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# Teacher-actionable insights in student engagement: A learning analytics taxonomy

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**Abstract:** In the emerging field of learning analytics (LA), actionable insight from LA designs tends to be a buzzword without clear understandings. Student engagement is commonly measured in LA designs and used to inform actionable insight. Moreover, in K-12 education, where the teacher is a key stakeholder, what teacher-actionable insights can be derived from LA designs? Towards providing greater clarity on this issue, we concretize a taxonomy of LA decision support for teacher-actionable insights in student engagement. Four types of decision support are conceived in this taxonomy with relevant teacher implications. Through this taxonomy, we hope to offer possible pathways for actionable insight in LA designs and make clearer the role of the teacher.

**Keywords:** Learning analytics, teacher, design, taxonomy, actionable insight

## 1. Introduction

In the field of data analytics, the term "actionable insight" often represents buzzwords without clear definitions. Recognizing this, Tan and Chan (2015) provide a three-tiered definition for actionable insights in general data analytics systems – analytic insight (understanding and inferring individual information), synergistic insight (contextualizing, combining and linking information), and prognostic insight (deriving information of future results). Similarly, in the field of education, there have been several conceptions and understandings of actionable insight. For instance, Cooper (2012, p. 4) defines actionable insight as analytics that are "concerned with the potential for practical action rather than either theoretical description or mere reporting". The report highlights that insight from learning analytics (LA) needs to provide a "level of clarity" such that a "rational person" can choose a path of action (Cooper, 2012, p. 4).

Additionally, Clow (2012, 2013) elaborated that in any LA design, there is a cyclical process of learners generating data, which is processed into metrics. This then informs interventions, and these actions affect learners. In particular, these actions can be performed by the learner, teacher, manager or policy maker (Clow, 2012).

Evident from extant literature is that the specificity of "actionable insight" in LA can be understood in several ways and from different stakeholders. Many LA designs have focused on providing interventions such as tasks and recommendations for the learner. However, comparably less attention is paid to a closely intertwined stakeholder, the teacher (Sergis & Sampson, 2017). While learner-actionable insights are important, in this paper, we examine teacher-actionable insights, especially within the K-12 education context, where the teacher more often than not plays a crucial 'make-or-break' role in the learning and teaching process (Hattie, Masters, & Birch, 2015).

In K-12 education, the role of the teacher is paramount in the learning equation. With younger learners, teachers are the learners' coach, lifeguard, instructor, technology decider, and more. This context is markedly different from Higher Education, where learners are relatively more independent of their teachers throughout the learning process, and where teachers play a more academic role. Higher education students tend to decide on their own technology and systems, as well as have access to a wide range of technologies and/or engage in online learning. On the other hand, in K-12, technology access is still an issue (Monroy, Rangel, & Whitaker, 2013; Rodríguez-Triana, Martínez-

Monés, & Villagrá-Sobrino, 2016), and blended learning is the dominant mode of learning with technology .

In a recent systematic literature review on teaching and LA (Sergis & Sampson, 2017), the research identified only 50 papers that examined the role of the teacher in the field of LA. Of these papers, only four papers (7.4% of the papers) provided concrete actionable insights for teachers. The bulk of LA designs (92.6% of the papers), provided unstructured and/or ad-hoc actionable insights for teachers. Also, many papers are exploring what types of LA are useful for teachers, and ways to provide better feedback for them. For instance, Van Leeuwen et al. (2017) details a high school teacher making sense of and responding to LA tools to offer the possibility of how LA can be used pedagogically for student learning.

What teacher-actionable insights can be derived from LA systems? Towards scoping this question, we premise the design of many LA systems in the area of engagement in learning. In the pedagogical core of learning there is an interaction between learners and the content, as well as between peer learners (Tan & Koh, 2017). Hence, student engagement is commonly measured in LA designs and used to inform actionable insight (Lu, Huang, Huang, & Yang, 2017). We posit that LA can provide teacher-actionable insights for understanding this engagement in learning. As such, we conceptualize a taxonomy of LA decision support for teacher-actionable insights in student engagement.

This taxonomy will be illustrated with examples from two prototype LA systems, My Groupwork Buddy (MGB) and the Collaborative Video Annotation and LA (CoVAA) Learning Environment. Briefly, MGB is a formative assessment tool for teamwork while CoVAA is a time-point based video annotation system.

## 2. Related work

### *2.1. Student engagement and LA*

Student engagement is associated with learning performance as well as student motivation and the reduction in school dropouts (Fredricks, Blumenfeld, & Paris, 2004; Wang & Eccles, 2012). While there are many definitions, student engagement is generally defined as a multi-dimensional construct consisting of behavior, emotion and cognition (Fredricks et al., 2004). Student engagement is commonly measured in LA through the engagement of students with the content, and with other peers in the system (Lu et al., 2017; Monroy et al., 2013; Tan & Koh, 2017; Tan, Yang, Koh, & Jonathan, 2016). Moreover, many of these sub-types of engagement are currently in LA designs.
A typical learning analytic design focuses on behavioral engagement which relies on the concept of participation (e.g., Monroy et al., 2013; Tan et al., 2016). Metrics for behavioral engagement include logins, page views, mouse clicks, time on page, task submissions, and other forms of trace data. There are also different levels of granularity for behavioral engagement metrics. A related behavioral engagement technique is social network analysis; it shows a description of connections between learners, i.e., who is talking to who.

Another level of engagement is the affective or emotional engagement. Although less common, this is also another emerging area that can be collected and detected by LA designs (e.g., Grawemeyer et al., 2016). These include emotions such as boredom and off-task behaviors, as well as positive emotions like happiness and curiosity. Past research has derived algorithms to measure off-task behavior. Sentiment analysis is also another technique that uses text and online discourse.

The third category of engagement is cognitive engagement. This deals with what the students' have learned, mastered, and understood. Many LA measure and assess students' knowledge, skills, and other learning. This can be in terms of the right answers to a quiz, the correct moves in a game, the number of attempts, a coded set of words and/or keywords in a dialogue etc. This is common in intelligent tutoring systems.

With engagement as a common backdrop in LA designs, we next describe the types of teacher-actionable insights in LA.

### 2.2. Teacher-actionable insights in LA

In the general field of analytics, drawing from many best practices of data science and system development, extant literature has conceived a continuum of analytics ranging from descriptive, diagnostic analytics, to predictive and prescriptive analytics (Gartner.com). Actionable insight can be derived from these various types of analytics. Many business solution providers advise developing predictive and prescriptive analytics, which emphasize system recommendations, in order to derive greater business value, although this is the most technologically challenging. Predictive analytics, similarly, is advocated in LA in order to provide likely future states of learners, and to design appropriate interventions to enhance learning outcomes (Clow, 2013). For instance, Lonn et al. (2012) developed a predictive model to classify students into three categories based on students' assessment grades and login activity on the Learning Management System. This provided an early warning system to allow teachers (academic advisors) to encourage students who were doing well, explore with students who could need more help, or engage with those who were possibly at-risk.

Nevertheless, descriptive analytics are still an important area for LA. To understand learning engagement, we first have to measure such descriptions of engagement. Descriptive analytics generally provide aggregations of metrics of engagement indicators, as described earlier.

As for diagnostic analytics, these are learning analytic designs that pinpoint relationships between two variables e.g., visualizations that plot effort and academic achievement (Nagy, 2016). Diagnostic analytics can also be derived from statistics and machine learning.

The primary challenge is turning data into actionable insights for teachers (Melero, Hernández-Leo, Sun, Santos, & Blat, 2015; Monroy et al., 2013; Rodríguez-Triana et al., 2016). Sergis & Sampson (Sergis & Sampson, 2017) identify and review 50 papers on teacher inquiry in LA and found that a majority of teacher actions do not provide an additional layer of decision support. For instance, they found that some designs identify different clusters of students, or a visualization of interactions of learners with teachers, without providing scripts or further structured support for teacher action. Teachers are left to their own resources and capabilities to take action.

On the other hand, the review also identified two types of teacher-actionable insights. First, Yen et al. (2015) provided explicit suggested instructions to the teacher using rule-based, pre-defined feedback templates that were informed based on data analyses. A second type of study used a script-aware monitoring process to provide actionable insight for teachers (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015). Teachers would first define key learning outcomes for students, and the LA design monitored students' progress, and provided feedback on students' progress to teachers. This feedback of the process allowed the teachers to better manage the learning process of students. These examples of actionable insights for teachers are specific recommendations to help teachers improve their teaching and learning practice.

As can be seen, there are different ways of implementing LA designs for teacher-actionable insights. The next section illustrates our proposed taxonomy.

## 3. Conceptualizing a LA taxonomy for teacher-actionable insights

Informed by extant literature, we conceptualize four types of LA decision support for teacher-actionable insights in student engagement: *descriptive, diagnostic, predictive* and *prescriptive*. The proposed taxonomy is depicted in Table 1. The second column in Table 1 describes the areas of teacher-actionable insight which is a more macro view of system feedback to the teacher. The third column highlights certain data science methodologies and techniques required while the last column provides implications of this decision support for teachers.

### 3.1. Descriptive

Descriptive analytics describes what students' activities on the system are, depicting indicators of student engagement for the teacher. It represents the foundational data structures in LA and asks, what are my students' engaged in? It describes what students' activities on the system are. For instance, in MGB, submission data (whether students have completed their teamwork reflection or not), is summarized for the teacher to easily find out who has not participated, and take appropriate action. In CoVAA, teachers are able to download a set of participation data including annotation type, critical lens tag, and comment description, which makes it convenient for them to examine and provide feedback on students' answers.

Many LA designs provide such engagement data in real-time so teachers are able to see and monitor the activities of students instantaneously. Descriptive analytics typically summarize these different engagement types (behavioral, emotional, and cognitive) for teachers using descriptive statistics in words, tables, graphs, charts and/or other visualizations and are the essentials of teacher dashboards. Still there are challenges in terms of what metrics to measure as learning designs become more sophisticated, and how best to represent them.

Teacher-actionable insight at this layer tends to directly relate to the metric or indicator measured e.g., submission data. Besides giving the teacher an aggregated understanding of the students, and/or comparison of learners, the LA engine typically does not provide further decision support for the teacher. Teacher actionable insight depends on the capacity and agency of the teacher to take action. Teachers have to make sense of the data and decide for themselves appropriate interventions (Melero et al., 2015). In that sense, descriptive analytics offers broad ranging areas of teacher-actionable insights, but also relies on the capacity of teachers to decide and perform more targeted interventions.

Table 1: A taxonomy of LA decision support for teacher-actionable insights in student engagement

| Type of LA decision support | Areas of teacher-actionable insights | Possible data science methodologies | Implications for teachers |
|---|---|---|---|
| Descriptive | What are students engaged in? What are they doing, feeling, and/or, learning? | Dashboard summaries, visualizations, descriptive statistics | Broad ranging areas of action, relies on the agency of teachers |
| Diagnostic | Why are students' engaged? | Visualizations, process mining, drill-down tools, correlations, data discovery, and data mining | More specific areas of action, but still requires teacher discernment for intervention |
| Predictive | What will students' be engaged in? Which groups of students' will be engaged? | Machine learning, regression analysis | Relieves load of teachers for certain areas of action, but could provide opportunities for teachers to look at other areas of engagement |
| Prescriptive | What can be done to engage students? | Machine learning, algorithms, predefined conditions | |

## *3.2. Diagnostic*

Diagnostic analytics tries to explain why students did what they did. Why did students engage in that manner? Why are students engaged? What patterns are there between pieces of data? This is analyzed after data is collected. Data science methodologies and techniques include visualizations, process mining, drill-down tools, correlations, data discovery, and data mining.

This LA design attempts to link relationships to explain student engagement (and all the different forms of engagement). This LA support helps teachers to pinpoint specific areas for possible interventions. Still, teachers should be discerning and decide pedagogically if they should intervene.

For both MGB and CoVAA, this layer of diagnosis is currently done in the back-end using existing statistical techniques by researchers, and shared with the teachers, as data-driven evidence for teachers to take action. In MGB, in attempting to explain why students were more cognitively engaged in teamwork, we performed a correlation and found a significant and higher association between peer-rated teamwork scores and students' goal-setting status check completion. In other words, there was a relationship between students who claimed they completed their target goals related to their teamwork behaviors, and their peer-rated teamwork dimensions. With this, one possible implication is that the teachers should ensure that students fulfil their targeted goals.

### *3.3. Predictive and prescriptive*

Predictive and prescriptive analytics are closely related. While predictive analytics provide empirical evidence of what students will be engaged in, prescriptive analytics provide recommendations to the student, reducing the immediate intervention required by the teacher. Predictive analytics provide empirical evidence of what students will be engaged in, or the groups of students who will become engaged. This layer provides teachers with foresight, what will happen based on probability estimates. Techniques include machine learning, regression analysis etc.

On the other hand, prescriptive analytics asks the question of "what can be done to engage students" and prescribes actions that the system takes on behalf of the teacher. It computes activities and responses that the system can do now based on predefined conditions, that were determined by diagnostic and predictive analyses.

Predictive analytics provides very clear and specific teacher-actionable insight. Decision support for the teacher is precise and could include filtering and identifying different clusters of students such as those potentially at risk from academic failure and dropout. It can also identify students who are potentially on an accelerated trajectory. Teachers' usage of system tools can also predict student achievement.

Prescriptive analytics then seeks to identify specific sets of activities that students can take, without the immediate intervention from the teacher.

While on one hand these two types of support may seem to reduce the need for the teacher, we posit that at the same time, this provides opportunities for teachers to go beyond the common set of responses to probe deeper into student engagement or examine new trends among their students.

Seemingly, this could help to relieve the load of teachers' direct instruction to the student, and could help the teacher to focus on other areas of student engagement that is not provided for by the system.

As such solutions require more time and testing, these analytics are part of the future work planned in MGB and CoVAA.

## 4. Discussion and Conclusion

This paper conceptualizes a taxonomy of teacher-actionable insights based on student engagement in LA designs. As can be seen in these four types of decision support, teacher-actionable insights range from broad to specific. While these types may seem to have some sort hierarchical relationship, e.g., each type being a more complex type of the other, we realize that each type could uncover engagement ranging from the superficial, simple to complex and deep. We do not offer any type as better than the other, but highlight that these are possible pathways of providing feedback to teachers, and that each pathway is important to examine student engagement. There are important teacher-actionable insights that can be highlighted for each category in the taxonomy.

In fact, the broader socio-cultural issues of teacher ownership and agency are a concern for each type. Many of these teacher-actionable insights require the teacher's capability and impetus to take action. This is echoed in many of the K-12 LA designs reported (Sergis & Sampson, 2017).

Helping teachers to discern and decide on actions to take is a process that requires the partnership of research, design and pedagogical teams.

It is hoped that this taxonomy will help learning designers, developers and teachers to consider the engagement of their learners from behavioral, affective and cognitive outcomes and the multiple pathways of LA. Moreover, this taxonomy could provide greater clarity of where their respective LA designs are at and where it could be heading towards. For instance, an LA design which is of type descriptive might want to consider building capacity and development towards predictive analytics, to provide opportunities for teachers to help students in other behavioral, affective or cognitive aspects.

An underlying assumption in this typology, is that all these types of LA need to show some measure of validity or reliability (such as its confidence level, statistical significance), and/or an acknowledgement of limitations or bias (Cooper, 2012). Especially for the descriptive level, this helps to scope decision areas for teachers, rather than overwhelm teachers with a large pool of possible indicators. It also highlights the importance of intentional LA design that makes explicit its pedagogical value (Knight, Shum, & Littleton, 2014; Koh, Shibani, Tan, & Hong, 2016; Lockyer, Heathcote, & Dawson, 2013). While the typology provides a heuristic in understanding the complexity and potential of teacher-actionable insight, these insights are in recognition of the learning design of the LA. In other words, the actionable insight should be in line with the overall learning goal and LA design.

This taxonomy is a first step towards providing a clearer framework of teacher-actionable insights in LA designs. It is based on current and international literature and trends. It also recognizes the importance of the role of the teacher, especially with regard to the K-12 context, and provides a conceptualization to map different kinds of LA designs in student engagement. Teacher-actionable insights in student engagement is a crucial area for the emerging field of LA, and in clarifying possible pathways, LA designs can be made more useful for teaching and learning.

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# Design of a Learning Analytics Dashboard Based on Digital Textbooks and Online Learning

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**Abstract:** In general, online learning provides functions such as access to video and learning materials, assessments what learners have learned, and participation in community activities. However, it is difficult to provide a learning environment that meets the achievement level or needs for each learner by providing such a function, and it is especially limited to prescribe in a proper situation. Learning analytics, which has received much attention in recent years, provides a tool to collect and analyze learning activity data. Since the process of collecting and analyzing data is generally performed in the system, the information presented by the analysis results is very important as an interface that users meet. Therefore, research on how teachers and students design intuitively to understand results and messages from data analysis bas a great implication on the place of learning analytics. This study introduces the process of designing a dashboard on users' requirements to intuitively express the collected data based on digital textbooks and online learning.

**Keywords:** Learning Analytics, Dashboard, Digital Textbook, Online Learning, Visualization

## 1. Introduction

Online learning is widely available today, catering to students of all age groups and interests in all subjects. Examples include the virtual classes and the Educational Broadcasting System (EBS)' college entrance preparation lectures for primary and secondary school students, the college lecture courses provided via the Cyber University and Korea Open Course-Ware (KOCW), and the remote training programs for teachers and other adult workers.

Online learning today typically involves providing video-recorded lectures, hardcopy textbooks in the forms of books or document files, evaluations by students on what they have learned, and online interactions among students.

The typical and current format of online learning, however, is incapable of providing effective help for students of different learning achievement levels or with different needs. Learning analytics has emerged recently as a potential solution to this problem. Learning analytics is a technology for collecting and analyzing data on the learning behavior of students and providing proper learning prescriptions and feedback at timely moments toward maximizing students' motivation and performance.

The emergences of data analysis technologies have inspired many to seek and develop their applications to learning. Examples include the learning management system (LMS) and virtual learning environments (VLE) analytics dashboards, predictive analytics, adaptive learning analytics, social network analytics, and discourse analytics (Cho, 2013). In this study, our focus is on learning analytics dashboards that can analyze and visualize data collected from digital textbooks and online learning activities. More specifically, our goal is to design a dashboard that can deliver such information in a more intuitive manner.

To this end, we first review the progresses that have been made so far with respect to learning analytics dashboards, identify the necessary elements of design, and develop a method for designing such a dashboard.

Second, we design a dashboard that provides visualized data on digital textbooks and online learning activities. For this, we analyze the patterns of users' use of online learning services and identify the dashboard functions they require. We also analyze users' preferred visualization methods.

Third, we analyze the visualization tools that can be used to create our dashboard.

## 2. Literature Review

A dashboard is the panel-type device installed in the cockpit of a car or an airplane facing the driver or a pilot and featuring diverse switches for operation. A dashboard used in learning analytics and other such systems can be defined as a device for visually displaying the most important information required for achieving one or more given goals. Such a device displays key information on one surface or panel so that users can easily check and monitor such information.

Learning activity data gathered via learning platforms are often in formats that are machine-readable. However, these data are not so comprehensible to users, whether students or teachers. Presenting these data in the form of an intuitive dashboard is crucial to enable users to understand the meaning provided by data.

Most of existing studies on the designs of these dashboards focus on providing learning support for online learning environments and teaching activities. Commonly visualized types of data include those on the learning output and hours, interactions between teachers and students, results on tests and assignments, and the use of learning content. Bar, pie, and line graphs are frequently used to display these data. There are also a number of studies analyzing how convenient dashboard designs are to users, reflecting the predominance of interests in computer science and software engineering in the discipline. There are also numerous studies analyzing the effectiveness of existing dashboards (Jin & Yu, 2015).

One important Korean study analyzing the educational effects of dashboards concern a university located in Seoul (Park & Cho, 2014). The authors of this study surveyed users' perceptions of online learning activities. Based on the findings of this opinion poll, the authors designed and developed their own dashboard, and investigated whether it was useful. The authors applied their dashboard to a virtual campus environment and analyzed students' virtual learning activities. The authors then surveyed participants in the virtual learning activities on how closely the dashboard catered to their expectations of needed information, how useful they perceived the dashboard to be, and how easy it was for them to understand and use the dashboard. The survey also asked open-answer questions regarding the improvements to be made to the dashboard. The conclusion of this study can be summarized as follows.

- Learning analytics dashboards should display only information that students themselves think is useful.
- While students in general understood the dashboard and its operation quite well, they indicated confusion and difficulty over interpreting the mixture of diverse types of information displayed in each single graph.
- The most important question students asked was whether the information provided by the dashboard was really useful to their learning.
- The preliminary opinion poll revealed that the degrees of students' active participation in virtual campus environments were dependent on the natures of the given subjects and the characteristics of professors.
- It is important to inform students that the data displayed by the dashboard on students' online learning activities do not decisively affect their final performance.

The Society for Learning Analytics Research (SoLAR) also provides a standard process for designing a learning analytics dashboard in the Handbook of Learning Analytics (Klerkx, Verbert & Duval, 2017). Below is a summary.

(1) Understand the given objective(s) by answering the following questions:

- What is the purpose of visualizing the given data?

- Who are the target users?
- What types of data are to be visualized?
- How can the given purpose be accomplished through the visualization of data?
- How can users communicate using the visualized data?

(2) Collect and process data. Gather raw data first. Next, calibrate and sort the data to analyze them. Finally, using the questions raised in Step (1), sort the relevant or useful data that are to be visualized.

(3) Map the data. This involves choosing the way to give forms to the answers given to the questions of Step (1). Select the scale to be used for each type of data (quantitative, ordinal, etc.) and find the method for visually encoding the given data.

(4) Document the process. Indicate what criteria were considered in making the decisions that were made, what alternatives were considered and eventually abandoned, and how the final product is better than the initial design.

(5) Add techniques for interaction. It is important for the teacher to understand the process of learning analytics in order to understand students' behavior better. This involves:

- Comparing the values and patterns of data with a view to identifying similarities and differences;
- Arranging the data according to diverse criteria and measures;
- Filtering the data that satisfy the given requirements;
- Visually emphasizing data with certain values;
- Gathering or grouping similar items together (using means, numbers, and other such criteria);
- Annotating the findings and opinions; and
- Ordering or recording certain attributes of the data to enable effective searching and browsing.

(6) Evaluate the product on an ongoing basis. The user-centered design (UCD) approach requires the developer to design, realize, and evaluate a given system repeatedly by taking into account the target user's perspective. Effectiveness, efficiency, and usability should be the three main criteria for evaluating the product.

Creating a learning analytics dashboard using this process would involve answering and reviewing the three key questions, i.e., (1) what types of information are to be displayed by that dashboard, (2) how the target types of information are to be displayed, and (3) what help the displayed information can provide for users.

## 3. Designing the Dashboard

### *3.1. Preliminary Survey*

In order to design a dashboard based on digital textbooks and online learning, it was necessary, first, to survey elementary school students and teachers—the main target users—before designing the dashboard. This preliminary survey was conducted to identify the patterns of users' use of digital textbooks and online learning services as well as the needs they have for a dashboard.

In order to collect opinions from various members, we classified the schools, teachers and students who will participate in the survey as the following criteria:

- The area where the school is located (e.g. city or rural area)
- Career, Gender and the academic year of their students (For Teachers)
- Academic year and gender (For Students)

Surveys for students and teachers are conducted using questionnaires. We gathered personal information that can distinguish the group, according to the above criteria for the collection and utilization of users' feedback.

The questions used in the preliminary survey were as follows:

(1) What devices do you usually use with your digital textbooks and online learning services? (Select from: PC, smartphone, or tablet.)
(2) When and in what situations are digital textbooks and online learning services used? (Select from: during class, before or after class as part of preview or revision, other situations, or not using at all.)
(3) What are the features or functions you use most frequently? (Select from: reading texts, video clips, submission of assignments, or evaluation.)
(4) We are trying to develop a service that gathers learning activity data from students and teachers using digital textbooks and online learning services, and display those data in a visually intuitive manner. Do you think such a service is necessary? (Select either yes or no.)
(5) (If the user chose "yes" to Question (4)) What types of information do you want the service to display? (Select from: progress with reading, progress with watching video clips, progress with submission of assignments, results of evaluation, or other.)
(6) (If the user chose "no" to Question (4)) Why do you think such a service is not necessary? (Select from: Not using such services often, fear of privacy violation, irrelevant to academic performance, or other.)

Based on these questions, we identified users' patterns of using digital textbooks and online learning services and determined whether they needed a dashboard of our design. We also used the findings of the preliminary survey to determine the best way to visualize data based on multiple requirements for the functions such a dashboard should have.

### *3.2. Survey on Users' Preference for Visualization Styles*

In visualizing data, we must consider (1) what types of data are to be shown to users and (2) how such data are to be presented to users.

We identified the following four features required by users for the dashboard based on digital textbooks and online learning services. The figures in the parentheses indicate the units to be used in displaying the data.

(1) Progress with text reading (%);

(2) Progress with watching video clips (%);

(3) Whether assignments have been submitted (Yes/No);

(4) Evaluation results (scores).

We developed multiple prototypes featuring these data or functions, and surveyed users' preferences for different styles of visualization. We also let users indicate whether they had preferred styles of visualization other than the ones we presented, and specify what these were. Users' answers were used to improve our prototypes.

As for the progress with text reading, we presented users with two examples (Figures 1 and 2) and asked them which they preferred. Figure 1 uses bubble charts to distinguish texts that have been read from the texts that have not been read, and also indicates the progress rate in percentage below the bubble charts. Figure 2 indicates the progress rate using a pie graph.

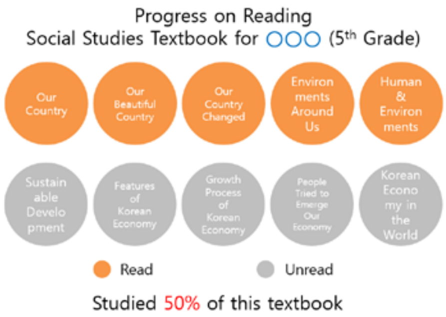



Figure 1. Progress Rate on Text Reading: Bubble Chart

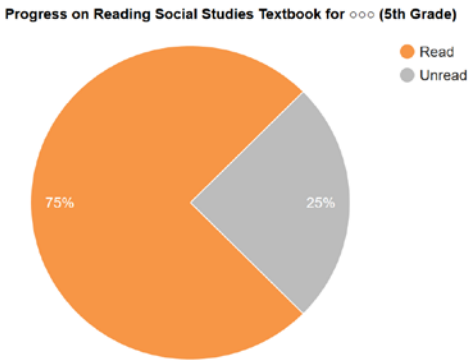



Figure 2. Progress Rate on Text Reading: Pie Graph

We also developed two different ways—a pie graph and a dashboard—to indicate the progress with watching video clips (Figures 3 and 4). Both prototypes indicate the average progress rate of other users next to each user's own graph so that the user can compare his or her progress with those of others.

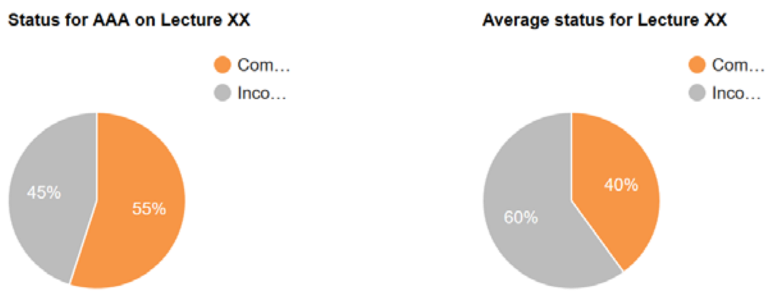



Figure 3. Progress Rate on Watching Video Clips: Pie Graph

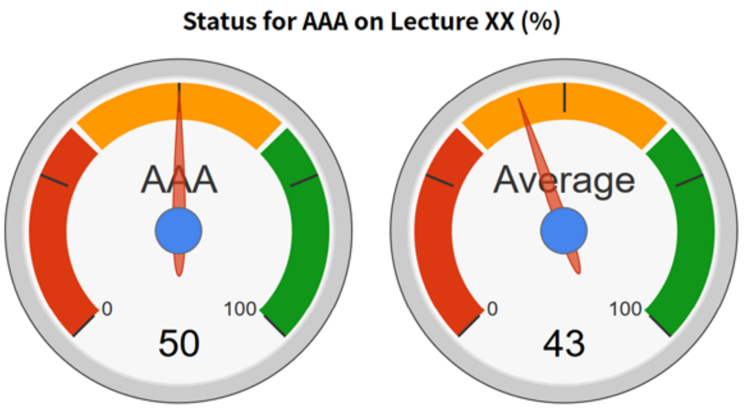



Figure 4. Progress Rate on Watching Video Clips: Dashboard

As for presenting information on whether assignments have been submitted, different types of information should be presented to different types of users (teachers or students).

Students would likely require information on the assignments they have recently submitted or on whether they have submitted required assignments. This can be visualized in two ways: using traffic lights (Figure 5) or simple "O" and "X" signs (Figure 6). If an assignment is due shortly, the dashboard should also indicate the approaching deadline and urge the user to hurry.

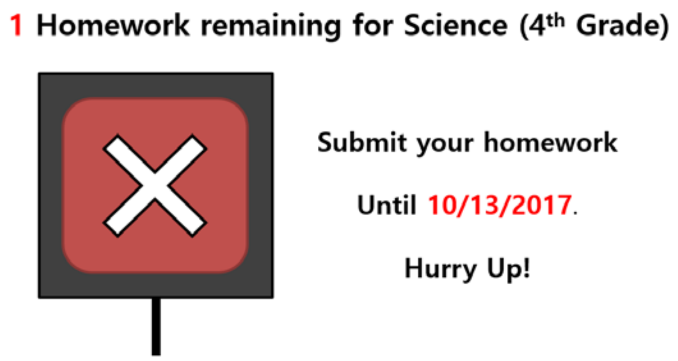



Figure 5. Submission of Assignments: Traffic Light (For a Student)

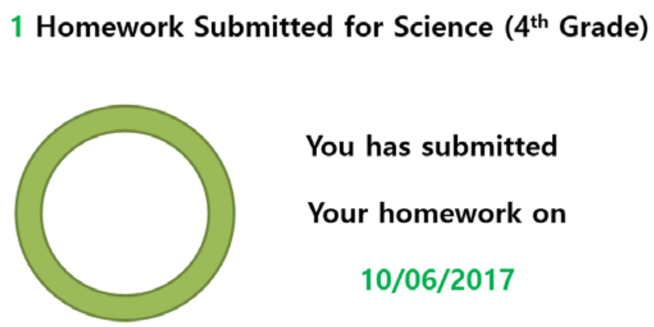
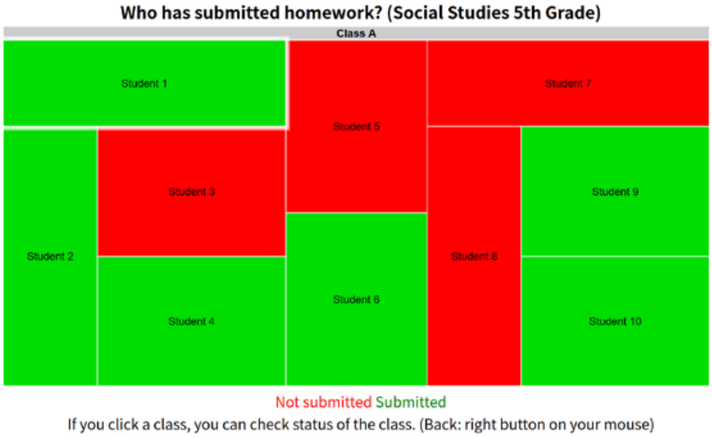
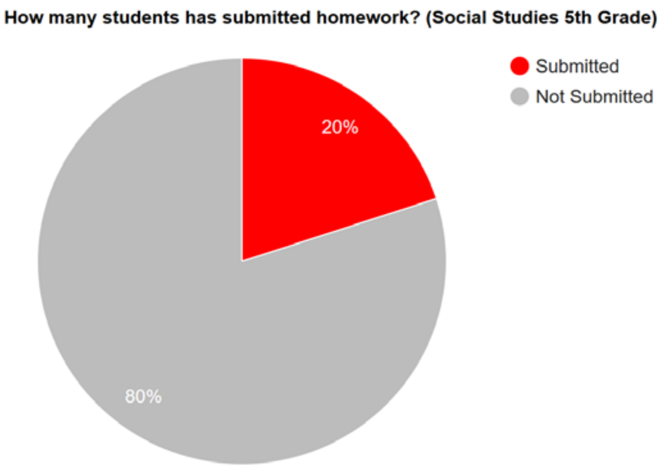



Figure 6. Submission of Assignments: O and X Signs (For a Student)

There are also two different ways to present information to teachers: either displaying whether each individual student has submitted a given assignment (Figure 8) or representing the ratios of students that have submitted assignments and students that have not in the form of a pie graph (Figure 8).




<u>Figure 7.</u> Submission of Assignments: Students' Status (For a Teacher)




<u>Figure 8.</u> Submission of Assignments: Submission Rate Pie Graph (For a Teacher)

The evaluation results or scores can be presented in the form of either bar graphs (Figure 9) or dashboards (Figure 10), both designed to enable the user to compare his or her results to those of others. The colors used on the bar graphs should differ by the level of scores given. If a student's score falls below the average, his/her score should be indicated in red. If the student's score is above the average, it should be indicated in green. Where necessary, words of encouragement may be added to the graphs or dashboards.

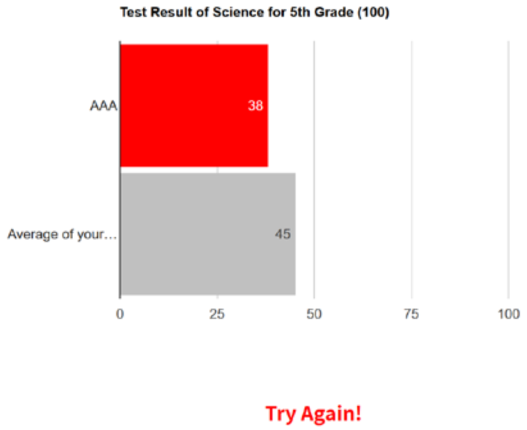



Figure 9. Evaluation Results: Bar Graph

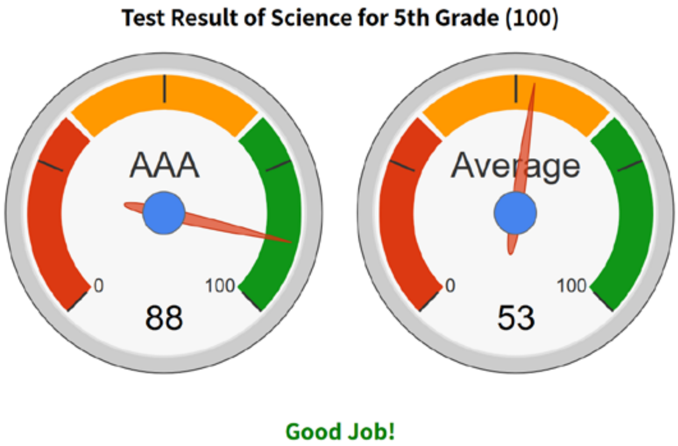



Figure 10. Evaluation Results: Dashboard

### *3.3. Dashboard Visualization Technique*

In order to implement a learning analytics dashboard based on the preliminary survey and the survey on visualization style preferences, we needed to review and determine which platform to use. To assist developers in this situation, there is an open source project that lists the frameworks, libraries, and software associated with visualization that can be used depending on the programming language and operating system (Fabio Souto, 2017).

If the platform in which the dashboard is displayed is only a mobile operating system such as iOS or Android, developers can use the library for each operating system. If you support the Android environment, you can use Java libraries such as DecoView, MPAndroidChart, and WilliamChart. If you use iOS, you can use Objective-C and Swift libraries such as BEMSimpleLineGraph, Charts, JBChartView, and PNChart. In particular, iOS's Charts library ported to iOS version of Android's MPAndroidChart (Daniel Cohen Gindi, 2017). If you need to support two operating systems, you can consider the Charts library on iOS and the MPAndroidChart library on Android.

However, if you need to consider web environment, you can prevent duplicate development using JavaScript library. Among the mobile operating systems, Android supports WebView (Google, 2017a) and iOS does WKWebView (Apple, 2017) to show web page written in HTML. This allows you to use the same JavaScript code to configure the same dashboard for multiple operating systems. Typical visualization libraries using JavaScript include D3.js (Data-Driven Documents, 2017), Google Chart Library (Google, 2017b), and Chart.js (Chart.js, 2017).

## 4. Conclusion and Suggestions

In this study, we review the process by which we designed a learning analytics dashboard based on digital textbooks and online learning activities. We first sought to identify users' patterns of using online learning materials and determine their needs for a dashboard. In order to find ways to visualize our dashboard in the most intuitive and convenient manner for users possible, we also developed a number of visualization prototypes. Finally, we surveyed and reviewed the possible platforms that could be used to support our dashboard.

This report provides only an overview of how the prototypes for the dashboard we propose could be designed and produced. Once these prototypes are developed, we will need to test them in terms of efficiency, effectiveness, and usability by applying them to actual services with learning analytics systems. Then we will need to identify what improvements and changes are to be made. We also need to look for dashboard designs and applications that users actually require.

## Acknowledgements

This work was supported by Institute for Information & communications Technology Promotion(IITP) grant funded by the Korea government(MSIT) (No.2016-0-00327, Technical development for distribution system of educational contents and services platform based on Multi-format Clipped Learning Assets as well as the global commercialization for accompanied growth)

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# A Study on Capturing Learning Data from Virtual and Mixed Reality Contents Through Data Collection API

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**Abstract:** In the fourth industrial revolution, which is called the intelligent information society, virtual and mixed reality contents and personalized learning that can maximize the learning effect are attracting attention. By developing Virtual Reality (VR) and Mixed Reality (MR) contents according to the learning topics, and learning activities characterized, immersion and authenticity of learning can be expected more than the current multimedia resources, such as videos and images. Furthermore, it can provide customized learning path by applying learning analysis technology to data using virtual and mixed reality contents which can induce the interest and attractive of learner. In this study, we introduce a method of extracting learning data generated from virtual and mixed reality contents, and converting it into a standardized learning data format for learning analytics.

**Keywords:** Virtual Reality, Mixed Reality, Learning Analytics, Data Collection, Standard

## 1. Introduction

Now that our society and economy is increasingly dependent upon knowledge and information, there are increasing attempts made, both in and outside Korea, at incorporating virtual reality (VR) and mixed reality (MR) technologies into the education curricula and foster active ecosystems for innovation in these technologies.

The International Organization for Standardization (ISO) and experts worldwide resort to Paul Milgram's "Reality-Virtuality Continuum," first introduced in 1994, to explain the distinction (or continuum) between Virtuality and reality. As Figure 1 shows, virtuality can be understood as forming the opposite endpoint of the continuum of reality. The part of the continuum that falls in between these two extremes can be summed up as mixed reality. Mixed Reality can be roughly divided into two subtypes, i.e., Augmented Reality (AR) or Augmented Virtuality (AV), depending on which endpoint on the spectrum it is closer to (Lee & Cho, 2017).

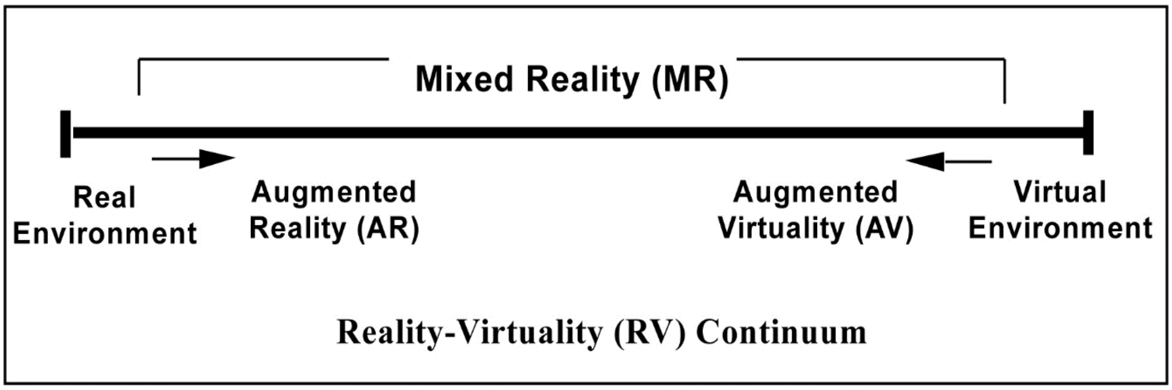


Figure 1. Reality-Virtuality Continuum (Paul, Takemura & Utsumi, 2007).

VR and MR technologies allow users to interact much more actively with their content by providing a wider range of newer interfaces and functions than the general web or mobile environments. In order to effectively utilize this in the field of education, data related to learning activities should be collected. It is possible to improve learning ability through the application of learning analytics technology and to recommend personalized learning resources by diagnosing the learner's knowledge level and competence. We expect to encourage more creative learning activities and participation.
To this end, we explain the xAPI and IMS Caliper, which is known as the representative data collection system in the field. Next, we look at the Learning Data Collection System and the Learning Analytics Reference Model. Finally, we suggest how to extract learning data from the virtual and mixed reality contents.

## 2. APIs for Collecting Learning Data

As there are diverse learning environments—platforms and software programs—supporting students' online learning, a number of standardization organizations have developed application programming interfaces (APIs) for profiling and collecting learning data. We introduce two main examples.

### *2.1. Experience API (xAPI)*

Advanced Distributed Learning (ADL) under the U.S. Department of Defense developed the Sharable Content Object Reference Model (SCORM), one of the e-learning content standards. It has developed the Experience API, which is a data collection system, and is called xAPI. In 2008, we started to needs analysis and developed a beta version under the name "Thin Can API" in 2011. After that, it gave an official name for the Experience API in 2013 and released the current version 1.0.3.

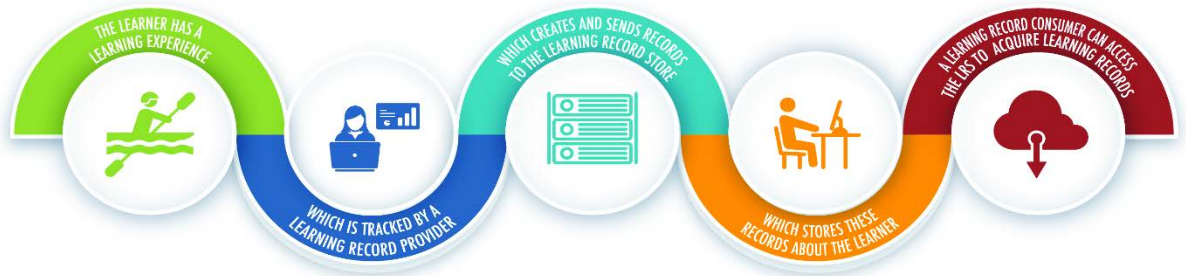


Figure 2. xAPI Data Flow.

xAPI defines data structures in ways that can explain users' activity streams systemically across diverse domains, including education. xAPI is mainly used, in education, to collect log-type data that are generated when SCORM-based applications are in use. The data collected by xAPI are gathered into a designated learning record store (LRS) and being transmitted to a learning management system (LMS) or transferred to reporting tool through the analysis (Cho, 2016).

### *2.2. IMS Caliper*

IMS Caliper, developed by IMS Global Learning Consortium, a leading organization for developing educational standards, consists of metric profiles and an open-source API that collect learning activity data.

IMS Caliper defines measures to be used to identify and collect data on different types of learning activities so that the accuracy and efficiency of data collection can be maximized. As Figure 3 shows, there is a wide range of learning activities, such as evaluation, media application, assignments, and debates. The types of learning activities will only increase in the future.


Figure 3. Learning Activities Defined in IMS Caliper Version 1.1 and Future Learning Activities To Be Developed.

IMS Caliper applies its standard only to gather data and the transmitted to event stores. Although analysis and reporting are central elements of learning analytics services, data-collecting APIs do not apply their standards to these elements (Cho, 2016).

## 3. Reference Models of Learning Data Processing and Analytics

### *3.1. Learning Data Binding Structure*

Both xAPI and IMS Caliper use a triple structure for describing data. This triple structure, which the Resource Description Framework (RDF) uses to express concepts, consists of subjects, predicates, and objects. Additional information consists of contextual information on the types of applications in use, timestamp, courseware, learning outcomes, and objects generated by users, and is expressed by enveloped data (Cho, 2016).

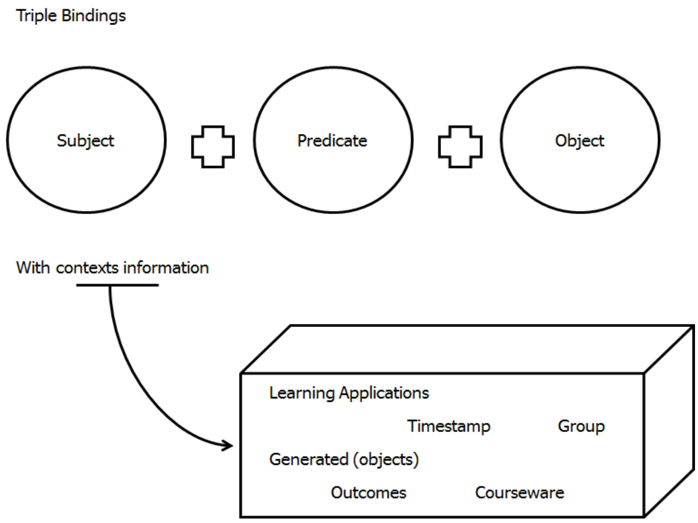


**Figure 4. Learning Data Expression Structure.**

### *3.2. Learning Data Flow*

Figure 5 summarizes the process in which learning data are generated and gathered together in a designated data storage. Both xAPI and IMS Caliper use this process to collect and transmit data. But additional functions must be inserted in between storage systems in order to convert different formats and content of the transmitted data into consistent forms (Cho, 2016).

The learning environment is classified into each different environment, according to the data collection API. xAPI and IMS Caliper Sensor define and collect the data they gather in different ways. Data collected by IMS Caliper are transmitted into event stores, while data collected by xAPI's recipes are gathered into LRSs. There is a data mapping and matching process between the two repositories, through which the data are transformed.

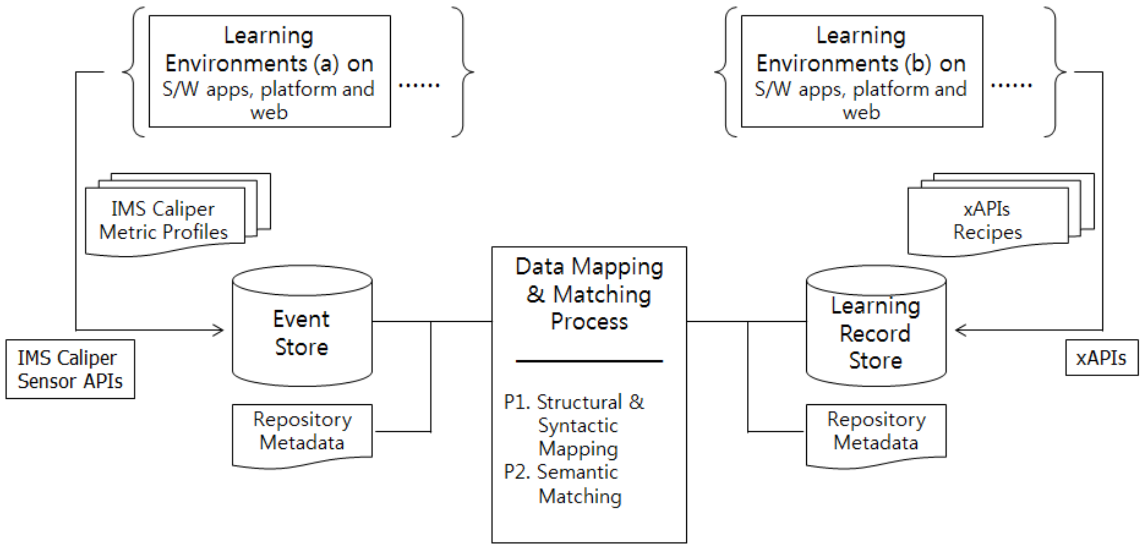


Figure 5. Learning Data Flow.

### *3.3. Reference Model of Learning Analytics*

The workflow featured in a reference model of learning analytics consists of teaching and learning activities, data collection, storage and processing, analysis, visualization, and prescription and advice. Figure 6 shows a top-level reference model of learning analytics.

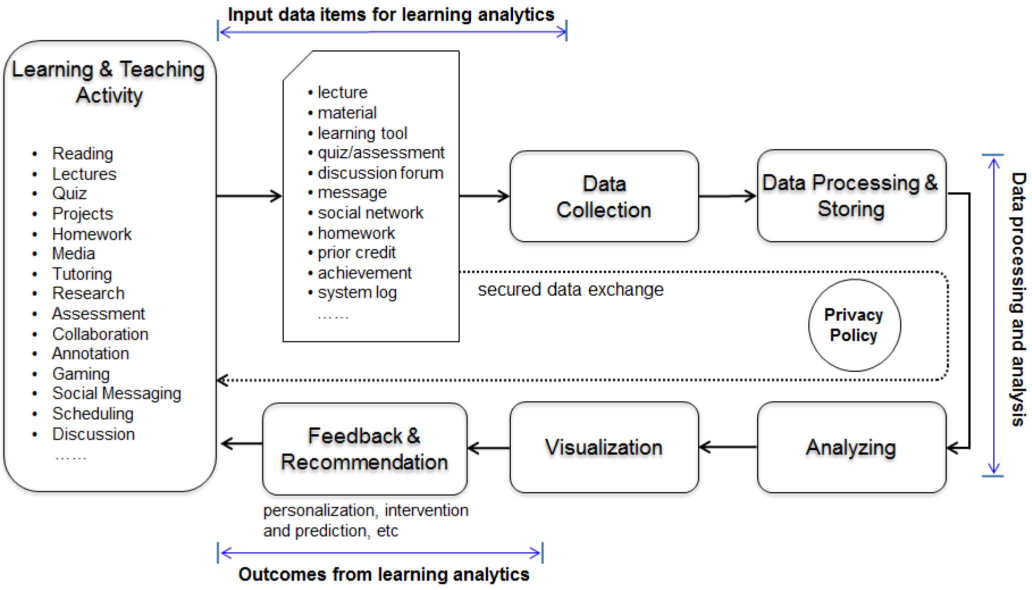


Figure 6. Reference Model of Learning Analytics: Workflow (Cho & Lee, 2016).

All processes can control and exchange data according to the privacy policy. The types and models of data used in learning analytics are standardized, unlike data used in other types of analytics. Standard APIs like xAPI and IMS Caliper can therefore efficiently collect the needed data.

## 4. Capturing Learning Data from VR and MR Content

### *4.1. Characteristics of VR and MR*

VR uses virtual images throughout, including virtual objects, backgrounds, and environments. MR, on the other hand, overlays real images or backgrounds with 3D virtual images or objects. VR and MR may appear similar at times, but they can be clearly distinguished by the extent to which reality is involved. VR computer games, for example, feature characters representing real players engaging in games against the characters of other players against a virtual backdrop. MR games, on the other hand, involve real players engaging in games against virtual characters. VR thus tends to be more immersive and MR tends to be more real.

### *4.2. Examples of VR and MR*

We introduce two main examples of VR and MR applications for education.

Example 1: Apollo 11 VR EXPERIENCE
*"Did you dream of becoming an astronaut or a space scientist as a kid?"*

Apollo 11 VR EXPERIENCE, from Immersive VR Education, provides an educational documentary and virtual tours of the Moon using the video- and audio-recordings kept by the National Aeronautics and Space Administration (NASA). With this program, students need no longer confine their role to mere spectators or audiences, as they can actively explore the same scenes and landscapes encountered at the historic landing of Apollo 11 in 1969. The program enables students to fly to the moon aboard Apollo 11 with (virtual) Neil Armstrong any time they want. Students can also move the command ship and the landing vessel to land on and explore the surface of the Moon (Lee & Cho, 2017).


Figure 7: Apollo 11 VR EXPERIENCE.

Example 2: Microsoft HoloLens
*"At times, the right mixture of reality and virtuality can be far more charming and effective than complete virtuality."*

Microsoft's HoloLens uses MR technology to enable students to view the hidden internal parts of the body, such as the bones, nerves, muscles, and internal organs, and how they function while alive even without dissecting the human anatomy themselves. Of course, perfect VR can be used to provide similar lessons in biology and anatomy. Microsoft's HoloLens, however, is especially effective because it presents such rarely seen information precisely in the mundane settings of the real world. The MR objects seen through HoloLens strike students as more real and natural than some graphics-generated images, and therefore effectively support biological and anatomical learning. Because it also allows multiple users to interact with one another in real-world spaces with respect to the virtual objects they together see, it can also support human-to-human communications (Lee & Cho, 2017).


Figure 8: Exploring the Human Anatomy Using Microsoft's HoloLens.

### *4.3. Capturing Learning Data*

AR and VR technologies allow users to interact much more actively with their content by providing a wider range of newer interfaces and functions than the general web or mobile environments. In order to make the most effective use of these technologies in education, it is critical to gather data on learning activities, and use these data in the analysis of students' learning attitudes and behavior.

Learning analytics is already widely employed in education to gather and analyze data on a wide range of learning activities, including learning time, evaluation results, debates, media operations, and the use of educational applications. The analysis rendered thus are used to provide individual students with customized assessments and advice. It is therefore important to capture and use the data generated by using VR and MR for education in learning analysis.

In this study, we design a procedure and method for capturing learning data from VR and MR applications used and for converting these data into proper and consistent formats for learning analytics. VR and MR applications are generally used with exclusive devices or mobile devices. Much of the data, except for those pertaining to rendering, remain concealed and resistant to capturing and review. We thus use the xAPI standard to capture standardized forms of data from VR and MR applications. We then convert these captured data into the IMS Caliper standard so as to discern the in-depth meanings they provide on learning activities.

The process of capturing learning data from VR and MR applications used and converting them into standardized forms for transmission is shown in Figure 9.

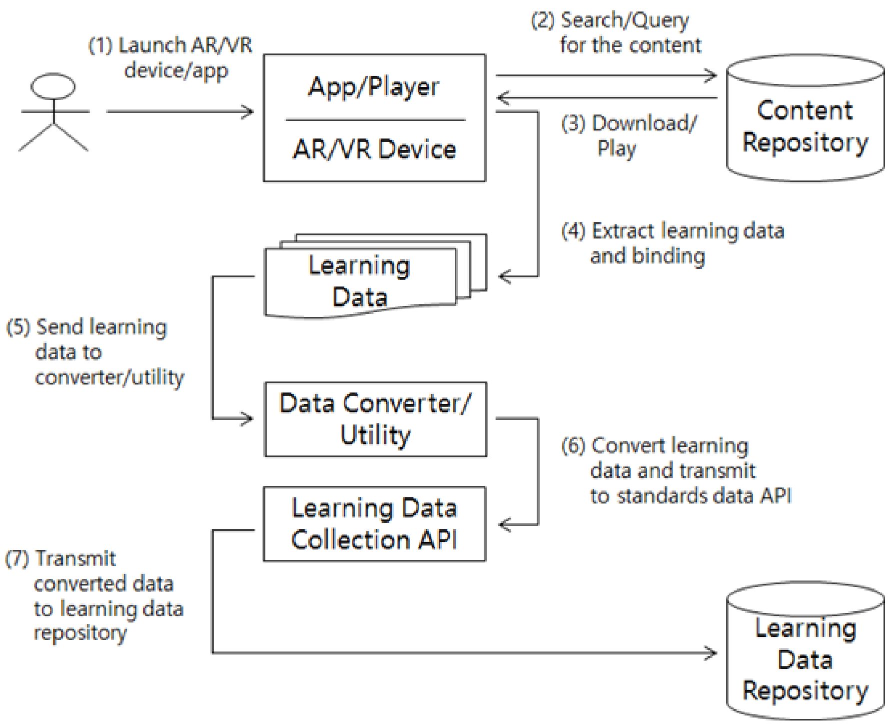


Figure 9: VR and MR Learning Data Capturing Flow.

The data capturing and processing process illustrated in Figure 9 can be explained as follows.

(1) The user runs a given VR or MR application on his/her device.
(2) The search results and queries that the user has entered are transmitted to the content repository, and the content list is viewed.
(3) The data on the content list are downloaded and the user replays the downloaded data on his/her device.
(4) The learning data generated by the user's use of the application are captured and bound.

(5) The captured learning data are then transmitted to the data converter or utility program. The data converter includes the classes of the learning data generated, the structural and syntactical mapping instance tables, and the semantic instance tables that express the meanings of learning data according to the given ontological rules. Here identification numbers, such as URIs, are assigned to the classes and properties of data profiles to complete the identification system and process.
(6) The transmitted data are then converted into standard forms (xAPI, IMS Caliper, etc.).
(7) The standardized data are then transmitted into and stored in the learning data repository. The repository checks the conformity of the stored learning data to the predefined rules on classes, properties, and semantic instance values. Only conforming data are stored, and non-conforming ones are excluded.

## 5. Conclusion

By capturing learning data generated by the use of educational VR and MR applications and converting them into proper formats for learning analytics, we can provide learning data we use.

Systemic collection of data is a critical success factor for accurate learning analytics. The inclusion of inaccurate or vague data into giving datasets will necessarily increase the amounts of efforts and time involved in processing and refining data, thus making it difficult to provide effective real-time analysis. That is why it is important to standardize the data collection systems (Cho, 2016).

By applying VR and MR applications and technologies that can stimulate students' interest and engagement and using effective learning analytics, we will be able to find more high quality learning pathways that keep students motivated to learn.


## Acknowledgements

This work was supported by the Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No.2016-0-00327, Technical development of distribution system of educational contents and services platform based on Multi-format Clipped Learning Assets as well as the global commercialization for accompanied growth).


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# Virtual and Mixed Reality for students: How to Control Human Factors

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**Abstract:** Emerging technologies, such as virtual reality and mixed reality, help teachers as well as students understand educational contents more easily. But we need to consider more deeply. Because most of the devices and contents that released recently are targeted at the game and entertainment market, it may well be doubted whether they are proper for education. Some people have difficulty in health and social aspects after experience virtual or mixed reality. In this paper, we introduce the human factors issues in the virtual and mixed reality area. If we know how to control human factors, virtual and mixed reality could be used more safely in education. We gathered the usage guides, best practices and guidelines about those. We analyze and put the parts commonly mentioned together. But the consideration of hardware itself is excluded. As a result, we propose human factor guideline for users and contents creators using virtual and mixed reality in education.

**Keywords:** Guidelines, Human Factors, Virtual Reality, Augmented Reality, Education

## 1. Introduction

Virtual reality (VR) and augmented reality (AR) are emerging around the world. Facebook has announced their plan to pioneer AR and Microsoft has shown an interest in applying VR, AR, and mixed reality (MR) to expand their Windows from monitors onto walls and table surfaces. Google, too, has been lead the popularization of VR and AR technologies with its affordable and efficient things such as Cardboard and platforms like YouTube.

With the Fourth Industrial Revolution (Industry 4.0) underway around the world, attempts are increasingly made to develop and adopt new technologies, such as robotics, VR, and artificial intelligence (AI). K-12 schools are expected to incorporate AR and VR into the classroom in the 2-3 years (The New Media Consortium, 2016). Also, aggregate market size of the educational AR and VR content are expected to $0.7bn by 2025 (The Goldman Sachs Group, Inc. , 2016)..

According to the survey on K-12 teachers in the United States, 85 percent of the participants expect that VR has positive effect to the students (Samsung, 2016). Another survey is conducted on in Germany (Samsung, 2015). It is similarly showed that 74 percent of the participants expect that VR would help keep students motivated better. The experiences such as operability, presence, and immersive learning that AR provides would likely affect the learning effect on students (Bogyeong Gye & Yeongsu Kim, 2008). There were researches that education using VR increase the efficiency of learning more than conventional teaching (Mads T Bonde, etc., 2014).

In using these technologies for more immersive experiences, however, some people experience physical symptoms, such as fatigue in the eyes, and also psychological symptoms including the inability to distinguish between the virtual world and the real world (Changmin Lee, 1999). Particularly, as K-12 students are undergoing critical periods in physical and mental development, it is crucial to consider various issues of human factors before introducing VR and AR into schools.

This study compares and analyzes the existing literature on the involved issues. We propose the human factor guidelines regarding the educational applications of VR and MR technologies. In chapter 2, we introduce some of the recent trends in the educational VR and MR content. In chapter 3, we introduce the human factors of VR and MR. In chapter 4, we analysis of the guides and best practices provided by major head mounted displays (HMDs) manufacturers. Finally, in chapter 5, we present the human factor guideline for using in education fields.

## 2. VR and MR Trends in K-12 Schools

Contents for education make up only a mere portion of the VR and MR market today. Once devices have been distributed in massive, however, investment in the educational applications of VR and MR will likely increase, leading the growth of the industry as a whole.

Table 1 provides a summary of the key features and functions of the 20 VR apps chosen by the one media as capable of transforming education in the future (The Tech Edvocate , 2017). Among those, almost 60 percent of the apps use VR. The most of these applications can be used on mobile devices (iOS and Android) rather than requiring higher-end devices like HTC VIVE. Similar to the surveys as mentioned earlier (Samsung, 2015, 2016), many of these applications are applied to school subjects, such as science, social studies, and art, that are likely to benefit from incorporating immersive content into their curricula.

In this chapter, we introduce recent trends in the educational applications of VR and MR that could be applied to the K-12 schools.

Table 1: Summary of the 20 VR apps chosen by the Tech Edvocate in 2017.

| App | Type 1 | Type 2 | Operating system | Subject | Function |
|---|---|---|---|---|---|
| Start Chart | AR | Image recognition | Mobile devices (iOS) | Science | Mobile camera app that displays constellations and information when projected onto the night sky. |
| Google Translate | AR | Image recognition | Mobile devices (iOS) | Language | Camera-like scanner that translates texts (in 30 languages). |
| Cleanpolis | VR | Graphics | Mobile devices (Android) | Science | Game for learning about climate change and carbon dioxides. |
| Public Speaking VR | VR | 360º image | Mobile devices (Android) | Social studies | Practicing giving presentations. |
| Quiver | AR | | Mobile devices (iOS) | Art | Coloring 2D images to view them in 3D. |
| Boulevard | VR | 360º image | Oculus Rift | Art | Virtual tours of six museums. |
| Unimersiv | VR | 360º image and graphics | Samsung Gear VR, Oculus Rift, Daydream, Cardboard, VIVE | Social studies, science | Virtual tours of historic scenes (ancient Greece, the *Titanic*, etc.) and the human anatomy. |
| Inmind | VR | Graphics | Android (Cardboard) | Science | Virtual tours of the human anatomy |
| Apollo 11 VR | VR | Graphics | Oculus Rift, HTC Vive, Playstation VR | Science | Virtual tours of outer space. |
| Earth AR | AR | LBS | Mobile devices (iOS) | Science | Viewing the Earth from new angles. |
| Cospaces | VR | | Mobile devices (iOS, Android) | - | Creative experiences in VR. |
| TiltBrucsh | VR | Graphics | HTC VIVE, Oculus Rift | Art | 3D drawing. |
| Anatomy 4D | AR | | Mobile devices (iOS, Android) | Science | Lesson on anatomy. |
| Sites in VR | VR | 360º image | Mobile devices (Android) | Social studies | Virtual tours (mosques, mausoleums, ancient cities, etc.). |
| King Tut VR | VR | Graphics | Mobile devices (Android) | Social studies | Virtual tours of the Egyptian Pyramids. |
| Flashcards-Animal Alphabet | AR | Image recognition | Mobile devices (iOS) | Language | Learning new alphabets /characters and words. |
| Image-n-o-tron | AR | Image recognition | Mobile devices (iOS) | Language | Learning new alphabets /characters and words |
| EON Experience | AR/VR | | Mobile devices (iOS, Android) | - | VR lectures on a comprehensive range of topics, from physics to history. |
| Titans of Space | VR | Graphics | Android (Cardboard) | Science | Virtual tours of outer space. |
| Discovery VR | VR | 360º image | Mobile devices (iOS, Android), Oculus Rift, Daydream, VIVE | Social studies | Virtual tours of exotic and hidden natural landscapes. |

### 2.1 VR-Based Contents

Contents using virtual reality can be divided into contents created by 360 images and contents made by 3D simulations. Most of this type is played through HMDs of See-Closed method.

- **Contents created by 360º images**: Panoramic pictures or moving images that capture objects in all the 360 degrees are used. This type is used mainly for the virtual tours of places that are not easily accessed due to locations and time limitation. These can most fruitfully be applied to social studies or science. 360º images contained of actual landscapes can make students feel as if they had been transported into those places. Creators also show only the intended images and thereby maximize the presence of the experiences by fix the target user's vision to the camera. This type has a merit of cost relatively. Also, it is possible to play on common mobile devices.

- **Contents by 3D simulations:** With authoring or graphics tools in computer, we can place 3D objects on virtual simulated spaces. Landscapes that do not exist in reality (ancient cities, future worlds, etc.) could be shown. Creators enable greater freedom in users' eye and body movements. As this tend to be costlier than 360-degree image- contents, there are mostly founded in game and entertainment fields that can generate profits. To play this, computer-based devices with high computational powers are required such as HTC VIVE.

### 2.2 AR-Based Contents

AR-based contents include marker- or image-recognition, location-based service (LBS), and projection-type. Because these contents overlay the real world with virtual objects, they require the use of mobile device or see-through devices.

- **LBS contents**: By gathering and identifying users' locations using global positioning systems (GPS) and/or gyroscope sensors, image are shown. These are mostly found in advertisements, marketing, and entertainment. A leading example is Pokémon GO. This type requires active movements of users. This technology could be applied to support field trips.

- **Marker or image-recognition contents:** The cameras mounted on the display devices recognized given markers or images to display additional information by overlapping those. Most of these are in the forms of AR cards or AR books. This is used to project onto images not only to show information in textbooks or relics at museums but also help little children learn alphabets and vocabularies.

- **Projection-type contents:** Small projectors are mounted on display devices, it project images directly onto users' retinas or eyeglasses to display the intended images. Since it needs to the high costs for implement the devices required for use, there are few contents have been developed so far. Recently, various companies are investing in the development of these types. It can be used for sharing same contents in classroom or auditorium for many students.

## 3. Human Factor Issues in VR and MR

Human factors and ergonomics refer to the areas of scientific research required to find theories, mechanisms, and data that are needed to optimize machinery and systems for human use (IEA, 2000). In this chapter, we introduce a number of VR- and MR-related human factor issues across four areas (Yeonghee Lee & Yong-Sang Cho, 2016).

### 3.1 Health Related Issues

The causes and symptoms of health-related human factor issues can be summarized as follows

- **Discomfort**: In experiencing VR or MR, users can feel unpleasant physical symptoms such as lightheadedness, dizziness, headaches, and nausea. These symptoms are commonly referred to as VR sickness, simulator sickness, motion sickness, and cyber sickness. It is occurred due to the inability of users to react physically to the visual stimuli they experience in virtual environments (Gyeonghun Han & Hyeontaek Kim, 2011).

- **Bad impact on vision**: Since the most of VR or MR devices are close to the users' eyes, excessive use of these can lead to a variety of symptoms affecting the eyes and vision, such as visual fatigue, blurs, double vision (Jeongmin Hwang, Jinhak Lee & Taesu Park, 1999 ).

- **Irlen syndrome**: Also known as the Pokémon shock or the Nintendo syndrome, the Irlen syndrome causes sudden seizures in users in response to rapidly flickering visual stimuli involving bright lights.

- **Musculoskeletal fatigue**: When using VR and MR devices in the same position for an extended period of time, which, if repeated, can exert duress on the user's musculoskeletal system, leading to fatigue and pain.

- **Hygiene**: Letting multiple users use the same device together or one user using his/her own device repeatedly without taking care to disinfect or clean the device regularly could turn these devices into sources of infectious or communicable diseases.

### *3.2 Safety Related Issues*

Safety issues related to VR and MR is the risks of injuries. Users using see-closed devices that blocked vision to display could fall, trip, or bump into surrounding objects, which increases the risks of their injuries. Even see-through devices that overlay the reality with virtual objects could increase risks of accidents, such as falls and car accidents, by overwhelming users' attention. Also, due to confusion between reality and the virtual world, users may try to sit on chairs or lean against walls those do not exist in reality, thus injuring themselves.

### *3.3 Social Related Issues*

In the social related issues, there are infringe of privacy and over-immersion. Users may (be tempted to) abuse the recording functions of their VR or MR display devices. Users may be too engrossed in the virtual world that they may become unable to distinguish between reality and the virtual world. Further, they could be engaged in violent or self-destructive behavior in reality. Excessive immersive user could think that the outcomes of such behavior could be "undone" or "reset" as in the virtual world.

### *3.4 Others*

There are Accessibility issue that related to whether VR and MR applications and devices can deliver the same beneficial experiences to people with physical disabilities, the infirm and the elderly, and the poor.

## 4. Analysis of User Manuals, Best Practices and Guidelines

We analyze the user manuals and best practice provided by the major HMD devices makers on the market such as Samsung, Sony, Oculus, Google and HTC. Some organizations, also, has making guidelines.

## 4.1 Health Related Issues

The amounts of information related health issues differ significantly from manufacturer to manufacturer. Some maker provided quite detailed and thoroughgoing guides, while others provided very simple manuals.

- **Discomfort:** Oculus recommends that the use of independent backgrounds such as sky or broad grassland. When users are running or driving, the usage of the horizon or a fixed background of a single color could provide as if he/she were in a vast "room" and thereby minimize the unpleasant sensation. If fixed positions such as a cockpit or a chair are placed against the virtual backdrop, the user could feel as if he/she were sitting down on such an object even when the surrounding image is moving, and thus feel less displeasure.

- **Warnings against seizures**: Most of the makers advise users who have had seizures such as epilepsy, to consult their doctors before using their devices. Oculus advises users to refer to "ISO/DIS 9241-391.2, Ergonomics of Human System Interaction – Part 391: Requirements, analysis and compliance test methods for the reduction of photosensitive seizures".

- **Interference with medical devices**: Most of the manufacturers indicated that the magnets or other radio wave-emitting parts contained in HMD and mobile devices could interfere with the radio signals of important medical devices, such as hearing aids and cardiac pacemakers.

- **Age restrictions**: There are various in the proper ages at which users may use their devices (Table 2). While manufacturers do not specify the criteria that went into determining the proper ages, some explain that age restrictions are needed particularly in order to protect children, whose visual and physical development is still underway, against possible harms of VR and MR. Most of makers recommend that users be at least 13 years of age in order to use their devices. Some makers even advise parents or adults supervision on over-13 teenagers using these devices.

Table 2: Age Restrictions of Electronic Devices

| Device | Details |
|---|---|
| Mattel View-Master® VR | It is designed for kids 7 and up. Mattel have worked with an ophthalmologist to ensure that View-Master® VR is optically safe for use by children |
| Sony Play Station VR | The VR headset is not for use by children under age 12. |
| Samsung GEAR VR | Under 13 restricted |
| Oculus Rift | 13 and older allowed |
| 3D TV | Under 10, it is needed adult supervision |
| Electronic devices | For 6 to 18 ages, it is recommended less than 2 hours of use per day |

- **Pre-use restrictions:** It is advised that users in poor health conditions to avoid using their products. The listed poor health conditions include feeling tired, sleep deprivation, problems with digestion, common colds, influenza, headaches, migraines, ear infections, and other such conditions induced by medications.

- **Stopping the use of devices:** Manufacturers advise users to cease using their products immediately upon experiencing any physical symptoms or displeasure, and to take sufficient rest until the symptoms dissipate. The symptoms developers warn against include feeling tired or pain in any parts of the body, seizures, cognitive dysfunctions, the fatigue of the eyes, nausea, paralysis, and seizures.

- **Warning against hearing impairment:** Manufacturers warn users against the possible hearing impairment that could be caused by using their products at high volumes for extended periods of time.

- **Visual and musculoskeletal fatigue:** Manufacturers warn users against the fatigue of the eyes and musculoskeletal pain they could experience for using their products repeatedly or for extended periods of time. Oculus recommends users to design virtual objects as if they were 0.75 to 3.0 meters away from their eyes. Microsoft advise users to design the virtual images for HoloLens so that those images would not exceed 60 degrees below the horizon, 10 degrees above the horizon, and 45 degrees on either side of the vertical line, as shown in Figure 1.

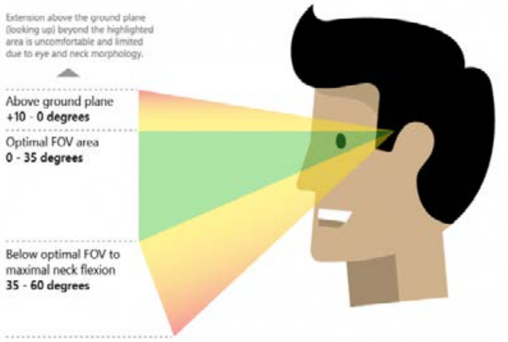


Figure 1. Recommended Angles of Vision to Minimize Fatigue (Oculus Best Practices)

### 4.2 Safety Related Issues

Safety related issues are summarized as below.

- **User environments:** Developers advise users to secure sufficient spaces free of physical obstacles and other risk factors, and also to use their products while sitting down. The sizes of spaces required differ significantly from device to device.

- **Heat**: Few ever mention the possibility of low-temperature burns from the heat of device. Instead, some makers warn against possible electric shocks or fires that could be caused by using third-party adapters and/or cables.

- **Clashes and falls:** When focusing on virtual object by wearing HMD devices or overlaying devices, peoples could be fall or clash into surrounding objects. Microsoft recommends that users place their HoloLens images 2.0 meters away from their vision in order to minimize the risks of clashes.

### 4.3 Social Related Issues

Break could be a handling method to social issues due to over-use. Makers recommend that users take breaks of 10 to 15 minutes for every 30 minutes of using their devices. Some makers also advise users to avoid using their products for extended periods of time. Taking breaks is helpful not only to minimize the fatigue on the eyes, but also to prevent users' over-immersion in virtual images.

## 4.4 Others

Even the content are same, it could differently affect to each users. Oculus advises creators of sensitive contents such as horror to include warning messages in the beginning of their contents. It helps for users test theirs sensitivity to such stories and determines their positions whether go on or not.

## 4.5 Guidelines proposed by Various Organizations in Korea

Various organization in Korea from government (MSIP the Ministry of Science and ICT) to the academic sector (Barun ICT Research Center), have developing guidelines on the use of VR and MR applications. Each guide is summarized in Figure 2, Tables 3 and 4.

In the guides of the Game Rating and Administration Committee (GRAC), there are many phrases that assumed the game situation. It is because they released just after that Pokemon GO became the topic. It contained personal information security and secret camera attention to reflect the characteristics of using the camera. Also, the phrases that reflect the characteristics that are used while moving (such as dangerous areas and private land access Prohibition, game prohibition during driving, prohibition of use during walking) are stated (Figure 2).


Figure 2. GRAC's AR Game Safety Rules

The MSIT's guideline stresses the human factors of using VR, requiring the minimization of dizziness, and the optimization of other mechanical factors, such as latency and frame rates (Table 3).

Table 3: MSIT's VR and AR Guideline in 2017

| | Aspect | Description |
|---|---|---|
| Usage | Take a break | Rest of 10 to 15 minutes for every 30 minutes of usage. |
| | User environments | Make sure that they have secured a sufficient and obstacle-free space for using their devices before starting to use them |
| | Hygiene | Clean the device before/after use or use with hygienic disposable pads. |
| | Heat from device | Warnings against possible burns from heated devices should be displayed at the beginning. |
| VR contents development | Latency optimization | Maintain VR latency below 20ms as much as possible. |
| | Frame rate optimization | The frame rates of VR applications should be synchronized with the refresh rates of VR HMD devices. Image-based content should maintain 30 FPS or higher, and graphic-based content (games), 90 FPS or higher. |
| | Virtual camera motion optimization | The frequencies of accelerated motions of virtual cameras (back and front, left to right, zoom-in, rotation, etc.) should be minimized. Virtual cameras should be designed to move at constant speeds. |
| | Rig structure | The rig systems should be designed so that the real images for 360° VR applications would approximate the no-parallax point. |
| | Stitching optimization | The location, lens distortion, and synchronicity of the camera should all be optimized. |
| | FOV(Field of View) coordination | Match the virtual camera field of view (cFOV) to the fixed display field of view (dFOV) as closely as possible. |
| | Sensory synchronization | VR applications should be designed so as to synchronize the visual and other sensory experiences. |
| | Motion platform synchronization | The latency between VR input and VR output should be kept at 150 ms or lower. |
| | UI layout | The UI should be given 3D objects and laid out over a 3D space. |
| | Sound | The directions of the sounds should change in response to the movements of the user's head. |
| AR content development | Enhanced reality | The colors, vividness, and light sources of virtual objects should be rendered more optimal and real. |

Table 4:. Guidelines for VR users and Commandments of VR guidelines of Barun ICT Research Center

| 10 Guideline for VR users | 10 Commandments of VR guidelines(2015) |
|---|---|
| **Precautions before using VR**<br>• Are you in good health?<br>• Do you have enough space to safely use VR?<br>• Are your devices working properly?<br>• Have you read the VR content precautions?<br>**Precautions while using VR**<br>• Stop using immediately if any side effects occur.<br>• Do not use for an extended period of time.<br>• Use under adult supervision<br>**Precautions for using VR in general**<br>• Rest before resuming your daily activities<br>• Do not use while moving around or driving.<br>• Store your VR device with care. | • Thou shalt safeguard against potential physical injuries.<br>• Thou shalt limit VR exposure time.<br>• Thou shalt prevent photosensitive epilepsy.<br>• Thou shalt warn against cybersickness.<br>• Thou shalt provide vibration intensity controls to avert vibration syndrome.<br>• Thou shalt prevent hearing loss.<br>• Thou shalt not use materials that irritate the skin.<br>• Thou shalt provide guidelines for proper posture to avoid muscular and physical fatigue.<br>• Thou shalt improve interface design considering both convenience and comport.<br>• Thou shalt abide by the laws and regulations for consumer safety and protection. |

In the guides of Barun ICT Research Center are stated that characteristic of content use to use should be confirmed. However, we didn't take into account that, since the violence and the bad expressions are implicitly excluded in the case of contents purposed for educate. Most of the items in their guides are designed to output guidance or warning message on the VR device rather than the content design itself (Table 4).

Most of guidelines focused mainly on reducing dizziness in content production. Because they concentrated on the technical side such as the use of the device or the production technique rather than the design of the content itself, it leaves much to be added.

## 5. Conclusion

Considering of human factor issues, user manuals, best practices and guidelines of other organization, we would like to propose the human factor guideline. It is summarized in Table 5.

Table 5: Summary of Our Human Factor Guideline

| | Aspect | Description |
|---|---|---|
| Usage | User condition | Check the user's condition before, during, and after using VR. |
| | Mechanical information | Check the specifications, user's guide, and age restrictions associated with the device before using it. |
| | User environments | Check the minimum areas or spaces required for using the given VR device/application, and eliminate possible obstacles and risk factors. Use VR while seated. |
| | Duration | Take frequent breaks while using VR. |
| | Heat | Beware low-temperature burns from heated devices. |
| | Refreshing | Refresh the user's attention every now and then to prevent him/her from confusing reality and VR. |
| | For young users (12 and under) | Parental or adult supervision is required. Do not let children use VR by themselves. |
| Development | Mechanical information | See guidelines provided by developers. |
| | Runtime | 10 minutes or less. |
| | Backgrounds | Exclude ethically sensitive backgrounds. Use vast and dark backgrounds for VR images. |
| | Texts | Minimize the use of texts. |
| | Colors and sounds | Make appropriate use of colors and sounds |
| | Sensory synchronization | VR applications should enable users predict or experience sensations accompanying visual stimuli. |
| | Camera motion optimization | Minimize the accelerated movements of virtual cameras. Maintain them moving at constant speeds as much as possible. |
| | UI layout | AR applications should be designed with adjustable UIs that users could adjust to fit their vision. UIs for VR applications should be given 3D objects and laid out over 3D spaces. |
| | Object placement | Virtual objects inserted and placed should be at certain distances from the user's vision so as not to obstruct it. |
| | Content operation and samples | Provide sufficient tips and examples on how to operate applications' content and help users get acquainted by providing them with samples. |

### *5.1 For Usage*

There are 7 aspects for the users consideration.

- **Check the status of users before, during, and after use:** If user is in a seizure-prone group or using medical devices, he/she must consult a doctor or other professionals. Do not use if you have a health problem because it may worsen your symptoms. During use, pay attention to the fatigue caused by hearing damage, photosensitivity seizures, and repetitive movements. If any abnormal symptoms appear, discontinue use immediately. After use, if you have persistent discomfort or abnormal symptom, take a rest and consult your doctor.

- **Check the status, user's guide and the age restrictions of the device:** Make sure the device is not damaged, clean (disinfected), and sufficiently charged before using it. Different devices have different age restrictions and operational requirements. Check these restrictions and requirements in advance in order to ensure safe handling. Since K-12 students are at the stage of physical and mental development, it is recommended that students take an actions as conservatively as possible.

- **Identify the range that can be safely used before use and remove obstacles around it:** As see-Closed devices completely block the user's gaze and see-through devices can confuse the user's eyes, it is possible to cause safety accidents during use. It is necessary to check the surrounding environment in advance and remove obstacles. Also, it is recommended to use in seated position. In particular, when many students are in the same space, be careful about clashes and falls between students.

- **Take breaks often:** When using virtual / mixed reality contents for a long time, somatic side effects such as dizziness, headache, nausea, and eyeball may appear, and mental side effects such as immersion may be experienced. Most manufacturers recommend a 10 to 15 minute break per 30 minutes of use, but it is expected that the continuous use of content on actual training sites will be shorter than 30 minutes.

- **Pay attention to the burn caused by device heat:** Most VR or AR devices are worn on users' bodies or used in close proximity to users' body. If excessive heat is generated in the equipment, it may cause bodily harm such as low temperature burns. The skin of the K-12 students is especially fragile, and in the case of low fever, students are also slow to recognize signs of burns while they are immersed in VR or AR applications.

- **Refresh users' attention after use:** People experienced VR or MR could confuse reality with the virtual world. Especially kids those lack of cognitive ability could confuse more than adults.
- **Do not let young students (age 12 or under) use VR or MR devices alone**: Be sure to observe and supervise by the guardian or guidance teacher. Almost of VR and MR devices have been developed for adult usage, and makers advise children aged 12 and under not to use these devices. Because young children are in critical phases of development, adult supervision and instruction is mandatory in letting them use VR.

### *5.2 For Contents Create*

There are 10 aspects for the contents creators to consider.

- **Check the guidelines provided by the manufacturer of the device you intend to play the content on:** Virtual and mixed reality devices have not yet been standardized, and the driving method and usage method are different for each manufacturer. In particular, referring to the manufacturing guidelines provided by some makers of devices, it may be useful for producing content optimized for the device. In some sensors, the body does not recognize a small child, or a teacher or adult around a child is recognized as a user. If sensors are used, it is needed to design for minimizing these errors.

- **The runtime of each application not be more than 10 minutes:** None of the guidelines surveyed for this study mentioned the proper runtimes of VR or AR applications. Given the experiences of contents creates and young students' age, contents that involve rapid movements of images is suitable for about five minutes, and contents that involve slow-moving images or plots is possible to run for 10 minutes or less.

- **Avoid using ethically sensitive or controversial backgrounds:** Some VR and AR applications have generated controversies by featuring ethically sensitive places as backgrounds. Ethics is considered to be an important factor in education, so caution is needed in selecting the background of learning content. Using vast and dark backgrounds can also help minimize dizziness.

- **Minimize the use of texts**: Many texts are less readable and can cause dizziness. Reduce text, and consider UI design in the form of images or 3D objects.

- **Make appropriate use of colors and sounds**: Bright colors, colors of low chromaticity, and colors that contrast the surrounding backgrounds can catch attention. Further research is needed, however, on the appropriate use of colors. Sound can also capture attention like colors. If eyesight and sounds do not match, the sense of reality may be degraded.

- **Synchronize sensory experiences:** Contents should especially provide situations or expressions that cater to users' expectations or predictions of synchronicity. Using same contents over and over, it reduces dizziness over time. Because it enables the user to predict subsequent situations better.

- **Optimize the movements of cameras**: Abrupt movements of virtual cameras in VR applications can be a major source of dizziness for users. As the vestibular system is sensitive to state changes, camera movement such as forward, backward, left and right movement, rotation, and zooming should be as constant as possible.

- **Adjust of virtual object to the user's eye level:** For VR content, it is recommended for the UI should be 3D objective in virtual space. Deployment of inappropriate UI can cause dizziness. It is better to make it appear only when it is not normally visible, or overlay it on a three-dimensional object.

- **Maintain proper distance when placing virtual objects**: Arranging the objects at a proper distance from the user in the virtual space can prevent the excessive movement of the body as well as securing the view of the user, thereby ensuring the comfort of use. Objects placed at sufficient intervals also appear more natural when they are overlaid on reality.

- **Provide examples and content samples of manipulations**: Even if you experience the same content, your user experience may be different. For safer use, it is advisable to present some of the contents as a sample screen in advance, so that you can get guidance on how to operate and understand the sensitivity of the user.

The contents discussed here are the result of analysis of various papers and data. Although we assumed that the main HMD manufacturer made their manual based on sufficient self-research results, it is needed additional medical research considered the usage environment in the education field.

This guideline should be updated regularly to reflect new trends in the standardization and development of VR and AR technologies. It will also need to gather expert's opinions including education site and developers of traditional educational contents.

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# Integration of Learning Analytics Research and Production Systems While Protecting Privacy

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**Abstract:** Learning analytics researchers often face problems when dealing with data that contains personally identifying information, and the protection of stakeholder privacy in analysis systems. As learning management systems become more important within education institutions, these systems are being subject to increasingly stringent standards to protect user privacy. This however has the potential to hinder learning analytics research because data collected in production cannot simply be transferred as is to research systems for real-time analysis. In this paper, we propose a system design that provides an interface between integrated production and research systems to allow user authentication, information, and learning analytics results to be seamlessly transferred between systems. The interface provides a level of anonymity to allow a greater degree of research freedom when analyzing data without exposing private data directly through research systems.

**Keywords:** Learning analytics, anonymized data analysis, seamless learning

## 1. Introduction

In recent years, Learning Management Systems (LMS) have become an integral part of higher education. As these services are becoming increasingly important to education, LMS are being managed as production environments with stringent security and processes to safeguard the integrity of the system. While data from LMS and other VLE (virtual learning environments) are essential to learning analytics research, a particular concern is the protection of data and privacy throughout the analytics workflow (International Organization for Standardization, 2016). On one hand, researchers must ensure that the privacy of key stakeholders, such as: students, teachers, and administrators are protected. On the other hand, the protection of data privacy can sometimes limit access to data, which can hinder learning analytics research.

This problem also raises issues when production and research learning environment systems are integrated during the development of new learning analytics research ideas, and performing experiments to evaluate their effectiveness in the field. Ideally, research systems would pre-emptively protect data and privacy by only handling anonymized data that has been stripped of information that can identify a person. However, this solution also has limitations as it can negatively impact personalized results, such as: a student comparing their personal progress in a course with that of the whole student cohort. There are also possible secondary uses of data collected by these systems that should be investigated, such as: the use of real data in learning analytics and data science education, community based learning analytics where data is available to stakeholders to freely perform their own analysis, and facilitating ‘data takeout’ where the stakeholder can export their personal data and transfer it to another system.

Traditionally, there has been little distinction made between the different roles that systems perform, with LMS and learning analytics systems inhabiting the same environment without abstraction. However, as LMS and learning analytics research mature, systems are becoming increasingly modular with personal data being stored in numerous locations, and anonymity by design will play an increasingly important role in the protection of personal data in integrated systems.

In this paper, we propose the design of integrated production and research learning systems that address the protection of stakeholder privacy, while trying to minimize the limitations of anonymized data analysis in research systems. We are currently in the process of developing and testing parts of a system based on this design with an anticipated small scale soft launch of the research systems from October 2017. The design presented in this paper is limited to the current requirements at hand, and does not try to address other possible requirements, such as: incorporating single-sign-on authentication which is left for open discussion. A long-term goal of this research is to implement the proposed system across various educational institutes ranging from K12 schools through to high education.

## 2. Overview of the Proposed Integration of Production and Research Systems

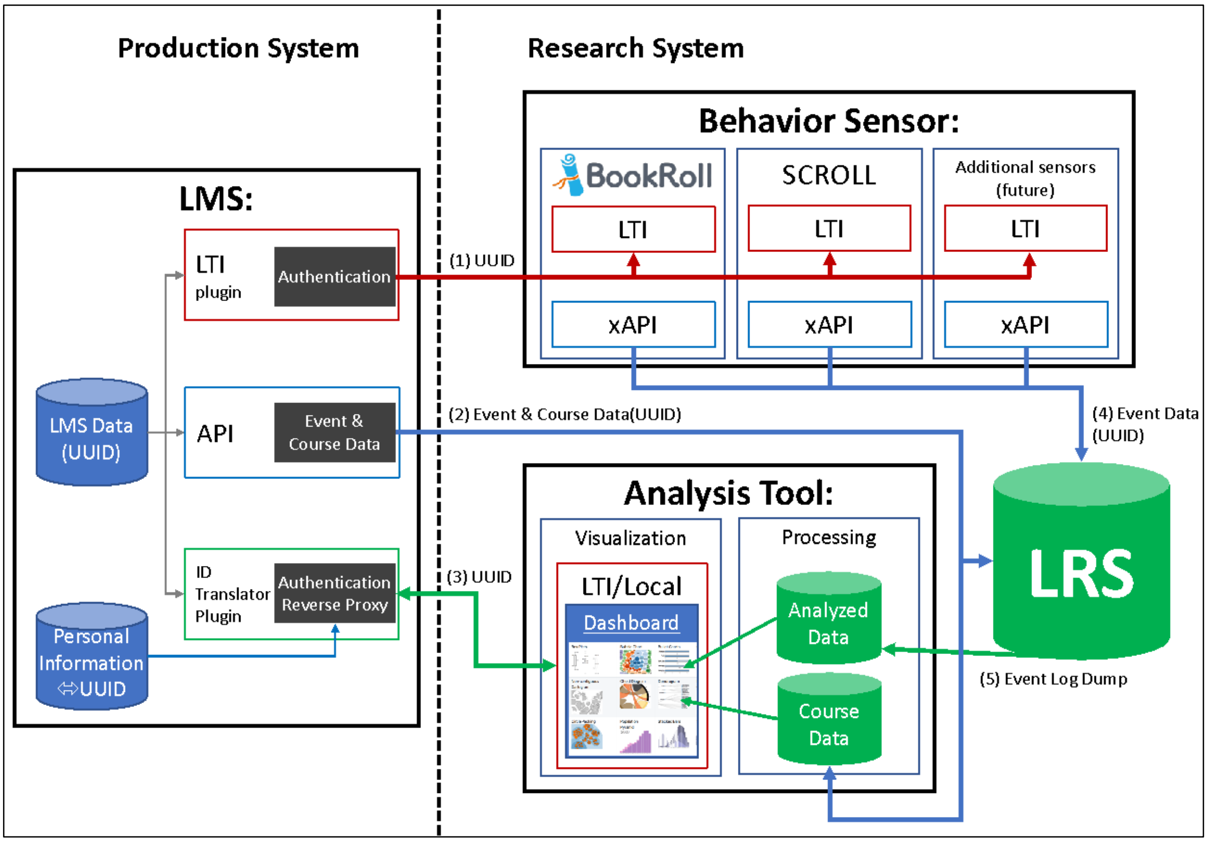


Figure 1. Overview of proposed design to integrate production and research based systems.

### *2.1. Learning Management System (LMS)*

In recent years, several interfaces have been proposed to allow the seamless and secure integration of external tools to augment existing LMS experiences. Some of these interfaces have been proprietary and thus limited the tools that can be integrated. IMS Global Learning Consortium (2016) published the Learning Tools Interoperability (LTI) standard for defining the process of connecting two systems, and how users will transition across these systems without having to authenticate once again with the destination system. During the LTI transition process, information about the user and the context in which the external tool was launched can be transferred from the source system to the target system. In many cases, personal information is usually transferred to the target system in this process. However, this can pose a problem when production systems are integrated with research systems. Personal information is usually handled in production systems that have been designed and secured to avoid breaches of user privacy. In contrast to this, research systems are generally not concerned with the design and security aspects required to ensure user privacy. This is influenced by various factors, including: the purpose of the system, time and funding constraints, and the fact that the design and management is usually carried out by a wide range of users from highly experienced professors to students who are just starting their first research. Because of these reasons, it is important to consider how user privacy can be protected when integrating production and research systems.

### *2.1.1. Anonymized Id Management*

We propose that the information that is transferred when connecting external tools should be limited to attributes that cannot directly be used to identify a user as a particular person. Most modern LMS utilize an internal universal unique identifier (UUID) to which personal information, such as: real name, student/teacher id, and email address are attributed. As shown in Figure 1, we propose that (1) UUID should be the only user identification information that is transferred to research systems. The relation between the LMS's internal UUID and personal information is only available within the production system and therefore reduces the risk of a user privacy breach. External tools will then attribute learner events with the LMS's internal UUID that is sent during the LTI launch process, therefore anonymizing (4) Event data collected in the research system side LRS (Learning Record Store).

Anonymized (2) Course and event data using the LMS internal UUIDs in place of personal information will also be exported from the LMS to an analysis tool and LRS. A simple plugin within the LMS is being developed to translate the UUIDs displayed in research system analysis results into the real name, id, or email address of students and teachers. The plugin will act as a LTI Tool consumer reverse proxy, which involves both authentication using (3) UUID with the LTI Tool provider, and translating UUIDs by retrieving the contents from the provider instead of the user directly transitioning to the external tool. This ensures that the students and teachers will be able to meaningfully interpret research system analysis. This is particularly important for research into predicting at risk students as anonymized results would be difficult to use for intervention support.

## *2.2. Behavior Sensors*

The actions in tasks that learners take during the course of their studies that occur outside the LMS need to be captured by *behavior sensors*. These tasks can take place in both formal and informal learning situations in seamless learning environments (Uosaki et al. 2013), and therefore it is important to collect data on the events that occur in both of these environments. We currently plan to implement the addition of two behavior sensor systems: a digital learning material reader called BookRoll, and an informal language learning tool called SCROLL (Ogata et al. 2011). The design of the system allows additional behavior sensors to be integrated into the proposed system. Currently the planned behavior sensors are proprietary independent systems and do not support open interoperability with other systems. We are currently developing standardized interfaces based on: LTI for seamless authentication transition from existing production LMS by anonymized (1) UUID, and xAPI (Advanced Distributed Learning, 2016) which is an open source statement API for outputting anonymized (4) Event data to a centralized independent Learning Record Store (LRS). As the main purpose of the data collected by *behavior sensors* is for research analysis, all users of the systems will be giving the option to opt-out on initial authentication if they do not consent to participation and will not have their actions logged.

### 2.2.1. *Digital Learning Material Reader*


Figure 2. A screenshot of the BookRoll digital learning material reader that will be deployed.

Digitized learning materials are a core part of modern formal education, making it an increasingly important data collection source in learning analytics. The reading behavior of students has previously been used to visualize class preparation and review patterns by Ogata et al. (2017). The digital learning material reader can be used to not only log the actions of students reading reference materials, such as textbooks, but also to distribute lecture slides, etc. Real-time analysis of students reading lecture slides can be visualized to inform a teacher that they need to slow down if too many students are reading previous slides of the current slide that is being explained. Conversely, the teacher may need to speed up if too many students are reading ahead of the current slide. Additionally, the reading logs could be analyzed to evaluate and find sections of learning materials that need to be revised. In the proposed system, we plan to deploy the BookRoll digital learning material reading system. As show in Figure 2, there are features to highlight sections of reading materials in yellow to indicate sections that were not understood, or red for important sections. Memos can also be created at the page level or with a marker to attach it to a specific section of the page. Users can also bookmark pages or use the full text search function to find the information they are looking for in later revision. Currently, learning material content can be uploaded to BookRoll in PDF format, and it supports a wide range of devices as it can be accessed through a standard web browser.

Initially, user behavior was logged in a local database and required that analysis be performed by either connecting directly, or exporting data from the database. In the proposed system, user behavior events will be sent by an xAPI interface and collected in a central independent LRS. The frequency and amount at which events will be sent will be configurable to enable either cost effective digest logging were a large number of events are sent in one request, or high frequency logging that is required for real-time learning analytics visualization.

### 2.2.2. *Informal Language Learning Tool*

In addition to collecting data on user behavior in formal learning situations, we also plan to deploy the SCROLL ubiquitous learning log system that was reported in Ogata et al. (2011) to collect data on user behavior in informal learning environments. SCROLL can be used to support the sharing and reuse of ubiquitous learning logs that are collected in the context of language learning. The addition of behavior sensors that capture event information outside traditional formal classroom contexts enables the support of research into seamless learning analytics of language learners. As the proposed system will collect data from both formal and informal learning environments, this will enable linking of knowledge learnt in either context in addition to information from the LMS, and could be analyzed to predict and extract behaviors of overachieving and underachieving language learners.

Additional integration of specialized language learning tools, such as: testing and exercise systems for the four major skills: listening, speaking, reading, and writing, into the proposed system would provide further opportunities to analyze in detail the behavior of language learners, however at the time of writing this is beyond the scope of this paper and will be addressed in future work.

### *2.3. Learning Record Store (LRS)*

The LRS is an integral part of the proposed system as it will be a central independent point to collect all event data from both the production LMS system and behavior sensors which are still in the research phase of the development cycle. While we have chosen to adopt xAPI as the mode of transporting events data from other systems to the LRS, this is not a strict limitation. We have decided to deploy the latest version of Apereo Foundation's OpenLRS (Apereo Foundation, 2017), which has the ability to support the storing and querying of event data from both xAPI and Global Learning Consortium's Caliper Analytics API (2015). Data from both interfaces are stored in a unified format within the LRS, which will aid data analysis as researchers will not have to spend as much time extracting, transforming, and loading data (ETL). The collection of data in an LRS also reduces information silos were data is only stored locally in a number of different modular systems, and has the potential to increase the availability of data for analysis. In the proposed system, we plan to automate the ETL process by taking incremental (5) Event log dumps from the LRS database as seen in Figure 1, and sending it to the Learning Analytics Tool for automated processing.

### *2.4. Learning Analytics Tool*

The Learning Analytic Tool will act as a dashboard portal system to display actionable results and outcomes of learning analytics in the form of visualizations. The portal is intended to serve a number of different stakeholders, from students comparing their individual progress against that of their anonymous peers, teachers checking the overall progress of the classes under their care, to administrators surveying the effectiveness of education they are offering in their institution. It is proposed that students and teachers will access the portal via a plugin within an LMS that will provide both authentication of the user and also translate the UUIDs that are displayed in the portal into their corresponding real identities depending on their role in the LMS. Teachers who are in charge of class will be able to view all the student identities of students within that specific class. However, students will only be able to view their own identity, and the identities of their peers will remain anonymous in the results of the analysis. Administrators will login into the portal through a local authentication system, and the visualizations will only contain anonymized results that protect the identities of individuals.

This tool will be split into two main parts. The first part is a processing system that will analyze raw (5) Event log dumps from the LRS along with (2) Event and course data from the LMS. This process will extract and calculate relevant metrics for actionable results and outcomes and store these in a local database for analyzed data. The second part is a visualization system platform which will host customizable visualizations of the analyzed data. The UUIDs that are displayed in the portal will be marked up with tags to enable quick and effective parsing and translation to the real identities by a plugin within the production LMS system.

## 3. Conclusion

In this paper, we propose the design of integrated production and research learning analytics systems where personal information is only stored in the production system. We address issues on user privacy by proposing the use of an LMS's internal UUIDs to anonymously collect and analyze learner behavior while using research systems. The visualizations of outcomes and actionable results from the research systems can then be viewed via a reverse proxy plugin that resides within the production

LMS system, and translates the anonymous UUIDs into the real identities based on the users' role within the LMS system.

An advantage of the proposed system is that as the data collected by the system does not contain information that can directly identify students, it allows the data to be openly analyzed within the connected research systems. In the future, we plan to allow students of courses, such as: learning analytics and data mining, to analyze the real data collected by the proposed system. We expect this will help in the development of education of these fields, and encourage students to pursue further research and analysis of their own learning behavior.

In future work, we will complete the implementation of the system and evaluate its effectiveness in meeting the needs of students, faculty staff, and researchers.

## Acknowledgements

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# Requirements for Learning Analytics in Flipped Learning

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**Abstract:** Learning analytics needs to collect and use data originated from various learning environments and analyze them to help learners, instructors, and institutions achieve the goal to improve learning and teaching. The selection of data to be collected and analyzed depends on the requirements of the learning analytics. The requirements in turn are typically derived from use cases of learning activities in the learning model. Most use cases for learning analytics, however, are based on traditional learning methods and thus do not reflect new types of learning methods such as flipped learning. In this paper, we present new use cases and requirements derived from the new pedagogical models and propose a standardization area to encompass new pedagogical models.

**Keywords:** Learning Analytics, Flipped Learning, Pedagogical Model

## 1. Introduction

Flipped Learning is a pedagogical approach in which direct instruction moves from the group learning space to the individual learning space, and the resulting group space is transformed into a dynamic, interactive learning environment where the educator guides students as they apply concepts and engage creatively in the subject matter (Flipped Learning Network, 2014). Flipped learning has the advantage of being able to concentrate more on leading the students' learning and reducing the dropout rate of the students (EDUCAUSE, 2012). Furthermore, flipped learning utilizes a variety of multimedia equipment and systems to effectively communicate learning materials and support learning in the classroom, and has environmental characteristics suitable for producing and analyzing learning activity information.

Based on our previous design and implementation of a reference model for learning analytics (Choi, Cho & Lee, 2014; Bae, Cho & Lee, 2015; Choi, You & Lee, 2016; ISO/IEC TR 20748-1:2016), recently we carried out a project to conducts a pilot application of learning analytics in the flipped learning classroom. In this project, we designed two pedagogical models on the basis of the flipped learning model and found intrinsic limitations of existing data models for learning analytics. In this paper, we present new use cases and requirements derived from the new pedagogical models and propose a standardization area to encompass new pedagogical models.

## 2. Pedagogical Model For Flipped Learning

The flipped learning model is a pedagogical model for improving the learning effect by expanding the participation and autonomy of the learners. Flipped learning as a type of blended learning reverses the traditional learning environment by delivering instructional content before class and moves learning activities, including homework in the traditional learning, into the classroom. In this paper we present a participatory learning process performed as a group activity. The learning process consists of,

1. *Pre-Learning* step where the scope of the content are defined and contents are delivered to students so that students are familiarized with new material before class;

2. *Pre-Class* step where students are motivated to prepare before class by asking students to respond to open-ended questions or attempt to solve some problems, taking into consideration of the characteristics of the students;
3. *In-Class* step where students participate in collaborative group activities and engage in active learning to deepen understanding; and
4. *Post-Class* step where evaluation and assessment occurs to extend student learning and to assess student understanding and mastery by reflecting on the design of the course.

In the following subsections, we describe two pedagogical models from which to derive new use cases of learning analytics by identifying the required functions in the model. We assume that a dedicated LMS-based platform is available to support the application of learning models.

### *2.1. Co-Authoring Model*

Co-authoring model is a discussion-based learning model that combines problem-solving learning, collaborative learning model, and the jigsaw model with flipped learning, and concentrates learning tools on the discussion. Problem-solving learning is a teaching model that solves problems through experiential learning experiences, focusing on the process of reaching rather than the outcome itself. In cooperative learning model, a small group of diverse students are set up to form common goals, to help each other and share responsibility to achieve the goals. In the Jigsaw Classroom (The Jigsaw Classroom 2017), as the name suggest, each member of a small group is responsible for a part of the task and is organized to achieve the goal of the whole small group so that everyone can actively interact without any participant being isolated. The goal is to collectively realize intellectual cooperative learning for problem solving and to exploit the effect of collaborative learning through collaborative authoring in conjunction with learning analytics. The learning process of co-authoring model is summarized in Figure 1.

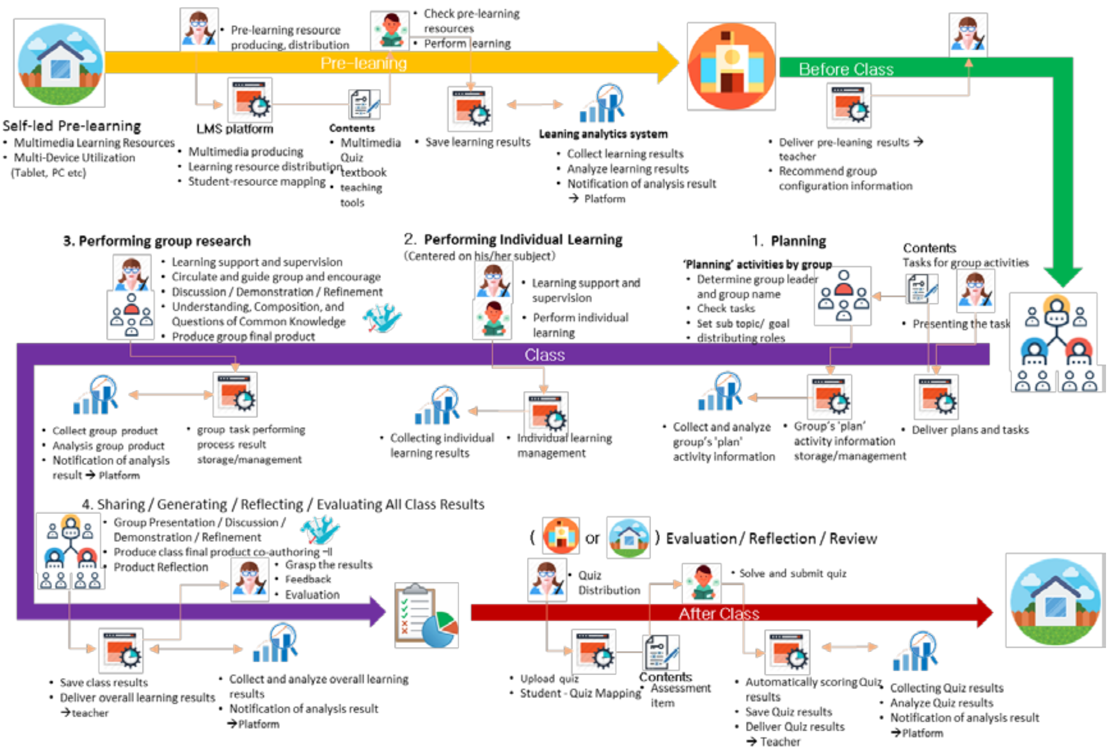


Figure 1. Flow Chart of Co-Authoring Model

### 2.1.1. Pre-Learning

Pre-learning involves the process of distributing and performing prior learning materials, and analyzing results and analyzing related activities. In pre-learning, the teacher writes and distributes pre-learning resources with the support of a dedicated platform, and the student connects to the platform and conducts learning. The results are stored on the platform again and transferred to the analysis system, which analyzes the information about the performance and the performance of the learning.

Table 1: Pre-Learning Activities

| Actor | Activity |
|---|---|
| Teacher | ○ Pre-learning resource producing and distribution |
| Student | ○ Check pre-learning resources<br>○ Perform learning |
| Platform | ○ Multimedia producing function<br>○ Learning resource distribution function<br>○ Learning - resource mapping function<br>○ Save learning results |
| Analytics Prediction | ○ Collect and analyze learning results<br>○ Notification of analysis result to the platform |
| Content | ○ Multi media<br>○ Quiz<br>○ Textbook<br>○ Teaching tools |

### 2.1.2. Pre-Class

In the Pre-Class step, a process of constructing a heterogeneous small group is performed based on the pre-learning result. In this step, the platform may recommend group formation to the teacher along with the pre-learning result. In this way, teachers can organize learners into small groups considering various factors such as personality and preference.

Table 2: Pre-Class Activities

| Actor | Activity |
|---|---|
| Teacher | ○ Identify the results of a small group consisting of 4 to 6 people<br>- It is possible to reconstruct a small group considering not only learning ability but also personality and preference of learners. |
| Platform | ○ Deliver pre-learning results to the teacher<br>○ Recommend group formation |

### 2.1.3. In-Class

The In-Class consists of planning, individual learning, and group exploration. In each process, the teacher utilizes the functions of the dedicated platform to perform tasks, provide learning support, and feedback, and the student connects to the platform and conducts learning. The results of each process are collected by the analysis system through the platform, and the analysis system analyzes this information and applies it to the subsequent learning process.

#### *2.1.3.1. Planning*

The Planning step is the process of preparing the task from the teacher's task assignment and preparing the goal setting and role sharing to solve each task. Teachers communicate tasks through a dedicated platform, and groups use platforms to identify tasks, set goals, and perform role sharing. The 'Plan' activities performed by each group are stored on the platform and delivered to the analysis system.

Table 3: Planning Activities

| Actor | Activity |
|---|---|
| Teacher | ○ Present the task |
| Student | ○ 'Planning' activities by group<br>- Determine group leader and group name<br>- Check tasks<br>- Set sub topic/ goal<br>- distributing roles |
| Platform | ○ Deliver plans and tasks<br>○ Group's 'plan' activity information storage/management |
| Analytics Prediction | ○ Collect and analyze group's 'plan' activity information |
| Content | ○ Task for group activity |

#### *2.1.3.2. Individual Learning*

In the Individual Learning step, individual learning takes place under the supervision and support of the teacher. Teachers can support students' individual learning process through a dedicated platform, and students perform individual learning based on their own topics. The platform stores the student's individual learning results and delivers them to the analysis system, which collects the results.

Table 4: Activities of Individual Learning

| Actor | Activity |
|---|---|
| Teacher | ○ Learning support and supervision |
| Student | ○ Perform individual learning |
| Platform | ○ Individual learning management |
| Analytics Prediction | ○ Collecting individual learning results |

#### *2.1.3.3. Group Research*

In the Group Research step, the co-authoring of the final result is carried out through discussion of the students in each group under the supervision of the teacher. In group research, the teacher performs group supervision and support, circulates the group, and conducts guidance and encouragement. Group compose and understand common knowledge through discussion, and as a result of these discussions, the final result is produced. The platform saves the task execution process and results of the division and sends it to the analysis system. The analysis system analyzes it and applies it to the subsequent learning process.

Table 5: Activities of Group Research

| Actor | Activity |
|---|---|
| Teacher | ○ Learning support and supervision<br>○ Circulate and guide group and encourage |
| Student | ○ Discussion / Demonstration / Refinement<br>○ Understanding, Composition, and Questions of Common Knowledge |

| | |
|---|---|
| | ○ Produce group final product |
| Platform | ○ group task performing process result storage/management |
| Analytics Prediction | ○ Collect group product<br>○ Analysis group product<br>○ Notification of analysis result to Platform |

### 2.1.3.4. *Sharing, Generation, Reflection, and Evaluation*

In the Sharing, Generation, Reflection, and Evaluation step, a series of processes from presentation and discussion of results by group, to analysis of activities related to generating and evaluating the overall class results are performed. Teachers use the platform to understand the results of each class and provide feedback and evaluation. All students also use the platform to produce the final results of the entire class through group presentations and discussions. The learning results of all students are collected by the analysis system through the platform and used in the subsequent learning process.

Table 6: Activities of Sharing, Generation, Reflection, and Evaluation

| Actor | Activity |
|---|---|
| Teacher | ○ Grasp the results<br>○ Feedback<br>○ Evaluation |
| All student | ○ Group Presentation / Discussion / Demonstration / Refinement<br>○ Produce class final product co-authoring<br>○ Product Reflection |
| Platform | ○ Save class results<br>○ Deliver overall learning results to Teacher |
| Analytics Prediction | ○ Collect overall learning results<br>○ Analyze overall learning results<br>○ Notification of analysis result to Platform |

### 2.1.4. *Post-Class*

In the Post-Class, the activity of evaluating, reflecting, and reviewing of the learning result and analyzing related information is performed. The teacher distributes the quiz through a dedicated platform, and the student uses the platform to perform quizzes and submissions. The platform stores the quiz results and delivers them to the analysis system. The analysis system collects and analyzes the quiz results and applies them to the subsequent learning process.

Table 7: Post-Class Activities

| Actor | Activity |
|---|---|
| Teacher | ○ Quiz distribution |
| Student | ○ Upload Quiz |
| Platform | ○ Student - Quiz Mapping<br>○ Student - Quiz Mapping<br>○ Automatically scoring Quiz results<br>○ Save Quiz results<br>○ Deliver Quiz results to Teacher |
| Analytics Prediction | ○ Collecting Quiz results<br>○ Analyze Quiz results<br>○ Notification of analysis result to Platform |

## 2.2. *Mutual Teaching Model*

The mutual teaching model, a kind of peer-to-peer learning model, combines the flipped learning model, STEAM education, and various types of experiential learning. In this model, each member of the group form an expert group with other members assigned with the same learning materials. They become experts in their field by exchanging, researching, and acquiring content about the learning materials they are working on in an expert group to teach their members. Typically learners use multi-device to conduct self-directed learning and refine results through discussion and mutual teaching. Figure 2 shows the overall process of the model.

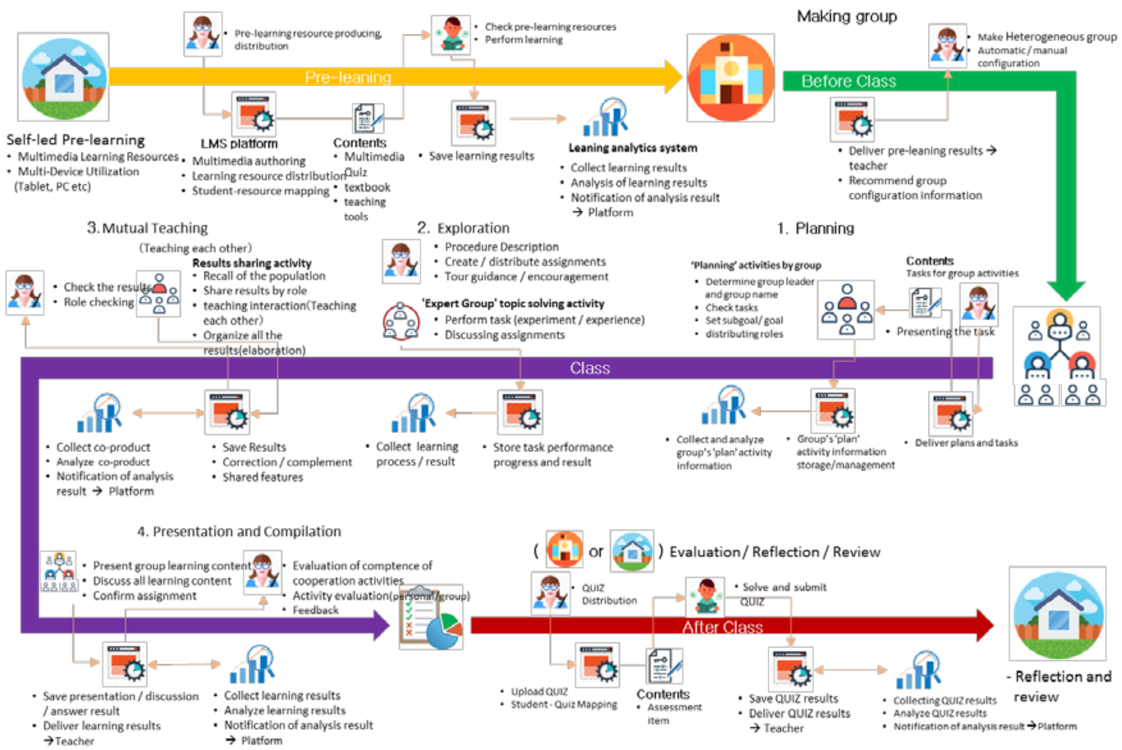


Figure 2. Flow Chart of Mutual Teaching Model

### 2.2.1. *Pre-Learning*

In the Pre-Learning step, individual diagnosis, learning through multimedia, and analysis of related information are performed. Teachers author and distribute prior learning materials with the help of a dedicated platform, and the student identifies and gain familiarity with prior learning resources through the platform. The results are collected through the platform and delivered to the analysis system, which analyzes it and uses it in the subsequent learning process.

Table 8: Pre-Learning Activities

| Actor | Activity |
|---|---|
| Teacher | ○ Pre-learning resource producing and distribution |
| Student | ○ Check pre-learning resources<br>○ Perform learning |
| Platform | ○ Multimedia producing function<br>○ Learning resource distribution function<br>○ Learning - resource mapping function<br>○ Save learning results |
| Analytics Prediction | ○ Collect and analyze learning results<br>○ Notification of analysis result to Platform |

| | |
|---|---|
| Content | ○ Multi media<br>○ Quiz<br>○ Textbook<br>○ Teaching tools |

### *2.2.2. Pre-Class*

In the Pre-Class step, a partial rearrangement may be made based on the pre-learning result information. The teacher receives the pre-learning result through the platform and can make small groups considering various factors such as the learner's personality and preference.

Table 9: Pre-Class Activities

| Actor | Activity |
|---|---|
| Teacher | ○ Identify the results of small groups consisting of 4 to 6 people<br>- It is possible to reconstruct a small group considering not only learning ability but also personality and preference of learners. |
| Platform | ○ Deliver pre-learning results to Teacher<br>○ Recommend Group configuration information |

### *2.2.3. In-Class*

The In-Class step consists of planning, exploration, mutual teaching, presentation and compilation. In each stage, the teacher presents tasks, explains the procedure, confirms the results, and provides feedback. Students perform learning through the platform. The platform collects related information and sends it to the analysis system. The analysis system analyzes it and uses it for later learning.

#### *2.2.3.1. Planning*

In the Planning stage, the process of preparing the goal setting and the role allocation to solve the task presented by the teacher is performed. Teachers deliver tasks through a dedicated platform, and groups use platforms to identify tasks, set goals, and perform role sharing. The 'plan' activities performed by each group are stored on the platform and delivered to the analysis system.

Table 10: Planning Activities

| Actor | Activity |
|---|---|
| Teacher | ○ Present the task |
| Student | ○ ‘Planning’ activities by group<br>- Determine group leader and group name<br>- Check tasks<br>- Set sub topic/ goal<br>- distributing roles |
| Platform | ○ Deliver plans and tasks<br>○ Group’s 'plan’ activity information storage/management |
| Analytics Prediction | ○ Collect and analyze group’s 'plan' activity information |
| Content | ○ Task for group activity |

#### *2.2.3.2. Exploration*

In the Exploration stage, a series of processes of organizing an expert group to perform tasks and collecting related information are performed. The teacher performs procedure description, assignment production and dissemination through a dedicated platform, and constructs expert group according to the role of each group to carry out the task. The platform collects information related to this process and delivers it to the analysis system.

Table 11: Exploration Activities

| Actor | Activity |
| --- | --- |
| Teacher | ○ Procedure Description<br>○ Create / distribute assignments<br>○ Circulate and guide group and encourage |
| Expert Group | ○ 'Expert Group' topic solving activity<br>○ Perform task (experiment / experience)<br>○ Discussing assignments |
| Platform | ○ Store task performance progress and result |
| Analytics Prediction | ○ Collect learning process / result |

#### *2.2.3.3. Mutual Teaching*

In the Mutual Teaching stage, the teacher confirms the results through the platform, and the students share the results of the inquiry stage and conduct mutual teaching. The results are stored on the platform and sent to the analysis system, which uses it for further learning and applies them to the subsequent learning process.

Table 12: Activities of Mutual Teaching

| Actor | Activity |
| --- | --- |
| Teacher | ○ Check the results<br>○ Role checking |
| Student | ○ Reassemble of the leaners<br>○ Share results by role<br>○ Mutual Teaching (Teaching each other)<br>○ Collect all the results (Elaboration) |
| Platform | ○ Save Results<br>○ Correction / complement<br>○ Shared features |
| Analytics Prediction | ○ Collect co-product<br>○ Analyze co-product<br>○ Notification of analysis result to Platform |

#### *2.2.3.4. Presentation and Compilation*

In the Presentation and Compilation step, each group presents learning contents, evaluates activities and compiles the learning results. Teachers evaluate competence of cooperation activities with the aid of a dedicated platform. All students use platform to discuss the contents assigned to each group and the whole. The platform stores information related to this process and sends it to the analysis system, which uses it for later learning results and applies them to the subsequent learning process.

Table 13: Activities of Presentation and Compilation

| Actor | Activity |
|---|---|
| Teacher | ○ Evaluation of capability of cooperation activities<br>○ Activity evaluation(personal/group)<br>○ Feedback |
| Student | ○ Present group learning content<br>○ Discuss all learning content<br>○ Confirm assignment |
| Platform | ○ Save presentation / discussion / answer result<br>○ Deliver learning results to Teacher |
| Analytics Prediction | ○ Collect overall learning results<br>○ Analyze overall learning results<br>○ Notification of analysis result to Platform |

### *2.3. Post-Class*

In the Post-Class, the activities of evaluating, reflecting, and reviewing of the learning result and analyzing related information are performed. The teacher distributes the quiz through a dedicated platform, and the student uses the platform to perform quizzes and submissions. The platform stores the quiz results and delivers them to the analysis system. The analysis system collects and analyzes the quiz results and applies them to the subsequent learning process.

Table 14: Post-Class Activities

| Actor | Activity |
|---|---|
| Teacher | ○ Quiz distribution |
| Student | ○ Upload Quiz |
| Platform | ○ Student - Quiz Mapping<br>○ Student - Quiz Mapping<br>○ Automatically scoring Quiz results<br>○ Save Quiz results<br>○ Deliver Quiz results to Teacher |
| Analytics Prediction | ○ Collecting Quiz results<br>○ Analyze Quiz results<br>○ Notification of analysis result to Platform |

## 3. Requirements for Learning Analytics

In Section 2, we presented pedagogical models to improve pedagogical effectiveness through group learning within the flipped learning educational environment. In these pedagogical models, various requirements for collecting and analyzing information through learning and analytics system are presented. In the course of designing the data model for actual implementation, however, we found some aspects of model that cannot be described by existing standards such as IMS Caliper Analytics (IMS GLOBAL Learning Consortium) or xAPI (Advanced Distributed Learning 2016). In this section, we identify the limitations of current standards and suggest directions for future standards.

### *3.1. Group Dynamics*

In the traditional learning models, the groups for collaborative learning are static in that members of a group are fixed and the groups persist throughout the learning process. However, in the aforementioned pedagogical model, a student can join more than one group at the same time and a new group can be created dynamically during the learning process. Explicit specification of groups and memberships is thus necessary in order to represent learning events associated with groups as well as members of the group.

### *3.2. Roles in a Group*

One of the notable features of flipped learning is that the role and membership of an individual in a group can change over time. The change itself is an event to be monitored and recorded for effective learning analytics. The history of changes also play a part of the learning analytics. Upfront specification of the changes of the role and the membership in one or more groups is thus desired for analysis of the tendency of students and the dynamics of the group.

### *3.3. Collaborative Work*

Student evaluation and feedback are fundamental and intrinsic aspects of learning analytics. In the collaborative pedagogical model as mentioned in Section 2, each group member may move to the expert group and work on group tasks as well as individual assignments. Current standards such as IMS Caliper Analytics focus only on individual or group activities, while the new models require individual evaluation over multiple groups or evaluation of multiple authors of a collaborative work in a group. Such evaluation is possible with clear specification of the relations among a group, members, and collaborative work. Consequently the events generated from the collaborative work need to specify these contextual information.

### *3.4. Group as an Actor*

For several learning activities in flipped learning model, the actor of the activities are best described by a group instead of a specific person. In the case of a group assignment, it may be described as a single submission by all the members of the group, but this would involve unnecessary repeated submission and transmission of events, which in turn can cause burden to the analysis process. If a group can be treated as an actor like a juridical person, the overhead caused by the repetition can be reduced and analysis can take advantage of agreed semantics about the group instead of inferencing from the raw data.

## 4. Conclusion

In this paper, we described two pedagogical models from which to derive new use cases of learning analytics in flipped learning by identifying the learning activities in the model. The derived uses cases are then examined to identify new requirements for learning analytics in flipped learning along with limitations of the existing standards such IMS Caliper Analytics. The key requirements come from the existence of a dynamic group that should be treated as a virtual actor. Future work includes the extended specification of existing standards to fulfill the identified requirements to encompass the proposed pedagogical models in flipped learning.

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