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Developing a National Data Metrics Framework for Learning Analytics in Korea*

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Educational applications of big data analysis have been of interest in order to improve learning effectiveness and efficiency. As a basic challenge for educational applications, the purpose of this study is to develop a comprehensive data set scheme for learning analytics in the context of digital textbook usage within the K-12 school environments of Korea. On the basis of the literature review, the Start-up Mega Planning model of needs assessment methodology was used as this study sought to come up with negotiated solutions for different stakeholders for a national level of learning metrics framework. The Ministry of Education (MOE), Seoul Metropolitan Office of Education (SMOE), and Korean Education and Research Information Service (KERIS) were involved in the discussion of the learning metrics framework scope. Finally, we suggest a proposal for the national learning metrics framework to reflect such considerations as dynamic education context and feasibility of the metrics into the K–12 Korean schools. The possibilities and limitations of the suggested framework for learning metrics are discussed and future areas of study are suggested.

Keywords : National data metrics framework, Learning analytics, big data analysis, K-12 schools

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Introduction

The study and practice of big data analysis have drawn much attention from different functions of society such as the economy, business, politics, and education at the national level in Korea (Kwon, 2013; Yoo & Yo, 2013). The educational applications of big data analysis have been studied from the learning analytics approach (Jo, Kim, & Yoon, 2014, March; Rha, Lim, & Cho, 2014, November), in which the e-learning activities of learners in higher education can be saved, analyzed, and displayed through dashboards in the Learning Management System. The Korean government recently launched another initiative of education that can affect the studies and practices of learning analytics in public school settings. An improved format of digital textbooks is to be distributed and used in some designated secondary schools from the Future School Design Project in 2015 (Choi, Jung, Lee, & Kim, 2014). Because the students are expected to be heavily involved in diverse learning activities through the new digital textbooks and other types of digital access sites, such as community forums by individual schools or other learning resource sites by local school districts, the current challenge is how to conduct learning analytics in this environmental change: What kinds of data should be collected, saved, and analyzed from the learning activities of students with digital textbooks and other tools to provide meaningful information to students, teachers, parents, policymakers, and other school administrators?

A first and fundamental step for the active and systematic implementation of learning analytics at the national level is to set a general framework for data selection: What sorts of data sets should be selected from the active use of digital textbooks and other tools by learners? Theoretically, learning analytics can be conducted in three ways according to data set type. First, some research problems can be analyzed from the existing general data set such as learners' access time intervals for MOOC videos (Guo, Kim, & Rubin, 2014). The data sets are already fixed and saved, and the questions are limited to primitive analysis of the current data set. Second, a data set has been designed and prepared by a specific data representation format such as Contextualized Attention Metadata or Activity Streams (Lukarov, Chatti, Thüs, Kia, Muslim, Greven, & Schroeder, 2014). This data set includes diverse users' activities beyond simple logging files, and more in-depth analysis of learning activities can be conducted. The final but theoretically possible approach is to have a comprehensive data set that can support more creative and extended studies of learning activities for diverse research questions such as the amount of annotations during a certain period of time (IMS Global Learning Consortium, 2013).

The aim of this research is to explore the possibility of a comprehensive data set scheme for learning analytics in the context of digital textbook usage within the secondary school environments of Korea. More specifically, this study intends to develop a comprehensive national metrics framework for learning analytics in Korea. When the IMS Global Learning Consortium defines a learning measurement framework, Caliper, it also suggests IMS Learning Metric Profiles (IMS Global Learning Consortium, 2013). The metrics refer to measurement indicators, and they can draw future research questions of learning analytics because they contain the concept of systematic and comprehensive measurement of data sets. IMS suggests a sample (non-definitive) of the types of metric that can be developed into a more consummated format for learning analytics. IMS has worked on defining standards of e-learning development, and has started to explore its leadership in measuring learning activities systematically for learning analytics. Its sample of learning metrics includes a rough version of learning activity metrics, in which such activities as reading, lecturing, and testing are listed, and in each activity, sub categories of measurement indicators, such as annotations, page/block use, and media use are suggested. In addition to these learning activity metrics, there are foundational metrics such as the context of the institution, the engagement of the time on the task, and the performance of grades. Although IMS suggests that its metrics are only a sample of the entire framework, learning activity metrics applicability is an emerging stage and needs to be set, clarified, and revised for its full version. This study intends to develop a nationwide metrics framework for learning analytics that can extend and reorganize the IMS suggestions of learning metrics samples.

Reviewing selected frameworks for learning analytics (Greller & Drachsler, 2012; Ifenthaler & Widanapathirana, 2014), this study tried to identify the components and dimensions of learning analytics (Koedginger, Corbett, & Perfetti, 2012) and to classify types of data sets according to the objectives of learning analytics (Verbert, Manouselis, Drachsler, & Duval, 2012). On the basis of the literature review, the Start-up Mega Planning model of need assessment methodology (Forbes, Forbes, & Hoskins, 2005) was described as this study sought to come up with negotiated solutions for different stakeholders for a national level of learning metrics framework. The Ministry of Education (MOE), Seoul Metropolitan Office of Education (SMOE), and Korean Education and Research Information Service (KERIS) were involved in the discussion of the learning metrics framework scope. Finally, we suggest a proposal of the national learning metrics framework to reflect such considerations as the dynamic education context and feasibility of the metrics into the K–12 Korean schools. The possibilities and limitations of the suggested framework for learning metrics are discussed and future areas of study are suggested.

Literature Review

Learning metrics framework

A growing number of studies have explored frameworks for learning analytics (Greller & Drachsler, 2012; Ifenthaler & Widanapathirana, 2014). The frameworks show learning analytics components and the relationships among components, which determine the effectiveness of learning analytics. Ifenthaler and Widanapathirana (2014) presented a holistic learning analytics framework that included ten components: individual characteristics, social web, physical data, online learning environment, curriculum, learning analytics engine, reporting engine, personalization and adaptation engine, institution, and governance. These components are closely related with each other in order to adapt to learning environments efficiently through analyzing learners' progression over time. Greller and Drachsler (2012) also suggested six critical dimensions of learning analytics: stakeholders, objectives, data, instruments, external limitations, and internal limitations. These dimensions should be carefully considered in implementing learning analytics to gain meaningful results. Although the frameworks include many components, it is essential in learning analytics to decide what kinds of data should be collected and analyzed.

The data to be collected may vary depending on the learning analytics objectives. Verbert et al.(2012) presented six objectives of using educational data for learning analytics: "predicting learner performance and discovering learner models, suggesting relevant learning resources, increasing reflection and awareness, enhancing social learning environments, detecting undesirable learner behavior, and detecting affects of learners" (p. 135). These objectives imply that learning analytics focuses on cognitive, affective, and social learning processes and learners' competencies (e.g., knowledge, motivation, metacognition, collaboration skills) that reciprocally interact with the learning processes. From the cognitive perspective, for instance, Koedinger, Corbett, and Perfetti (2012) presented a taxonomy of learning processes including (a) memory and fluency-building, (b) induction and refinement, and (c) understanding and sense-making. These learning processes are closely related with knowledge components such as facts, rules, and principles (Koedinger et al., 2012). In addition, Ferguson and Shum (2012, April) asserted the necessity of social learning analytics in order to investigate interactive learning processes, the quality of interpersonal relationships, and dispositions of learners. For learning analytics, it is necessary to collect and analyze data that indicate the quality of the learning process and of learners' competencies.

A few researchers make efforts to collect data, which are closely related to learning processes and competencies, at the level of actions. Verbert et al. (2012) presented data properties that specifically define what data elements can be collected from technology-enhanced learning. As shown in Figure 1, data properties mainly capture the characteristics of actions, which are divided into such categories as *attempt, create/delete, write/edit, select/unselect, search, and send/receive*. In addition to the action types, data properties include information about learners/teachers, resources, contexts, and results, which can be used to describe actions in detail. Ifenthaler and Widanapathirana (2014) suggested collecting data that indicate learning performance, such as login frequency, time on task, time per session, task completion rate, discussion activity, support access, and assessment outcomes. These learning performance data can be decomposed and organized according to the learner action model in Figure 1. Verbert et al. (2012) showed that dataTEL, PSLC DataShop, and Mulce data sets include different data elements according to the learning environment (e.g., intelligent tutoring system, computer-supported collaborative learning platform) from which data sets are derived. Researchers can decide what data elements should be included in a data set by considering the objectives of learning analytics, as well as the interactions between learners and learning environments.

Learning analytics research also needs a framework for learning activities that are a larger unit of analysis than actions. According to activity theory (Jonassen and Rohrer-Murphy, 1999), an activity (e.g., instructional design) consists of multiple goal-directed actions (e.g., analyzing tasks, writing learning objectives, developing instructional materials). The IMS Global Learning Consortium (2013) provided learning activity metrics that include several categories of learning activities such as reading, lectures, quizzes, projects, homework, assessments, and collaborations. Each activity includes several actions that can be measured for learning analytics.

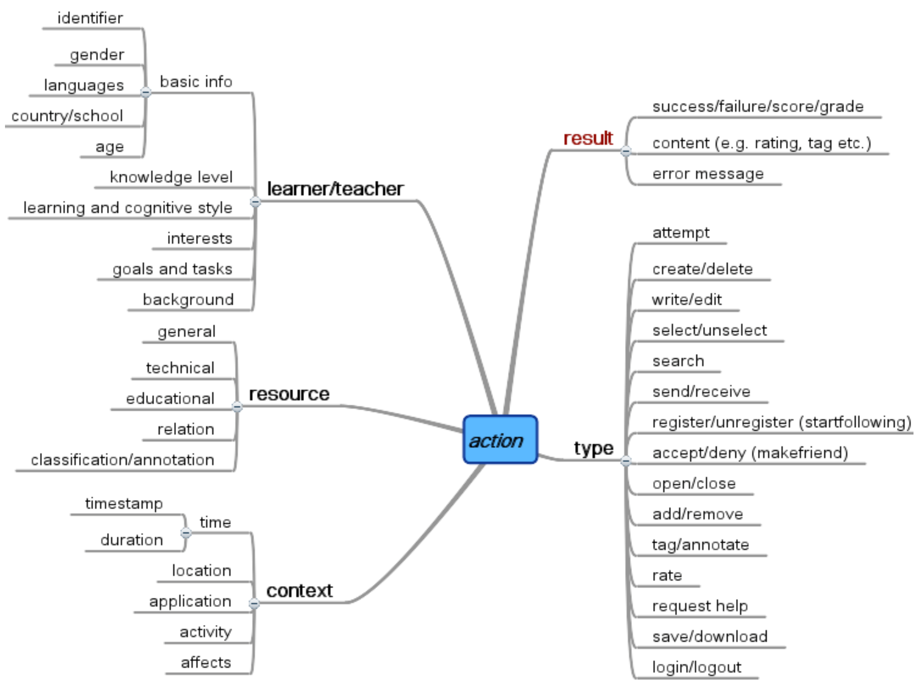

Figure 1. Learner action model (Verbert et al., 2012, p. 137)

For instance, reading can be measured with annotations, page/block use, media use, and lookups; and collaboration can be measured with connections, associated contexts, message profiles, and frequency. Some measurements such as scores, attempts, and view times can be used across multiple activities. In addition, IMS suggested foundational metrics (e.g., contexts, engagement, performance) that are generally applicable to all activities.

IMS Learning Activity Metrics help to organize and optimize measurements for each specific component of learning activities to begin to baseline consistent metrics (IMS Global Learning Consortium, 2013). It is a system enabled to collect the qualified data from a variety of learning channels (e.g., learning content, learning tool, LMS), and it helps to improve the accuracy of learning analytics. Consequentially, *standardized learning activity metrics* help to facilitate interoperability and scalability.

The IMS metrics of learning activities are not finalized yet. Although the metrics provide insight about what data can be collected at the level of learning activities, the metrics can be further elaborated and reorganized in regard to learning activity categories, and measurements. In particular, types of learning activities may vary across different educational systems because learning activities in school reflect the educational needs of a country. For instance, many Korean secondary schools recently had a Free Learning Semester during which students focus on their career explorations without any examination to measure their academic achievements. This new system was developed to prevent the negative effects of exam-oriented education and to help students to explore diverse careers based on their interests and talents. For developing a national metrics framework for learning analytics, it is necessary to investigate what activities and actions are important in the context of a national education system.

Methodology

The Start-up Mega Planning model of needs assessment (Forbes, Forbes, & Hoskins, 2005), an adapted model of Roger Kaufman's Mega Planning (Kaufman, 1992), was used as a guiding framework to conduct this research because the model allowed us to identify needs at various levels (mega, macro, and micro) for the desired data metrics framework had to satisfy different needs at least three levels of layers; national, organizational, and individual. Simultaneously, the metrics were expected to serve as a guiding tool for both conceptual and technical aspects of data collection and analysis.

At the initial meeting with the stakeholders of the project, expectations at different levels were expressed as a vast range of needs. The KERIS and MOE expressed national level needs, whereas SMOE showed organizational and school-level needs. MOE demanded educational data for policy making, while

SMOE wanted to use the data generated in the process of using the e-textbook for analysis to help improve individual learner performance during the classroom activities. SMOE wanted to put more emphasis on the improvement of the nation's educational performance. The computer specialists wanted to keep the data structure as simple as possible by setting the unit of data collection as concretely as possible, whereas the education specialists wanted to keep the unit of data collection at the conceptual level rather than at the concrete. The biggest challenge the project team faced was accommodating these varying, often conflicting, needs of different stakeholders. Even though each the stakeholders unanimously expressed his/her interests in collecting useful data from various educational activities, it seemed obvious that the development process would be quite complex, requiring continuous negotiations among stakeholders.

In order to bring together the various voices on building data metrics, the research team considered a variety of needs assessment frameworks and design methods in planning our study, including McKillip's (1987), Mager and Pipe's (1984), and the design of various systems and conceptual artifacts (Jones, 1992). Eventually, we chose to use the Start-up Mega Planning model of needs assessment. Although this model continues to be applied to various organizational contexts, it has not been applied to educational planning at the national level to the best of our knowledge. To adapt the Start-up Mega Planning model to our project, we added a component of the negotiation process to moderate the needs of different stakeholder groups, such as policy makers, practitioners, and researchers.

Integration of negotiation into start-up mega planning model

Figure 2 depicts the negotiation-based needs assessment approach, which integrates the negotiation component into the Start-up Mega Planning model. The original components specified in the Start-up Mega Planning model are highlighted in gray.

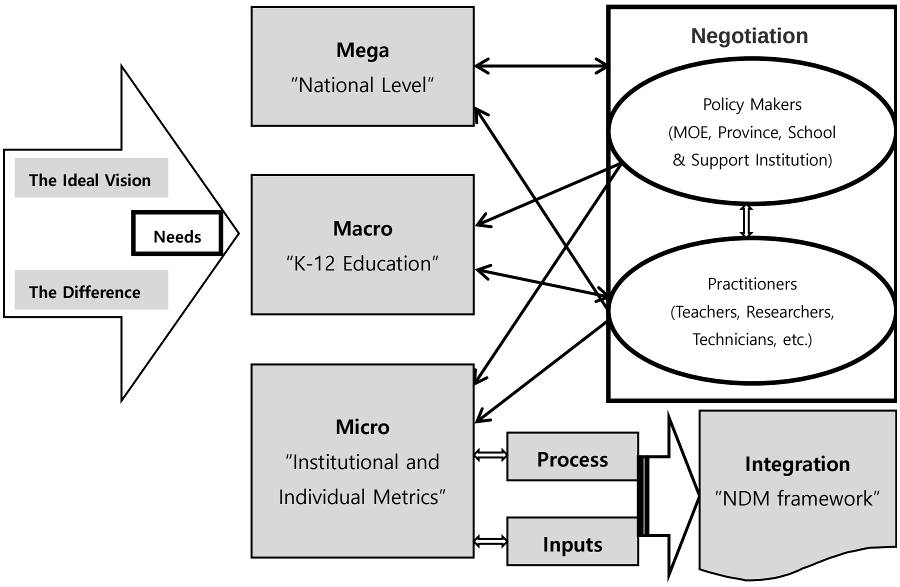

Figure 2. Negotiation-based needs assessment approach used in the study

The ideal vision

Through the information sharing and feedback sessions with stakeholders, the ideal vision was initially defined as developing data metrics for effective use of the big data that can be collected from many sources, such as e-textbooks, educational network services (edunet.net), LOD, and smart phone apps. Eventually, the term "Creative Use of Big data in Education (CUBE)" emerged as a catch phrase. The ideal vision was defined as the development of learning activity metrics that can be used for various educational purposes under the assumption that the metrics facilitate "the creative use of the big data in education." Even though the ideal vision was vague and unclear, stakeholders, as well as the research team, were satisfied because the term CUBE signifies many facets of educational big data analytics.

The difference

The difference was obvious: no such framework existed in Korea. There was widespread agreement that the adoption of big data would be beneficial and enable efficiency; developing a basic data metric at the national level has yet to be attempted in education.

Mega planning

This stage will clarify to which area the project will commit to contribute. As for the commitment-building sessions, information on the current state of big data analytics was shared and the scope of the data metrics framework was discussed with MOE, SOME, and KERIS. The result was that the project will involve developing the metrics primarily in the context of K–12 education for the improvement of students' performance. Moreover, it was decided that the emerging data metrics framework will first be applied to the future school project as an initiative in which a middle school is being renovated with various futuristic facilities and equipped with technology and new concepts. At the end of this stage, the research team developed a blueprint of learning data metrics. The research team tried to draw the blueprint as flawlessly as possible.

Macro planning

This stage is to specify objectives within the mega framework. In this process, IMS learning activity metrics were intensively studied and modified. Problem-solving meetings were held with educators, policymakers, big data analysis specialists, and program developers in order to negotiate the contents of the metric framework. The blueprint of the data metrics framework was intensively reviewed and revised, and finally, the initial data framework emerged. Shortly after the development of the initial data framework, an international forum on big data and learning analytics was piloted to settle the feasibility of the framework. Advice from the learning analytics experts was seriously considered and the framework was revised further.

Micro planning

This stage is to identify objectives and targets to be met by each sector and individual within K–12 education. Classroom observations and interviews with school teachers and administrators were conducted to check the usability of the framework at a practical level. The initial framework was presented to the stakeholders as an initial product of the project.

Process

In order to check the feasibility of the framework functioning as a facilitation tool for actual learning analytics situations, learning analytics on four different areas were simulated: meta cognition, self-directed learning, subject interest, and collaboration. The simulation method was used because the future school is planned to open in 2016; the actual data were yet to be collected. The simulation results showed that the framework is useful in at least three different directions: suggesting areas of meaningful big data collection, formulating the analysis problems, and selecting the related data for the analysis.

Input

Korean schools are already heavily dependent on IT use in classrooms. Infrastructure to gather big data is well established in K–12 education. The future school will provide data for learning analytics based on the framework. The data collection is scheduled to begin in 2016.

Integration

The National Learning Metrics framework was suggested as a final product with a set of recommendations. The stakeholders of the project agreed to the proposed framework at the final presentation and discussion session.

Negotiation

During the entire needs assessment process, continuous negotiations were held via individual and group interviews, small group meetings and public hearings. Present at these negotiations were stakeholders including policymakers from MOE, SOME and KERIS, school principals and teachers, researchers, and technicians. Forums and seminars were organized within the research team or with national and international experts in big data and learning analytics. In total, 17 negotiations were held and resulted in the mega, macro, and micro plans for this research.

Proposed National Data Metrics Framework

The structure of the framework

Learning data can be collected before, during, and after students' learning. The final form of the metrics framework reflects them in a visual format. The context consists of the information on the learner's situation as it relates to the learning environment and to the learner's characteristics. Learning activity consists of the total conceptual division of the learning patterns, which can be divided into three categories: tools, basic activities, and combined activities.

Three data sources: context, learning activity, and performance

Contextual data

Contextual data are important because they set up the baseline for collecting and analyzing learning activity data. In a way, the contextual data are the most important element for the interpretation of learning analytics. We included the contextual data as an important part of the metrics. The thirteen salient contextual data components are: institution, course, learner profile, course context, path, usage context, activity usage, time on task, session time, last access, activity affinity, content affinity, and task patterns. The data can be collected either before or during the students' activities.

Learning activity data

Learning activity data are the collection of engagement data in a digital format. They are the results of an individual student's learning process, and are mainly collected from classroom activities when the students are using digital devices such as an e-textbook and Linked on Data (LOD) resource connections. In Figure 3,

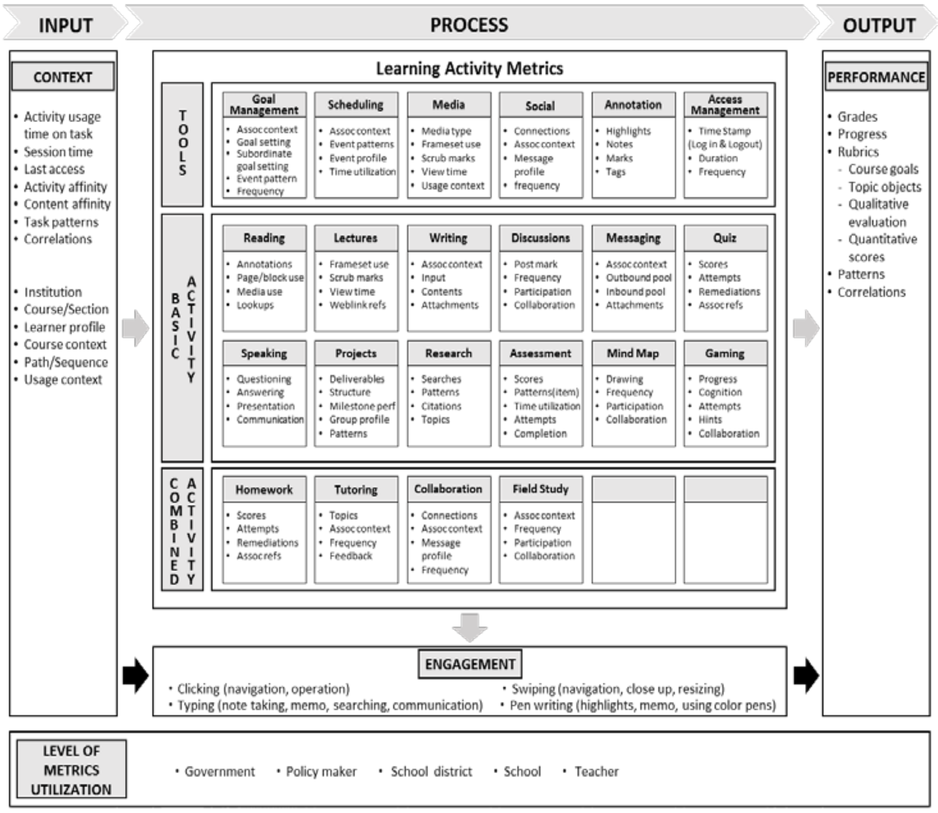

Figure 3. Proposed national learning metrics framework

learning activity metrics are elaborated in two different parts, namely, learning activity metrics and engagement, in order to show that the upper parts are a conceptual part of learning activities and the lower parts are the computer-collected tangible data.

Learning activity metrics.

Learning activity metrics show the collection of learning activities and actions derived from dynamic teaching and learning situations. In order to explore learning activities, we reviewed literature and learning cases in a Korean K–12 school context. From the results of literature and case reviews, several activities have been added to the learning activity metrics.

These learning activity metrics are necessary to provide a learning context for learning analytics. Systems cannot measure learning activities and actions directly. However, we are able to guess the contextual meaning of students' behaviors from the learning activities. Therefore, it is important to provide learning activity metrics for understanding learning contexts.

Learning activity metrics consists of three layers: tools, basic activities, and combined activities. The first layer contains tools to support teaching and learning activities, such as goal management, scheduling, media, social, annotation, and access management. For example, goal management is a tool to help set up and manage the activities of the learning objectives. Scheduling is also a tool for support to manage learning schedules. A unit of tools contains four or five sub-tools. For instance, social includes connections, association context, message profile, and frequency.

The second layer, basic activities, includes simple units of activities such as reading, writing, discussion, and assessment. These activities are derived from case reviews of Korean K–12 classes, using digital devices and e-textbooks.

The third layer, combined activities, includes those that combine more than two basic activities. For example, homework requires not only basic activities such as reading and writing, but also tools such as media and annotation.

Six new learning activities were added into sample versions of learning activity metrics through this study: goal management, access management, writing, speaking, mind mapping, and field study. These activities were derived from exploration of learning activities in a Korean K–12 educational environment. For example, many subjects, such as literature and foreign language, allow students to create a mind map in Korean secondary school environments. Similarly, field study is a teaching and learning method that many lessons use popularly in Korean elementary schools.

Some units of these activities include a few learning actions. Actions represent measurement units within each learning activity. For instance, a reading activity has four actions as annotations, page and block use, media use, and lookups. Each action can be measured in the learning system.

Engagement.

Computer systems cannot recognize learners' learning activities or actions directly. For example, if learners create a cognitive map while reading a textbook, two learning activities, reading and mind mapping, are conducted. The computer does not recognize the conceptualized activities such as reading and mind mapping, but it recognizes certain elemental actions such as drawing, clicking, and swiping. We manifested the elemental, computer-recognizable components under the category of engagement.

Engagement is the smallest unit that can directly measure human behavior when students do something for learning. In particular, when students can use e-textbooks, applications, smart tablets, and PCs for learning, the engagement can be digitalized from digital devices and applications in online and face-to-face learning environments. It is necessary to collect engagement units because computer systems can recognize only the digitalized numbers.

Engagement is based on basic events, time and data input, and output generated from a computer. Basic events of engagement are raw data generated while students use digital devices such as e-textbooks and smart tablets. We can collect raw data, *what* users do, basically, with digital devices. Although computer systems do not recognize what learners do for learning, it can detect which functions are operated. For instance, computer systems can record whether the highlight function is used. We do not know what learning activity is needed to use this highlight function. Basic events of engagement include four elements: clicking, typing, swiping, and pen writing. Each element consists of two, three, or four sub-elements. For example, clicking is classified in two sub-elements: navigation and operation. Pen writing is subdivided into highlight, memo, and color pen use.

Moreover, when users study using digital devices, digital devices can record the time taken for actions. We can answer several questions through digital devices. For instance, when do individuals start to take notes? How long they have been taking memos? How often do students use color pens? These time records can support measuring learning activities.

Data input and output can also be important elements in engagement. Through using digital devices, there are data generated automatically. If learners access a learning system, login data can be generated. In addition, students can make an artifact while they study using digital devices. For instance, students can make a

Table 1. Elements of engagement

Engagement	Elements	Sub-elements
Basic events	Clicking (C)	C1. Navigation C2. Operation
	Typing (W)	W1. Note taking W2. Memo W3. Searching W4. Communication
	Swiping (S)	S1. Navigation S2. Close up S3. Resizing
	Pen writing (P)	P1. Highlights P2. Memo P3. Using Color pens
Time (T)		T1. Timestamp T2. Duration T3. Interval
Data input and output	Login-Logout, Installation, Download, Save, Print, Record, Capture, Bookmark	

bookmark, an image by capture, or an audio file by recording. These events and artifacts can generate data in learning systems. Table 1 shows elements of engagement that can directly measure learning actions during the learning process.

Performance

Performance data was collected when learners ended their learning. The performance represents output indicators at the levels of learning, course, and institution. Generally, instructors, courses, and institutions obtain these performance data and try to analyze these data on a small scale because stakeholders related to learning are familiar with performance data such as grades or scores. This data contains the results of quantitative scores and qualitative evaluations: grades, progress, rubrics, patterns, and correlations.

Conclusion

This research was conducted to develop a framework of national-level data sets for learning analytics. Korea has already started to develop nationwide electronic books for advancement in the information society. Recently, the country has been under the operation of a project to establish future schools. In a scheme for the development of electronic textbooks and future schools, related experts and authorities began to discuss the possibilities of systemized learning analytics, considering that a variety of learners' activities using information communication devices can be stored with current technologies. To analyze learning activities of secondary school students at the national level systematically, it is necessary to consider what types of data sets should be collected. In other words, useful data should be screened and selected first out of learning data that may be created through internet-based learning services, including electronic textbooks used inside and outside classrooms, and learning management systems under the education precinct and Korean Education and Research Information Service (KERIS), to which learners can have access.

This research experimentally proposes a framework with metrics perspectives for the development of the data sets that are necessary for learning analytics at the national level. Because this is a national level framework, extensive data will be collected, and requests from numerous people and organizations will be reflected. In developing the data metrics framework, a needs assessment methodology is adopted that will integrate and reflect all views from the MOE, offices of education, KERIS, school principals, teachers, education technology experts, and network specialists. Data metrics defines measurable data. The data metrics framework, used for learning analysis, consists of components and dimensions of quantitative data that should be collected to generally analyze and understand learning procedures and the results of learners. The data metrics scope for learning analytics is divided into context, learning activities, engagement, and performance. Although learning activities are the central point here, it shows a big picture of the data metrics framework as it is composed of the context on the front, engagement in the middle, and performance on the back. Learning activities are divided into learning tools, basic activities, and combined activities. With the basic activities in the center, it is composed of the tool and combined activity layers that support basic activities. Basic activities focus on data related to learning activities, and include annotation action inside the reading activities and the action for use of pages and blocks. Combined activities consist of several basic activities. As an example, homework activities include data related to the scores, number of times of attempt, and resubmissions that are displayed during the execution of the tasks. The performance that represents the outcome of learning activities includes grades, quantitative scores, qualitative evaluations, and learning patterns.

The proposed data metrics framework in this learning analytics research still contains potential characteristics from the theoretical level. Nonetheless, this framework has significance, considering the following three types of dimensions.

First, it shows how the framework for the systematic data collection, used for learning analytics, can be composed in an educational application of big data. Learning analytics have been attempted to a limited extent on the basis of the existing data. As an example, learning patterns are analyzed by using log-in data, learning consistency time, and in a number of cases of writing on the forum that are collected through the learning management system at universities (Park & Jo, 2014). This partial application approach spotlights part of the possibilities that the learning analytics or an educational application of big data can bring. The metrics framework piloted by the IMS in the learning analytics dimension shows how the general data sets can analyze the learning activities, and this research further enhances this framework. To systematically conduct learning analytics, it should be determined what kinds of data should be collected and arranged. The framework finalized in this process helps users to understand precisely what types of data are stored by the diversified Internet-based education institutions and helps them to use these institutions for future research.

Second, it depicts how the data metrics framework, which allows national level learning analytics, can be structured. Korea has the environmental characteristics necessary for attempting big data level learning analytics. Since 2000, the Korean government has been carrying out education information projects. Recently, the country has supported educational and learning programs with an information communication technology base through the electronic textbook and future school projects. In line with this plan, the country is also executing its plan to lead the practice of learning analytics as a part of the national education information project. The purpose of this plan is to establish a national data set to execute systemized learning analytics as secondary school students start to use digital textbooks based on mobile devices. This plan will not only show how access to big data is possible through the learning data sets at the national level for public education, but also prove how evidence-based education that uses information communication technology can be realized in the dimension of school education.

Third, the data metrics framework in this research has its significance in that learning analytics are based on learning activities. Taking the learning activities as the base of the analytics unit is closely related to the learning design approach of the IMS. The IMS Learning Design (LD), which is presented as an alternative for setting of the standard of e-learning design and development, guides the design as to what type of learning activities students conduct under e-learning conditions, instead of focusing on the teacher design. In line with that, the illustrated metrics framework of the IMS for learning analytics is also focused on learning activities. The data metrics framework proposed in this research is based on the illustrated framework of the IMS. It reflects and shows, with learners visible, diversified learning activities of the actual Korean education system. It also divides the basic activities of learners, which enable all data created by the computer into such engagement as clicking, typing, swiping, and pen writing.

Our proposed data metrics framework is experimentally derived from the research of related documents and books and a needs assessment methodology to analyze national-level learning. Accordingly, through the course of operations of such data sets in real situations, more research is necessary to verify those that can be realized and those that cannot. Through this procedure, related authorities and organizations may further promote and support diversified learning analytical research by determining how general data sets can be constructed for systemized learning analytics.

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