System Architecture of Learning Analytics in Intelligent Virtual Learning Environment

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Abstract: The system architecture of learning analytics in intelligent virtual learning environment, which should observe online students while they study learning content via the Internet. The purposes of the development of this system architecture were to analyze and design learning analytics system architecture, and to propose this system architecture. Regarding the architecture design, the researcher employed the system development life cycle (SDLC) which are seven phases: planning, system analysis and requirements, system design, development, integration and testing, implementation and operation and maintenance. The researchers relied on learning analytics and intelligent virtual learning theories so that the students and instructors should acquire the effective and efficient learning from the system. The results of this research could be summarized that the system architecture consists of two stakeholders: students and instructors. In addition, there are three subsystems: data analysis, learning analytics and report management. Moreover, there are three databases to support the system i.e. user database, analytics database and report database.

Key words: Learning analytics, intelligent environment, virtual learning environment.

1. Introduction

Students today are not the same as those in the old era. They are learning in brand new environments, using tools that did not exist as short as five years ago. The reality is that there are no longer traditional or online students; students everywhere are taking courses both online and in traditional classrooms. As instructors and administrators, they have the opportunity to help students to adapt themselves to traditional courses. Hence, these students can become successful in online environments [1]. One of the hardest adjustments for students transitioning from a traditional classroom to an online environment is feeling connected to their instructor. Many times, in online courses, students use their usernames to join the class while instructors become virtual computers responding back to questions and grading projects. But, this does not have to happen with a few key tricks to creating an environment where online instructors become real. Information and Communication Technology (ICT) Web applications [2], [3] and the impact these resources are having on education are rapidly creating new challenges for instructor and learners faced with learning online. Teaching and learning in an intelligent virtual environment happens differently than in the traditional classroom and can present new challenges to instructors and learners participating

in this online learning environment [4]. There is a need in intelligent virtual learning to identify the challenges and consider best practice solutions to ensure instructors and learners' success in this new learning environment. Moreover, Learning Analytics is founded and integrates the learning environment.

This Learning Analytics (LA) is found in the research and methodologies that are related to data mining, social network analysis, visualization data, machine learning, learning sciences, psychology, semantics, artificial intelligence, e-learning, and educational theory and practice [5]. One of the most adopted definitions in the literature for LA is defined as the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs [6]. The LA is used for teaching and learning processes and it refers to the interpretation of the data produced by the students in order to assess academic progress, to predict future performance and identify potential problems [7]. In higher educational institutions, the application of LA focuses on relevant data to students and instructors, using for this purpose, analytical techniques aiming to improve the learning outcomes of students through a better learning guidance, resources and curriculum interventions [8]. LA is the third wave of development of instructional technology, as study by Fiaidhi [9]; the first wave began in 1991 with the appearing of Learning Management System (LMS) and the second wave integrating to the LMS a broader educational enterprise involving students in social networks, Web 2.0. Using LA, according to [6], the findings can improve the effectiveness of learning and its benefits which include: Customization of the learning process and content; Provision of students with information about their performance and of their colleagues and suggesting activities that address identified knowledge gaps; Provision of the instructors with information of students who need additional help, which teaching practices have more positive effects. LA exists in various organizational levels with micro, meso and macro levels where each level gives access to a different set of data and contexts. For instance, the analysis of a classroom may include social network analysis in order to assess levels of individual engagements, whereas the institutional level analysis may be concerned with improving the operational efficiency of the university or comparing performance with other universities [8].

In this study, researchers examine online learner-centered assessment and how it helps with online teaching and learning to measure the students' progress, and take corrective measures if necessary, through the lens of LA. LA focuses on the transformation of education, by changing the very nature of teaching, learning, and assessment. LA is defined by the Society for Learning Analytics Research (SOLAR) [10] 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. Learner-centered assessments shift the move from grades, marks and credits to learning, outcomes, and graduating with the skills needed as a professional. It used an application which was developed to provide instructors the opportunity to use the power of learner analytics to intervene and provide feedback to students who were not doing well in their courses. The paper proceeds as follows. The purposes where by the directions are developed. The research scope is presented. The research results are discussed, while the paper concludes with strengths and limitations of the research.

2. Research Objectives

The aims of this research were as followings:

1) To analyze and synthesize the conceptual framework for system architecture of learning analytics in intelligent virtual learning environment.
2) To design the system architecture of learning analytics in intelligent virtual learning environment.

3) To develop a proposed system architecture of learning analytics in intelligent virtual learning environment by using system development life cycle.

3. Scope of Research

This research had the research scopes as followings:

1) The samples were eleven experts teaching Information Technology, purposively selected from higher education institutes located in Bangkok, Thailand. These experts were with expertise in learning analytics, intelligent learning and virtual learning environment.
2) The tools used in this research were proposed system architecture and an evaluation form developed with a five-point Likert scale. The participants were asked to rate their level of agreement by using a scale ranging from "lowest to "highest".

4. Research Methodology

A system architecture of learning analytics in intelligent virtual learning environment, is a research and development program that consists of seven phases, which are in line with the System-Development Life Cycle (SDLC) [11]. SDLC is a multistep, iterative process, structured in a methodical way, and is used to model or provide a framework for technical and non-technical activities to deliver a quality system with meets or exceeds a business's expectations or manage decision-making progression. Following are the seven phases of SDLC.

4.1. Phase 1: Planning

The purpose of this first phase is to find out the scope of the problem and determine solutions. Resources, cost, time, benefits and other items should be considered here.

4.2. Phase 2: System Analysis and Requirements

The second phase is where the team considers the functional requirements of the project or solution. It is also where system analysis takes place or analyzes the needs of the end users to ensure the new system can meet their expectations.

It is noted [12] that the overall LA process is often an iterative cycle and is generally carried out in three major steps: 1) data collection and pre-processing, 2) analytics and action, and 3) post-processing. Data collection and pre-processing includes educational data that is the foundation of the LA process. The first step in any LA effort is to collect data from various educational environments and systems. This step is critical to the successful discovery of useful patterns from the data. The collected data may be too large and/or involve many irrelevant attributes, which call for data pre-processing (also referred to as data preparation) [13]. Data pre-processing also allows transforming the data into a suitable format that can be used as input for a particular LA method. Several data pre-processing tasks, borrowed from the data mining field, can be used in this step. These include data cleaning, data integration, data transformation, data reduction, data modeling, user and session identification, and path completion [13]-[15]. Analytics and action are based on the pre-processed data and the objective of the analytics exercise. Different LA techniques can be applied to explore the data in order to discover hidden patterns that can help to provide a more effective learning experience. The analytics step does not only include the analysis and visualization of information, but also actions on that information. Taking actions is the primary aim of the whole analytics process. These actions include monitoring, analysis, prediction, intervention, assessment, adaptation, personalization, recommendation, and reflection. Post-processing: For the continuous

improvement of the analytics exercise post-processing is fundamental. It can involve compiling new data from additional data sources, refining the data set, determining new attributes required for the new iteration, identifying new indicators/metrics, modifying the variables of analysis, or choosing a new analytics method.

4.3. Phase 3: Systems Design

The third phase describes, in detail, the necessary specifications features and operations that will satisfy the functional requirements of the proposed system which will be in place.

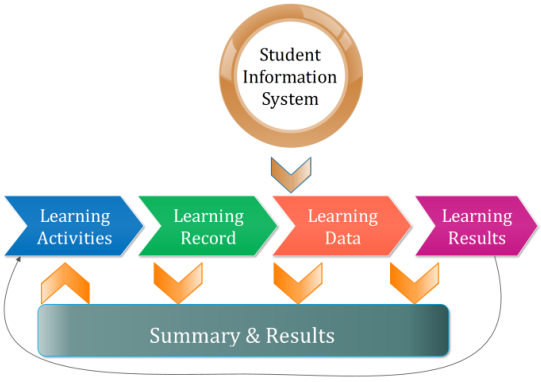

Fig. 1. Data analysis process.

Fig. 1 shows the process of evaluating data using analytical and logical reasoning to examine each component of the data provided. This form of analysis is just one of the many steps that must be completed when conducting a research experiment. Data from various sources is gathered, reviewed, and then analyzed to form some sort of finding or conclusion. There are a variety of specific data analysis method, some of which include data mining, text analytics, business intelligence, and data visualizations. The data analysis process firstly starts with learning activities that are activities designed or deployed by the instructor to bring about or create the conditions for learning. Then, learning record should allow reporting against the records, and allows for exporting of raw learning data and it keeps data into the summary and results process. Learning data retrieve data from student information enrich decisions about learning that leads to increased results for every student.

4.4. Phase 4: Development

The development phase marks the end of the initial section of the process. Additionally, this phase signifies the start of product. The development stage is also characterized by installation and change.

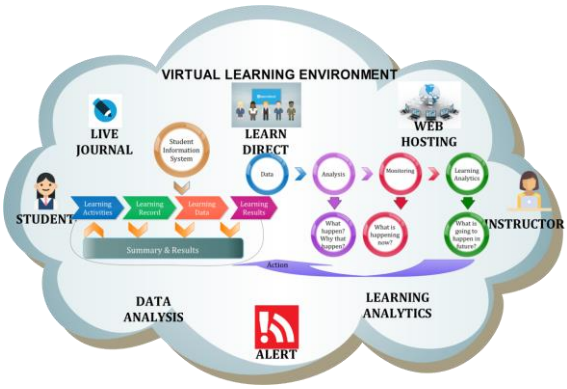

Fig. 2. Data analysis and learning analytics in virtual learning environment.

Figure 2 shows that two stakeholders i.e. students and instructors are involving in the environment. There are two important processes i.e. data analysis and learning analytics are also implementing in this environment. Four components i.e. live journal, learn direct, web hosting and alert are included.

4.5. Phase 5: Integration and Testing

This phase involves system integration and system testing of programs and procedures normally carried out by a Quality Assurance (QA) professional to determine if the proposed design meets the initial set of business goals.

4.6. Phase 6: Implementation

The sixth phase is when the majority of the code for the program is written, and when the project is put into production by moving the data and components from the old system and placing them in the new system via a direct cutover.

4.7. Phase 7: Operation and Maintenance

The last phase is when end-user can fine-tune the system, if they wish, to boost performance, add new capabilities, or meet additional user requirements.

5. Research Results

The system architecture of learning analytics in intelligent virtual learning environment could be applied to higher education and the summary results were divided into two sections as follows:

5.1. The Results of the Proposed System Architecture of Learning Analytics in Intelligent Virtual Learning Environment

The system architecture of learning analytics in intelligent virtual learning environment was proposed by the researchers for approach the technique that based on an idea of presentation conceptual system. The conceptual method used different techniques to implement this architecture. In Figure 3, it represents two stakeholders: Students and Instructors. When students connect to the learning analytics system, they should use any devices such as mouse, keyboard, and webcam. A mouse is used to move while students surf the learning content. Additionally, keyboard is used to type the keystroke in order to respond the learning content. Webcam displays the student's image through facial recognition. All types of devices from students that connect to data analysis process. This data analysis process should analyze data from students by fuzzy neural network and neural network technique. After that, it recognizes users' information to data analysis. While learning analytics process retrieved learning log, it implements JavaScript and AJAX technique in analytics database. The instructor should take an action for feedback to the student though report management after the instructor gets the personality analytics from learning analytics process. The report management should display the results of student's status to student and finally, the students should concern their learning process while instructor observed via this learning analytics system.

5.2. Results of the Suitability Evaluation on the Design of System Architecture of Learning Analytics in Intelligent Virtual Learning Environment

According to Table 1, the researchers interviewed eleven experts to acquire the most important elements that should be in the system architecture of learning analytics in intelligent virtual learning environment and the result shows that this system should be in the virtual learning environment, with learning analytics and provide report information, the average mean was 4.77 and S.D. was 0.83, respectively. The average mean for student information was 4.69 and S.D. was 0.48, respectively. The suitability evaluation on the design of system architecture of learning analytics in intelligent virtual learning environment is under ten

evaluation components. Overall suitability was rated at the high level ($\bar{x}$=4.50, S.D.= 0.72).

Table 1. The Suitability Evaluation on the Design of System Architecture of Learning Analytics in Intelligent Virtual Learning Environment under Ten Evaluation Components

Evaluated Components	Evaluation outcome		Suitability level
	$\bar{x}$	S.D.	
Virtual Learning Environment	4.77	0.83	Highest
Learning analytics	4.77	0.83	Highest
Alert	4.15	0.55	High
LMS	4.31	0.85	High
Learning records	4.15	0.55	High
Stakeholders	4.15	0.55	High
Data	4.62	0.65	Highest
Student Information	4.69	0.48	Highest
Learn Direct	4.62	0.65	Highest
Report Information	4.77	0.83	Highest
Overall Suitability	**4.50**	**0.72**	**High**

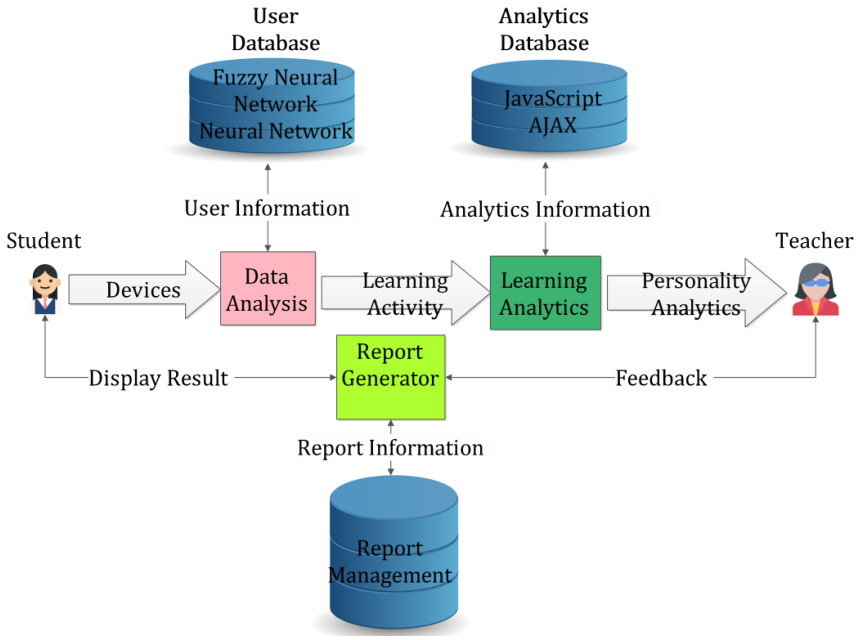

Fig. 3. System architecture of learning analytics.

6. Conclusion

The researchers designed and developed system architecture of learning analytics in intelligent virtual learning environment as a tool to support learning in students. Teaching and Learning Analytics technologies have been proposed as the means to support instructors' data-driven reflective practice. Given that these technologies are considered a top priority in educational research and innovation. The conclusion can be made as follows: 1. The system architecture consists of ten main elements, i.e. (1.1) Virtual Learning Environment (1.2) Learning analytics (1.3) Alert (1.4) LMS (1.5) Learning records (1.6) Stakeholders (1.7) Data (1.8) Student Information (1.9) Learn Direct and (1.10) Report Information. The ten main elements were further discussed in the discussion part. 2. The suitability evaluation of the quality system architecture of learning analytics in intelligent virtual learning environment under ten evaluation

components showed that the overall quality of the system architecture was rated at a high level ($\bar{x}$=4.50, S.D.=0.72).

7. Discussion

Since the findings illustrated that the system architecture consisting of ten main elements were rated at high level regarding the overall suitability, more theories and information about these elements were synthesized to gain more understanding. The synthesized information of these ten main elements as follows:

7.1. Virtual Learning Environment

Virtual Learning Environment produced a method for collecting and logging data from the virtual world of learning activities, and observed how the data could be analyzed or interpreted. This environment could be used as a tool for both individual learner, and also for giving different views into the data for teachers. According to Sclater, Berg, and Webb [16], Greller and Drachsler [17], Ifenthaler, and Widanapathirana [18], Ruipérez-Valiente [19] and Rabelo *et al*. [20], these researchers suggest that gathering data of learner actions in the virtual learning environment could provide both insight into the learning process, but also create methods to enhance or evaluate learning. Large sample sizes towards big data could aid in creations of a predictive model that could advise both the students and teachers.

7.2. Learning Analytics

Learning analytics implied that recorded user activity data could give an insight into the learning process. Sclater, Berg, and Webb [16], Greller and Drachsler [17], Ifenthaler, and Widanapathirana [18], Ruipérez-Valiente [19], Rabelo *et al*. [20] and Lepouras *et al*. [21] state that the data gathering system collected mouse click, keyboard entries by the students and the time spent in the exercise. All the events in the system were recorded with a timestamp allowing further analysis of total time of the exercise and also creating and visualizing timeline patterns of data trails created during the experiments.

7.3. Alerts

Alerts are typically displayed to students through a dashboard. Sclater, Berg, and Webb [16], Ifenthaler, and Widanapathirana [18], and Lepouras *et al*. [21] summarize that a dashboard provides a consolidated view of multiple sources of data used to deliver feedback, direct students toward resources and provide performance indicators. It can be used by students to self-regulate learning based on feedback. Feedback enables students to monitor the progress of their learning goals and if needed, adjust their strategies for achieving those. Dashboards provide students with timely, or depending on the system, real-time feedback providing students with increased opportunities for feedback compared to traditional methods such as waiting for assignment feedback.

7.4. LMS

LMS is used for generating the report. Sclater, Berg, and Webb [16], Greller and Drachsler [17], Rabelo *et al*. [20] and Lepouras *et al*. [21] suggest that the reporting capability of an LMS gives learners an insight into the effectiveness of their online training programs through the provision of reports based on real-time data, tracking learners' activity, progress, and competencies.

7.5. Learning Records

Learning records were expressed around the performance of dashboards when required to process big data. Sclater, Berg, and Webb [16], Ruipérez-Valiente [19], Rabelo *et al*. [20] and Lepouras *et al*. [21] imply that thus, they extracted, transformed and loaded to determine what data is stored in the learning

records warehouse.

7.6. Stakeholders

Stakeholders were critical roles in any learning analytics such as leadership team members, teachers, students, IT, learning innovation, implementation teams, legal, etc., but in this system architecture served for students and teachers. Sclater, Berg, and Webb [16], Greller and Drachsler [17], Ifenthaler, and Widanapathirana [18], Ruipérez-Valiente [19] and Rabelo *et al*. [20] recommend that learning analytics is not only about data, systems, and dashboards; it is also about finding factors that contribute to students' failures and successes and designing intervention strategies that work in learning context.

7.7. Data

Data collected were usually used. That data will include a variety of data points, like engagement data, time on task, activity performance and achievement. It should all be taken in the context of the learner and their specific circumstances and needs. Sclater, Berg, and Webb [16], Greller and Drachsler [17], Ifenthaler, and Widanapathirana [18], Ruipérez-Valiente [19] and Lepouras *et al*. [21] comment that data must always be interpreted within the right context. On its own it does not mean much and can easily be misinterpreted.

7.8. Student Information

Student Information was now attempting to place in the analytics driving element. It is a vital element for any educational institution. It includes data such as prior educational qualifications, ethnicity and gender, the courses and modules in which students are enrolled, records of absence and assessment results. Sclater, Berg, and Webb [16], Greller and Drachsler [17], Ifenthaler, and Widanapathirana [18] and Ruipérez-Valiente state that more sophisticated student information system can contain many other aspects of the institution's business.

7.9. Learn Direct

Learn Direct went beyond what is possible for an individual instructor to accomplish; Greller and Drachsler [17], Ifenthaler, and Widanapathirana [18], Ruipérez-Valiente [19] and Lepouras *et al*. [21] summarize that they can track learners and learning across multiple sources and, at their best, can reveal information about student learning and course improvement opportunities.

7.10. Report Information

According to Ifenthaler, and Widanapathirana [18], Ruipérez-Valiente [19], Rabelo *et al*. [20] and Lepouras *et al*. [21], report information had access to a variety of powerful and useful site-wide reports for learning analytics, including security, question instances, logs and comments.

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