Integrating Learning Analytics Frameworks into the Teacher Dashboard

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Introduction

Learning analytics refers to the "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" (Long & Siemens, 2011, p. 34). As learners interact within the virtual learning environment, it provides tremendous opportunities to extract information on learners' behaviors and performances (Ferguson, 2012). Over recent years, learning analytics research has been done to enhance learning management systems to maximize efficiency, thus learning analytics dashboards (LADs) have attracted the attention of education researchers and developers. LAD is a tool that gathers, analyzes, and reports information on multiple dimensions including data that track computer-mediated user activity, such as time spent and resource use, student learning artifacts, such as learners' posts, learning assessments such as quizzes, and social interaction and collaborations (Arnold & Pistili, 2012; Bodily & Verbert, 2017). It is characterized as a visual display of the necessary information collected from students' learning activities. Information is consolidated and arranged on a single screen, so users can monitor at a glance (Few, 2006). In this way, it provides teachers with a direct understanding of student performances and teachers were able to keep track of student performance, manage activities, and give feedback in a more efficient way (Park & Jo, 2015; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013; Verbert, Govaerts, Duval, Santos, Van Assche, & Klerkx, 2014)

Literature Review

Studies on LADs have been conducted in online learning environments and investigated different LADs and their effects on student cognition, self-regulated learning, and self-efficacy (Corrin & de Barba, 2014; Park & Jo, 2015). Corrin and de Barba (2014), for example, have found students have mentioned how the feedback from the LAD is related to self-regulation and goals. The result contributed to the finding that it has influenced student motivation towards the subject and provide them with guidance in the process. Similarly, Park and Jo (2015) has conducted an experimental study with students and made a survey on students' perceived usefulness, conformity, level of understanding of graphics, and their behavioral changes. The result showed that students' satisfaction in the LAD correlates with their degree of understanding and behavioral change.

Some studies are conducted from the teachers' perspective. The dashboard provides these instructors an opportunity to check students' progress, manage learning activities, and provide necessary feedback. Applying learning analytics dashboards helps teachers to gain access to student data in a real-time manner, thus enabling them to give more effective feedbacks or make instructional decisions. Studies on designing LADs for teachers through learning analytics frameworks, however, are pretty limited, especially considering it potential instructional benefits for educational practices. As identified by Sedrakyan, Malmberg, Verbert, Järvelä and Kirschner (in press), many studies on educational dashboards lacks theoretical support as an evidence-based foundation for building the tool so that it can assess the needs of learners and teachers. Recent research on the use of learner data found that the field needs frameworks and guides to deploy educational initiatives effectively (Gašević, Dawson, & Siemens, 2015).

Methodology

The study intends to investigate and build frameworks in order to design and integrate LADs that assist teachers to set pedagogical objectives and make instructional decisions. As LADs are becoming popular in recent years, teachers need to know how to interpret hidden meanings from the data and adjust their instructions accordingly with the help of the tool. Therefore, there are still questions about what is the "right" information to be presented and how they should be displayed (Schwendimann et al., 2017). Integrating learning analytics frameworks would enable researchers and educators to model LADs and apply it to create an effective learning environment. In this particular case, teachers will be using a LAD designed for them in a media-enhanced environment for sixth-grade space science. In the serious game, students use different kinds of tools and apply their knowledge of space and science to solve an open-ended scientific inquiry. As the problem-solving procedure produces rich learner data to explore, learning analytics would enable instructors to gain insights into the learning process in the game and to help people to improve their skills and performance (Loh, Sheng, & Ifenthaler, 2015).

Theoretical Framework

Through the review of previous literature, there are several studies conducted to build and renovate frameworks for understanding and implementing learning analytics in educational practices. These frameworks reveal several important dimensions of learning analytics that help researchers to integrate LADs in a real learning environment. The table below presents critical dimensions and values and illustrates the process from translating raw data into meaningful interpretation for teachers, as well as the stakeholders involved in the process and the overall objectives of the LAD (Table 1).

Table 1

Framework Generated from Previous Studies

Dimension	Values
Stakeholders	Students: data subjects Instructors: data users
Objectives	Reflection: identify student behaviors on activities, analyze performances, identify problems and things need to be changed, provide timely feedback Prediction: Identify problems from students and provide timely scaffolds and feedback
Data	
Learner Profiles	Demographic information, including gender, age, and education history
Learner checkpoints (learning events)	Relevant access to resources and time and location of access, including learner logins and time spent on content, and submission of answers

Learning process (learning tasks)	Usage information on learner behaviors and presence, such as attempts to use hints, notes taken in activities, and interactions in group works
Instruments	Techniques and theories to analyze data collected
Pedagogical strategies	Problem-based learning, student-centered learning, etc
Techniques	Statistics, regression analysis, clustering, etc
Presentation	Data visualization

In a broader perspective, it would be crucial to identify the stakeholders, objectives, data, and instruments in order to integrate LADs as a learning analytics tool (Greller & Drachsler, 2012). In this sense, stakeholders include instructors who will be acting upon the results provided and learners who are subjects that provide the data through their interactive behaviors. As identified by Aljohani et al. (in press), instructor level is the foundation of LADs and the aim is to provide instructors valuable information and the freedom to choose the tools that they want to use for their teaching. Since teachers will be the users of the LAD, the tool should be able to address and be based on instructors' course objectives, teaching strategies, and assessment methods.

The objectives refer to the fundamental goals of LA such as reflection, which refers to the self-evaluation of data users in order to gain deeper understandings and prediction that can be used to model learner activities. For teachers, reflection with the help from LAD would be extremely beneficial if they are able to reflect upon their strategies and styles through the examination of datasets of students, thus adjusting their pedagogical strategies in a meaningful way (Greller & Drachsler, 2012). Predictions made through the analysis also enables teachers to identify problems in the class and provide in-time assistance to students when necessary (Greller & Drachsler, 2012; Macfadyen & Dawson, 2010).

In the meantime, LAD enables researchers and educators to generate educational datasets from the system and use them in a learner-oriented way to achieve the objectives. Therefore, the instrument is also an essential dimension in the framework, as it includes different techniques and pedagogical theories to frame and analyze the particular learning context. The overview of several frameworks by Elias (2011) conducted the critical steps of these processes: gathering data, aggregating data, displaying data, and refining the learning system. Started from raw learner data from the system, instruments such as data mining techniques and strategies help to transform these unstructured data to understandable information to the users (Elias, 2011; Greller & Drachsler, 2012). These processes reveal the importance to design LADs through various techniques, including classical statistical analysis, data mining techniques, and social network analysis (Aljohani et al., in press). LADs also provide opportunities for data visualization, regression analysis, and machine learning. As a critical tool for data visualization, LADs can present a large amount of information to instructors through techniques like charts and graphics (Elias, 2011).

The last important dimension in the various types of data retrieved through the system and it represents the metrics researchers used to measure student learning activities and behaviors. For teachers, LAD provides dramatic opportunities to incorporate scaffolding to students through an analysis of online behaviors and interactions (Dawson, 2010). Hernández-Leo et al. (2018) identified the learning analytics layers that explores how data on student interactions can be used to understand their experiences. According to the study, learning analytics layers include the metrics of engagement, progression, achievement and satisfaction of learners. Data are collected through learner behaviors emerging from the learning activities and other forms of actions. There are several kinds of data classes in the learning analytics layers which include profiles, checkpoints, process, performance, satisfaction (Hernández-Leo et al, 2018). Similarly, Nguyen, Gardner, and Sheridan (2018) categorized them into learner profiles, learning events, and learning tasks. Learner profiles include static information such as demographics and data on learners past experiences (Sergis & Sampson, 2017). Learning events mainly encompasses data on relevant access to resources and tools, such as login frequency, time spent, and submission of an assignment (Lockyer, Heathcote, and Dawson, 2013). Different from learning events that generate time and location of certain so-called checkpoints, learning tasks, which is also referred to process analytics, give usage of learner behaviors and presence in learning activities (Lockyer et al., 2013; Sergis & Sampson, 2017). Checkpoint and process analytics together help to interpret learning outcomes and facilitate instructional decisions. In checkpoint analytics, the data capture if the student has reached the prerequisites by assessing relevant resources, while process analytics give insight into learner information processing and knowledge application (Elias, 2011).

The four main dimensions highlighted the process that needs to be considered when designing LADs for instructors in order to maximize the benefits of LA. On the other hands, these aspects are integrated as a whole since it characterized the dynamic process of how LA works. The design of LADs, therefore, should align with the needs of stakeholders and the objectives to be achieved. It also needs to utilize appropriate instruments, including pedagogical strategies and data mining techniques in the particular learning context with different data classes collected.

Application of the Framework

This section applied the above framework to investigate how it can support the design of LADs (Figure 1). The learning context in this case is a serious-game enhanced science class for 6-grade students. The game is situated in a 3D environment developed with Unity and students need to use different kinds of tools in the game and apply their knowledge of space and science to solve an open-ended scientific inquiry. Through the problem-solving process, students are applying their knowledge about the solar system and figuring out the solution through collaborative work. There are many similar serious games that track in-game behaviors by players in a given context and it relied on meaningful measurable variables to calculate learning outcomes (Serrano-Laguna et al., 2017).

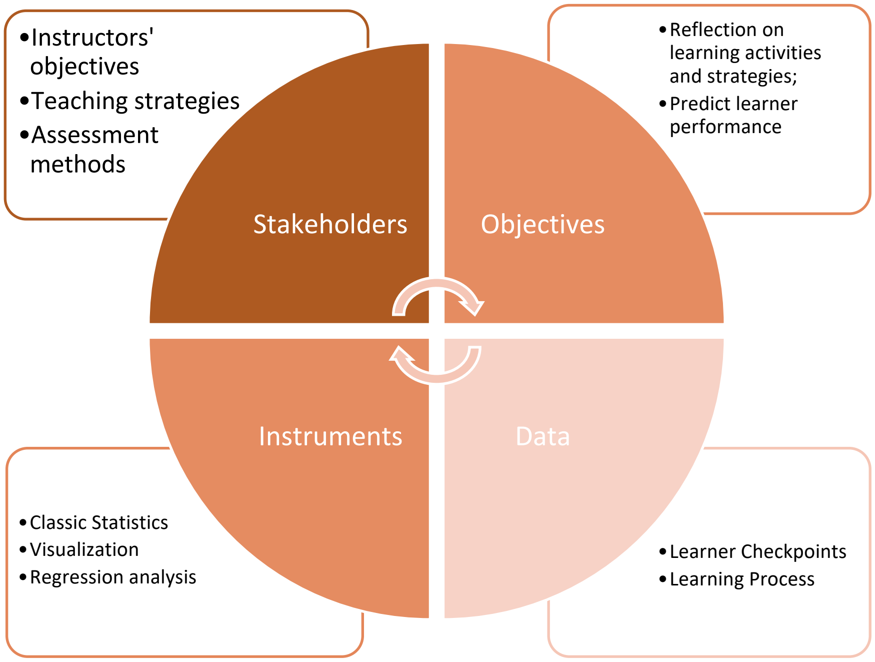

Figure 1. Example of Applying the Framework to the Dashboard

As identified in the framework, the primary step would be to discover the needs of teachers. The design and development of LADs requires need assessment, rapid prototyping, usability testing, and participatory design approach (Abel & Evans, 2013; Roberts, Howell, & Seaman, 2017). Abel and Evans (2013), for example, they used a participatory design approach through brainstorming exercises, card sorting, and rapid prototyping. Roberts et al. (2017) conducted the study on four focus groups and elicited their reactions to dashboards. General themes were generated through the interview such as “make it meaningful” and “to compare and not to compare”. They were also invited to draw a picture of their desired dashboards and results showed their preferences on numerical statistics and communication channel. When we conducted interviews with the instructors, we have identified several feedbacks that they game concerning the features. Some of them find it useful to separate students by class so they are able to identify problems within each class and some mentioned that student notes and individual usage by days are helpful for them to track their activities and identify issues throughout the process. By embedding these features into the LAD, the design will fit the needs and objectives of teachers better and effectively.

With regards to instruments and data, since dashboards are critical tools to visualize data, we applied several common methods include graphs, tables, and gauge, to present learner data. Researchers found that graphical representation of data can assist instructor to comprehend data and evaluate their own performances (Mazza & Dimitrova, 2007). Therefore, our design incorporates information including learner checkpoints (learning events), including login frequency, time spent on each tool, and submission of answers. It also includes data on the learning process, such as notes taken and justifications they provided. Besides these, it would be also helpful to track hints if they attempt to use any throughout the game and collaborative work within groups, such as allocation of tasks and roles in the team. Based on the objectives from teachers, methods including classical statistics and regression analysis can also be incorporated in the dashboard.

Conclusion

Learning analytics tools provide a promising way to improve learning experiences through their design. Based on previous literature on the various critical dimensions of learning analytics, the paper presents a framework that facilitates the design and integration of LADs in the classroom to help teachers to achieve pedagogical objectives and make instructional decisions. Well-considered designs of the tool would enable teachers to understand hidden information from learner data and make adjustments to their activities in the classroom. The framework highlighted the importance of instructors' needs, including their teaching strategies and assessment methods. The objectives of designing the LAD should be clear and deeply embedded in the dashboard so as to meet the fundamental needs of users. Among all the techniques and data classes that can be included in the dashboard, the design choice would also be made in accordance with the overall goal that intended to be achieved in the learning environment. These aspects are critical to be considered and implemented throughout the design and development process. Future research can delve into the details of each dimension and explore the deeply integrated relationship between them to better assist instructors in various specific learning environments.

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