Informing learning design with learning analytics: Can multimodal analytics improve the design of learning experiences?

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Abstract. One of the most important segments in today's development and use of e-learning systems is the adaptation of content and building of user profiles based on the learning behavior of each individual user. The data collected during learning sessions in such systems should be utilized to assist both, teachers and students. Teachers should follow the student learning progress and try to adapt the course to user's specific needs. On the other hand, students should also have access to data to self-monitor their progress and possibly adapt their learning approach. Collecting and visualizing learning analytics from different sources and channels can provide important information for analysis and adaptation of the teaching and learning processes. Besides, it is also relevant to detect the benefits that learning analytics can bring, the preferred forms of analytics, and how they affect and complement one another. Therefore, the focus of our research is to investigate the benefits of learning analytics and their influence on the design of adaptive learning environments. The gathered data will be used to further develop the analytics and adaptive component of an existing programming tutoring system.

Keywords: Learning analytics, learning design, multimodality.

1 Introduction

Educators and learning researchers engage in designing positive learning experiences and maximization of skills and competences students need to gain. The enhancements that educators want to introduce in the learning ecosystems nowadays replace the traditional materials and practices with technology-based learning systems.

The learning ecosystem and the learning as a process are of complex nature, and both require technological approach to be understand holistically. Past research has emphasized that learning analytics attempts to understand learning in its full complexity [1], but educators have been focused mostly on metrics such as performance and assessment. For example, one of the most known and practiced learning analytics in Technology-Enhanced Learning (TEL) is collecting and analyzing historical and current user activity data from e-learning systems, and study students' learning paths (i.e. trajectories) [2, 3]. Hence, the question that arises is *whether user activity data from learning systems can be utilized to inform educators and students about the learning dynamics and learners' progress?*

Majority of the studies analyzed in a systematic review study [4] revealed that learning and learner's behavior are influenced from the structure and the context of the learning environment as learners interact with its elements and try to make sense of it. Therefore, the aim of this study is to enhance existing learning environments with analytic tools and adaptive capabilities in order to facilitate greater understanding of the learning processes, needs and behaviors of the students. In order for learning systems to utilize data for making decisions, assisting students, or mimicking teachers, several adaptive capabilities need to be developed. The main focus of the study is to investigate *how user activity data can be utilized via learning analytics and adaptive capabilities in the context of Programming Tutoring System (ProTuS) to support students and teachers.* To do so, the authors present the context of the study alongside with the proposed research design and the visual analytics capabilities of ProTuS.

2 Related work

In the academic context, e-learning tools should provide not only the basic learning functionalities (e.g. presentation of learning material, testing, etc.), but also additional capabilities related to other academic goals such as continuous assessment, tracking student progress, personalization and adaptive features [5]. Moreover, e-learning tools should also provide various reports about the student's knowledge state (e.g. lectures learned, fulfillment of learning objectives, scores on assignments and quizzes, etc.) [6]. These reports might be used by students, to increase their awareness and understanding of their learning progress, but also by teachers, to collect data how students learn and when learning takes place. If teachers have rich data that shows student's misconceptions and lack of understanding, they could make informed interventions to accommodate user specific needs and behaviors. On the other hand, making the data from the learner model available to the students for exploration and interaction, presents an approach called "*Open learner modelling*". This approach is known for its ability to increase student engagement, motivation, and knowledge reflection [7].

Different approaches for student modelling and learning analytics have been investigated and used to build new frameworks and models [6, 8–11]. As a result, most of the studies agree that with a simple open learning model, the performance of the students becomes significantly better than the students who hadn't been provided an access to their models [1, 4, 7]. The analysis of how tools for learning analytics are used and the features they provide was presented in [12]. The authors showed that these tools can provide the teacher with important information about the learning process for every single learner and how, if possible, their learning experience can be improved.

Different research showed that open learner model and learning analytics dashboards have a positive effect on students' problem solving and meta-cognitive skills [8, 10, 13]. Moreover, most of the existing studies are the result of data collection from a single source, whether that is a single e-learning tool or specific research method. Therefore, considering the inherently blended nature of the learning, the authors propose a study with which they will go one step further and use several tools and learning analytics methods to collect data. In this study, the authors plan to leverage the benefits each data source can bring, and provide guidelines for integration of heterogeneous data and multimodal interaction.

3 Context of the Study

The study will take place at the Norwegian University of Science and Technology (NTNU) with students enrolled in the Web Technologies course. Approximately 300 first year undergraduate students will take part in the experiment. The students will be encouraged to use education material and learning analytics features of several educational tools (i.e. ProTuS, Kahoot, Blackboard) and already prepared video lectures.

The aim of the study is to harmonize and integrate data coming from different sources, in order to better understand how students' use, interact and learn if they have several educational tools at hand. The focus will be on the learning dimension and the various learning analytics to discover important learning phenomena (e.g., moment of learning or misconception), to get better understanding of learner's characteristics and needs, and understand the features that make learning more effective [14]. In other words, the authors would like to monitor students' skills development and evaluate their engagement in real-life settings over an extended period of time, while enriching the existing data. Moreover, the outcomes from this research will be used to extend ProTuS by implementing new visual analytics components.

Table 1. Data collection

Subjects	Data collection instruments	Data	Measures	Data extraction
Students; Teaching assistants; Teacher	Pre-post knowledge test; Quizzes (Kahoot); Pre-post attitude surveys; Observations; Focus group; Blackboard/ProTuS logs; Eye-tracking	Scores; Behaviors; Attitudes; Prior experience; Interaction; Notes;	Grade; Performance; Reactions; Expertise; Saccade	Satisfaction; Motivation; Preferences; Progress; Attention; Cognitive load

The study will be mainly covering the post-positivism paradigm, as quantitative data will be the most convenient data to collect from the e-learning systems (i.e. Blackboard and ProTuS), Kahoot and the embedded videos. Data, such as click-streams, assignment submissions, scores, etc. will be collected throughout the semester. The authors are not excluding the opportunity to carry out an eye-tracking study. Eye-tracking is considered as an objective technique that can provide insights into many aspects of human cognitive abilities, such as problem solving, reasoning, and mental strategies. Furthermore, students will receive pre-post attitudinal surveys so that the authors can get a general understanding of their attitude towards the design and the context of the course, as well as the various functionalities of the different e-learning systems. Although quantitative data is more convenient to collect and readily available as a machine-readable data, the authors will also conduct interviews with groups of students, arrange few focus group sessions, and carry out observations for student interaction and collaboration using Kahoot and ProTuS. Table 1 summarize the data collection instruments and expected information outcomes.

Next, the data will be analyzed and interpreted for the purpose of generating or answering hypothesis. The data will be coded (i.e. converting into numeric format) and prepared for analysis using statistical software (e.g., SPSS, R). For qualitative analysis, the researchers plan to code the data in an inductive or deductive manner, in order to extract design improvements for ProTuS or the teaching approach. Depending on the type of data collected, the data analysis techniques used will be quantitative (e.g. regression) or qualitative (e.g. content analysis). Because learning phenomena are complex and uncertain, the authors believe that multi-method approach will be more suitable, due to the leverage of the strengths of each research method. Thus, the data will be triangulated to facilitate data validation through cross verification from two or more sources to overcome research biases. Table 2 presents indicative data analyses methods (subject to the distribution/quality of the collected data).

Table 2. Data analysis

Subjects	Analysis	Measures	Variables	Example
Students; Teaching assistants; Teacher	Univariate analysis (frequency distribution, central tendency and dispersion); Bivariate analysis (correlation); Multiple linear regression	Grade; Performance; Reactions; Expertise; Saccade	Independent = gender, GPA; Dependent = task completion	How well do gender and grade point average (GPA) predict time spent on completing a task?

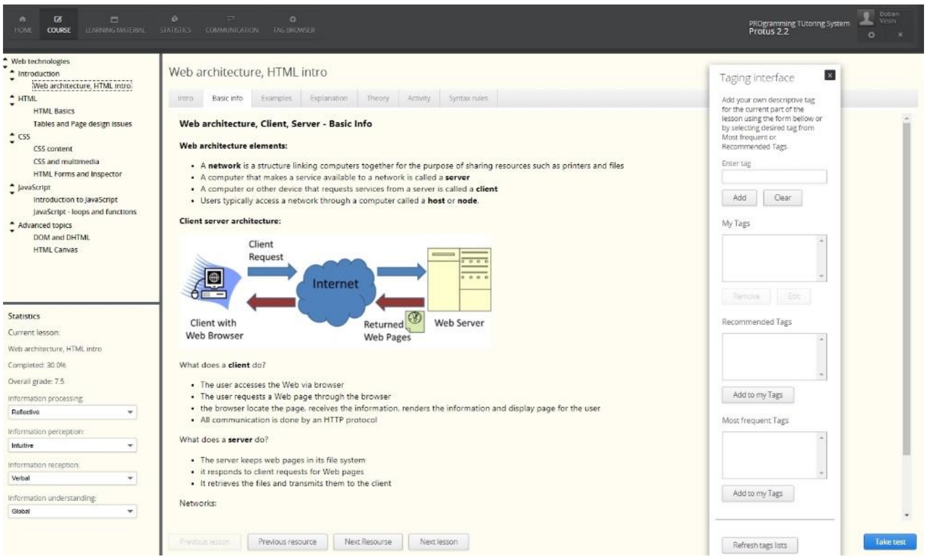

Fig. 1. ProTuS – Programming tutoring system

4 ProTuS

ProTuS is a tutoring system designed to provide learners with personalized courses from various domains [15]. It is an interactive system that allows learners to use teaching material prepared for different courses and conduct formative assessment for each lecture (see Figure 1 previous page) [16]. ProTuS tracks and records every action of the learner, which material he/she visits, which option chooses and how much time learner use for specific activities. Based on the gathered data, ProTuS provides basic reports about students' actions, progress and test results within its *Statistics* component.

The goal of the research is the development of visual learning analytics capabilities within *Statistics* component. Needs and preferences of students for specific reports and visualization options will be investigated and implemented. The component will indicate how student progress through education material, track results of automated assessment and provide visual reporting based on the gathered data (Figure 2).

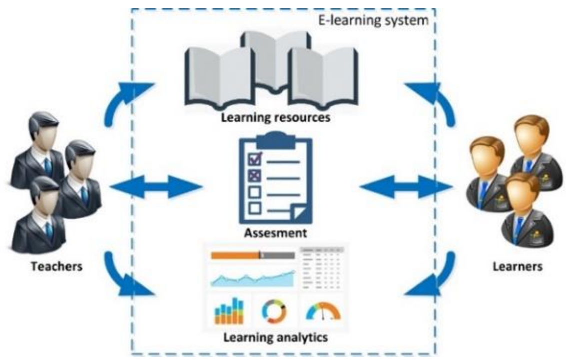

Fig. 2. Visual analytics cycle in ProTuS

5 Conclusion

Collecting and visualizing learning analytics from different sources and channels could provide important information for improvements in the design process. If suitable and efficient student monitoring routines are incorporated into an e-learning environment, the undertaken analysis could provide a teacher with important information of how learners interact within the system, and how to potentially improve their experience as users. Collected data can also be used to investigate which reasoning skills students lack and which concepts students have difficulties to grasp. On the other side, the generated analytics could also help students to engage in self-reflection and self-monitoring of their own performance and progress, and seek solutions accordingly. Finally, this study should offer a different perspective to the researchers in TEL by providing information on student learning not just in competencies and skills, but also in terms of attitude change, learning habits and learning gain.

Acknowledgements. This work was supported by the Research Council of Norway under the project FUTURE LEARNING (255129/H20).

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