning analytics tool. By following the principles of Technology Acceptance Model, the study is done with a sample of educators who experimented with a LOCO-Analyst tool. Our study also determined specific analytics types that are primary antecedence of perceived usefulness (concept comprehension and social interaction) and ease-of-use (interactive visualization).

Keywords: quantitative evaluation, e-learning, feedback, learning analytics, LAAM, ontologies

1 INTRODUCTION

Many well-acclaimed educational systems, such as Moodle[1] or BlackBoard/WebCT[2], are available for educators for structuring their online courses, preparing learning contents and designing student activities according to their preferred teaching styles. Numerous online communication tools, such as Elluminate[3], are also available for educators to interact and collaborate on learning activities with students. However, when it comes to personalization of the student learning process, the support offered by learning systems is rather limited (Willging, 2005; Dawson et al., 2008; Essalmi et al., 2010, Dabbagh & Reo, 2011).

Educators who adopt online learning systems are often required to constantly adapt and evolve their online courses to assure high performance and learning efficiency of their students (Gasevic et al., 2007). Effective adaptation requires a comprehensive and insightful awareness of students' learning experiences, comprehension, and their interactions in the learning systems. By having access to the learning analytics on students' completion status of lessons and quiz scores, educators should have a better sense of: students' ability to follow and comprehend the course contents; the topics students found difficult; students' social interactions and knowledge contributions; and the like. Educators, thus, require a learning system that

[1] http://moodle.org
[2] http://www.webct.com
[3] http://www.elluminate.com

provides learning analytics on their online courses that are both *comprehensive* and *informative*.

One way to attain *comprehensibility* is to interlink semantically all the major elements (i.e., data) of a learning process, including learning activities (e.g., reading and discussing), learning content, learning outcomes, and students (Jovanovic et al., 2007). Learning analytics derived from semantically interlinked data can provide a more comprehensive picture of students learning experiences and outcomes, and thus support personalization of student learning process. To be *informative*, learning analytics should be such that an educator can quickly and easily get an overall insight into a certain aspect of the learning process (this can be achieved, e.g., by using effective visualization of users' interactions).

The current breed of online learning systems, however, offers limited support for such insights. Many learning analytics are superficial and include, for instance, simple statistics such as, when and how many times students logged in, or low-level data about students' interactions with learning content (e.g., pages viewed). In addition, traditional course evaluations done at the end of a semester are too late for adapting courses for current students and often lack reliable feedback. As it has been shown, most students enrolled in online courses do not complete standard course evaluation forms and their response rate is far lower than for students attending conventional classroom-based courses[4].

Recognizing the above stated issues associated with online learning systems, there has been a significant research interest recently in various aspects of learning analytics (Long et al., 2011). While many approaches and tools for learning analytics have been proposed, there is limited empirical insights of the factors influencing potential adoption of this new technology. To address this research gap, *we propose and empirically validate a Leaning Analytics Acceptance Model (LAAM), which we report in this paper, to start building research understanding how the analytics provided in a learning analytics tool affect educators' adoption beliefs*. In particular, we investigated how the provided learning analytics inform the usage belief of educators, i.e., *ease-of-use* and *usefulness* perceptions, and how these beliefs are mutually associated with the intention to adopt the tool. In our study, we considered several factors.

First, pedagogical knowledge and information design skills of individuals can influence their perception of the usefulness of learning systems (Bratt, 2009). Furthermore, McFarland & Hamilton's (2006) refined technology acceptance model recognize prior experience as one of the context factors that could potentially impact the perceived usefulness of a system. These studies suggested that the participants who evaluate online learning systems could have varied perceptions of the systems' utility based on their own pedagogical background and experience. In our study, we asked educators to enlist their academic role and years of experience. Based on their responses, we examined how the evaluator's role and years of experience influenced their perception of the usefulness of the analytics provided in a learning analytics tool. We present our results in this paper.

Second, studies have shown that decisions to adopt technology-based systems are influenced by the evaluators' perceived utility of such systems (Bratt, Coulson, & Kostasshuk, 2009). The *Technology Acceptance Model* (TAM) theory (Davis, 1989) – whose roots lie in Fishbein and Ajzen's (1975) Theory of Reasoned Action – posits that perceived usage beliefs determine individual behavioral intentions to use a specific technology or service. Studies in related domains have shown that perceived usage belief (usefulness) is one of the strong drivers influencing users' intentions of adopting a software tool for practice (Davies, 2006; Recker, 2010). We found it relevant to examine how the usage belief perceptions of educators would influence their behavioral intention or commitment to adopt a learning analytics tool for their practice.

Third, the relation between the *ease-of-use* belief and intention to adopt is not very clear, however. Some studies suggest there is a direct association between ease-of-use and intention to adopt (Davis, 1989; Gefen et al., 2002). Others fail to report such an association (Warkentin, Gefen, Pavlou, & Rose, 2002). Venkatesh et al. (2003), however, suggest that perceived ease-of-use indirectly influences intention to adopt through perceived

[4]T. Anderson, Online Student Course Evaluations, http://terrya.edublogs.org/2008/11/10/online-student-course-evaluations/

usefulness. Faced with these conflicting studies, we examined how the users evaluating a learning analytics tool related their ease-of-use beliefs with their perceived usefulness and intention to adopt the tool. In our survey, we measured the ease-of-use construct by asking questions about the tool's intuitiveness. Moreover, Malhotra and Galletta (1999) observed that sustainability of one's perception or attitude is an indicative of usage behaviors. In this study, we examined how an individual's use of the features of a tool influences perception, which can in turn be associated with later evaluations.

Finally by leveraging the data we collected during this study, the paper aimed to identify the variables that could be acted upon to improve the pedagogical utility (Bratt, 2007) of a learning analytics tool, in general, and its GUI (Graphical User Interface) feature, in particular. We analyzed the associations between the items to identify the best predictors of the perceived utility and usability of a learning analytics tool.

To create the LAAM model, to conduct an empirical study, and to investigate the impact of the abovementioned factors in our study, we used LOCO-Analyst, a learning analytics tool, as an object of our study. LOCO-Analyst provides learning analytics on different objects of interest at varying levels of granularity (overview of the tool is provided in the Appendix).

Section 2 provides overview of the proposed LAAM model, including the definition of research questions (which fed the development of our theoretical model). Section 2 covers method including our research design and context-specific details of the empirical study. The study results are provided in Section 4 using descriptive and inferential statistics. Discussions on the results are also covered in this section. After presenting the related work in Section 5, we conclude the paper in Section 6.

2 Learning Analytics Acceptance Model – LAAM

Following Davis (1989), we can understand perceived *usefulness* as the degree to which an educator believes that using a specific online learning system will increase his/her task performance. *Ease-of-use* is the degree to which an educator expects the use of the learning system to be free of effort. We built a LAAM research model to investigate our research questions and hypotheses. Figure 1 shows a high-level view of the model. This model is intended to provide a visual conceptualization of the scope of this study. The model is built on the measurement items (questions) included in our survey instrument listed in Table 1 (the survey instrument is described in Section 3.2). An expanded view of the model is shown in Figures 2, 3 and 4. We broke down the representation of the detailed model into three separate but identical figures for easy comprehension of the depicted associations among the items. Each rectangle in the Figures 2-4 represents a single measurement item of the survey. To provide a visual association between the high-level and the detailed level models, we also used color codes. The boxes filled with blue color, for instance, represent the *ease of use* items, the usefulness related boxes are white-filed; red color shows past experience related questions; and the green color represents the outcome variable i.e. the behavioral intention to adopt the tool.

The building of LAAM model is motivated by the Technology Acceptance Model. For constructing and validating the proposed LAAM model, we use the following four research questions, some of which are operationalized as hypotheses.

RQ1 – *How do educators perceive usefulness of a learning analytics tool that implements educator-oriented learning analytics?*

The first research question aims to reflect the factors that LAAM considers to determine the usage beliefs of educators about a learning analytics tool. The factors included in LAAM can be examined by evaluating participants' responses to the questions enquiring the helpfulness of each kind of learning analytics offered in a tool. Malhotra and Galletta (1999) observed that sustainability of one's perception or attitude over a period of time is an indicative of the usage behavior. In our empirical study, we asked the Tool Assessments questions labeled as "Q1a" to "Q1g" (Table 1 and Figure 2). The questions from Table 1 and Figure 2 should be understood as examples of questions formulated to investigate particular analytics types that a learning analytics tool contains. In our case, those questions were formulated to reflect learning analytics of the LOCO-Analyst tool. In the case of other learning analytics tools, similar questions should be formulated to examine specific analytics the tool at hand has. Those questions are to be asked while the participants are engaged with the tool by performing the activities specific to the learning analytics enquired. Questions Q2 to Q13 are more general in nature and can be used for any learning analytics tool (provided that their formulation is updated to refer to another tool). Questions Q2-13 are to be completed after the participants have completed the tool assessment activities. These questions are supposedly responded on the basis of the usage perceptions the participants built during the evaluation of the tool's features at the assessment stage.

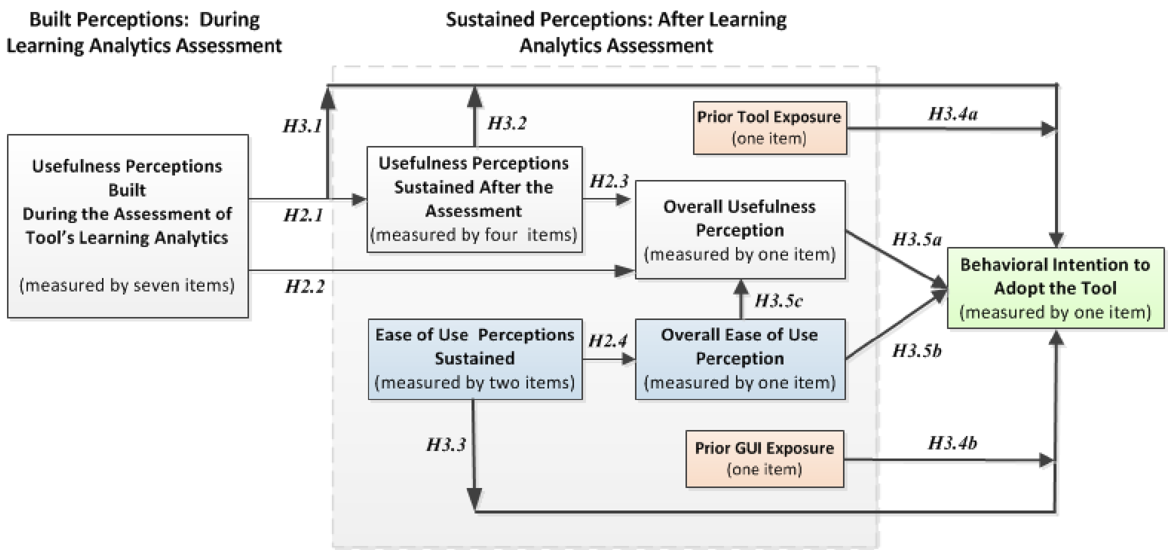

Figure 1. A high-level view of the LAAM model depicting associations between the early and retained usage beliefs about learning analytics, as well as the associations with the behavioral intention to adopt such a tool. (In the above model we superimposed hypotheses labels to create a mapping between the model and the hypotheses examined in this study. Thin lines show our RQ2 related associations and corresponding hypotheses, while the thick lines represents our RQ3.)

The next element of LAAM examines the relationship between the usefulness responses obtained during two different stages of a study (during and after the evaluation).

RQ2 – *How the perceptions built when an individual engages with the features of a learning analytics tool are associated with later evaluations?*

- We hypothesized that users' perceptions at the tool assessment stage would be positively associated with their evaluations during later stages. Specifically, we built the following hypotheses (shown in Figures 2 - 4). *H2.1* – There is a positive association between educators' assessment of usefulness of the analytics enquired during the *Tool Assessment* stage and the perceived *Usefulness of Analytics* during the post-assessment stage, as depicted by H2.1a to H2.1h in Figure 2.
- *H2.2* – There is a positive association between educators' assessment of usefulness of the analytics enquired during the *Tool Assessment* stage and the perceived *Overall Usefulness* of Analytics (Q10), as depicted by H2.2a to H2.2g in Figure 3.
- *H2.3* – There is a positive association between educators' perceived usefulness of individual analytics

as measured through the *Usefulness of Analytics* Questions (Q2, Q3, Q4, Q6) and *Overall Usefulness of Analytics* (Q10), as depicted by H2.3a to H2.3d in Figure 2.

- *H2.4* – There is a positive association between educators' ease-of-use perception of individual analytics as reflected through the *Ease-of-use Analytics* Questions (Q7 & Q8) and the *Overall Ease-of-use perception* (Q9), as depicted by H2.4a to H2.4b in Figure 2.

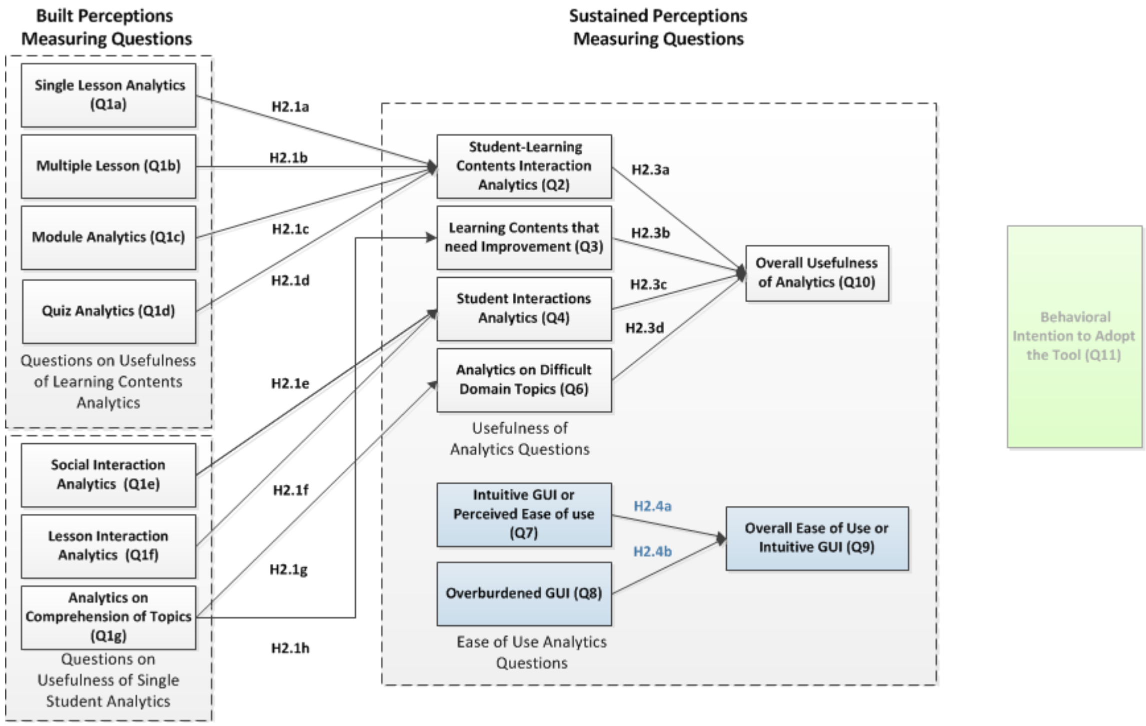

Figure 2. Hypothesized LAAM model of associations between tool assessment and post assessment items in this study. (Relations with the behavioral intention to adopt the tool i.e. Q11 are shown in Figures 3 & 4.)

RQ3 – *How do the usage beliefs of educators influence their intention to adopt an online learning tool for their practice?*

We hypothesized (*H3*) that the usage beliefs of educators would significantly influence their intention to adopt an online learning tool for their practice. Specifically, we built the following hypotheses (also depicted in Figures 2 and 3).

- *H3.1* – There is a positive association between educators' assessment of usefulness of the analytics enquired during the *Tool Assessment* stage (Q1a-Q1g) and the *Behavioral Intention to Adopt the Tool* (Q11), as depicted by H3.1a to H3.1g in Figure 3.
- *H3.2* – There is a positive association between educators' perceived usefulness of individual analytics as reflected through the *Usefulness of Analytics* Questions (Q2, Q3, Q4, & Q6) and *Behavioral Intention to Adopt the Tool* (Q11), as depicted in by H3.2a to 3.2d Figure 4.
- *H3.3* – There is a positive association between educators' ease-of-use perception of individual analytics as reflected through the *Ease-of-use Analytics* Questions (Q6 & Q7) and the *Behavioral Intention to Adopt the Tool* (Q11), Figure 4. This hypothesis is decomposed into following two sub-hypotheses.
    - *H3.3a* - There will be a positive relationship between evaluator's assessment of Intuitiveness

of the analytics (Q7) and the Behavioral Intention to Adopt the Tool (Q11);
    - *H3.3b* - There will be a negative relationship between evaluator's assessment of Overburdened GUI (Q8) and the Behavioral Intention to Adopt the Tool (Q11).
- *H3.4* – The users' Prior Exposure to Similar tools or experience significantly influences their *Behavioral Intention to Adopt the Tool* (Q11), as depicted in Figure 4. We have decomposed this hypothesis into following two sub-hypotheses.
    - *H3.4a* – There is a positive association between educators' Prior Exposure to Similar Tool's Analytics (Q12) and the Behavioral Intention to Adopt the Tool (Q11);
    - *H3.4b* – There is a positive association between educators' Prior Exposure to Similar Tool's GUI (Q13) and the Behavioral Intention to Adopt the Tool (Q11).
- *H3.5* – Educators' overall ease-of-use and usefulness perceptions (Q9 and Q10) significantly influences their *Behavioral Intention to Adopt the Tool* (Q11), as depicted in Figure 4. We have decomposed this hypothesis into following two sub-hypotheses.
    - *H3.5a* – There will be a positive relationship between educators' ease-of-use perceptions (Q9) and the Behavioral Intention to Adopt the Tool (Q11);
    - *H3.5b* – There will be a positive relationship between educators' overall usefulness perceptions (Q10) and the Behavioral Intention to Adopt the Tool (Q11);
    - *H3.5c* – The ease-of-use perceptions (Q9) would positively influence the Behavioral Intention to Adopt the Tool (Q11) through the perceived usefulness of a learning analytics (Q10).
- *H3.6* – The educators' *Roles* influence their *Behavioral Intention to Adopt the Tool* (Q11).

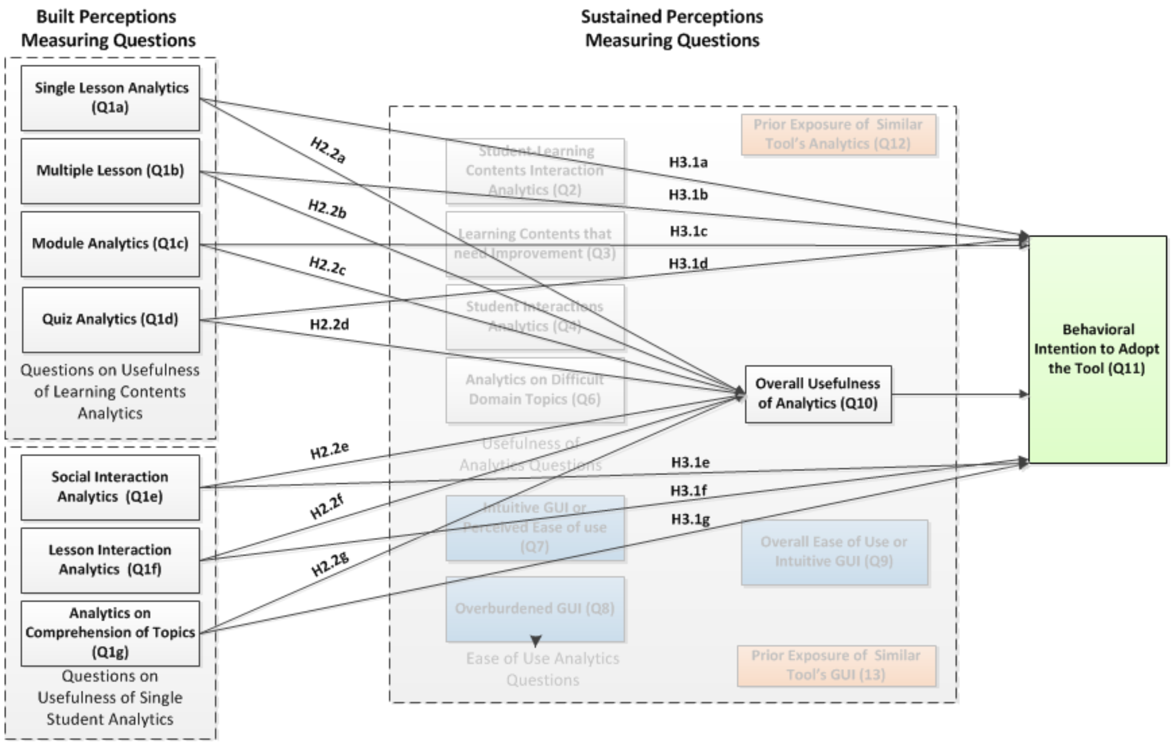

Figure 3. Hypothetical LAAM model of tool assessment relations with usefulness and behavioral intention.

The final element of LAK aims at determining which features and feedback types are significantly related to or could predict the perceived utility and usability of a learning analytics tool and/or its individual components.

RQ4 - *Are there any significant predictors of the perceived utility and usability of a learning analytics tool?*

In particular, this element aims to identify any potential relationships between the different kinds of feedback and functionality of the learning analytics tool, and how they are perceived by different groups of potential users. Having identified those relations, we could inform future research and development in the learning analytics area.

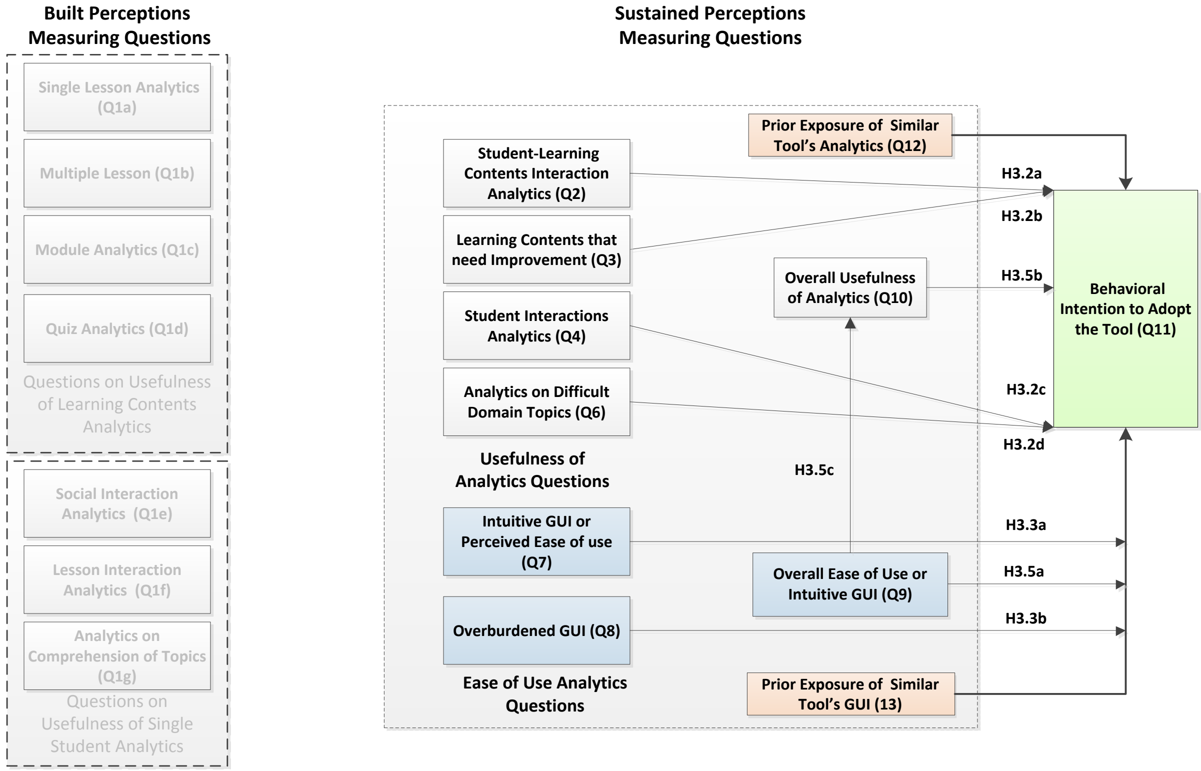

Figure 4. Hypothesized model of post assessment relations with usefulness and behavioral intention.

3 METHOD

3.1 Design

The purpose of this study was to evaluate the proposed LAAM by using it for evaluation of a concrete learning analytics tool. In our case, we decided to use LOCO-Analyst (see Appendix for details), which offers the following types of learning analytics: single lesson analytics; composite lesson analytics; module analytics; quiz analytics; social interaction analytics; lesson interaction analytics; and topic comprehension analytics (see Table A1 in the Appendix). The participants' usage belief perceptions were measured as their responses to the questionnaire items which were based on the identified factors in LAAM. This type of data collection is consistent with other relevant studies in the field (see Section 5.1), which evaluated similar tools for educators and involved educators as their participants. In our design it is of substantial importance to have a clear distinction from studies designed to investigate the effect of learning technologies on learners where, of course, objective variables are more preferred. However, as theory of TAM indicates, technology acceptance is predicted by usage intentions measured by questionnaires.

3.2 Participants

For this study we recruited 22 participants from Simon Fraser University (SFU), University of Belgrade (UB), Athabasca University (AU), and a private Canada-based company developing and offering technology and content for professional training. We distinguished three roles of the participants: (1) *instructor* – a person who had independently instructed at least one entire course; (2) *teaching assistant* – a person with teaching assistant experience only; and (3*) researcher/learning analyst* – a person who did research related to learning analytics, or had practical experience in this field (e.g., working for a company focused on online education). The distribution of the study participants among these three roles was as follows: six instructors, eight teaching assistants, and eight researchers/learning analysts. The average experience of the participants in their role was 6.45 years (SD = 5.58, N=22); instructor 10.67 years (SD=7.09, N=6); teaching assistants 3 years (SD = 1.06, N=8); and researcher/learning analysts 6.75 years (SD=5.23, N=8). The vast majority of participants came from Computer Science or Information Systems background: 21 out of 22 participants. However, the only non-computer science participant had already experience in teaching and analyzing computer science courses, had no difficulty in understanding the used materials, and expressed to have felt fully competent to participate in the study. All participants agreed to take part in the experiments, and received neither financial nor non-financial credits for their participation. All participants who responded to our invitation to take part in the study successfully completed all the tasks of the study.

3.3 Materials

The elements of LAAM are measured by using a questionnaire-based survey instrument. To measure user perception of usefulness of a tool's features, we used 5-point Likert scale items with values ranging from 1-strongly disagree to 5-strongly agree. Each Likert-scale question had an associated open-ended part. The participants were asked to explain their answers in 1 to 2 sentences. For the demographic questions, however, the Likert scale was not used. Instead, we asked the participants to specify their data. The survey items were grouped into three sections.

1. Demographic and concluding questions: The demographic part included two questions about participants' academic roles and experience. The concluding part had three questions. They sought participants' suggestions for improving the LOCO-Analyst tool, asked their overall opinion about the learning analytics provided in the tool, and enquired about their behavioral intention to use the tool in their courses.

2. Usefulness of Learning Analytics and functionality questions: The questions in this category were aimed at gathering the participants' opinion on various learning analytics and some other features provided in the tool. These questions were organized into: *questions regarding the feedback about the learning content* (i.e., single lessons, composite lessons, learning module, quiz), and *questions regarding a student's learning activities* (i.e., activities in discussion forums and chat rooms, usage and annotation of learning content). Respondents were required to answer seven of the questions while they performed tool activities associated with each question. We also call these assessment questions; they are labeled with Q1a to Q1g in Table 1. There were five more question in this group (i.e., Q2 to Q6). Respondents were required to answer Q2 to Q6 after they completed the assigned tool activities. These responses reflect the perceptions respondents built about the learning analytics and features during their earlier interaction with the tool.

3. Graphical User Interface (GUI) related questions: There were four questions related to GUI in the survey. We asked three questions (Q7 to Q9) to elicit participants' opinion about ease-of-use or intuitiveness of the interface and the information presented in. We also asked how was the LOCO-Analyst's GUI aspect compared to some related tools (Q12).

LOCO-Analyst is a learning analytics tool which makes use of Semantic Web technologies to provide educators with context-specific analytics on the various aspects of the learning process taking place in an online learning environment (more material on the LOCO-Analyst is provided in the Appendix). In addition to the survey instrument, we used the LOCO-Analyst tool in this study. We asked participants to evaluate the features of the LOCO-Analyst tool for answering our survey items. As the participants were dispersed geographically, we prepared demo videos to provide them with instructions on how to use the tool. Additionally, we provided videos for the assessment of each type of learning analytics listed in Table A1. The items in the questionnaire specified the relevant video to watch before answering the items. These videos are still available on the LOCO-Analyst's web site[5]. To exemplify different kinds of feedback, we used the log data and the content of one learning module (Programming Languages) of the "Introduction to Computer Science for Non-Majors" course[6]. We opted for this introductory computer science course considering all the participants would be familiar with it. Initially, we considered the option of enabling the participants to test LOCO-Analyst on their own courses, but quickly realized that it was not feasible since we would have to get access not only to the content of their courses but also to the log data. The issues of learning content copyright and log data privacy made this option less viable.

3.4 Procedure

The recruited participants were emailed a document explaining the purpose of the study and outlining the video tasks they would undertake as they responded to the survey items. The participants were given options, along with how-to instructions, either to download and play the videos from their local machines or to stream them directly from the hosting website. After familiarizing themselves with the LOCO-Analyst tool through demo videos, the participants were asked to download the tool and complete tasks related to the functionality presented in the videos. That is, they had seven specific tasks, each one related to the functionality of the tool implementing one of the seven types of learning analytics as given in Table A1 (in the Appendix). For each kind of learning analytics, their task was to try to interpret the meaning of the learning analytics in the context of the given course and assess its usefulness. The participants were asked to work independently on the tasks. A research associate was available to assist, if required. We emailed our survey instrument to the participants when we sent them instructions about the study earlier. The participants were requested to return the completed questionnaire by email. Once we received responses from all the participants, we used the Microsoft Excel and JMP applications to organize and analyze our data.

3.5 Analysis

We analyzed the survey data using standard descriptive statistics mean and standard deviation as well as inferential statistics. Using the standard descriptive statistics to analyze the type of the data we had, is a common practice as reported by Blaikie (2003). While there are two schools of thoughts on analyzing the Likert-scale data i.e., *ordinal* vs. *interval* (Carifio & Perla, 2008), we followed the later. There is a significant amount of empirical evidence that Likert scales can be used as interval data (Carifio & Perla, 2007; Carifio, 1976). Accordingly, we used the parametric statistics (e.g., ANOVA, Pearson's correlation and multiple regression) for the analysis of differences among groups, correlation, and regression analysis. For variables whose data were not normally distributed, we used parametric tests over log-transformed data. This approach is more dominantly applied over non-parametric tests in evidence-based disciplines such as medicine (Keene, 1995). Moreover, it is consistent with the findings of the previous research in educational and psychological measurement (Rasmussen & Dunlap, 1991).

4. RESULTS AND DISCUSSION

In this section, we present results of our statistical analysis and their interpretation. The findings reported here

[5] tiny.cc/hdqmz

[6] The course was deployed within the iHelp Courses Learning Management System at the University of Saskatchewan; iHelp Courses' usage tracking data were used for testing LOCO-Analyst's functionality

are based on the analysis of 22 usable responses collected from the respondents. We used the JMP tool to perform all our statistical tests. The threshold of $p < 0.05$ was chosen to designate the statistically significant level. Cronbach's alpha coefficient for internal consistency reliability of the survey items was $\alpha = 0.90$, which is rated as good according to George and Mallery's (2003) rule of thumb.

4.1 Perceived Usefulness (RQ1)

We analyzed the descriptive statistics of the survey items to examine our first research question that was: how educators perceived the learning analytics and visualization features implemented in the tool. The analyzed descriptive statistics are shown in Table 1. For each question, we have reported central tendency measure i.e., Mean (M), Standard Deviation (SD) and the number of valid responses (N). We have organized the presentation and discussion of these results in four groups: (1) Perceived usefulness of different types of learning analytics; (2) Perceived usefulness of the learning analytics for improving the course contents and course instruction; (3) Perceived value of the tool's GUI; and (4) Overall usage belief of the tool.

Perceived usefulness of the different types of learning analytics: There were seven questions in this group (Q1a – Q1g) and the users answered these questions during the tool assessment stage. Each question got a mean score greater than 4 from the maximum of 5, as shown in Table 1. The minimal score was 4.27 (SD = 0.77) out of 5. These results suggest that the educators highly valued the types of learning analytics provided in the tool.

Perceived usefulness of the learning analytics for improving the course contents/instruction: For this group of questions (Q2 – Q6) the minimal perceived value was 3.54 (SD =1.01) out of 5. This minimal value, observed for the question Q5, is considerably lower than values for the other questions in this category. Specifically, the difference between the participants' average opinion regarding Q5 ("The information provided by the tool helps me determine how to improve the students' online interactions") and their opinion regarding other questions of this category reveals that the feedback provided by the tool is suitable for gaining an insight into the weak points of students online interactions, but not for getting suggestions on how to improve the identified weaknesses. This is actually what we had expected since LOCO-Analyst is currently not capable of offering suggestions for course improvement. On the other hand, some participants believed that by revealing the weak areas, the tool implicitly helps users to improve the students' interactions during the learning process.

Perceived value of the tool's GUI: Considering the questions about the tool's GUI (Q7 – Q9), we observed that the participants found the GUI rather intuitive (Q7) with a mean score of 4.5 (SD = 0.8) out of 5 and in general expressed a highly positive opinion about it (Q9) with a mean score of 4.50 (SD = 0.6) out of 5. However, the results also showed that the information burden posed by the tool's GUI (Q8) was not fully solved (it has also been observed in the formative, 2006 study (Jovanovic et al, 2008)). We believe that this might be caused by the increase in the amount of information that the new version of the tool provides to educators through extension of existing and inclusion of a new learning analytics types. It seems that the benefit gained by introducing new visual elements (suggested by the formative evaluation in 2006) was neutralized by introducing additional information for educators.

Overall usage belief of the tool: Regarding this last category of questions (Q10 – Q13), we found that the study participants were satisfied with the tool, as their responses to the questions Q10 and Q11 revealed. Mean scores for these questions were 4.68 (SD = 0.48) and 4.04 (SD = 0.90) out of 5, respectively. The other two questions (Q12 & Q13) got significantly lower values, 3.33 (SD = 0.86) and 3.25 (SD = 0.55) out of 5, respectively. Further, examination of the responses revealed that the great majority of the participants chose the answer "Uncertain". This is caused by the participants' low level or lack of experience with other tools for feedback provisioning.

Table 1. Descriptive statistics for the evaluation study: the first column of the table is the category of the questions; the second column shows the question statements as they were given in the questionnaire; finally, the third column shows the mean, standard deviation, and number of valid answers for each question.

Category	Question Description in the questionnaire	Mean, Std Dev, N
Perceived value of learning analytics types during assessment	Q1a: Feedback about individual lesson	4.41, 0.59, 22
	Q1b: Feedback about a group of (related) lessons	4.36, 0.66, 22
	Q1c: Feedback about a learning module as a whole	4.29, 0.64, 21
	Q1d: Feedback about students' performance on a quiz	4.73, 0.46, 22
	Q1e: Feedback about the student's activities in discussion forums and chat rooms	4.68, 0.57, 22
	Q1f: Feedback about the student's interaction with the learning content (lessons)	4.41, 0.73, 22
	Q1g: Feedback about the student's comprehension of the studied topics (based on his/her annotations)	4.27, 0.77, 22
Perceived usefulness (usage belief) of the tool for improving the course contents	Q2: The tool enables me to get an insight into the students' interactions with the learning content	4.45, 0.67, 22
	Q3: The information the tool provides helps me identify what needs to be improved in the learning content	4.27, 0.70, 22
	Q4: The tool provides relevant information regarding the students' interactions within the online learning environment.	4.41, 0.80, 22
	Q5: The information provided by the tool helps me determine how to improve the students' online interactions.	3.54, 1.01, 22
	Q6: The tool helps me identify the domain topics the students were having difficulties with.	4.57, 0.68, 21
Perceived GUI (ease of use) of the tool	Q7: LOCO-Analyst's GUI (Graphical User Interface) is intuitive enough	4.50, 0.80, 22
	Q8: LOCO-Analyst's GUI is overburdened with information	2.50, 1.34, 22
	Q9: My general opinion about the GUI	4.50, 0.60, 22
General perception of the tool	Q10: All in all, I found LOCO-Analyst a handy tool for feedback provisioning	4.68, 0.48, 22
	Q11: I would like to be able to use LOCO-Analyst in my teaching practice	4.04, 0.90, 22
	Q12: LOCO-Analyst provides me with more useful feedback than other similar tool(s) I have used/tried	3.33, 0.86, 21
	Q13: LOCO-Analyst is more intuitive than the other tools capable of for feedback provisioning I have used/tried	3.25, 0.55, 22

4.2 Sustainability of the Usefulness Perceptions (RQ2)

For this research question, we expected that educators' usefulness perceptions of the learning analytics measured during different stages of the study would be consistent. Figures 5 and 6 show the related correlations.

For hypothesis 2.1, we expected a positive association between the educators' assessment of usefulness of the analytics enquired during the *Tool Assessment* stage and the perceived *Usefulness of Analytics* during the post-assessment stage. We also expected that the educators' usefulness perceptions built during the *Tool Assessment* stage would be positively reflected in their responses to question pertaining to the overall usefulness of learning analytics. We observed strong correlations between the hypothesized constructs with few exceptions.

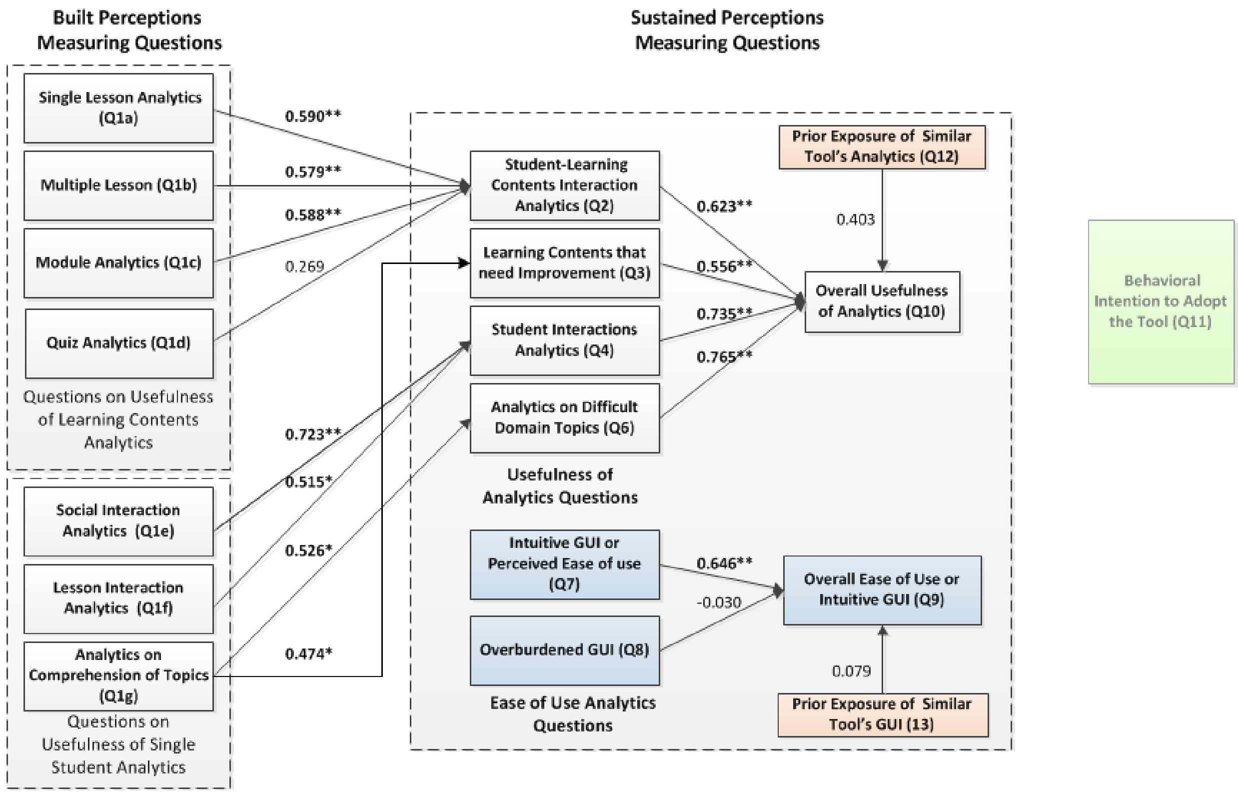

Figure 5. The LAAM model showing Pearson's correlation values for associations between tool assessment and post assessment items. The values appended by ** and * are significant at the 0.01 and 0.05 levels respectively (2-tailed).

For analytics related to the learning contents (H2.1a, H2.1b, and H2.1c), an analysis using Pearson's correlation coefficient indicated that there are significant linear relationships between the usefulness perceptions of: *Single Lesson* Analytics and *Student-Learning Content Interaction* Analytics, $r(20) = 0.59$, $p < 0.004$; *Multiple Lesson* Analytics and *Student-Learning Content Interaction* Analytics, $r(20) = 0.58$, $p < 0.005$; and *Module* Analytics and *Student-Learning Content Interaction* Analytics, $r(20) = 0.59$, $p < 0.005$. These correlations suggest that the usefulness perceptions that the participants built during the tool assessment stage have been sustained and reflected during their ratings of the content-related learning analytics. This sustainability of usefulness perception can further appear in their overall usefulness-rating of the tool. A non-significant association between the *Quiz* and *Student-Learning Content Interaction* analytics (H2.1d) suggest that educators probably did not perceived the quiz analytics as a part of learning contents. For the single student analytics (H2.1e through H2.1h), we, however, found strong correlations supporting our perception sustainability hypotheses as expected; the following correlation statistics demonstrate this. For analytics related to interactions (H2.1e and H2.1f), we found strong correlations in the following usefulness perceptions: *Social Interaction* Analytics and *Student Interaction* Analytics, $r(20) = 0.72$, $p < 0.000$; and *Lesson Interaction* Analytics and *Student Interaction* Analytics, $r(20) = 0.52$, $p < 0.014$ as shown in Figure 5. Hypotheses H2.1g and H2.1h, which seek associations between comprehension and difficult topics, reveal persistent usefulness perceptions: *Comprehension of Topics* Analytics and *Difficult Domain Topics* Analytics, $r(20) = 0.53$, $p < 0.014$; and *Comprehension of Topics* Analytics and *Learning Contents Needing Improvement* Analytics, $r(20) = 0.47$, $p < 0.026$.

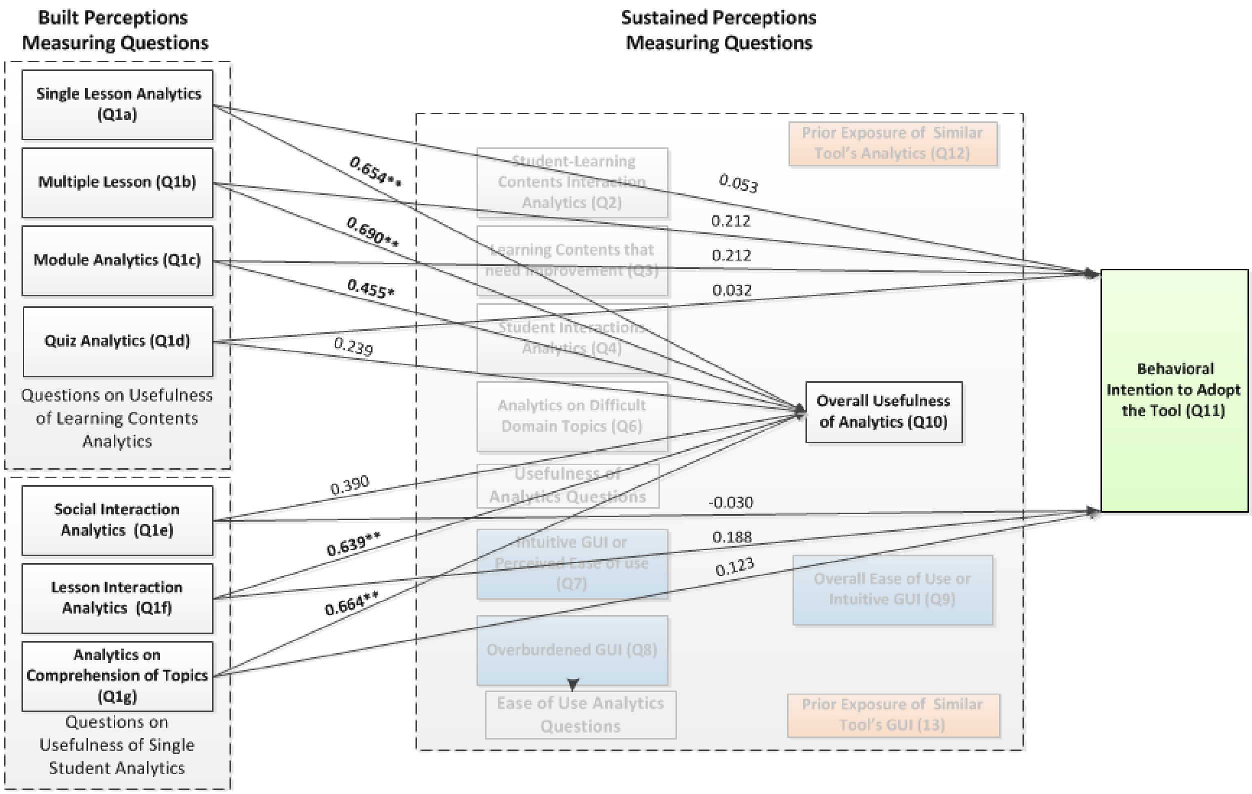

Figure 6. The LAAM model Pearson's correlations for association between tool assessment items and overall usefulness as well as Behavioral Intention to Adopt the Tool.

We observed a similar pattern of associations for the H2.2 set of hypotheses supporting the view that the initial usefulness perceptions were sustained all the way through to the overall rating of the tool. There were significant associations between usefulness perceptions of the Tool Assessment items and the Overall Usefulness of the learning analytics, as shown in Table 2. The correlation between *Lesson Interaction* Analytics and *Overall Usefulness* of Analytics was close to significant: $r(20) = 0.39$, $p < 0.073$.

Table 2. Observed correlation for H2.2 set oh hypotheses.

First Variable	Second Variable	Correlation Coefficient
H2.2: There is a positive association between educators' assessment of usefulness of the analytics enquired during the *Tool Assessment* stage and the perceived *Overall Usefulness* of Analytics (Q10)		
Single Lesson Analytics	Overall Usefulness of Analytics	$r(20) = 0.65$, $p < 0.001$
Multiple Lesson Analytics	Overall Usefulness of Analytics	$r(20) = 0.69$, $p < 0.000$
Module Analytics	Overall Usefulness of Analytics	$r(20) = 0.46$, $p < 0.038$

For the H2.3 set of hypotheses, we found that the Overall Usefulness of Analytics responses reflected educators earlier perceptions about the usefulness of analytics, as shown in Table 3.

The correlation between intuitive GUI and Overall GUI was also significant: $r(20) = 0.65$, $p < 0.001$. These results support most of the hypotheses. The usefulness perceptions the educators built during their interaction with the tool were strong and consistently reflected in their later evaluations of the tool's features.

These results also lend support to the RQ1 findings that the educators highly valued the types of learning analytics provided in the tool. We also found that the quiz analytics and social interaction analytics did not have linear relationships with overall analytics. These results suggest that the educators have an overall positive perception of the utility of the learning analytics tool even when some of the features of the tool do not show positive association with the overall usefulness perception.

Table 3. Observed correlation for H2.3 set oh hypotheses.

First Variable	Second Variable	Correlation Coefficient
H2.3: There is a positive association between educators' perceived usefulness of individual analytics as reflected through the *Usefulness of Analytics* questions and *Overall Usefulness of Analytics* (Q10).		
Student-Learning-Content Interaction Analytics	Overall Usefulness of Analytics	$r(20) = 0.62, p < 0.002$
Improvement of Learning Contents Analytics	Overall Usefulness of Analytics	$r(20) = 0.56, p < 0.007$
Student Interactions Analytics	Overall Usefulness of Analytics	$r(20) = 0.74, p < 0.000$
Difficult Domain Topics Analytics	Overall Usefulness of Analytics	$r(20) = 0.77, p < 0.000$

In order to determine which of the variables can best predict a general opinion about the perceived utility of the feedback provisioning tool for educators (Q10), the regression model was used. The obtained result is given in Table 4.

The reported p value (max 0.0006) for each coefficient reveals that the three variables presented in Table 2 (namely, Q4, Q6 and Q7) significantly predict the participants' general opinion about the tool. The reported statistics related to overall equation show that these variables also explain a significant proportion of variance in the participants' general opinion about tool ($R^2= 0.93$, $F(3, 20) = 81.46$ and $p < 0.001$). This result reasserts, what we have had expected, that the key values appreciated by educators are: information about students (mutual) interactions and their comprehension of the course content, coupled with an intuitive and easy to follow presentation of that information.

Table 4. A summary of multiple regression analysis for variable Q10: the perceived utility of the feedback provisioning tool for educators.

Variable	Unstandardized coefficient		Standardized coefficient
	B	SE B	β
Constant	1.02	0.24	
The tool's feedback regarding students' interactions (Q4)	0.25	0.04	0.30
The tool's feedback regarding students' comprehension of course topics (Q6)	0.37	0.04	0.52
Intuitiveness of the user interface (Q7)	0.18	0.04	0.42
$r = 0.96, r^2 = 0.93, p < 0.001$			

Similar to the perceived utility of the tool for educators, we also tested which of the variables would be the best predictors for the general impression about the graphical user interface of the tool (Q9). Again, a regression analysis is used and the obtained results are presented in Table 5.

The reported p values for each coefficient reveal that all three variables given in Table 3 significantly (Q1e and Q1g, $p<0.01$, and Q1a, $p<0.05$) predict the participants' perceived value of the tool's user interface. That is, the user interfaces applied for presenting and interacting with the learning analytics about individual lessons, about the students' activities in discussion forums and chat rooms, and the students' comprehension of the studied topics (based on their annotations) are the best predictors of the overall perceived value of the user interface of the feedback provisioning tool. The three analytics types (Q1a, Q1e, and Q1g) also explain a significant proportion of variance in the perceived value about the user interface of the tool ($R^2= 0.70$, $F(3, 21) = 22.11$ and $p < 0.001$).

Table 5. A summary of multiple regression analysis for variable Q9: the general impression about the graphical user interface of the tool

Variable	Unstandardized coefficient		Standardized coefficient
	B	SE B	β
Constant	-0.21	0.61	
The tool's feedback about individual lesson (Q1a)	0.37	0.14	0.36
The tool's feedback about the student's activities in discussion forums and chat rooms (Q1e)	0.37	0.14	0.35
The tool's feedback about the student's comprehension of the studied topics (Q1g)	0.31	0.10	0.40
$r = 0.84$, $r^2 = 0.70$, $p < 0.001$			

These results were important for us to further examine how the educators' strong usefulness perceptions would translate into the behavioral intention to adopt the tool itself. We would further discuss these associations in section 6 to identify the tool's improvement factors.

In our survey we also collected some demographic data including academic *role* and years of *experience* in current role. In addition to analyzing the associations between usefulness perceptions as described in this section above, we also found it relevant to examine the influence of *role* and *experience* on educators' usefulness perceptions of the learning analytics (Q1a-1g). We operationalized *role* as a nominal variable with three categories instructor; teaching assistant, and learning analyst. We converted years of experience into nominal scale of Low, Medium, and High using quintile values of 33% and below, between 33% and 66%, and above 66% respectively. We did not find any statistically significant differences due to varying roles or experience. A two-way ANOVA test did not reveal significant interaction effect, , $F(3, 14) = 0.77$, $p = 0.61$. The main effects for both role and experience level were also not significant, $F(1, 14) = 2.02$, $p < 0.17$ and $F(1, 14) = 0.0098$, $p = 0.92$ respectively. Data was independent and equal variance was assumed. We used log-transformation of *sum of responses* variable as the data was not distributed normally – as revealed by the Shapiro-Wilk Goodness-of-fit test ($W= 0.87$, $p < 0.011$). ANOVA models are considered robust against moderate departures from the assumptions of normality (Elliott & Woodward, 2007). This result suggests that all the user groups found the learning analytics given in the tool equally useful. A mean score of over 4 for all items related to the learning analytics (Q1a to Q1g in Table 1) also suggested that the learning analytics provided suitable level of information about the learning content to all user groups. Similarly, we observed non-significant effects for items measuring usefulness perceptions of *learning contents* (i.e. Q1a-1d). So all the participants, independent of their pedagogical roles, have a similar opinion about the usefulness of analytics related to the learning contents. The minimum mean is 17.37 out of 20 for the learning contents variable and over 4 for its constituent variables. However, we found significant difference in means across pedagogical roles: learning analyst ($M = 13.62$, $SD = 1.06$, $N = 8$), teaching assistants ($M = 12.37$, $SD = 1.92$, $N = 8$), and instructors ($M = 14.33$, $SD = 1.03$, $N = 6$), $F (2, 21) = 3.50$, $p= 0.05$. The Tukey multiple comparisons performed at the 0.05 significance level found that mean Student Activity perceptions for instructors were significantly higher than for teaching assistants.

Having obtained these results, we performed one-way ANOVA on the items (i.e., Q1a to Q1g) individually. We observed a significant difference between pedagogical roles and their perception of learning analytics on *student's interaction with learning contents* (Q1f). The average scores of the usefulness perception of student's interaction with learning contents were found to be different across roles, $F (2, 21) = 4.84$, $p= 0.019$. The Tukey multiple comparisons performed at the 0.05 significance level found that the mean usefulness of interaction analytics for instructors ($M = 4.83$, $SD = 0.40$, $N = 6$) was significantly higher than for teaching assistants ($M = 3.87$, $SD = 0.83$, $N = 8$). The mean score for learning analysts ($M = 4.62$, $SD = 0.51$, $N = 8$) was also found to be significantly higher than that for teaching assistants. One possible interpretation of the significant difference observed between pedagogical roles is that the level of interaction details and sophistication provided in the tool are appreciated by the groups who understand and overlook the whole learning process in greater level of details and responsibility over those who only had some teaching assistance experience. Thus, instructors have shown more appreciation for this kind of analytics presented in the tool.

We, however, did not find a significant effect of educators' prior exposure of a specific tool (e.g. Reload Content Packaging Editor[7]) on their evaluations (perceptions) of learning analytics. As there are many tools that educators can use for creating and managing their online courses, it is natural to expect that many of them would not be familiar with all of them.

We found the results gained through the exploration of this research question very interesting. For example, the detection of learning patterns from a visual representation of a student's interaction with learning content, as the one shown on Figure A1, can be more easily done by an experienced instructor than a teaching assistant; hence, instructors have obviously shown more appreciation for this kind of feedback.

4.3 Behavioral Intention to Adopt the Tool (RQ3)

The third research question examined the relation between the usage beliefs (i.e., usefulness and ease-of-use perceptions) and the behavioral intention to adopt the tool. We assumed that the usage belief would positively influence users' behavioral intention to adopt the tool in practice. All the hypotheses (H3) are depicted in Figures 3 and 4. An analysis using Pearson's correlation indicated that all but one hypothesized associations are statistically insignificant as shown in the Figure 6 and 7. These results suggest that most of the educators' usefulness and ease-of-use perceptions about the learning analytics are not a significant indicator of their intention to adopt the tool. The only significant association was observed for the *Learning Contents that Needs Improvement* analytics. Pearson's correlation coefficient indicated that there is a significant linear relationship between the *Learning Contents that Needs Improvement* analytics and the *Behavioral Intention to Adopt the Tool*.

Previous studies have shown mixed results for the relation between the *ease-of-use* belief and intention to adopt (Davis, 1989; Gafen et al., 2002). Our results revealed no significant relationship between ease-of-use perception and behavioral intention to adopt the tool either directly or mediated through the usefulness perceptions. We, however, found that the ease-of-use perceptions are strongly correlated with the usefulness perceptions, $r(20) = 0.75$, $p<0.000$. These results indicated that the usefulness and the ease-of-use perceptions about the learning analytics were not sufficient factors for educators to show their behavioral intention for adopting a learning analytics tool for their practice.

The descriptive statistics of the *Behavioral Intention to Adopt the Tool* item (Q13) revealed that 36% (8 of 22) respondents were uncertain about their intention to adopt the tool, while the remaining 64% respondents were positive about it. Klein and Sorra (1996) suggested that the users who perceived the utility of an information system to be congruent with their values (i.e., internalized) are likely to be committed and enthusiastic in their use. Kelman (1958) also noted that internalization results in a lasting change in attitude and promote adoption. Assuming that the usage beliefs were likely to be internalized more in the instructors than other pedagogical roles, we subsequently examined (H3.6) the effect of pedagogical role on behavioral intention to adopt a tool.

For hypothesis H3.6, we used a one-way ANOVA test to compare the means of the dependent variable (behavioral intention) for the three pedagogical groups: instructors, teaching assistants, and learning analysts. The average behavioral intentions were found to be different across pedagogical roles, $F(2,21) = 4.82$, $p = 0.020$. The Tukey multiple comparisons performed at the 0.05 significance level found that the mean behavioral intention score for instructors ($M = 4.5$, $SD = 0.83$, $N = 6$) was significantly higher than that of the learning analysts ($M = 3.37$, $SD = 074$, $N = 8$), but not significantly higher than the teaching assistants ($M = 4.37$, $SD = 0.74$, $N = 8$). The mean scores for teaching assistants were also found to be significantly higher than the

[7] Further referred to simply as 'Reload'

learning analysts.

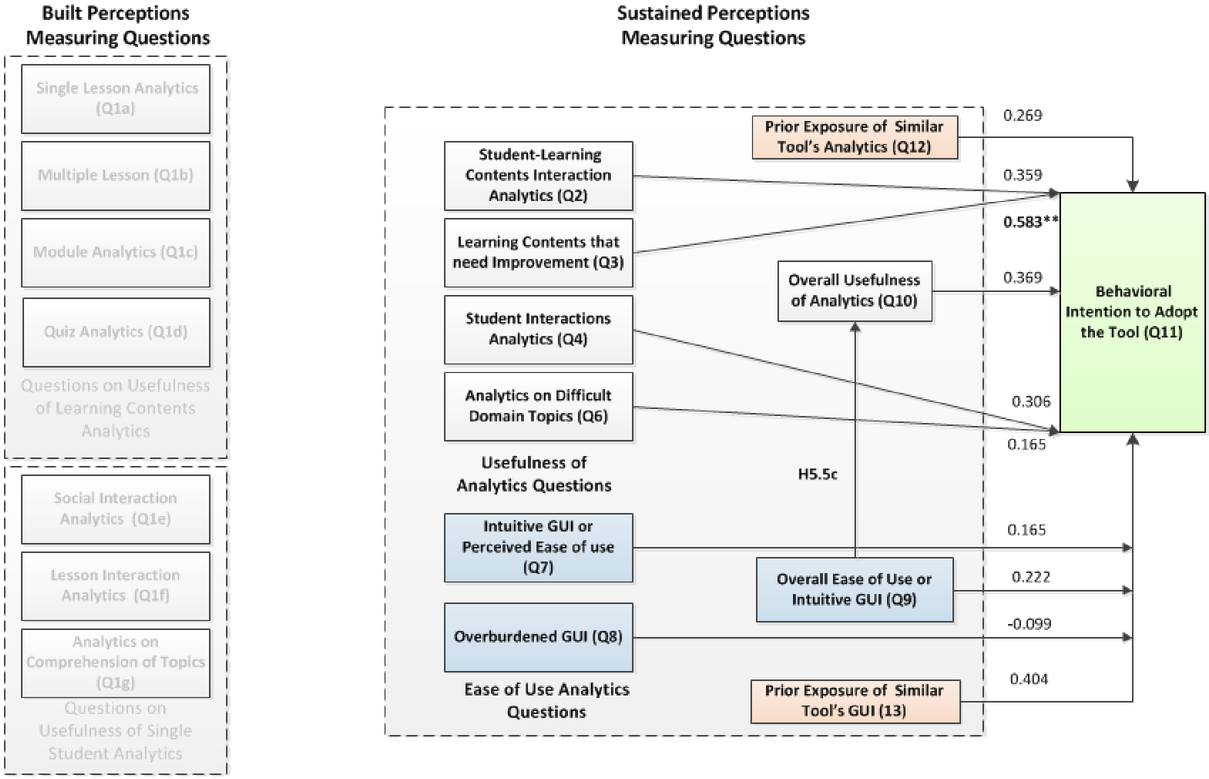

Figure 7. The LAAM model showing Pearson's correlations for association between post assessment items and overall usefulness as well as Behavioral Intention to Adopt the Tool.

These results suggest that during the evaluation of learning analytics systems, the evaluators' pedagogical role is a significant factor that influences their decision to adopt the tool for their online courses. Previous studies, as mentioned earlier, have suggested that the decisions to adopt technology-based systems are influenced by the perceived utility of such systems. Our study suggests that all the educators might have positive usage beliefs about the utility of a learning analytics system, but the ones who are engaged in online teaching courses are better placed to internalize the perceived utilities of the tool faster than those who are not. The online instructors are, thus, more likely to make up their mind during the evaluations to adopt the tool for their practice.

4.4 Identification of Additional Variables Influencing LOCO-Analyst's Perceived Usefulness (RQ4)

Aiming to identify additional variables that influence users' perceptions of the usefulness of a learning analytics tool and the intuitiveness of its GUI, we performed a Pearson's correlation analysis. We examined the significant correlations between the questionnaire items, and explored the kinds of relations between those items. The final objective was to identify the variables that we should act upon in order to improve our tool in general, and its GUI, in particular. We have listed correlations that we identified as strong (0.8~1) or moderate (0.6~0.8) in Table 6. In the following paragraphs we discuss the correlations that we identified as significant.

Table 6. The correlation between variables where correlation coefficient is higher than .6 and p < .05.

First Question (Variable)	Second Question (Variable)	ρ-coefficient; p value
Q6: The tool helps me identify the domain topics the students were having difficulties with	Q1a: Feedback about individual lesson	0.66; < 0.01
	Q1b: Feedback about a group of (related) lessons	0.71; < 0.01
Q7: LOCO-Analyst's GUI (Graphical User Interface) is intuitive enough	Q1e: Feedback about the student's activities in discussion forums and chat rooms	0.60; < 0.01
	Q2: The tool enables me to get an insight into the students' interactions with the learning content	0.61; < 0.01
Q13: LOCO-Analyst is more intuitive than the other tools capable of feedback provisioning I have used/tried	Q12: LOCO-Analyst provides me with more useful feedback than other similar tool(s) I have used/tried	0.65; < 0.01
Q9: My general opinion about the GUI	Q1a: Feedback about individual lesson	0.81; < 0.01
	Q1b: Feedback about a group of (related) lessons	0.66; < 0.01
	Q1c: Feedback about a learning module as a whole	0.69; < 0.01
	Q1g: Feedback about the student's comprehension of the studied topics (based on his/her annotations)	0.72; < 0.01
	Q2: The tool enables me to get an insight into the students' interactions with the learning content	0.64; < 0.01
	Q6: Helps me identify the domain topics the students were having difficulties with.	0.65; < 0.01
Q10: All in all, I found LOCO-Analyst a handy tool for feedback provisioning	Q1a: Feedback about individual lesson	0.65; < 0.01
	Q1b: Feedback about a group of (related) lessons	0.68; < 0.01
	Q1d: Feedback about students' performance on a quiz	0.68; < 0.01
	Q2: The tool enables me to get an insight into the students' interactions with the learning content	0.69; < 0.01
	Q4: Provides relevant information regarding the students' interactions within the online learning environment	0.71; < 0.01
	Q6: Help me identify the domain topics the students were having difficulties with.	0.79; < 0.01
	Q7: LOCO-Analyst's GUI (Graphical User Interface) is intuitive enough	0.72; < 0.01
	Q9: My general opinion about the GUI	0.76; < 0.01
Q11: I would like to be able to use LOCO-Analyst in my teaching practice	Q3: The information helps me identify what needs to be improved in the learning content	0.77; < 0.01

Q6 - Q1a, Q1b: This correlation was something that we have expected, that is, what we aimed to achieve. Specifically, the tool's feedback about lessons, both individual (Q1a) and composite (Q1b), was designed with the goal of providing educators with information about the course topics that are difficult for the students (Q6) and thus require the educator's attention.

Q7 - Q1e, Q2: This correlation could be explained by the fact that the feedback about students' activities in forums and chat rooms (Q1e) as well as about their interaction with the course content (Q2) is presented with lots of visual elements (charts and graphs, as those show on Figures A1 and A2). We believe that those visualizations (some of them interactive) have contributed to the intuitiveness of the user interface. This is an important observation for the further development of learning analytics tools in general, as it indicates the importance of information visualization for facilitating the comprehension of learning analytics by the end users.

Q13 - Q12: The implication of this correlation – the way the learning analytics are presented (Q13) significantly influences how their usefulness is perceived by the end users (Q12) – is directly related to the previous one. It further intensifies the importance of intuitive interfaces for the perceived value and thus acceptance of a learning analytics tool.

Q11 – Q3: This correlation implies that users would appreciate tools that could provide them with some hints/suggestions on how to improve their courses (besides pointing out the problems). However, LOCO-Analyst was designed as a problem detection tool, not problem solving tool. Accordingly, in its present state, it is capable of indicating potential problems to the user, but is not able to suggest how to resolve those problems. We have already started exploring potential approaches (e.g., using libraries of problem-solution patterns) to extend LOCO-Analyst with the features that would facilitate the user's task of solving the identified problems.

5 RELATED WORK

5.1 Empirical Studies of Educator-directed Learning Tools

Research efforts oriented towards educators and the learning analytics they require are rather scarce, and there is even less reports on comprehensive evaluation studies aimed at assessing the developed learning analytics tools. In particular, we have found only two papers reporting on the methodology and the results of such evaluation studies. One paper by Mazza et al. (2007) reports on the evaluation of the CourseViz tool, whereas the other, by Kosba et al. (2007) presents the evaluation study of the *Teacher ADVisor* (TADV) (Kosba et al., 2005).

The objective of the evaluation study reported in (Mazza et al., 2007) was to assess: (1) effectiveness of the CourseViz tool – i.e., whether it helps instructors to gain some understanding of what is happening in distance classes or not; (2) efficiency of the tool – i.e., can instructors infer the required information quickly; (3) usefulness of the tool – i.e., to what extent the provided information is useful for the instructors. The evaluation consisted of three phases: (1) focus group: this was a kind of formative evaluation; organized as a 2h session during which the moderator presented the tool and asked the participants (five instructors) to comment on what they have seen, give suggestions, etc.; (2) an experimental study: the participants (six instructors) were divided into two groups: one group used WebCT with CourseViz, the other regular WebCT (without CourseViz); the participants were asked to perform a few tasks (each one related to one kind of feedback that CourseViz offers) and the moderator measured: the time it took them to finish each task, the tool used, the accuracy of the "solution"; (3) structured interview: performed after the experiment and based on a predefined set of questions. In terms of its design, this evaluation study was obviously more diverse and used more methods than ours, though with significantly less participants (6 vs. 22 in our study). Further, its focus was primarily on qualitative evaluation of the results, whereas we focused on deep quantitative analysis of the collected evaluation data (we have also done an extensive qualitative analysis of the results, but that is out of the scope of this paper and can be found in (Ali et al., 2012)).

The TADV framework is aimed at providing learning analytics based feedback to both teachers and students. The evaluation study reported in Kosba et al. (2007) assessed both kinds of learning analytics based feedback that TADV generates. However, as this paper is focused on the learning analytics directed to educators, we report here only on the elements of this evaluation study that targeted teacher-oriented feedback. The study participants (three instructors and 30 students) were divided into two groups: (1) the experimental group supported by the TADV feedback generation mechanisms, and (2) the control group for which feedback generation was suppressed. To assess the appropriateness of the feedback that TADV generates for instructors, the instructors participating in the study were asked to evaluate each feedback generated for them using a three-item scale: appropriate, don't know and inappropriate. The usefulness of TADV's feedback for instructors was elicited by analyzing their opinions gathered during a group interview. Similar to the study presented above, this study was also focused on qualitative analysis of the collected data. In addition, it was only partially focused on educators and the feedback directed at them, and put more emphasis on student-directed feedback.

5.2 Future Work

We conclude this section with some recent research work that we have found relevant for our future work on further enhancement of the Learning Analytics Acceptance Model.

Macfadyen & Dawson (2010) did a comprehensive analysis of usage tracking data captured by a LCMS in order to identify the students' online activities that most accurately predict their academic achievement. They identified that the total number of posted discussion messages, sent email messages, and completed assessments as three key variables affecting students' final grade. In addition, they have leveraged SNAPP tool for detection of variables influencing the development of an online learning community. We find this work highly related to our work on the learning analytics acceptance model to enhance the pedagogical value of the learning tools. We also intend to use different measures of social network analysis for examining their influence on usages beliefs and behavioral intentions of adopting a learning analytics tool.

In workplace learning settings, traditional approaches to evaluating course design and learner performance (e.g., exams) are often not applicable and despite numerous efforts, evaluation of the true impact of (online) training is still an open issue (Murray & Efendioglu, 2007). Aiming to address this problem, Macfadyen & Sorenson (2010) have developed Learner Interaction Monitoring System (LiMS) which captures fine-grained data about learners' activities within online learning environments and by analyzing those data generates a descriptive profile of a learner available for inspection to the learner him/herself and managers. This profile contains a kind of 'behavioral grade', which LiMS computes by comparing the learner's use of the training material with its expected use (as defined by the educator). LiMS is developed as a browser plug-in and as such available for any web-based learning platform. It can be customized to allow educators to inspect some specific aspects of learners' behavior or course content. We have found this work highly related to and relevant for our future work, especially as it addresses the needs of workplace learning settings that we explored within the IntelLEO (Intelligent Learning Extended Organization)[8] EU project. Unfortunately, besides the cited paper we were not able to find any more details about LiMS.

6 CONCLUSION

In this empirical study we proposed and validated a Leaning Analytics Acceptance Model for adopting an learning analytics tool based on the perceived usage beliefs of educators about the learning analytics provided in a tool. To our knowledge, there have been no previous attempts that tried to build and empirically validate theoretical models of the factors influencing the beliefs for adoption of learning analytics tools. We hope that the model contributed and empirically studied (Figures 2, 3 & 4) in this paper will help in building this understanding. The contribution of this kind is needed if the area of learning analytics wants to be proactive in providing strategies, which will motivate educators and institutions for adoption of learning analytics tools. It is our hope that the contribution of this paper can be useful for educators and institutional decision makers who need to decide which specific types of learning analytics they need to select and how their choices and context specific factors (e.g., envisioned users) might affect the potential adoption of the learning analytics tools. More importantly, it is our hope that LAAM can be an initial step towards building a theory of adoption of learning analytics tools by identifying important constructs to be measured, so that their relationships and relationships with other relevant constructs can be investigated in future studies.

This study should be considered only as an early step in the research efforts of understanding of the adoption phenomena related to learning analytics. In that light, it is important to consider some potential threats to validity of our findings. We investigated both the internal and external validity threats. For internal validity of our study, we considered the possibility of some con-founding factors affecting the study and analysis (Chin, 2001). In our experiment, the participants could have responded to the questions differently based on the following confounding factors: *difference in the educational role, experience,* and *motivation.* As reported and discussed in Section 4.2 the educators' pedagogical role did not influence their perception of certain kinds of learning analytics (e.g., analytics on learning contents), whereas it did influence the perception of other kinds of learning analytics provided by the tool (e.g., analytics on an individual student). The analysis of participants experience in working with e-learning tools did not reveal significant differences between people familiar with this kind of tools and people who were not (see Section 4.2). We excluded the motivation as a confounding factor because the participation in the study was on a voluntary basis, and none of our participants left the experiments, while a great majority responded to the optional open-ended questions, as reported in (Ali et al., 2012).

The *external validity* investigates if the obtained results can be generalized. Specifically, in our case the question is whether we can generalize our results to similar tools in the e-learning domain. Two main confounding factors are population and ecology (Chin, 2001). An important issue related to the population factor, is the fact that in our study the population was predominately composed of individuals with Computer Science or Information Systems background (21 out of 22 participants). Therefore, replicated experiments with other populations are needed to validate the general applicability of our LAAM model and results. Another important factor influencing the external validity is the learning analytics tool (LOCO-Analyst) used in this study. Replicated experiments with other emerging learning analytics tools are needed to confirm further the external validity of our findings. Moreover, such studies will likely need to further investigate, refine and extend the proposed theoretical LAAM model (Figures 2-4). We hope that the results reported in this paper (Sect. 3.4) could help in that effort. Furthermore, alternative methods (e.g., surveys inspired by (Recker et al., 2011)) could be leveraged to validate the (updated) theoretical model with much larger educator populations (several hundreds or thousands) and more advanced statistical analyses (sequential equation modeling).

In our future work, we also plan to study learning analytics that can guide educators *how* (not only *what*) to improve their course design/content, and thus, extend LAAM to investigate their impact. This will include exploration and definition of metrics that can help an educator identify whether a certain pedagogy or planned learning objectives are achieved and to what extent. In addition, we plan to experiment with the learning analytics when multiple e-learning tools are in use, which is the case in the increasingly popular Personal Learning Environments (Attwell, 2007).

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[8] http://www.intelleo.eu

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APPENDIX

OVERVIEW OF LOCO-ANALYST

LOCO-Analyst is a learning analytics tool aimed at providing educators with context-specific analytics on various aspects of the learning process that takes place in a learning environment. Learning analytics has been 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"[9].

The learning analytics provided in the LOCO-Analyst help educators to improve the content and the structure of their web-based courses. In particular, educators are provided with statistics and insights regarding: (1) the activities students perform or participate in during their interaction with the online learning environment (e.g., an LMS); (2) the usage analytics and the comprehensibility level of the learning content deployed in the online learning environment; and (3) contextualized social interactions among students (i.e., social networking) in the virtual learning environment. LOCO-Analyst, thus, generates a variety of analytics for the educators enabling them to get insights into the most relevant information for a selected object. We arranged various types of learning analytics into groups based on their context. These groups are: single lesson analytics; group of lessons analytics; module analytics; quiz analytics; discussion forums and chat analytics; interaction analytics and comprehension (Table A1). We elicited these types primarily from our 2006 study, but we incorporated the findings of other similar empirical studies as well (e.g., Mazza & Dimitrova (2003), Zinn & Scheuer (2006)).

The learning analytics in LOCO-Analyst are derived from the analysis of the user-tracking data. The analysis of data is grounded in the notion of *Learning Object Context*, whereby learners interact with learning contents by performing certain activities (e.g., reading or chatting) with a particular purpose in mind (Jovanovic et al., 2007). The purpose of Learning Object Context is twofold: i) allows for identifying and representing the context in which the (user-tracking) data was generated, and ii) facilitates the abstraction of relevant concepts from user-tracking data of various e-learning systems thus enabling the integration of data across heterogeneous systems. Using the Learning Object Context we were able to capture and contextualize trace data from different online learning systems despite differences in their formats.

As a Semantic Web tool, LOCO-Analyst is built on top of the LOCO (Learning Object Context Ontologies) framework (Jovanovic et al., 2008). The framework enables formal representation of and reasoning over the learning object context data. We used the LOCO ontologies framework to formalize the contextualized data we captured through trace logs. By grounding the generation of our learning analytics on a formalized learning object context model, we made LOCO-Analyst independent of any online learning environment. This offered us a flexibility to use LOCO-Analyst on top of any existing online learning system. Furthermore, the tool exploits semantic annotation (Popov et al., 2003) to interrelate diverse kinds of learning artifacts such as lessons, tests, and messages exchanged during online interactions.

We implemented LOCO-Analyst as an extension of Reload Content Packaging Editor[10], an open-source tool for creating courses compliant with the IMS Content Packaging[11] specification. By extending with the Reload editor, we ensured that educators could effectively use the same tool for creating e-learning courses and receiving automatically generated learning analytics about their use, which they could further use for modifying and enhancing the courses.

[9] https://tekri.athabascau.ca/analytics/
[10] http://www.reload.ac.uk/editor.html
[11] http://www.imsglobal.org/content/packaging/

Table A1. Types of Learning Analytics provided in LOCO-Analyst with their details. Figures for analytics groups G1-G4 are given in the Supplementary Material at the end of the online version of this paper.

Code	Learning Analytics Group	Main Analytics Included in the Group
G1	Single lesson	Basic statistical indicators related to the lesson 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. Fig. A4, in the Appendix, presents a screenshot of the LOCO-Analyst's main screen when these types of learning analytics are displayed to the user.
G2	Group of (related) lessons	Similar analytics as for single lesson but at a level of topically-related group of lessons (Fig. A5 in Appendix).
G3	Learning module	Same as for the previous two but on a higher generality level, referring to a learning module[1] as a whole (Fig. S6 in Appendix).
G4	Quiz performance (of a student)	Overview of quiz results, including basic statistics on difficult question, and comparison of quiz-performance in other modules (Fig. A7 in Appendix).
G5	Discussion forums and chat rooms activities (of a student)	Number of messages sent or received in forums and chat-rooms; an insight into the social network established through the students' online communications (Fig. A2).
G6	Interaction with learning content (of a student)	Visual representation of the student's engagement with the different lessons of different learning modules; one view is given in Fig. A1.
G7	Comprehension of topics (as derived from student's annotations)	Learning analytics on different kinds of annotations student used to annotate lessons with, including tags, comments, and highlights (Fig. A3).

[1]A learning module consists of a relatively independent unit of a course, which focuses on a specific subject area taught within the course (often corresponding to one chapter of the course textbook).

Jovanovic et al. (2008) provide a detailed explanation of the tool's features, its architecture and the semantic technologies it uses for providing the learning analytics. In what follows, we present the new features that were introduced in the tool.

Data visualization in LOCO-Analyst

In this paper, we have chosen to present a selected set of data visualizations due to the space limit. The selected visualizations mainly show how we presented the learning analytics about learning activities of individual students. Specifically, we present visualizations of students' interaction with learning contents and their mutual interactions in chat-rooms as shown in Figure A1 and Figure A2 respectively.

Visualization of Student's Interactions with Learning Content: The Figure A1 shows one of the visualizations of student's interactions with learning content available from the used online learning environment. The figure shows four types of student interactions based on the context of student activity i.e. forum, chats room, learning content, or annotation. LOCO-Analyst uses tabs to organize the learning analytics specific to each activity : (1) Forum tab – for students' interactions in discussion forums; (2) Chats tab – for interactions in chat rooms; (3) Learning Contents tab – for interactions with the learning content; and (4) Annotations tab– for learning analytics on the students' annotations (e.g., notes, comments, tags).

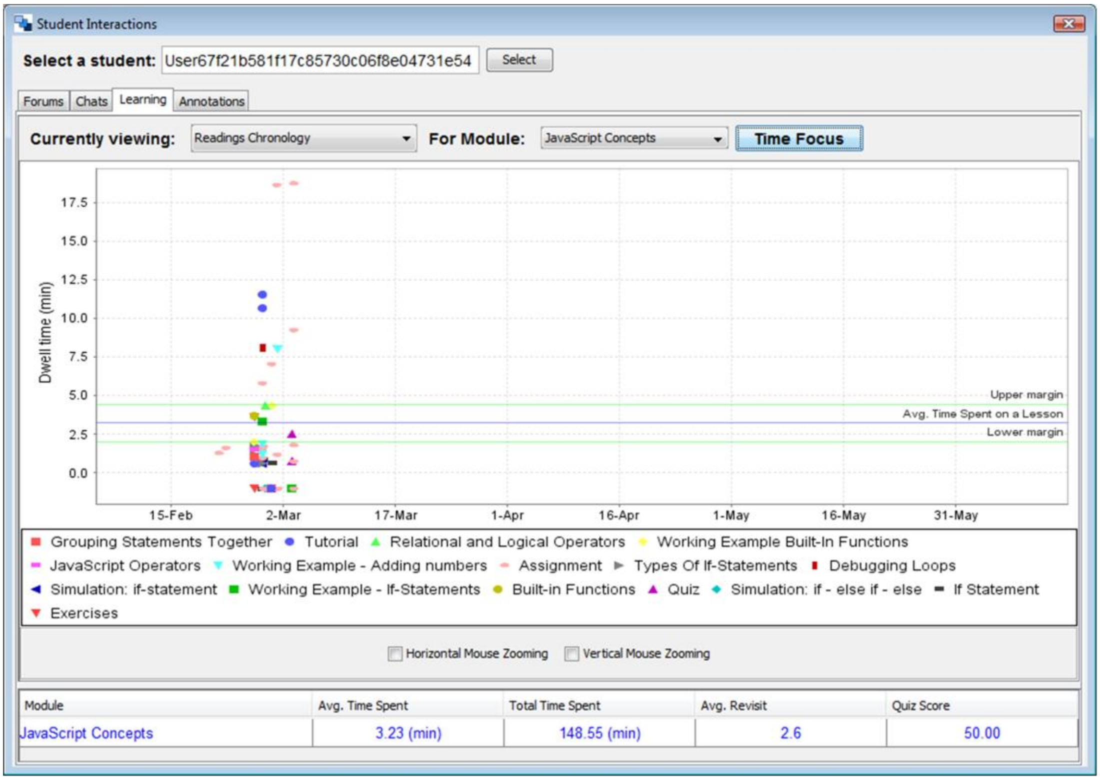

Figure A1. A screenshot showing student's interactions with the learning content (Type G6 in Table A1).

The Figure A1 specifically shows a student's interaction with the learning content, in particular, a learning module on 'JavaScript' concepts'. Colours and shapes represent different lessons in the module. The visualization is aimed at enabling educators to gain an overall impression of the student's learning behaviour – to recognize some general pattern and/or trend in his/her behaviour, and potentially some deviations from that pattern/trend.

Visualization of Chat-room Interactions of a Student: The Figure A2 shows analytics about a student's chat-room interactions with peers. The left half of the screen provides statistics about the messages exchanged by the student. For instance, the student in Figure A2 participated in one chat room only – asking for help and exchanging tips and hints. Below this table, LOCO-Analyst provides a list of frequently chatted peers or chat-mates. For each chat-mate, the list entry states the number of one-to-one chats between them, as well as the number of chats they both participated with others.

The right side of the screen displays an interactive graph to visualize the social network established through the chatting activity of the given student. The visualization highlights two associations: (1) the peers the student chatted with – coded in yellow (represents inner circle, also labelled as B in Figure A2); and (2) the peers the student did not chat with – coded in blue (represents outer circle, also labelled as C in Figure A2).

The student herself is coded in pink (a central node, labelled A in Figure A2). The graph is interactive; double-clicking on any node places it in the centre.

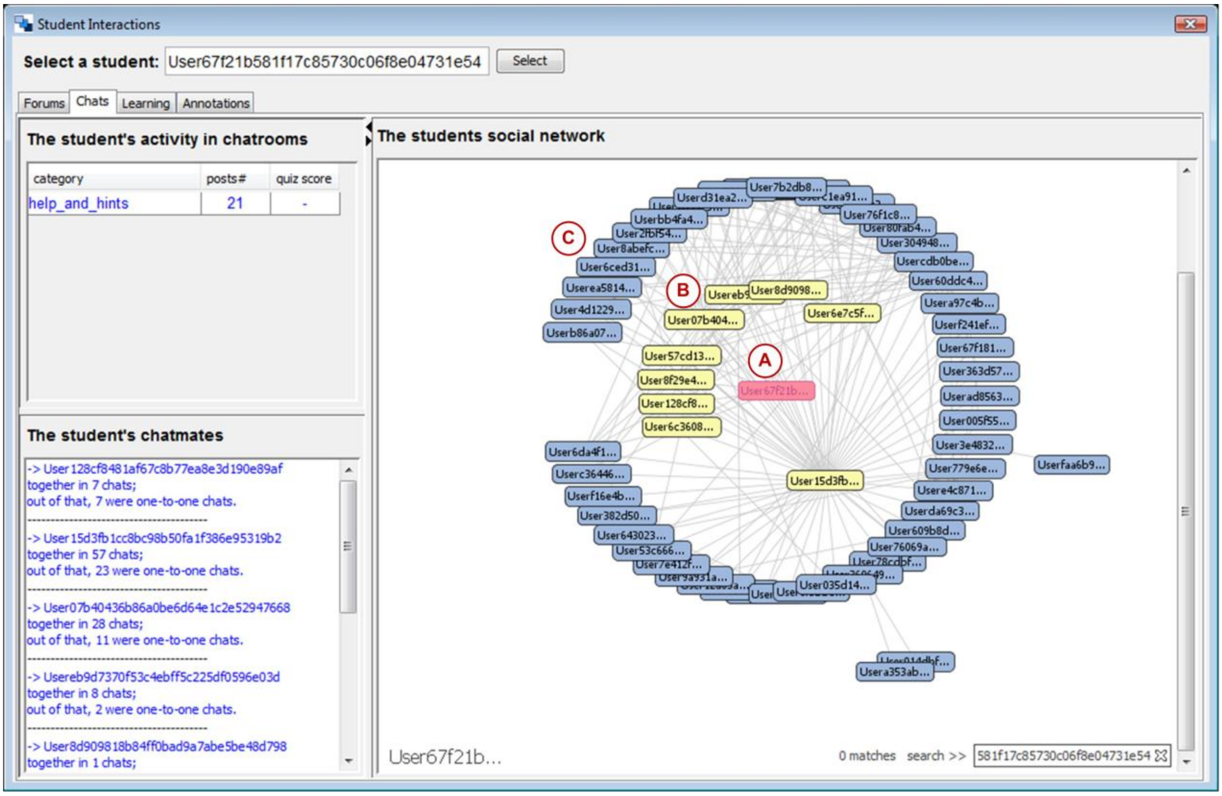

Figure A2. A screenshot showing feedback about a learner's chatting activity (part of G5 feedback listed in Table A1)

Crowd-sourced tags as a source of learning analytics

Research suggests that evaluation or encoding of information can reflect improved learning or students' better understanding of the learning content (Barnett, DiVesta, & Rogozinski, 1981; Bretzing & Kulhavey, 1981; Huffman & Spires, 1994; Rickards, Fajen, Sullivan, & Gillespie, 1997; Rinehart & Thomas, 1993; Slotte & Lonka, 1999). Based on these findings we tried to leverage students' collaborative tags (i.e., folksonomy) to estimate and report their perceived comprehension of the learning contents. To inform educators with learning analytics about students' comprehension of content based on their tags, we extended the functionalities and design of our LOCO-Analyst. In particular, we added a panel for annotations and related outcomes.

On the left side of the panel, there is a tag cloud showing all the tags students created to annotate the course content. The tags created by the current student are shown in blue and is interactive (i.e., it can be clicked on using the mouse button); tags of other students are not interactive. These are painted in grey. This allows the educator to identify to what extent the understanding of the course content by the given student overlaps with that of his/her fellow students. After an educator selects a tag by clicking it, (e.g., tag "montreal" is selected in Figure A3), the course content annotated with that tag is presented as a tree structure (upper-right part in Figure A3). The root of the tree represents the course, branches are lessons annotated with the selected tag (in Figure A3, there is just one lesson annotated with the "montreal" tag) and tree leaves are parts of the lesson content annotated with the selected tag. After the instructor selects one annotation (i.e., a tree leaf; the first one in the given example, Figure. A3 label A), the part of the lesson forming its 'context' is presented in the Annotation Preview panel (Figure A3 label B) and the student's notes related to that annotation (if available) are listed in the Notes Preview panel (Figure A3 label C).

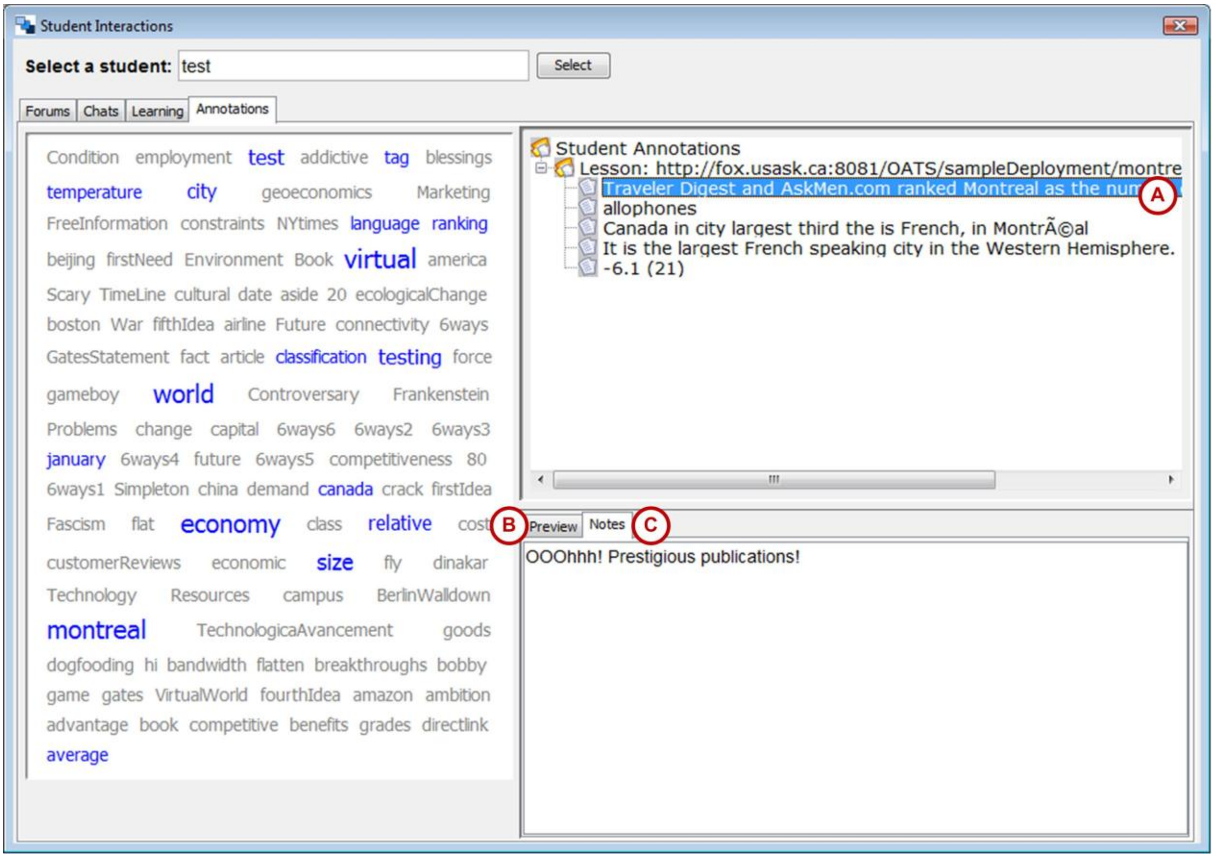

Figure A3. A screenshot showing feedback based on student's annotation of the course content (Feedback G7 in Table A1)

The supplementary material for this paper that will also be available online (if the paper gets accepted for publishing) will include the following screenshots illustrating different kinds of feedback that the LOCO-Analyst tool offers to educators. Videos that are available on the LOCO-analyst's web site[12] provide detailed insights into each kind of feedback presented below.

[12] tiny.cc/hdqmz

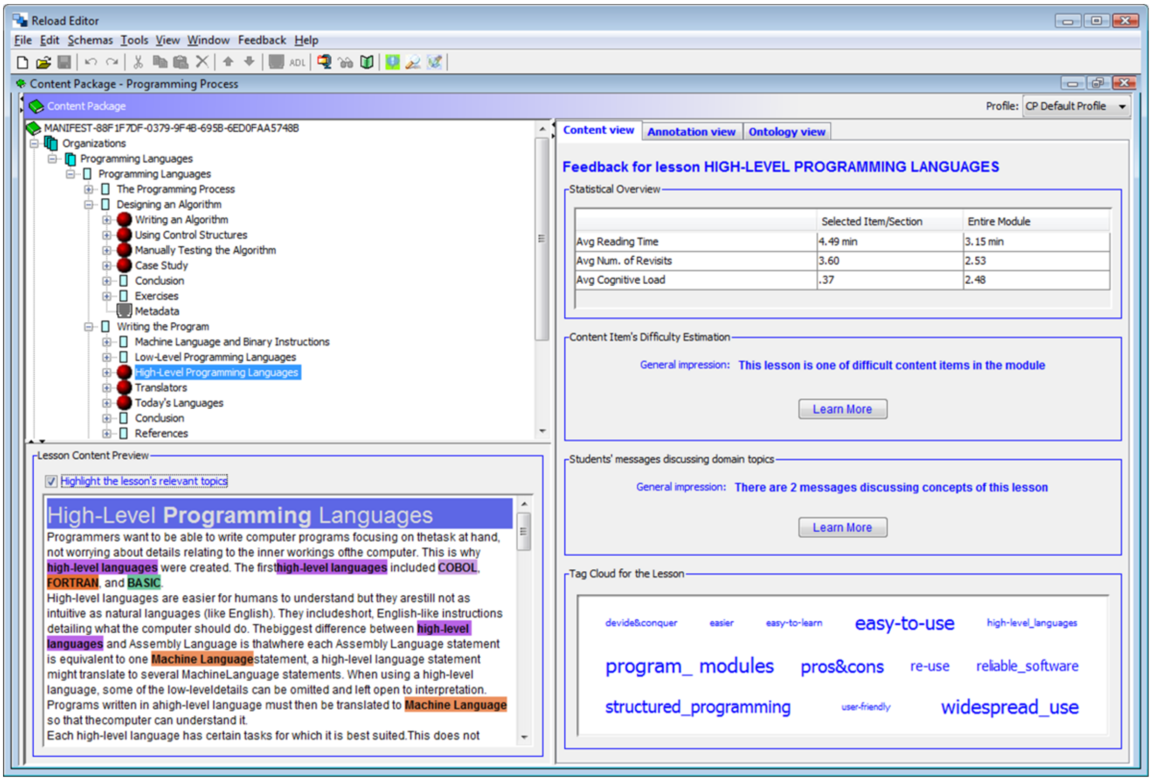

Figure A4 A screenshot presenting the learning analytics on single lesson. (Learning Analytics type G1, Table A1)

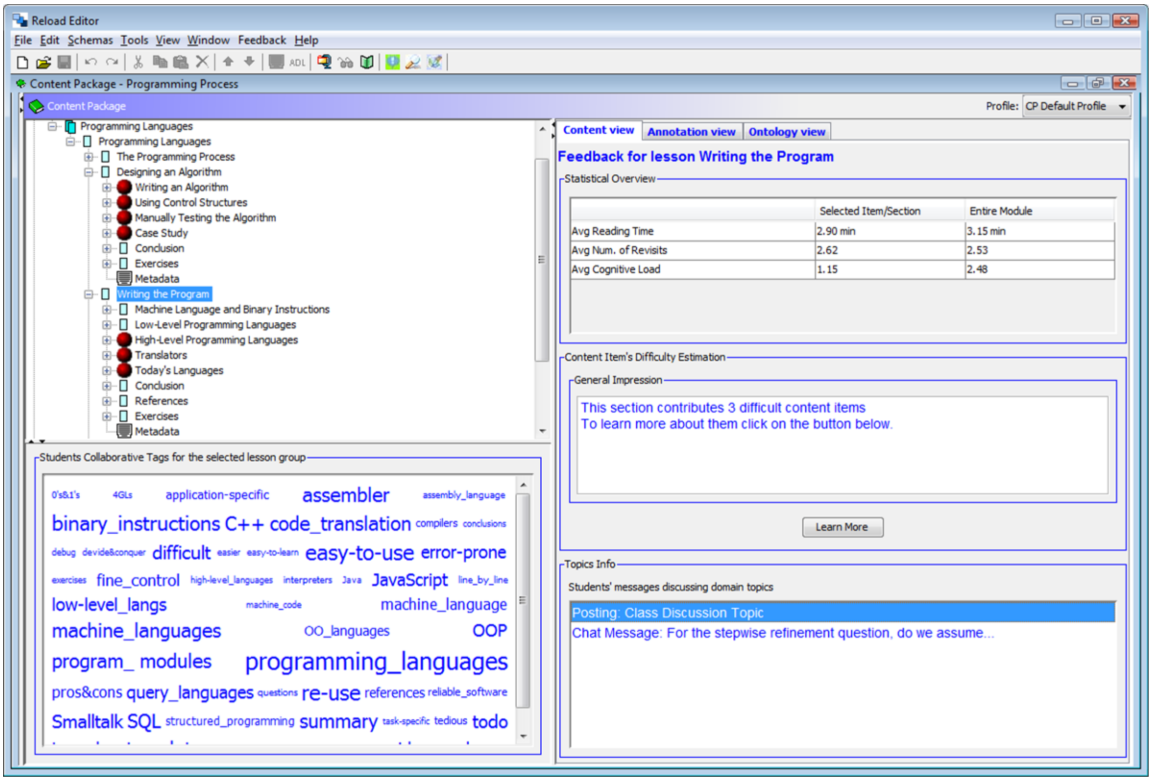

Figure A5 A screenshot presenting the learning analytics on group of related lessons. (Type G2, Table A1)

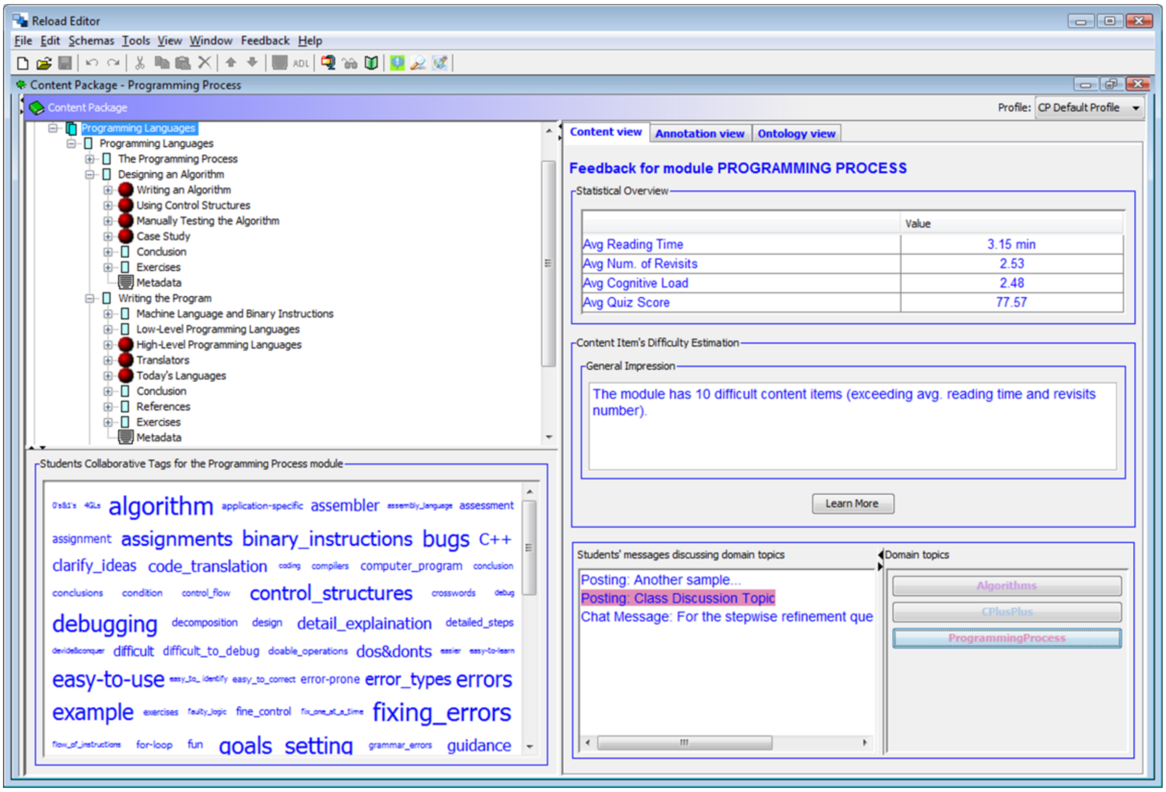

Figure A6 A screenshot presenting the feedback about a learning module of an online course (Type G3, Table A1)

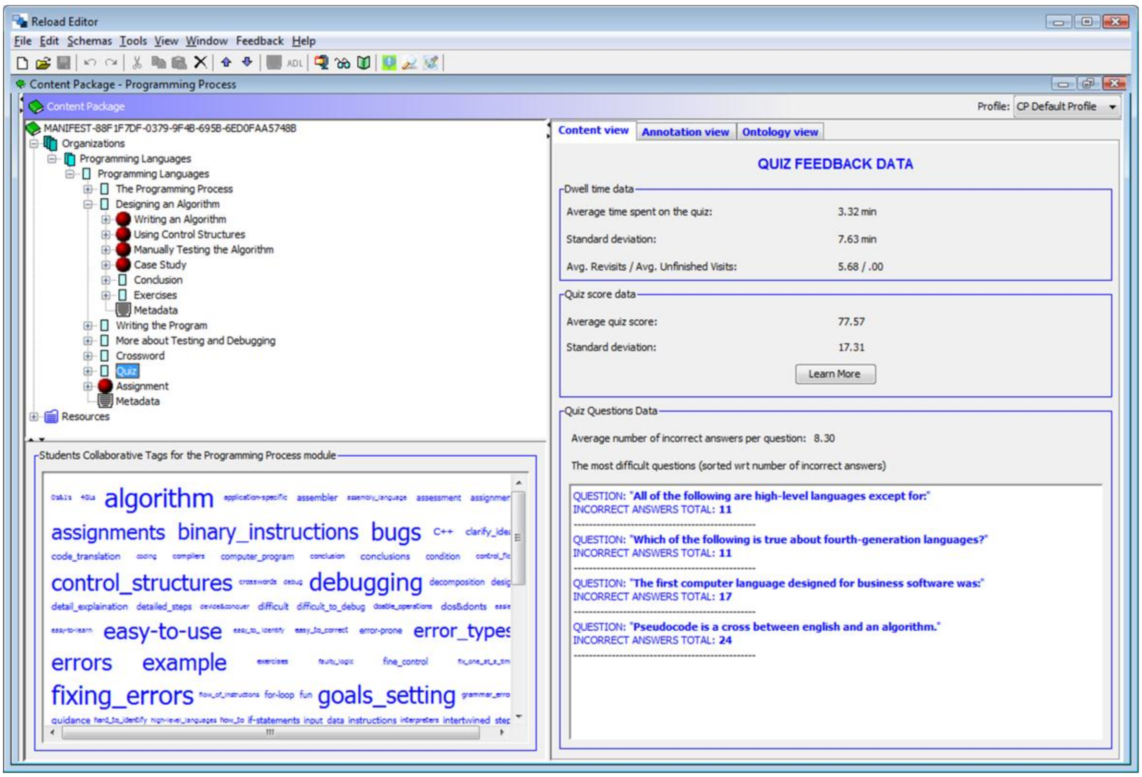

Figure A7 A screenshot presenting the feedback about students' performance on a quiz (TypeG4, Table A1)