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Utilizing Online Activity Data to Improve Face-to-Face Collaborative Learning in Technology-Enhanced Learning Environments

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Graduate School of
Convergence Science and Technology
Seoul National University
Program in Digital Contents and Information

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Abstract

We live in a flood of information and face more and more complex problems that are difficult to be solved by a single individual. Collaboration with others is necessary to solve these problems. In educational practice, this leads to more attention on collaborative learning. Collaborative learning is a problem-solving process where students learn and work together with other peers to accomplish shared tasks. Through this group-based learning, students can develop collaborative problem-solving skills and improve the core competencies such as communication skills. However, there are many issues for collaborative learning to succeed, especially in a face-to-face learning environment. For example, group formation, the first step to design successful collaborative learning, requires a lot of time and effort. In addition, it is difficult for a small number of instructors to manage a large number of student groups when trying to monitor and support their learning process. These issues can amount hindrance to the effectiveness of face-to-face collaborative learning.

The purpose of this dissertation is to enhance the effectiveness of face-to-face collaborative learning with online activity data. First, online activity data is explored to find whether it can capture relevant student characteristics for group formation. If meaningful characteristics can be captured from the data, the entire group formation process can be performed more efficiently because the task can be automated. Second, learning analytics dashboards are implemented to provide adaptive support during a class. The dashboards system would monitor each group's collaboration status by utilizing online activity data that is collected during class in real-time,

and provide adaptive feedback according to the status. Lastly, a predictive model is built to detect at-risk groups by utilizing the online activity data. The model is trained based on various features that represent important learning behaviors of a collaboration group.

The results reveal that online activity data can be utilized to address some of the issues we have in face-to-face collaborative learning. Student characteristics captured from the online activity data determined important group characteristics that significantly influenced group achievement. This indicates that student groups can be formed efficiently by utilizing the online activity data. In addition, the adaptive support provided by learning analytics dashboards significantly improved group process as well as achievement. Because the data allowed the dashboards system to monitor current learning status, appropriate feedback could be provided accordingly. This led to an improvement of both learning process and outcome. Finally, the predictive model could detect at-risk groups with high accuracy during the class. The random forest algorithm revealed important learning behaviors of a collaboration group that instructors should pay more attention to. The findings indicate that the online activity data can be utilized to address practical issues of face-to-face collaborative learning and to improve the group-based learning where the data is available.

Based on the investigation results, this dissertation makes contributions to learning analytics research and face-to-face collaborative learning in technology-enhanced learning environments. First, it can provide a concrete case study and a guide for future research that may take a learning analytics approach and utilize student activity data. Second, it adds a research endeavor to address

challenges in face-to-face collaborative learning, which can lead to substantial enhancement of learning in educational practice. Third, it suggests interdisciplinary problem-solving approaches that can be applied to the real classroom context where online activity data is increasingly available with advanced technologies.

Keyword: learning analytics, online activity data, face-to-face collaborative learning, technology-enhanced learning environment

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Table of Contents

Abstract i

Chapter 1. Introduction 1

1.1. Motivation 1

1.2. Research questions 4

1.3. Organization 6

Chapter 2. Background 8

2.1. Learning analytics 8

2.2. Collaborative learning 2 2

2.3. Technology-enhanced learning environment 2 7

Chapter 3. Heterogeneous group formation with online activity data 3 5

3.1. Student characteristics for heterogeneous group formation 3 6

3.2. Method 4 1

3.3. Results 5 1

3.4. Discussion 5 9

3.5. Summary 6 4

Chapter 4. Real-time dashboard for adaptive feedback in face-to-face CSCL 6 7

4.1. Theoretical background 7 0

4.2. Dashboard characteristics 8 1

4.3. Evaluation of the dashboard 9 4

4.4. Discussion 1 0 7

4.5. Summary 1 1 4

Chapter 5. Real-time detection of at-risk groups in face-to-face CSCL 1 1 8

5.1. Important learning behaviors of group in collaborative argumentation 118
5.2. Method 120
5.3. Model performance and influential features 125
5.4. Discussion 129
5.5. Summary 132
Chapter 6. Conclusion 134
Bibliography 140

List of Figures

Figure 1-1. Two types of online activity data 5
Figure 1-2. Organization of this dissertation 6
Figure 2-1. Purdue's Course Signals 17
Figure 3-1. Heterogeneous group formation 38
Figure 3-2. Online activity data in the edX platform 45
Figure 3-3. High and low engagement heterogeneity 49
Figure 4-1. Default status of student dashboard 84
Figure 4-2. Student dashboard with higher level of feedback using additional pop-up window 84
Figure 4-3. Three status of opinion counts section 85
Figure 4-4. Three status of interactivity section 88
Figure 4-5. Three status of argumentation elements section 91
Figure 4-6. Instructor dashboard 94
Figure 4-7. Timeline of the experiment 96
Figure 4-8. Students' in-class activities on a Trello board 97
Figure 5-1. A screenshot of the collaboration tool 121
Figure 5-2. Prediction accuracy for each elapsed time from the beginning of face-to-face collaborative learning 127
Figure 5-3. The change of the variance of action count during class 130

List of Tables

Table 2-1. Types of learning activities and behaviors................ 12

Table 2-2. Comparison of traditional methods and flipped classroom 30

Table 3-1. Student characteristic variables 47

Table 3-2. Group heterogeneity variables 47

Table 3-3. Descriptive analysis of student characteristic and group heterogeneity.. 52

Table 3-4. Correlation analysis of group heterogeneity and F2F group achievement 54

Table 3-5. Hierarchical regression analysis on group heterogeneity 55

Table 4-1. Survey items for investigating the perception of learning process and outcome 101

Table 4-2. Survey items for investigating the perception the dashboard system.. 102

Table 4-3. Results of t-test and descriptive statistics for comparing group process 104

Table 4-4. Results of t-test and descriptive statistics for comparing group achievement 104

Table 4-5. Results of t-test and descriptive statistics for comparing student perception of learning 105

Table 5-1. Group activity features of collaborative learning ... 123

Table 5-2. Influential features in each phase............................ 128

Chapter 1. Introduction

1.1. Motivation

Advances in technology led to many changes to various fields in our society. As the amount of knowledge and information increases, critical problems of modern society become harder to solve with the knowledge and experience of a single individual. For this reason, communicating and collaborating with others to solve complex problems is highlighted. The importance of collaborative problem-solving skills is evident in the 21C competences frameworks, as put forth by leading international organizations such as the OECD and the UNESCO. All of these frameworks include communication and collaboration skills as the essential competencies for the future society and education (Voogt & Roblin, 2012).

In this 21C society, collaborative learning is getting more attention than before, as it provides students with opportunities to develop 21C competences. Collaborative learning has many educational benefits; students can share their experiences and knowledge as well as cognitive processes in problem-solving, thereby expanding their cognitive domains (Hathorn & Ingram, 2002). It also promotes students' critical thinking (Goodyear, Jones, & Thompson, 2014) and provides experience in conflict management and co-regulation (Blaye, Light, & Rubtsov, 1992; Doise & Mugny, 1984).

Despite the educational benefits of collaborative learning, there are many issues in its design and management, especially in a face-to-face setting. First, inherent in its design, the group formation process tends to lack efficiency. Group formation is the first step in collaborative learning as an important determinant of the success and failure of collaborative learning (Cohen, 1994; Johnson & Johnson, 1999; Pelled, Eisenhardt, & Xin, 1999). In order to form groups in an effective manner, student characteristics, such as academic achievement, need to be identified in advance so that they can be considered when assigning students to particular groups. Many methods including surveys, questionnaires, and paper-based assessments have been used to collect and evaluate the characteristics. However, these traditional methods tend to require a lot of time and effort for both instructors and students. This problem can be a bottleneck in the group formation process, and a barrier to implementing collaborative learning in a classroom setting.

The second issue is that providing adaptive support for many groups is difficult in managing face-to-face collaborative learning. Students who participate in collaborative learning can face various problems such as failure of task coordinating (Baker, Greenberg, & Gutwin, 2001; Erkens, Jaspers, Prangsma, & Kanselaar, 2005; Järvelä et al., 2014), ineffective communication, or emotional conflicts between group members (Kwon, Liu, & Johnson, 2014). Each of these problems requires an adaptive, problem-specific (Azevedo, Johnson, Chauncey, & Burkett, 2010). However, in a face-to-face setting, such is hardly provided given only a small number of instructors in managing a large number of student groups. Hence students are less likely to receive adaptive support, which hinders the effectiveness of collaborative learning in class.

The last, but not least, issue is to detect at-risk groups who need instructional support. For successful collaborative learning, it is crucial to detect at-risk groups and help them overcome their problems early in learning process (Van Leeuwen, Janssen, Erkens, & Brekelmans, 2015). Otherwise, they would waste their learning time and use their limited time resource unproductively. Moreover, this issue is aggravated in a large class because it is challenging for a few instructors to monitor all collaboration groups and identify at-risk groups. If at-risk groups are not detected and managed during the class, they may not earn expected achievements in face-to-face collaborative learning.

These issues can be addressed by utilizing educational data collected with various technological methods. With advances in technology, technology-enhanced learning environments abound (Greller & Drachsler, 2012). Student learning activities both online and offline can now be mediated, coordinated, and recorded with the support of these technologies. This amasses a variety of online activity data (Blikstein & Worsley, 2016), and researchers can now obtain an in-depth and comprehensive understanding of learning by utilizing the data (Hwang, 2014).

This dissertation aims to utilize the online activity data in an effort to tackle the issues of collaborative learning. Specifically, it collects different types of data to addresses the aforementioned issues in a face-to-face setting. First of all, student online activity data is collected before a face-to-face class to identify meaningful student characteristics to investigate a more efficient group formation method. For in-class adaptive support, student online activity data is collected during a face-to-face class to build a learning analytics dashboard which provides adaptive feedback to a large number of student groups. Lastly, a machine learning algorithm is applied with the online activity data to detect at-risk student groups, based on group learning behaviors. This dissertation is expected to be a basic research of the field of learning analytics and present practical cases where online activity data can be utilized in educational practices.

1.2. Research questions

The purpose of this dissertation is to improve face-to-face collaborative learning by utilizing online activity data. For the purpose, this dissertation addresses the following research questions:

RQ1. What is the influence of group heterogeneity, derived from before-class online activity data, on group achievement?

RQ2. What is the effect of learning analytics dashboard, created with during-class online activity data, on learning process and outcome?

RQ3. How accurately can the prediction model, based on during-class online activity data, detect at-risk groups? What learning behaviors contribute most to group achievement?

To answer the research questions, two types of online activity data were utilized (Figure 1-1). The first type of data is before-class online activity data. This data was collected from an online learning system in which students participated before face-to-face collaborative learning. This data was utilized for the first research question to identify student characteristics before the face-to-face class. The second type of data is during-class online activity data. This data was collected during face-to-face collaborative learning in real-time. This data utilized for the second and third research questions to implement learning analytics dashboard for providing adaptive support and build prediction model for at-risk group detection.

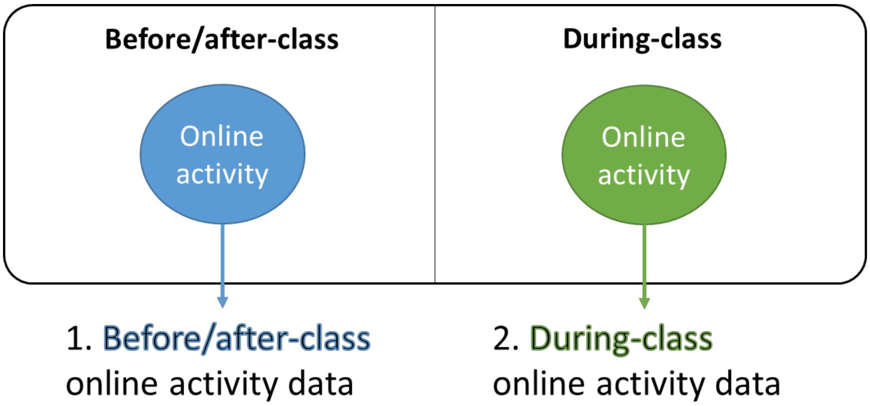

Figure 1-1. Two types of online activity data

1.3. Organization

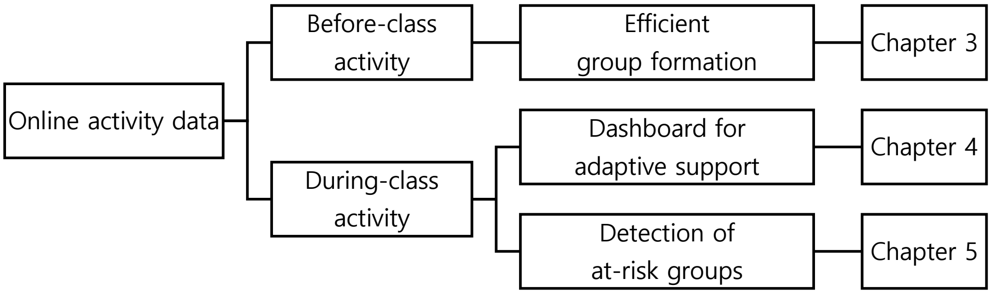

Figure 1-2. Organization of this dissertation

The organization of this dissertation is summarized in Figure 1-2. First, the theoretical background and literature review are present in chapter 2. A series of three studies regarding the issues of face-to-face collaborative learning are placed from chapter 3 to 5. In chapter 3, before-class online activity data is explored to find whether it can capture relevant student characteristics for group formation. If meaningful characteristics can be captured from the data, the entire group formation process can be more efficient because the task can be automated by executing specific algorithms. In Chapter 4, learning analytics dashboards are presented to provide adaptive support during a face-to-face class. By utilizing during-class online activity data, the dashboard system would monitor each group's current learning status, and provide adaptive feedback according to the status in real-time. In Chapter 5, during-class online activity data is utilized to build a predictive model to detect at-risk groups. The model is trained based on various features that represent important learning behaviors of a collaboration group. Finally, the conclusion of this dissertation is drawn in chapter 6.

Chapter 2. Background

2.1. Learning analytics

As the development of Internet technology has facilitated construction and operation of online learning environments, online learning experience is becoming more common. In the early days of online learning, the advantage was emphasized, which students can make a plan for managing their learning in their own pace without time and space restriction (Behrens & DiCerbo, 2014). It was a great advantage of online learning in contrast with the traditional learning that was implemented in a physical classroom. Meanwhile, the educational data that is collectable in an online learning environment gained considerable attention because of its possibility of being utilized for educational purposes (Behrens & DiCerbo, 2014; Gašević, Dawson, & Siemens, 2015; Greller & Drachsler, 2012; Viberg, Hatakka, Bälter, & Mavroudi, 2018).

In this regard, new research methodologies have been introduced to discover potential values of educational data. Learning analytics is one of the new methodologies utilizing student’s learning data for educational purposes (Greller & Drachsler, 2012; Pardo, 2014, 2017). According to the Horizon Report (the result of the Horizon Project conducted by the New Media Consortium), learning analytics has been expected to be the core technology of education every year since 2012. Learning analysis refers to a process of measuring, collecting, analyzing, and reporting of data about students and the learning context for the purpose of understanding students and optimizing learning environment (Siemens & Long, 2011). It includes a genetic set of techniques and algorithms that are applied to the educational domain for finding patterns in educational data and uses the findings for deep understanding of students and their learning (Pardo, 2014; Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2018; Viberg et al., 2018; Yang & Li, 2018).

Learning analytics has been used not only for understanding students but also for designing and managing learning environments more efficiently and effectively (Larusson & White, 2014; Tanes, Arnold, King, & Remnet, 2011; Wise, 2014). In-depth information about learners and their learning processes captured from the data can be used to manage and improve learning environments. For example, student characteristics can be identified by investigating students' learning patterns in the educational data, and then the characteristics can be used for designing more effective instructional interventions by understanding the learning outcomes as a result of the characteristics (Jo, Kim, & Yoon, 2015; Kim, Park, Yoon, & Jo, 2016; Koedinger, Kim, Jia, McLaughlin, & Bier, 2015). The information also allows students to monitor and regulate their own learning by showing their current learning status (Roberts, Howell, & Seaman, 2017; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013), and enables learning environments to provide adaptive support based on the status (Kinshuk, 2016; Roll, Wiese, Long, Aleven, & Koedinger, 2014). In addition, at-risk students who want to drop out of their learning course can be identified by utilizing the data, and consequently they can be provided with appropriate instructional interventions to support them (Baldi & Sadowski, 2014; Gašević, Dawson, Rogers, & Gasevic, 2016)

Like learning analytics, there is another research field where educational data is also used for promoting student’s learning and developing learning environments; Educational data mining. (Baker & Inventado, 2014). Learning analytics and educational data mining represent the emergence of data-intensive approaches to the education domain (Behrens & DiCerbo, 2014; Winne, 2017). The two fields have the potential to make invisible learning patterns visible by utilizing educational data, consequently, gain more value under the patterns to practical applications of education (Bienkowski, Feng, & Means, 2014). While learning analytics and educational data mining are sharing fundamental purposes, improvement of education, they also have a few distinctions in several details. In terms of goal, learning analytics puts considerably greater focus on leveraging human judgment, and educational data mining places considerably greater focus on automated discovery (Siemens & Baker, 2012). The differences in these goals differ from the approaches they use primarily. Learning analytics takes white-box approaches that explain and understand the learning process to improve it by informing humans, while the educational data mining takes black-box approaches that are technology and data-driven, and result-oriented (Nistor & Hernández-Garcíac, 2018). The two fields thus have different focuses. While LA focuses on informing and empowering teachers and students, EDM focuses on automated optimization, without human power, by computers (Baker & Inventado, 2014).

In the field of learning analytics, various types of educational data have been used. The most popular type of educational data in learning analytics field is activity data of student (Di Mitri, Schneider, Specht, & Drachsler, 2018; Elias, 2011; Lang, Siemens, Wise, & Gašević, 2017; Nistor & Hernández-Garcíac, 2018; Siemens, 2012). The activity data is the data generated by learning behaviors in learning activities. Types of activity and examples of learning behavior for each type are summarized in Table 2-1. The type of activity data varies depending on when and where the learning activities are performed. The activity data can be separated into online and face-to-face activity data depending on where the learning behavior occurs. In addition, depending on when the learning behavior occurs, the activity data also can be divided into before/after-class and during-class activity data.

Among the various types of activity data, the data to be noticed is online activity data in which online learning behaviors are recorded. As technology has developed, it has become possible for online activity to be a primary activity of a class rather than a supplemental one of a class (e.g., Granberg & Olsson, 2015; Sung, Yang, & Lee, 2017; Volk, Cotič, Zajc, & Istenic Starcic, 2017; Zurita & Nussbaum, 2004). In other words, students can participate in online learning activities using mobile technology even during a class, and thus their online learning behaviors can be recorded as activity data, namely during-class online activity data.

Table 2-1. Types of learning activities and behaviors

Types		When: Before/after-class	When: During-class
Where	Face-to-face	• Participating in the field trip for information gathering with peers before class • Making up a homework worksheet after class	• Taking a note or talking with peers during class • Asking questions to solve difficult problems during class
	Online	• Watching video lecture at home before class • Writing a new post in discussion board after class	• Posting a piece of writing on an online discussion board to share with other peers during class • Adding comments on the posts during class

As technology-enhanced learning environments are spreading more widely, both before/after- and during-class online activity data is becoming more available and collectable. Consequently, we can expect that practical issues of education field can be addressed by utilizing the data. The following sections describe several topics of application in the field of learning analytics.

2.1.1. Capturing student characteristics

In general, instructors need to identify the characteristics of their students such as the level of prior knowledge, interests, for making plans or preparing strategies to teach them. For example, if an instructor is planning to implement group-based activities in face-to-face class, it is necessary to identify student characteristics for effective group formation, which is the first step of collaborative learning as already described. Although the instructor can use traditional methods to identify the characteristics of students, other methodologies are applicable in an advanced learning environment where educational data can be collected.

Researchers who are interested in learning analytics have suggested that student’s learning data can be used as a useful resource to capture student characteristics based on pedagogical theories (Jo et al., 2015; You, 2016). In particular, with emphasis on interpretation and explanation in the learning analytics field, studies have been conducted to extract and capture student characteristics from learning data based on pedagogical theories. For example, Jo and colleagues (2015) extracted proxy variables representing learner's time management strategy from student’s online learning behaviors. They used total login time, frequency, and regularity as student characteristics for the conceptual construct of the time management strategy. By using the learner characteristics variables with the theoretical basis, it is possible to obtain implications for the learner who is expected to have low achievement and why it is important to observe any online learning behavior. You (2016) also argued that the use of data in educational research should have a theoretical framework. She extracted the significant behavioural indicators of learning related to the learner 's self-regulated learning from online activity data and used it as a learner characteristics variable. She verified the importance of self-regulated learning in online learning by using measures related to meaningful learning behaviours. Another example of student characteristic extracted from online activity data is engagement. Engagement is the student characteristic associated with the achievement (Greene, 2015; Miller, Greene, Montalvo, Ravindran, & Nichols, 1996). Engagement has been measured by questionnaires, but with the recent spread of technology-mediated learning, learning behaviours associated with engagement are extracted from online log data and used as learners' engagement (Henrie, Halverson, & Graham, 2015). The quantitative observational measures that researchers used to measure learners' engagement were time on task, number of posts to a discussion board, and number of on-task or off-task behaviours.

2.1.2. Learning analytics dashboard

One of the most popular applications of learning analytics is dashboard (Arnold & Pistilli, 2012; Charleer, Moere, Klerkx, Verbert, & De Laet, 2018; Duval, 2011; Roberts et al., 2017; Verbert et al., 2013). A dashboard is a visual display that shows the most important information required to accomplish one or more purposes, and it is a tool that allows users to easily monitor the information needed to be delivered at a glance by arranging important information on a single screen (Few, 2013). Dashboards help users make flexible decisions by visually presenting current and past status data and delivering critical information efficiently (Aljohani et al., 2018; MacEachren, 1992). As various kinds of learning activities become available in online environments, records of learning-related activities and interactions are being accumulated as digital information. Learning analytics researchers argue that these data can contribute to the improvement of teaching and learning by designing and providing appropriate intervention based on data analysis (Aljohani et al., 2018; Charleer et al., 2018; Verbert et al., 2014). In this regards, dashboards based on learning analytics have been used as tools to provide learner and instructor with the necessary information to improve teaching and learning.

Learning analytics dashboards that support learning activities can be categorized into student dashboard and instructor dashboard. The student dashboard mainly provides information on the frequency and time of learning activities, the possibility of achieving goals, and guidance on the learning process. This information gives students the opportunity to monitor or reflect on their learning (Arnold & Pistilli, 2012; Azcona, Hsiao, & Smeaton, 2018; Charleer, Klerkx, Duval, De Laet, & Verbert, 2016). The instructor dashboard helps instructors to grasp learning status of their class intuitively and encourage student's learning, support at-risk learners, and flexibly adjust curriculum and instructional goals. (Van Leeuwen, Janssen, Erkens, & Brekelmans, 2014; Verbert et al., 2014; Verbert et al., 2013).

In order for the learning analytics dashboard to effectively support learning activities, a variety of factors need to be considered. First, it is crucial for the dashboard to visualize information, rather than in textual form, in order to present the information to be transmitted on a single screen efficiently and effectively (Few, 2006, 2013; Sun & Vassileva, 2006). For this purpose, the dashboard screen should be designed with consideration of various visual variables, such as position, color, and shape, so as to increase the efficiency of information process and decrease the cognitive load of the process (Boukhelifa, Bezerianos, Isenberg, & Fekete, 2012). Second, the information represented in the dashboard needs to be personalized. (Charleer et al., 2016; Teasley, 2017). When information about the learning situation is personalized, feedback based on the information can be used more effectively for the learner because the information is more relevant for the situation and is likely to be utilized for improvement of the current learning situation (Roberts et al., 2017). The use of personalized information also can mediate the adverse effects of feedback such as comparative feedback by avoiding presentation of the overall learning situation (Teasley, 2017). Lastly, if the learning analytics dashboard supports face-to-face learning, information and feedback need to be delivered in real time (Martinez-Maldonado, Kay, Buckingham Shum, & Yacef, 2019; Verbert et al., 2014). The face-to-face learning context has a relatively limited learning time. If there is a long delay in information and feedback delivery, it will be difficult for learners to use learning time efficiently.

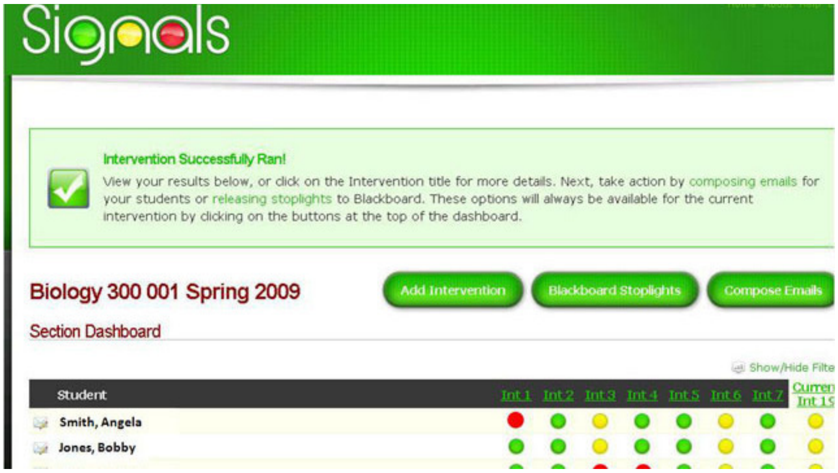

Figure 2-1. Purdue's Course Signals (Arnold & Pistilli, 2012)

Learning analytics dashboards are developed and used for a variety of purposes, including usage tracking, predictive analytics, and social network analytics. Well known example of learning analytics dashboard is Purdue University' s Course Signals (CS) (Arnold & Pistilli, 2012). Arnold and Pistilli (2012) describe CS as a system that enhances learning outcomes using real-time undergraduate information as the semester progresses (Figure 2-1). They developed a CS program that allows students to understand their grades and ask for help when they need. The system integrates the assignment scores and attendance records collected in course management system with library usage information and provides students with feedback to help them identify their grades, and consequently they take actions to achieve better grades.

2.1.3. Predicting at-risk students

Predicting at-risk students is a classification task for identifying students who need help to prevent them from dropping out learning courses or attaining a low-level of achievement (Dalipi, Imran, & Kastrati, 2018; Marbouti, Diefes-Dux, & Madhavan, 2016; Yang & Li, 2018). This task is usually performed by building a predictive model based on various machine learning techniques such as logistic regression, decision tree, support vector machine, and neural network (Dalipi et al., 2018). The machine learning techniques are usually trained based on educational data that consists of student' s learning behaviors or artifacts.

This task became widely known in data science field as MOOC (Massive Online Open Course) had a significantly low level of course completion rate (Dalipi et al., 2018; Halawa, Greene, & Mitchell, 2014; Whitehill, Williams, Lopez, Coleman, & Reich, 2015). As MOOC became popular, many educators expected that this new learning environment would contribute to the development of education by raising educational satisfaction and solving education inequality because it allowed anyone to access high-quality educational materials for free (Mohamed, Yousef, Chatti, & Schroeder, 2014). However, learners easily gave up course completion because most learning courses in MOOC are free and not penalized for dropping out a course. This low course completion rate was enough to change this expectation into a concern. For this reason, many MOOC researchers used large-scale learning data, which is another potential of the massive online learning platform, to predict students who were expected to stop taking courses under the assumption that they could intervene to prevent the students from leaving the courses when they could know who were at-risk students. In this regard, a large number of drop-out prediction studies were conducted in many MOOC online courses (Dalipi et al., 2018; Halawa et al., 2014; Kloft, Stiehler, Zheng, & Pinkwart, 2014; Lee & Choi, 2011) This prediction task is also introduced not only in KDD (Knowledge Discovery and Data mining) Cup 2010 which is one of the most popular data mining competition hosted by the annual conference of SIG KDD (Toscher & Jahrer, 2010), and also in many competitions on Kaggle which is the most popular data mining and machine learning competitive platform.

The predicting at-risk students regarding achievement was usually performed in a higher education context. As universities provide an online learning environment for their students, and large amounts of learning data accumulate in the LMS (Learning Management System), researchers are beginning to investigate ways to leverage the data to provide effective learning support. In the higher education context, the drop-out problem was not as serious as the MOOC context because most online learning courses are run as required courses. Therefore, researchers who use educational data in the higher education context have become more interested in learners' achievement. They have been investigating methods and strategies to detect and support learners who are expected to achieve low achievement using LMS data. For example, Kim and colleagues (2016) argued that predicting potential low achievers in early phase of an online learning course and providing timely intervention can help the at-risk students get back on the course. They presented a process of data mining to construct proxy variables that represent student's critical learning behaviors influencing achievement based on theoretical and empirical evidences. The variables were used not only for building a predictive model that identifies the at-risk students in advance, but also for deriving effective strategies to help the students not to attain a low-level of achievement in the online course. You (2016) also conducted research to identify key learning behaviors that have a significant impact on prediction of learners' course achievements using LMS data. This study focused more on learners' self-regulation and showed that the regularity of learning is the strongest predictor of course achievement. In other words, based on the interpretation that learners can make high achievement when they are instructed to study regularly, it suggests the possibility of designing effective instructional interventions.

As we have seen, there are two approaches to at-risk student prediction: a black-box approach that focuses on an accurate prediction based on sophisticated and advanced machine learning algorithms, and a white-box approach that investigates the effective ways to support student's learning based on interpretable factors from a predictive model. Each approach is related to the educational data mining (EDM) and learning analytics (LA), respectively. There have been criticisms that both approaches should not only present correlational results that show only the availability of predictions and results, but should have a direct impact on the improvement of learning

(Reich, 2015). Studies predicting the majority of at-risk students suggest that further studies with this practical effect should be undertaken (e.g., Hung, 2008; Kim et al., 2016; You, 2016). Based on this need, Burgos and colleagues (2018) designed specific intervention for at-risk students based on a predictive model built on LMS data, resulting in a drop-out rate reduction. They used historical student course grade data to create a model that predicts whether a student will complete the course or not. Based on the prediction, they performed tutoring plans for the at-risk students. As a result, the drop-out rate was reduced by 14% comparing the previous academic years in which no intervention was provided. This study implies that we can design an effective intervention for improving student's learning based on the models that help us identify students who need help.

As the importance of collaborative problem-solving abilities is emphasized, there is a claim that we need to have interests in the achievement of the group as well as the individual as the prediction task in the education field (Hernández-García, Acquila-Natale, Chaparro-Peláez, & Conde, 2018). It is necessary to investigate the group's learning behaviors that affect the group achievement in future studies as much of the strong behavioral characteristics of individuals. When the behavioral characteristics of a group that have a significant effect on the achievement of the group are defined, it is possible to provide a better learning experience and foster higher group achievement in group-based learning activities by designing sophisticated interventions.

2.2. Collaborative learning

Collaborative learning has been defined in a variety of ways, it generally refers to process that two or more students learn and work together to accomplish shared tasks (Baker, Hansen, Jonier & Traum, 1999; Dillenbourg, 2002). It is a group-based activity where students work together throughout various performing stages to accomplish shared goals (Dillenbourg, 1999). In collaborative learning, all group members actively take part in every activity phase and do not clearly distinguish their roles, whereas, in cooperative learning, the roles of each group member are relatively definitely distinguished (Panitz, 1999). For the successful collaborative learning, specific goal and direction should be shared and group member should interact in every learning process. Besides, these interactions process group members' discussion and argument, and structuring shared knowledge is important throughout the learning process (Chi & Wylie, 2014).

Collaborative learning has a lot of positive effects on learning. Through the process of collaborative learning, students are able to transfer their knowledge and learn from peers' errors (Johnson, Johnson, & Smith, 2014; Panitz, 1999), expand cognitive domains (Cress & Kimmerle, 2008), enhance critical thinking (Goodyear et al., 2014), and manage group conflicts (Neo, 2003; Njenga, Oboko, Omwenga, & Muuro, 2017). However, many studies argue that not all collaborative learning brings a positive learning outcome. For example, because collaborative learning requires communications or coordination skills which are not needed in individual learning, the cognitive load of students can be increased and it can be an additional burden on learning (Kirschner, Paas, & Kirschner, 2009). In addition, if group members participate in the group activity passively or interact unproductively, there are negative phenomena such as free-riding phenomenon, in which other group members perform tasks because they are performing tasks (Kerr & Bruun, 1983; Sinha, Rogat, Adams-Wiggins, & Hmelo-Silver, 2015; Verdú & Sanuy, 2014).

In this regard, with a view to preventing the unfavorable effects and implementing collaborative learning successfully, it is necessary to design and manage collaborative learning with a high level of efforts. One of the most renowned efforts for success is group formation. Details are given in the next section.

2.2.1. Group formation

Because effective collaboration does not occur by simply letting students in the same place and work together, group members should be carefully organized (Cohen, 1994; Dillenbourg, 2002; Johnson & Johnson, 1999). Many researchers have highlighted that group formation is the first step of effective collaborative learning, which is assigning students to groups with intention. (Amara, Macedo, Bendella, & Santos, 2016; Cruz & Isotani, 2014; Sadeghi & Kardan, 2016).

There are three different approaches for group formation, called; random selection, self-selection and instructor-selection (Sadeghi & Kardan, 2016). The random selection is a strategy that assigns members of a group randomly, without particular criteria or rules. It is the fastest and simplest strategy that allows for mixing all students with the hope of obtaining heterogeneity inside each group. However, it has a disadvantage that an inappropriate group can be formed such as a group in which all group members participate passively in learning activities. Self-selection is the way in which students determine their group members by themselves. It is advantageous that students do not need extra time and effort to establish a good rapport with group members; however, there is still the possibility of the inappropriate groups. Lastly, the instructor-selection is a strategy in which the instructor selects group members based on specific pedagogical criteria. Although this approach requires efforts for members to become familiar, it ensures that each group of learners will have a productive mix of student characteristics.

Because it is a complex task to form groups considering various student characteristics, there have been researches on algorithms to automate group formation (Cruz & Isotani, 2014). Dascalu and colleagues (2014) argued that it is necessary to distinguish automated algorithms as a new group formation strategy. Automated algorithms for group formation have used various student characteristics and optimization algorithms. For example, Graf and Bekele (2006) considered student's personality traits and performance for group formation. They used student’s characteristics as group work attitude, interest, achievement, motivation, self-confidence, shyness, performance of the subject, and fluency of instruction. Ant Colony Optimization algorithm was used to maximize the heterogeneity of formed groups based on the pre-identified student traits. Dascalu and colleagues (2014) used student's background for group formation; what he is interested in, what skills he wants to improve, expectations, and self-assessment of a series of skills. They used a Particle Swarm Optimization to form multidisciplinary teams based on these student characteristics. Lin and colleagues (2010) emphasized the need of automated group formation algorithms, especially when a large number of students need to be organized into collaboration groups. These algorithms automate the task that assigns students to appropriate groups, however, they have limitations in that they still require the use of traditional methods such as survey or questionnaires to collect their input manually. In addition, some of the studies proposed merely automated algorithms based on artificially generated data rather than authentic data collected from real students (i.e., Lin, Huang, & Cheng, 2010).

2.2.2. Collaborative argumentation

Argumentation is an effective problem-solving and problem-solving activity that is based on evidence (Jonassen & Cho, 2011; Jonassen & Kim, 2010). Although argumentation activity can be implemented as an individual activity, it can also be implemented in the form of collaborative learning for the enhancement of collaborative problem-solving skills demanded by modern society. This form of collaborative learning, which embraces argumentation activity, is collaborative argumentation. Collaborative argumentation is a group-based activity where students work together to construct and critique arguments (Chinn & Clark, 2013; Jonassen & Cho, 2011). In collaborative argumentation, peers participate in a discourse on a shared issue, and thus various opinions can be shared and argued, and claims and evidence are expanded and developed. Through careful discussion of each other's point of view, the peers can synthesize the discussions and converge on an integrated conclusion (Chinn & Clark, 2013; Clark, D'Angelo, & Menekse, 2009; Evagorou & Osborne, 2013).

Collaborative argumentation has various educational effects. It can be helpful for students to improve not only argumentation skills but also conceptual understanding (Chinn & Clark, 2013; Jonassen & Cho, 2011). In collaborative argumentation, students can understand the shared learning topic deeper as well as build effective arguments through the process of describing contents of the discussion to other peers (Buckingham-Shum, 2003). In addition, with the spread of a computer-supported learning environment, collaborative argumentation also employs support of technology to create, share, and construct argumentation collaboratively in various digital formats. It is a type of technology-enhanced learning environment and known as argumentation-based computer-supported collaborative learning (ABCSCL) (Noroozi, Weinberger, Biemans, Mulder, & Chizari, 2012; Van Amelsvoort, Andriessen, & Kanselaar, 2007). This learning environment uses advanced technology to scaffold students to create and construct effective argumentation collaboratively (Clark et al., 2009; Jeong & Joung, 2007).

In order to achieve the positive effects of collaborative argumentation, instructional supports are needed. First, students need to be supported to consider the essential elements of argument: claim, grounds, and qualifications (Noroozi et al., 2012; Toulmin, 2003). The claim is an expression of the viewpoint that is advanced in the argumentation. The grounds are supporting materials for the claim, e.g., observations, theories, and rules. The qualifications include qualifier which is expressing a potential limitation and rebuttal which is an extra explanation about the claim is invalid. However, students are not likely to consider the counter-arguments because they thought the inclusion of the counter opinions might weaken their argumentation (Brooks & Jeong, 2006; Jonassen & Cho, 2011). They are also reluctant to express opposition to the opinions of other peers when participating in collaborative argumentation to avoid emotional conflict with them (Clark et al., 2009). So, instructional supports are needed for the elements, especially for the qualifications. In addition, all students need to be encouraged to participate all the phases of the learning process with other peers by communicating and interacting with them. It is because this learning activity is also a kind of collaborative learning that requires equal participation and interaction.

2.3. Technology-enhanced learning environment

Technology-enhanced learning environment (TELE) is attracting attention for its effectiveness and efficiency in learning. TELE refers to a learning environment where students solve problems or constructing knowledge by using technology actively (Jonassen &

Rohrer-Murphy, 1999). The advance of technology combined with the constructivism has facilitated and transformed the learning environment from instructor-centered to student-centered (Jonassen & Land, 2012). In this context, technology is used to support social interaction (Bayne, 2015; Gillet et al., 2017), creation and construction of resources and ideas (Volk et al., 2017), deep learning as cognitive tools (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015; Verdú & Sanuy, 2014) and facilitates experimentation, manipulation, and idea generation (Volk et al., 2017; Zurita & Nussbaum, 2004).

In TELEs, technology allows opportunities for enhancing student' s learning. In the environments, students are able to access the Internet to find and share new information and to communicate with other peers without the restrictions of time and distance. Even during a face-to-face class, they can participate in online activities by using notebooks, smartphones, or tablet PCs. In this regard, it possible to collect activity data that records students' learning behaviors by using the technologies (Greller & Drachsler, 2012). The activity data can be utilized to understand students and their learning by employing learning analytics; students are able to receive effective feedback or support based on the understandings (Pozzi, Manca, Persico, & Sarti, 2007; Van Leeuwen et al., 2014). TELE has been applied in various types and ways. In the following section, two types of TELE will be described for a better understanding of the environments: the flipped classroom and computer-supported collaborative learning.

2.3.1. Flipped classroom

Flipped classroom has been widely acknowledged as an effective pedagogical method for both students and instructors (Bishop & Verleger, 2013; Chen, Wang, Kinshuk, & Chen, 2014; Galway, Corbett, Takaro, Tairyan, & Frank, 2014; Garrison & Kanuka, 2004). For students, it fosters student ownership of learning and increases interactivity during actual class time (O'Flaherty & Phillips, 2015). Students can lead their learning at their desired pace, at the time they want, and in the place of their choice. They can also participate in interactive group-based activities in face-to-face learning. For instructors, the flipped classroom provides flexibility in designing a learning environment.

The concept of flipped classroom has various definitions, but the common point is that it flips the traditional teaching methods (Bishop & Verleger, 2013; Chen et al., 2014; O'Flaherty & Phillips, 2015). It moves the lecture materials out of the lecture room as self-paced online learning, and student-centered activities, such as collaborative learning, are implemented in a classroom. It shows differences in the learning process, the method of operation, and the role of the instructor in comparison with the traditional teaching and learning methods (Han, Lim, Han, & Park, 2015). A comparison of traditional teaching and learning methods and flipped classroom is shown in Table 2-2. In traditional methods, in-class activities that provide instructor's lecture are implemented beforehand. Students are usually provided an assignment that has to be done out-of-class, usually at home, after the in-class lecture in a physical classroom. In a flipped classroom, the order of the learning process is flipped. Students are participating in self-paced online learning in advance as out-of-class activities. In-class activities, student-centered activities such as collaborative learning, are implemented rather than teacher-centered lectures because students already learned basic knowledge or skills. Therefore, the role of the instructor also changes. In traditional methods, the instructor is a lecturer, while facilitator and adviser in flipped classroom.

Table 2-2. Comparison of traditional methods and flipped classroom (Han, et al., 2015, translated from Korean)

Category		Traditional methods	Flipped classroom
Learning process		In-class → out-of-class	Out-of-class → in-class
Activities	Before/after -class	Assignment	Self-paced online learning
	During -class	Instructor's lecture	Student-centered activities
Role of instructor		Lecturer	Facilitator and adviser

A flipped classroom allows in-class learning time for higher-order tasks by replacing lectures for knowledge acquisition to home assignments (Bishop & Verleger, 2013). Before attending face-to-face class, students individually study learning contents with online materials such as video lecture, and when they come to the class, they participate in student-centered activities such as discussion or problem-solving based on contents they have already studied with the online learning contents as home assignments (Hughes, 2012). That is, flipped classroom exchanges what was previously class content with what was prior homework (Pierce & Fox, 2012). In a flipped classroom, students can study learning materials at their own pace, engage in diverse learning contents when they need, and master the prerequisite concepts for face-to-face class. This structural feature of the flipped classroom can secure more face-to-face learning time for students to participate in higher-order tasks because they are already prepared for the high-level activities before they come to the face-to-face class (Arnold-Garza, 2014; Moraros, Islam, Yu, Banow, & Schindelka, 2015).

Previous studies identified the effect of a flipped classroom. Instructors and students were found to be satisfied with a flipped classroom in which they can experience more flexible and various student activities on both online and offline (Baepler, Walker, & Driessen, 2014). This flexibility also allows student' s autonomy in online or pre-class so that they learn at their own pace and adjust their cognitive load appropriately (Abeysekera & Dawson, 2015; Goodwin & Miller, 2013). In addition, flipped classroom facilitates higher ordered thinking and gives opportunities to apply learned concept for practical problem-solving (Forsey, Low, & Glance, 2013; Moraros et al., 2015). Several studies reported that flipped classroom has positive effects for improving communication ability, thinking skill, and self-confidence (Gilboy, Heinerichs, & Pazzaglia, 2015; McLaughlin et al., 2014). These findings in previous studies imply that the flipped classroom can be effective instructional models in higher education courses by allowing students' higher order skill development.

The advantages of flipped classroom can be taken by the strong connection between the parts: online and the face-to-face learning. The face-to-face learning is designed on the extension of online learning, hence, the two parts of flipped classroom are closely related to each other. In general, student-centered activities are implemented in the face-to-face part in which students solve practical problems based on what they learned in online learning and lead learning through self-regulation. If students were insufficiently engaged in online learning, they would hardly be expected to perform well in face-to-face learning (O' Flaherty & Phillips, 2015; Strayer, 2012). Hence, the two parts of flipped classroom need to be connected tightly to obtain advantages of flipped classroom.

In this regards, researches have been studied about effective strategies for seamless connection between the online and face-to-face activities in flipped classroom. One example is project-based flipped classroom. Warter-Perez and Dong (2012) applied project-based learning to the one-semester course and provided proper learning content online according to the project progressed. In the face-to-face class, activities that share the progress of the project were implemented to link online and face-to-face activities closely. Another example is the use of quizzes. Talley and Scherer (2013) used online quizzes to provide instant feedback to students' quizzes. The results of the quizzes are considered for planning and designing face-to-face activities, and as a result, the connection between online and face-to-face activities is strengthened. The use of these strategies can strengthen the connection between online and face-to-face activities, and it can be expected to take the advantages of flipped classroom.

2.3.2. Computer-supported collaborative learning

Since collaborative learning has been in the limelight as a beneficial learning method to improve critical competencies for the 21st century, researchers and instructors have endeavoured to enhance its effectiveness by employing new technologies to provide chances for students to interact with other peers without constrained in time and distance. These technologies brought about the new learning environment named computer-supported collaborative learning (CSCL) that refers to collaborative learning which is centered on interactive technologies such as the Internet and smart devices (Stahl, Koschmann, & Suthers, 2006).

CSCL aims at leveraging the benefits of collaborative learning by the adoption of new technologies in learning environments. The technologies enable students to interact more effectively and efficiently through applications to promote shared understanding and communication tools to support interaction (Stahl, 2002; Strijbos, Kirschner, & Martens, 2004). Since the technologies encourage students to construct their knowledge and learning artifacts in a more collaborative manner, it can facilitate the learning process of collaboration and allow students to improve student's higher-order thinking skills (Moreno, 2005).

A face-to-face setting offers a rich learning environment for collaborative learning because it allows students not only verbal but also nonverbal communication such as facial expressions and gestures (Hymel, Zinck, & Ditner, 1993; Johnson & Johnson, 1996). Thus, face-to-face learning context can be more beneficial for collaborative learning that requires active interactions (Ocker & Yaverbaum, 1999; Summers, Waigandt, & Whittaker, 2005). In this regard, the importance of face-to-face collaborative learning have been highlighted; there have been efforts to apply computer technology in a face-to-face learning environment (Nussbaum, et al., 2009; Zurita & Nussbaum 2004). The face-to-face CSCL encourages students to take part in both face-to-face and technology-mediated learning, using a shared device or one device for one student. (Nussbaum, et al., 2009). Nowadays, mobile technology enables student to use advanced technologies such as smartphone or tablet PC even in a face-to-face class; they can access to the Internet not only for finding new information but also interacting with other peers to participate in learning activities (Granberg & Olsson, 2015; Sung et al., 2017; Volk et al., 2017). By using the technology, the students can interact in a technology-supported way for synchronization and coordination of learning activity status, mediating their social interactions.

Chapter 3. Heterogeneous group formation with online activity data

With the development of Internet technology, technology-enhanced learning environments that combine online and face-to-face (F2F) learning have gained increasing interest as an alternative model for instruction. A notable example is the flipped classroom, which typically consists of two parts: online learning and F2F learning (Bergmann & Sams, 2012; Bishop, 2013; O’Flaherty & Phillips, 2015). In online learning, students learn the basic concepts and skills at their own pace with online learning content such as video lectures and online quizzes before they attend the F2F class. In F2F learning, collaborative learning is often implemented to engage students in the process of internalizing and building their knowledge through interactions with peers (Bergmann & Sams, 2012; Bishop, 2013). Since students learn the prerequisite material in advance, they can spend more time on peer interactions to solve authentic or complex problems. This contextual feature, which encourages collaborative learning, offers several benefits for students’ learning experiences, such as participation, satisfaction, engagement, and academic achievement (Gannod, Burge, & Helmick, 2008; Murphree, 2014; Stone, 2012).

Since collaborative learning is based on students’ interactions, the matter of how to form groups plays an important role in its effectiveness (Cohen 1994; Johnson & Johnson, 1999). Many studies have recommended *heterogeneous grouping*, in which each group includes members with diverse characteristics (Bryant & Albring, 2006; Chan et al., 2010; Graf & Bekele, 2006; Walker, Greene, & Mansell, 2006). Heterogeneous groups promote intragroup interaction because group members must communicate to fill in the gaps due to their diversity, and active peer interaction can enhance group performance (Cohen, 1994; Pelled et al., 1999). In particular, a high level of group heterogeneity is beneficial for solving ill-structured problems, which have no single solution or answer, because it increases the opportunities for presenting a variety of opinions or solutions (Cho & Jonassen, 2002). Since the flipped classroom often deals with solving authentic and ill-structured problems via active peer interaction, forming heterogeneous groups for its F2F learning may be a favorable selection for effective group-based activities.

3.1. Student characteristics for heterogeneous group formation

A number of student characteristics have been considered as bases for heterogeneous group formation. The student characteristics that have mainly been focused on are *demographic information* (Harrison, Price, & Bell, 1998; Pelled et al., 1999; Zhan, Fong, Mei, & Liang, 2015) and *academic status* (Cohen, 1994; Kinchin & Hay, 2005; Wiedmann, Leach, Rummel, & Wiley, 2012). In terms of students' demographic information, researchers have suggested that this should be related to the learning task for better group performance. When the group members' demographic characteristics are related to the group task, the characteristics can serve as functional backgrounds for solving problems. Subsequently, group heterogeneity based on the task-related characteristics enhances group performance (Pelled et al., 1999). Students' academic status, along with demographic information, has been studied in further research. According to Cohen (1994), students' academic status is an important criterion for group formation to promote productive interaction, because it is the most powerful characteristic, due to its relevance to classroom activities. For example, Kinchin and Hay's (2005) study showed that groups with diverse knowledge structures concerning the learning topic outperformed groups with similar knowledge structures. They concluded that students' different knowledge structures brought different perspectives to their discussion of a topic, so it made their collaborative learning more effective. Wiedmann and colleagues (2012) reported that the diverse achievement group created a range of solutions during their group invention task. They suggested that groups with at least one high-performing member may be more effective because the high-performing member could help other students to benefit from the group task. In summary, students' task-related demographic characteristics and their academic status such as perspective or achievement level on the learning topic should be considered in heterogeneous group formation.

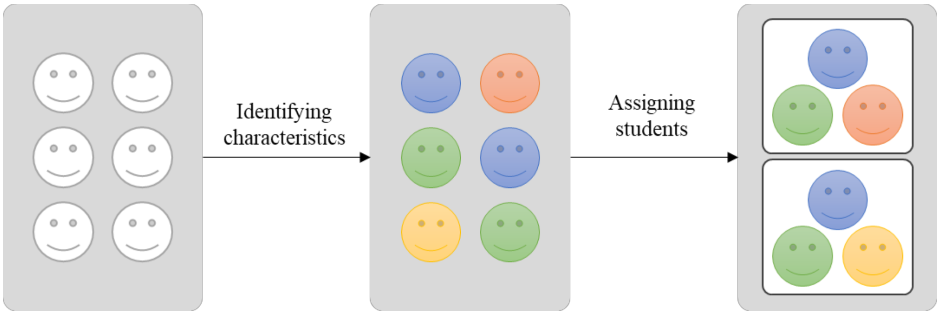

Figure 3-1. Heterogeneous group formation

In order to form heterogeneous groups, these student characteristics should be identified in advance, so as to assign students to adequate groups (Figure 3-1). An important thing for us to be aware of is that these student characteristics, either demographic information or academic status, typically have been identified by traditional methods such as direct observation, surveys, questionnaires, interviews, or paper tests. Even several group formation algorithms that automatically assign students to groups used these manual methods to obtain student characteristics for their input parameters (Graf and Bekele, 2006; Lin et al., 2010; Moreno, Ovalle, & Vicari, 2012; Wang, Lin, & Sun, 2007). In general, these traditional methods tend to be time-consuming and laborious because they require not only that students spend time answering the target questions but also that instructors analyze and integrate the results. For the demographic characteristics, we would use the traditional method because demographic information does not need to be identified several times (Zhan et al., 2015). However, for academic status, which tends to change depending on the learning topic (Lin et al., 2010), traditional methods are inefficient because continuous and repetitive assessments would be needed to evaluate the characteristics that are dependent on the learning topics or tasks. In particular, since the online learning engagement, which determines student’s preparedness for F2F learning in the flipped classroom (O’Flaherty & Phillips, 2015), is influenced by multiple factors including instructional tasks (Vonderwell & Zachariah, 2005), the benefits of heterogeneous grouping may cost too much effort given such inefficient methods. Since instructors often feel burdened with the development and management of online learning modules, as well as with the preparations for F2F lectures in the flipped classroom (Arnold-Garza, 2014; Schlairet, Green, & Benton, 2014), such efficiency issues can aggravate the instructor’s difficulties for re-formation of heterogeneous groups in flipped classrooms, especially when many students are participating.

We anticipate that we can overcome these issues by taking advantage of the structural and contextual features of the learning environment—the flipped classroom—where online activity data are available before F2F group activities. The data can be utilized to identify students’ academic status based on online learning behaviors, by applying learning analytics (Henrie et al., 2015; Jo et al., 2015; You, 2016). Since online behaviors reflect students’ authentic learning behavior, the characteristics identified are comparable to those of intrusive data collection via traditional methods (Greller & Drachsler, 2012). In addition, the student characteristics identified from online activity data can be used as valid information for F2F activities, because F2F learning is closely intertwined with online learning in flipped classrooms (O'Flaherty & Phillips, 2015). Since utilizing online activity data is unobtrusive (Greller & Drachsler, 2012) and can be automated (Bishop, 2013), we can efficiently identify student characteristics flexibly, according to changing learning topics. This approach makes it possible to track changes in academic status so as to maximize the benefits of heterogeneous groups throughout the course continuously.

In this regard, we identified student characteristics from online activity data as well as demographic information and investigated the possibility of utilizing the data when designing a F2F activity. Since collaborative learning is the prevalent type of F2F activity in flipped classrooms, we focused on heterogeneous group formation for effective group collaboration. For this study, we planned a two-week flipped classroom session. In the online learning, students learned the fundamental concepts of pedagogical theories to solve an ill-structured problem. In the F2F learning, collaborative learning was implemented that required collaborative argumentation to arrive at a group solution for the problem. We collected students' online activity data to identify their academic status, namely different perspectives, engagement, and quiz scores. We also used students' demographic characteristics that may reflect personal and experiential differences among group members approaching educational tasks. The student characteristics were used to devise each group's heterogeneity, and we investigated which of the heterogeneity contributes to the F2F group achievement.

3.2. Method

3.2.1. Participants

Our research was conducted in a class on "Introduction to the Study of Education." The class was a flipped classroom for undergraduate students in a four-year university in Seoul, South Korea. Of the 104 students in the class, 60 students participated in this research, from whom we excluded seven students because they did not complete their online learning course. As a result, the data of 53 students were analyzed (35 females, 18 males, mean age 22.85). Students were assigned to sixteen groups randomly, each with three or four members, and participated in F2F collaborative learning. After the flipped classroom course was completed, we conducted interviews. Eight students voluntarily participated in an interview (5 females, 3 males, mean age 23.8, from six different majors). This research closely followed the Seoul National University IRB protocol (No. 1603/002-009).

3.2.2. Learning environment

Online learning

We planned a two-week-long flipped classroom for this study. During the first week, students participated in online learning activities, the main activities of which were to select an option from the two possible choices for solving the ill-structured problem provided and to use the online learning materials to build theory-based evidence in support of the selected option. The following were the primary online learning materials.

Ill-structured problem: Considering that the students were pre-service teachers, we presented an ill-structured problem involving an actual classroom context. The problem was this: *"There is a newly appointed science teacher who is teaching high school students. The teacher's students are facing a university entrance examination. The teacher is considering the following two options: (A) Student-centered classes in which the students can understand the principles of science and apply them to the real world. (B), Classes, even they were led by a teacher, that helped the students receive good grades on the entrance examination and enter a good university. If you were the teacher, which class would you select for the students? Select one of the two options and write arguments based on the theoretical background to support your selection."* The students were asked to select one of the two options as their individual opinions and write arguments to support their choices with reference to the online learning materials.

Video lectures and online quiz: Students were provided two video lectures that contained several pedagogical theories, such as teacher-centered learning, student-centered learning, problem-based learning, and personalized learning. The total duration of the two video lectures was 42 minutes. After the video lectures, ten multiple-choice questions were provided, each with four options. Seven of these were simple recall questions regarding the basic concepts learned from the video lectures (e.g., What is the right statement about personalized learning?). The remaining three were application-level questions using basic concepts in a practical situation (e.g., Which of the following is a good example of personalized learning?). When students chose a wrong answer in their first attempt, the system provided one chance to correct the answer.

Discussion board: An online discussion board was available for students to upload questions, share their opinions, and elaborate on their arguments. The students could read the others' opinions and revise their arguments by referring to the postings on this board. In addition, students could change their opinions before they attended the F2F learning.

F2F learning

In the second week of the course, students attended F2F learning. The main activity during the F2F lecture was collaborative learning to construct a group solution to the ill-structured problem presented in the online learning course. Students needed to integrate their opinions into a single group opinion with the appropriate pedagogical background through group discussion. The detailed descriptions of the F2F learning are as follows.

Lecture introduction, Q&A session: The instructor briefly introduced the activities of F2F learning and held a Q&A session about the online learning content. The instructor reviewed the online quizzes, explaining the right answer to the questions for which many students chose the wrong answers.

Collaborative learning for group solutions: Student groups engaged in collaborative argumentation for 60 minutes to arrive at a group solution to the ill-structured problem presented at the beginning of the online learning. When group members chose different opinions to solve the online learning problem, their task was to integrate their heterogeneous opinions into one single group opinion with grounds based on the theoretical background that support that opinion. They could refer to the online learning materials and their textbook for supporting evidence. Each group was required to hand in their group solution to an online submission system in an electronic file format.

Consolidation: The instructor gave a summary lecture and let a few volunteers present their group solutions to the whole class, then provided brief feedback about their group solution.

3.2.3. Data collection

For this study, we used four types of data: students' demographic data, online activity data, group solutions, and interview data. Students' demographic data were collected from the university's default course management system, which possessed the students' basic demographic information for the purpose of course management. The online activity data were collected by our online learning platform, on which *Open edX* operates; Open edX is an open source platform for creating, delivering, and analyzing online courses (Ruiz, Díaz, Ruipérez-Valiente, Muñoz-Merino, & Kloos, 2014). This platform was used for the online learning part of our flipped classroom, and it logs every online learning behavior of each student as an event. Figure 3-2 shows a sample event recorded as the behavior of "pauses a video lecture." Group solutions were collected by the online submission system and evaluated by two researchers. The results of the evaluation were used as each group's F2F group achievement. In the interviews, we recorded and transcribed the whole conversation between the interviewer and the interviewees, with the consent of the interviewees.


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}
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Figure 3-2. Online activity data of the edX platform

3.2.4. Data processing and analysis

Student characteristics

Students' demographic data was obtained from a simple survey that was conducted at the beginning of the new semester for course management. *Gender*, *Major*, and *School year* were identified from the survey. Students' academic status was identified from the online activity data. *Engagement* was defined as the valid online learning duration (Kong, 2011; Laakso, Myller, & Korhonen, 2009; Lehman, Kauffman, White, Horn, & Bruning, 2001). The online learning platform recorded each student's online learning behaviors as events (e.g., playing a video, checking problems, replying to a post, etc.) as they occurred. Each student's valid online learning duration was extracted from the online activity data by eliminating empty sections in the sequence of online learning events (details in Appendix A). *Quiz score* was the number of correct answers on ten online quizzes. *Opinion* was the option finally selected for the ill-structured problem during the online learning. The definitions of six students' characteristics are summarized in Table 3-1.

Table 3-1. Student characteristic variables

Student characteristic	Definition	Source
Gender	Student's gender	Demographic data
Major	Student's major	
School year	Student's school year	
Engagement	Valid online learning duration (mins)	Online learning data
Quiz score	Number of correct answers on online quizzes	
Opinion	Selected opinion for the ill-structured problem	

Table 3-2. Group heterogeneity variables

Group heterogeneity	Definition
Gender heterogeneity	The negative absolute difference between gender counts within a group
Major heterogeneity	The number of unique major categories divided by the number of group members
School year heterogeneity	The variance of school years within a group
Engagement heterogeneity	The variance of valid online learning duration within a group
Quiz score heterogeneity	The variance of online quiz scores within a group
Opinion heterogeneity	The negative absolute difference between group members' opinion counts

Group heterogeneity

Group heterogeneity variables (see Table 3-2) were derived from the aggregation of the six student characteristics for each group. Every group heterogeneity variable was designed to present the degree of diversity among group members with regarding each group member's characteristic listed in Table 3-1. The group variable's value was *high* when group members had heterogeneous characteristics, but it was *low* when group members had homogeneous characteristics. *Gender heterogeneity* is the degree of gender discrepancy within the group. It is defined as the negative absolute difference between group members' gender. For example, if there were three female students and one male student in the same group, the group's gender heterogeneity would be $-|3-1|=-2$. The negative sign in the definition means that higher heterogeneity indicates a more balanced gender within a group. We thought that majors with similar characters would not provide sufficient experience diversity, so we categorized the 12 different majors into the following four major categories: language, social science, science, and arts. *Major heterogeneity* was defined as the number of unique major categories divided by the number of group members. For example, when there are four students in a group, one with a language major and three with science majors, then there are two unique major categories among four group members and the major heterogeneity of the group would be $\frac{2}{4}= 0.5$. *School year heterogeneity* is the variance of group members' school years. *Engagement heterogeneity* is the variance of group members' online learning duration. It indicates how diverse the students were who participated in the online learning. An example comparing high and low engagement heterogeneity is shown in Figure 3-3. *Quiz score heterogeneity* is the variance of online quiz scores within a group. *Opinion heterogeneity* is the degree of opinion discrepancy within the group. It is defined as the negative absolute difference between students' opinions on the ill-structured problem in the same way as gender heterogeneity.

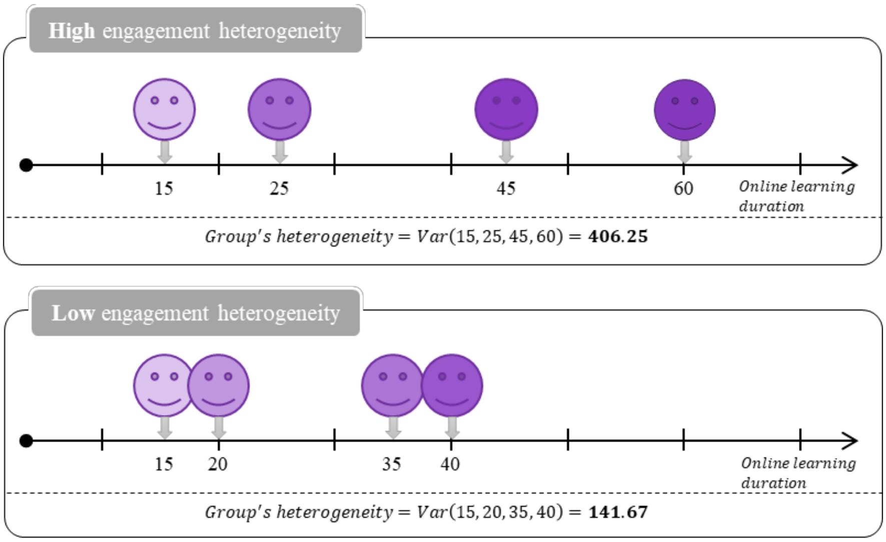

Figure 3-3. High and low engagement heterogeneity

3.2.5. F2F group achievement and interviews

Each group solution was used for evaluating F2F group achievement. Two researchers independently evaluated the quality of each group’ s solution with a rubric that had been developed based on studies of Mccann (1989) and Yeh (1998). There were three categories in our rubric: logicality (reasons given in support of a claim and consideration of the contrary opinion), understanding (an understanding of educational concepts and principles), and expression (sentence fluency and conventions). Each category of the rubric was rated from 1 to 4 points. The inter-rater reliability (Cohen’ s kappa) ranged from 0.71 to 0.81, and all disagreements about the quality of the solution were resolved through discussion.

After the flipped classroom course, interviews were conducted with eight interviewees to investigate how the student characteristics influenced F2F collaborative learning. In particular, we focused on investigating if the students’ academic status captured from the online activity data were influential to F2F collaborative learning. In each interview, we explained the purpose of the interview, informed the interviewee that the interview conversations would be recorded for analysis, and obtained a participation agreement. After the interviews, we transcribed the interview conversations and divided the transcripts into segments of ideas. We coded the segments with a word or phrase indicating what the segments meant and grouped similar codes; redundant segments were excluded. Next, similar codes were aggregated into a few themes that were closely related to the relevance of online activity data to the design of F2F activity. The themes were refined through constant comparison with codes and raw data.

3.3. Results

3.3.1. Descriptive analysis

The result of the descriptive analysis of student characteristic and group heterogeneity variables is summarized in Table 3-3. More female students participated in this study (35 females, 18 males). Except for the major category of art, there was a similar number of students in each major category. Major heterogeneity average was 0.75 out of 1. The average school year was high ($M = 3.32$, $SD = 0.73$). Engagement was distributed, with a large variance ($M = 83.81$, $SD = 40.53$), while the quiz scores ($M = 9.45$, $SD = 0.72$) and school years ($M = 3.32$, $SD = 0.73$) were distributed with small variances. In terms of opinions, more students selected opinion A ($Count = 36$) than opinion B ($Count = 17$).

3.3.2. Correlation analysis

The six group heterogeneities were subjected to correlation analysis with the F2F group achievements (see Table 3-4). The results showed that F2F group achievement had a significant positive correlation with Engagement heterogeneity ($r = 0.604$, $p < 0.05$), and Opinion heterogeneity ($r = 0.570$, $p < 0.05$). No significant correlation was found between the other group heterogeneities.

Table 3-3. Descriptive analysis of student characteristic and group heterogeneity

Variables		**Student characteristic (n = 53)**			**Group heterogeneity (n = 16)**	
		Count	**Mean**	**SD**	**Mean**	**SD**
Gender	Female	35	-	-	-1.69	1.20
	Male	18				
Major	Language	16	-	-	0.75	0.24
	Social science	19				
	Science	14				
	Arts	4				
School year		-	3.32	0.73	0.51	0.31
Engagement		-	83.81	40.53	1714.91	1933.62
Quiz score		-	9.45	0.72	0.49	0.48
Opinion	Option A	36			-1.44	1.09
	Option A	17				

3.3.3. Hierarchical regression analysis

A two-stage hierarchical regression analysis was conducted with F2F group achievement as dependent variable (see Table 3-5). In the first stage, the demographic group heterogeneity variables failed to account for a significant amount of the variance in F2F group achievement ($F(3,12) = 1.338$, $p = 0.308$). In the second stage, group heterogeneity variables derived from the online activity data were added to the model. Introducing the *online* group heterogeneity variables explained an additional 54.8% of the variance in F2F group achievement, and this change in R^2 was significant ($F(3,9) = 8.176$, $p < 0.01$). The second regression model turned out to be significant for predicting F2F group achievement and the model explained 79.9% of the variance. When all six independent variables were included in the second stage, Engagement heterogeneity ($\beta = 0.783$, $t = 3.996$, $p < 0.01$) and Opinion heterogeneity ($\beta = 0.732$, $t = 3.632$, $p < 0.01$) had positive coefficients and they were significant in predicting the F2F group achievement.

Table 3-4. Correlation analysis of group heterogeneity and F2F group achievement (n = 16)

	Variables	1	2	3	4	5	6
1	Gender heterogeneity						
2	Major heterogeneity	−0.020					
3	School year heterogeneity	0.199	−0.145				
4	Engagement heterogeneity	0.472	0.082	−0.196			
5	Quiz score heterogeneity	0.432	−0.255	0.324	0.189		
6	Opinion heterogeneity	0.214	0.108	−0.344	−0.063	−0.335	
7	F2F group achievement	0.436	0.011	−0.154	0.604*	−0.195	0.570*

Note. $*p < 0.05$ (2-tailed).

Table 3-5. Hierarchical regression analysis on group heterogeneity (n = 16)

Model	Predictors	F2F group achievement					
		β	t	VIF	F	R^2	ΔR^2
Step 1	Gender heterogeneity	0.486	1.905	1.042	1.338	0.251	
	Major heterogeneity	-0.016	-0.064	1.022			
	School year heterogeneity	-0.254	-0.985	1.063			
Step 2	Gender heterogeneity	-0.120	-0.523	2.237	5.957**	0.799	0.548**
	Major heterogeneity	-0.110	-0.705	1.095			
	School year heterogeneity	0.280	1.488	1.585			
	Engagement heterogeneity	0.783	3.996**	1.718			
	Quiz score heterogeneity	-0.065	-0.329	1.735			
	Opinion heterogeneity	0.732	3.632**	1.795			

Note. Dependent variable: F2F group achievement. $**p < 0.01$, (2-tailed).

3.3.4. Interviews

Through the interviews, we investigated how students perceived the influence of group heterogeneity on the group interaction and learning outcome. We could see that online learning engagement affected collaborative learning. The students who were highly engaged in online learning responded that they spent quite a lot of time watching the video lectures and made extra efforts, such as writing notes and participating in discussion boards. This means that the valid online learning duration could be used as a convincing measure for identifying engagement. The highly engaged students had great help establishing grounds based on pedagogical theories for their group opinion. When there was at least one highly engaged student in a group, the other, non-engaged students who had not been actively engaged online were able to overcome their lack of prior knowledge through peer interaction. In contrast, when all group members were non-engaged, the interactions were not productive. The group consequently could not draw on an adequate theoretical rationale, and the members even showed off-task interaction. As a result, making groups heterogeneous based on engagement in online learning has the effect of preventing failure in F2F activity by preventing the creation of a weak group.

> *"When I participated in the online course, I took notes on the video lectures. I also participated in the discussion board... the*

online course helped me to find appropriate theories. I was able to quickly recall what I needed to add to our group solution." (Student H)

"Because the theoretical background should be included in the group solution, I regret I skipped some parts of the video lectures. However, one of my group members seemed eager to study the online course. Thanks to that, the theoretical basis of our group solution was well-written." (Student G)

"There was a student who did not seem to study the online course. I did not study very hard either... but I did notice that (s)he did not know the contents of the lesson. When we discussed and shared our thoughts, (s)he had a story that seemed to have little to do with the topic of the group task." (Student C)

In addition, the impact of opinion heterogeneity was clear. Students started collaborative argumentation with a brief introduction to the opinions they had chosen in online learning, and when they had diverse opinions, they needed more communication due to the high opinion heterogeneity. Even though the heterogeneity prolonged their collaborative argumentation and made it difficult to integrate their views into a single group opinion, students perceived that they could create a better group solution because they had to consider the various viewpoints in their arguments. In contrast, when all the group members had the same opinion, they needed little interaction with their peers. Consequently, their group solution was likely to lack consideration of varying viewpoints. In addition, there was a tendency to offtake due to less interaction. As a result, students' individual opinions extracted from the online activity data may be explained as having been used as factors substantially affecting the F2F activity.

> *"There was someone who had a different opinion from mine. I think we were able to find a better solution when we shared opinions with each other and considered each other's point of view." (Student B)*
>
> *"It was so hard to integrate our various positions. However, I think that various positions helped us to think more." (Student E)*
>
> *"Our group had the same opinion about the problem. Writing the group solution did not take long since we did not need to integrate our opinions into one. We spent the rest of the time on what we wanted to do… However, I think various ideas did not come out. When we wrote our group solution, we overstated its contents." (Student F)*

3.4. Discussion

The purpose of this study was to investigate the possibility of utilizing online activity data to design F2F activities in a flipped classroom. The flipped classroom is an example of technology-enhanced learning environments that are becoming increasingly widespread and important. Since flipped classroom consists of a close interconnection between online and F2F learning (O'Flaherty & Phillips, 2015), the student characteristics identified from online learning behaviors could provide valid information for designing F2F activities. The results of hierarchical regression analysis indeed showed that group heterogeneity variables derived from the online activity data significantly increased the explained variance of F2F group achievement. Interviews also revealed that the student online learning characteristics, especially the online learning engagement and the selected opinion, positively contributed to the group members' interaction productivity, which led to a better group achievement.

A *high* Engagement heterogeneity, which means group members have diverse engagement in online learning, promoted productive interaction and prevented forming weak groups. Online learning engagement affects students' preparedness for F2F activities in flipped classrooms (O'Flaherty & Phillips, 2015). A variety of preparedness resulting from the engagement heterogeneity introduced peer tutoring between members who have different levels of understanding of the pedagogical theories taught in the online learning.

This peer interaction has a positive impact on learning for both groups of students, those who give tutoring and those who receive it (Cohen, 1994). Through their interaction, they were able to develop the grounds for support of their group resolution. It is hard to expect that a homogeneous group consisting merely of non-engaged students would have such a productive interaction. In this regard, a high level of engagement heterogeneity can prevent forming weak groups that would lack productive interactions by including at least one highly engaged student in a group (Wiedmann et al., 2012).

Engagement has been considered one of the critical factors that are influencing student's achievement (Greene, 2015; Greene & Miller, 1996; Greene, Miller, Crowson, Duke, & Akey, 2004; Klem & Connell, 2004; Miller et al., 1996). It has been usually measured by questionnaires or interviews; however, as the technology-enhanced learning environment expands, where online activity data is collectible, the data started to be used for measuring a level of engagement (Henrie et al., 2015). For measuring engagement, researchers analyzed the several patterns of online learning behaviors such as time on task (Kong, 2011; Laakso et al., 2009; Lehman et al., 2001), number of participating in a writing task or discussion board (Nakamaru, 2011; Wise, Speer, Marbouti, & Hsiao, 2013), number of on-task or off-task behaviours (Wise et al., 2013) and attendance (Hayden, Ouyang, Scinski, Olszewski, & Bielefeldt, 2011; Heafner & Friedman, 2008). In this study, we measured the engagement using time on task of each student. Because the online course we provided had various learning activities including video lectures, online quiz, and discussion board, we should embrace an overall learning pattern rather than focus on a specific activity. In addition, because the online course was implemented only for a week with a limited amount of learning materials, we concluded that it is not appropriate to use counting related to attendance or task behaviors. For the above reasons, we calculated the valid online learning duration, which is an overall time on task, and used it as engagement. Future studies may use a different learning pattern to measure engagement depending on its online learning context.

A *high* Opinion heterogeneity, which means group members had diverse point-of-views, promoted active interaction and provided students with opportunities to consider different perspectives for solving the ill-structured problem. Since group members needed to integrate their diverse opinions into a single group opinion, they argued with their peers and tried to persuade those who had different opinions. Through the integration process, each student's opinion served different viewpoints in solving the common problem. As can be seen from the interview results, it would be necessary to have an active discussion in the group of students with different viewpoints. Since a variety of viewpoints is favourable to solving ill-structured problems (Cho & Jonassen, 2002), a higher level of opinion heterogeneity enabled groups to make better group solution. In addition, the different knowledge that group members derive from different opinions may provide a rich theoretical basis to support the group's integrated opinions (Kinchin & Hay, 2005).

On the other hand, the analysis showed that group heterogeneity variables derived from student's demographic characteristics did not influence group achievement but a few limitations existed in the analysis. As for the major heterogeneity, the average value over the 16 groups was fairly high at 0.75, where the maximum possible value was 1 (when all members of a group have different majors). The high average value occurred even after categorizing the twelve majors into four major categories. The associated standard deviation was 0.24 which could be considered to be marginally large (see Table 3-3), but a larger variance might have allowed major heterogenity to be more influential. As for the school year heterogeneity, the average school year of the students was 3.32 at a four-year university and the heterogeneity' s variance over the 16 groups was limited. The lack of variance might have restricted the discrimination power over the groups. In addition, it is known that a strong relationship between demographic characteristics and group task strengthens the influence of demographic heterogeneity (Pelled et al., 1999), but in our study, the relationship between the demographic characteristics and the group task was rather weak. As a result, the influence of demographic characteristics might have limited.

We expected that quiz scores could also be a source of group heterogeneity that would lead to productive interactions, due to differences in students' achievement level. However, this factor did not greatly affect F2F activities. This seems to be due to an excessively high average quiz score (*M* = 9.45, *SD* = 0.72), which might indicate that the quiz difficulty was too low, even though it included 30% of application level problems. The additional opportunities to correct the first wrong answer could also have made the quiz score much higher. In addition, we cannot ignore the possibility of dishonesty or gaming in the online learning context (Rowe, 2004), because students who participated in the online learning at low engagement levels (about 20 minutes) nonetheless often received nine or ten points on the quiz. The total length of video lectures was 42 minutes, an unreliable situation. Although online quizzes could be a good strategy to induce students to participate in the flipped classroom (Spanjers et al., 2015), it was limited in its ability to discriminate students' academic status, such as levels of understanding. In order to make the online quiz score more relevant, more careful strategies should be planned.

The results of this study highlight the possibility of utilizing online activity data for effective F2F activity design. The relevant student characteristics that have significant effects on F2F group achievement were identified from online activity data, and their influence was supported through interviews. Our approach of utilizing online activity data is unobtrusive, allowing repeated measurements without disturbing learning activities. In addition, this approach is highly efficient because it is automatable, which means that fully automated group formation algorithms can be developed by combining existing group formation algorithms and student characteristics automatically identified from online activity data. Such fully automated algorithms will be useful in learning contexts that need frequent group re-formation. This possibility of automation indicates that the range of automation mentioned in Bishop's study (2013) can be extended beyond the online part and become a part of the F2F part. By acquiring the advantages of such online data utilization, efficient and effective learning environment design will be feasible.

The results of this study reveal the possibility that out-of-class online activity data can be utilized for group formation; we expect to form heterogeneous groups who perform better in an efficient way. Nevertheless, this study has several limitations. First, the results do not prove a causal relationship between the group heterogeneity, derived from the online activity data, and group achievement. In order to verify the possibility of efficient and effective group formation, rigorous quasi-experimental studies need to be conducted. Second, this study was conducted over a relatively short intervention duration with a small sample size (16 groups with three or four members). Therefore, future studies should aim to replicate results in a larger scale of settings for a longer time to confirm and generalize the findings.

3.5. Summary

Students should be allowed to spend their time learning, and their characteristics should be identified so that effective F2F activities can be designed. Identifying student characteristics through traditional methods, however, unavoidably interrupts student learning and burdens instructors with additional work. We anticipate that this issue can be overcome by utilizing the online activity data that will become increasingly available with the proliferation of technology-enhanced learning environments that blend online learning and F2F learning. In this study, we presented the possibility of utilizing online activity data as an alternative resource to obtain relevant student characteristics that are crucial information to the design of effective F2F activities. Utilizing these data can make the task of identifying student characteristics more efficient. Consequently, students can spend more time on learning without distractions, and instructors can re-design F2F activities as needed. In this regard, our approach will further facilitate student learning and reduce instructors' additional workloads in the management of flipped classrooms, especially where class size is large.

This study shows the possibility of utilizing online activity data to improve the efficiency of group formation process. However, in order to actually implicate this possibility, it is necessary to consider the following points. First, the advantages of our approach were found in a learning context where online and face-to-face learning are closely intertwined. The two parts of our flipped classroom, online and face-to-face, had a strong connection because they were aligned with the same ill-structured problem. It was thus possible to utilize the online activity data to identify the student characteristics that were relevant to face-to-face collaborative learning. Therefore, care should be taken to take the possibility of online activity data to utilize for the efficiency enhancement. Second, it must be borne in mind that the possibility can be also depending on the quality of the data. The online activity data we collected allowed us to identify two relevant characteristics of the face-to-face learning because the data records every detailed students' learning behavior. If the data had not had a sufficiently detailed records, our approach might have failed to identify any relevance. When discussing the possibility of data utilization, the quality of the data becomes a necessary condition.

Our approach would become increasingly promising because the high-quality educational data that records student's learning behaviors in detail will become increasingly available with the development of technology. Student characteristics identified from the high-quality data will be more valuable, thereby making the characteristics more relevant to a variety of F2F activities. Instructors will be able to design effective learning activities based on pre-identified relevant characteristics, and students will be able to learn in F2F activities with personalized learning materials according to their learning status. This change will not only strengthen the connection between online learning and F2F learning but also improve the effectiveness of technology-enhanced learning environments. We hope that our approach can contribute to facilitating this change and help further promote educational data applications.

Chapter 4. Real-time dashboard for adaptive feedback in face-to-face CSCL

Collaborative argumentation is a group-based activity where students work together to construct and critique arguments (Anderson, Rourke, Garrison, & Archer, 2001; Nussbaum, 2002). In this activity, students collaboratively contribute reasons and evidence from different perspectives for building up a shared understanding of the issue (Chinn & Anderson, 1998). This activity can be helpful for students to improve conceptual understanding and to enhance problem-solving skills (Cho & Jonassen, 2002).

With the spread of computer-supported collaborative learning, where computer system supports collaborative argumentation, known as argumentation-based computer-supported collaborative learning (ABCSCL), it has been found to support creating, sharing, and constructing arguments in various digital formats (Noroozi et al., 2012). This advanced learning environment has been considered as an important instructional technology for scaffolding and structuring argumentative learning (Jeong & Lee, 2008). It also helps students to achieve productive arguments as well as a deeper understanding of the learning topic (Buckingham-Shum, 2003).

However, a technologically advanced learning environment does not guarantee good learning outcomes in collaborative argumentation (Noroozi et al., 2012). There could be several reasons for the need for instructional support for collaborative argumentation in academic settings. First, students typically tend to support their own views instead of considering counter-arguments against the opposing views because they think that counterarguments make their arguments less persuasive (Nussbaum, Kardash, & Graham, 2005). Second, students should actively participate in the process of developing the group's arguments, but they may passively engage in the learning process (Kwon et al., 2014) or have shallow levels of interaction among group members (Verdú & Sanuy, 2014) Third, students may have difficulty in coordinating roles or regulating learning in collaborative learning situations (DeChurch & Mesmer-Magnus, 2010). And last but not least, students do not consider the various elements necessary to write a good argument (Jeong & Joung, 2007).

In order to overcome these issues of collaborative argumentation, students need to be guided to create proper arguments and generate well-established interactive argumentation according to their learning situation (Kuhn, 2009; Kuhn & Udell, 2003, 2007). This adaptive support allows students to benefit from collaborative learning, however, it is difficult in large face-to-face classrooms where a small number of instructors need to manage a large number of collaboration groups because it is hardly feasible for a few instructors to monitor and support those many groups simultaneously (Cohen, 1994; Kinshuk, 2016).

In this study, we address this issue in collaborative arguments using a learning analytics dashboard. A dashboard is a tool that allows user to quickly and easily identify the most important information required to achieve a specific purpose (Few, 2013). A dashboard is one of the common interventions employing learning analytics that support instructors as well as students alike and that allows them to gain insight into the learning process (Charleer et al., 2018). In computer-supported collaborative learning, learning activities are recorded in the system as log data (Van Leeuwen et al., 2014). The development of technology enables online access even in face-to-face classrooms and allows for collecting high granularity activity data (Kinshuk, 2016; Zurita & Nussbaum, 2004). This collected data can be used to provide a variety of instructional interventions through learning analytics. So, we can expect to implement an adaptive support system that monitors current learning situation and provides proper support to address issues of collaborative arguments.

The purpose of this study is to develop a learning analytics dashboard that adaptively supports collaborative arguments in face-to-face learning by utilizing students' activity data. The following research goals were set up: (1) Investigating the characteristics of learning analytics dashboard to support collaborative argumentation, (2) Investigating the effects of the dashboard on learning process and results of the group, and (3) Investigating student perception of the dashboard. To achieve these goals, design principles for a dashboard system are synthesized based on previous researches in section 4.1. In section 4.2, the features of the dashboard system are presented, and its effects of are reported in section 4.3. Lastly, the lesson learned about the development and implementation of the system is described, and discuss considerations for effective learning analytics dashboard in section 4.4.

4.1. Theoretical background

The main goal of this study is to develop a system that supports collaborative argumentation in a face-to-face and computer-supported setting. For better learning processes and outcomes, the system should adaptively support the group activity to foster interaction between peers and promote autonomy in (face-to-face) learning by monitoring essential indicators of learning behaviors.

4.1.1. Monitoring learning process during collaboration

The system that provides adaptive support for collaborative learning is required to monitor the learning process of both individual and group in collaboration. A collaborative learning process is interactive and dynamic (Dillenbourg, 1999). To support the learning process adaptively, it is crucial to monitor how students engage in the learning process (Wang, 2009). Many researchers mentioned that the first step of designing and developing a collaboration support system is to determine *how* and *what* learning behaviors should be recorded by the system (Jermann & Dillenbourg, 2008; Kinshuk, 2016; Soller, Martínez-Monés, Jermann, & Muehlenbrock, 2005).

Monitoring starts with raw data collection that records learning behaviors. This data can be collected from various sources. First, learning tools can be used to collect the data. Most computer-based learning tools record user activity as log data. For example, online discussion boards or chats where learning activities take place include postings written by students and interactions between students. Tabletops have been used as an interactive learning tool in face-to-face learning environments that also collect the log data (e.g., Martinez et al., 2019; Maldonado, Kay, Yacef, & Schwendimann, 2012). These records are useful for capturing and analyzing the collaborative process. Second, various sensors can be used to collect the monitoring data. In recent years, new multimodal data collection technologies have enabled us to collect a wider variety of student information (Blikstein & Worsley, 2016). For example, external sensors such as a 3D accelerometer, Kinect, and smart bands can be used to detect and record the learner's behaviors and bio-signals. Lastly, self-report data can also be used for monitoring. If there is data that must be monitored, even though it is difficult to collect through a learning tool or sensors, the user may be asked to enter the data directly into the system. The self-report data can be the way to overcome technical difficulties in implementation or limitations of available resources, however, it should be noted that the use of such manual data may hinder the automation of system operation. If the user should input too much data, the usability of the system may be hindered, or the data may be suffering from low-reliability issues because the users would be annoying to input some data. Therefore, if self-report data is inevitably needed, the data collected should be minimized and a simple and intuitive input interface should be provided.

The collected raw data is used to extract and identify *indicators* representing essential learning behaviors that need to be monitored continuously during the learning process. The necessary indicators can vary depending on the learning context. These indicators are used to determine whether the current learning situation is desirable or not. Because the variables reflecting the contextual characteristics of the course can have a significant impact on an academic achievement (Gašević et al., 2016), the indicators should be selected with consideration of the learning content and activities of the target course.

The important indicators for collaborative argumentation are *Opinion balance, Participation and interaction,* and *Elements of good argumentation*. Because diverse opinions are helpful for learning gain in collaborative argumentation (Clark, D’Angelo, & Menekse, 2009; Nussbaum & Schraw, 2007; Weinberger & Fischer, 2006), students were guided about that not all argumentations took the same point-of-view. When the individual argumentations were in the same position, the instructor recommended the addition of one more card espousing a different position to balance their opinions.

For effective collaborative learning, it is necessary for all group members to participate in the problem-solving process (Dillenbourg, 1999; Jonassen & Kim, 2010; Panitz, 1999; Renzi & Klobas, 2000). The instructor, therefore, guided students to requisitely write individual opinions at the beginning of the collaborative argumentation. In addition, interaction among group members not only plays an important role in collaborative learning that deals with ill-structured problems (Blasco-Arcas, Buil, Hernández-Ortega, & Sese, 2013; Cohen, 1994; Gress, Fior, Hadwin, & Winne, 2010), but also can be more productive when there is a shared representation (Clark et al., 2009). Thus, the instructor encouraged students to comment to the other opinions within their group.

A good argumentation can be made with clear claims, appropriate reasoning with objective evidence, and considering counter-arguments (Noroozi et al., 2012; Toulmin, 2003). Therefore, we emphasized that the four elements, '*claim*, *reasoning*, *evidence*, and *counterargument,*' need to be considered when writing the argumentation. Students were not only attending the collaborative argumentation. They also learned pedagogical theories with a textbook at the beginning of the class before starting the group argumentation activity. These theories could be backgrounds that helped solve the ill-structured problems presented in each lesson. Because one of the learning objectives was applying the learned theories to the real situation, we added *'theory'* in the set of elements so that students wrote a theoretical background for their argumentation (Jonassen & Cho, 2011). We also added *'originality'* to the set, hoping that students would write their own unique arguments rather than the ordinary ones that could easily be found in other materials from the Internet. This was also a way to prevent ethical issues such as plagiarism. These six elements were introduced during the class with labels that could be added to each card on the Trello board so that students could consider all the elements when they were writing their argumentation.

The systems that support collaborative learning adaptively should monitor indicators representing both individual students' and group's learning status. It is because that collaborative learning should be supported not only at the individual level but also at the group level (Järvelä et al., 2016). In collaborative learning where all group members actively participate in their problem-solving process, each group member must perform a particular role or responsibility (namely individual accountability), while their contribution should be regulated at group level to achieve their common goals. When monitoring both levels, it is possible to clearly diagnose whether the problem situation in collaborative learning is an individual-level or a group-level problem. Because an accurate diagnosis of the collaboration group's problem can lead to appropriate supporting that has a substantial impact on the effectiveness of collaborative learning (Webb, 1991), monitoring individual and group level indicators is needed to design an adaptive collaborative learning support system that provides appropriate support.

4.1.2. Providing supports with appropriate content at the right timing

Adaptive support system is required to provide learners with the appropriate *contents* at the appropriate *timing* (Gibbs & Simpson, 2005). Such relevance of support has a more significant impact on learning outcomes than the amount or quality of support in collaborative learning (Webb, 1991). In order to provide the appropriate content, it is crucial to determine proper indicators to accurately diagnosis the learning status are desirable or not. The indicators can be determined by referring to the prior literature considering the characteristics of the learning context. For instance, in collaborative learning, the interaction between group members has a significant influence on the learning outcome (Cohen, 1994), so it is necessary to monitor the number of comments that were shared between each group member and it can be used to identify the social interaction between them and whether or not there is an isolated member.

Although previous studies can help us select proper indicators according to the learning context, it is often difficult to establish relevant baselines that are the criteria for evaluating current learning status. For example, if there were nine comments in a group with four members, the previous studies do not tell the exact number of comments that is required for desired learning status. For the exact baselines, relative standards (e.g., average, median) can be used. In Van Leeuwen and colleagues' study (2015), the instructor compares the individual activity with the classroom average. This descriptive criterion is advantageous in that it changes flexibly according to the learning situation, however, it should be used with caution because it may have adverse effects such as a boomerang effect (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). To prevent these side effects, an absolute standard can be set as the baselines by referring to the exact amount of exemplary activities based on the record of previous classes or instructional guidelines agreed in the learning context. These criteria should be set with careful consideration of the contextual characteristics of the learning.

Adaptive support should be provided at the appropriate timing for learners. The timing of feedback is critical as much as the content of the feedback (Coll, Rochera, & De Gispert, 2014). In particular, this timely support is critical in face-to-face learning contexts because the learning contexts have limited learning time. Without the supports, students may use their learning time inefficiently and unproductively so it is difficult to expect they achieve well in the class. To support at the right time, student activity should be monitored with high temporal granularity. When monitoring is done in real time, it will be possible to know the best timing for support based on the monitoring of the proper indicators.

For the efficiency and effectiveness of support, color cues can be useful. One famous example that used the color cue is Course Signals at Purdue. Its dashboard visualizes students' learning outcomes as a traffic-light color (Arnold & Pistilli, 2012). In addition, it would be effective to provide visual elements as well as textual material detailing them. Visual elements such as charts and colors are effective in delivering intuitive and concise summaries but are not sufficient to express specific details. Both of these need to be provided because the intent and detail of the feedback provided by the system can be expected to change the behavior of the learner when it is clearly expressed and delivered (Winstone, Nash, Rowntree, & Parker, 2017).

4.1.3. Giving an appropriate level of autonomy in the learning process

The system that supports face-to-face learning context is not for controlling the learners but for facilitating their autonomy to monitor, reflect, and regulate their learning process. Learners should be given the opportunity to overcome the difficulties they encounter during their learning activities autonomously. Even if a group is identified as having difficulties through monitoring and evaluation by a system, the group should not be provided at the highest level of support. Instead, it is more beneficial for the weak group to reflect and regulate to overcome their problems autonomously (Dillenbourg, 1999; Winstone et al., 2017). Respecting learners' autonomy in the learning process and providing learners with an appropriate level of control over their tasks is an effective strategy for improving learners' internal motivation (Keller, 1987). In particular, when a collaboration group addresses unstructured problems, direct instruction and intervention can have a negative impact on student participation and interaction (Cohen, Lotan, & Leechor, 1989). This autonomy also helps to induce students to use the feedback. Winstone and colleagues (2017) pointed out that students had a low level of willingness to accept feedback and reported that students were willing to use feedback when they were taking some degree of responsibility for their task. Because the main agent of learning is the learner, autonomy should be given so that they can manage their own learning process in accordance with their choices and decisions, and the supporting system should not interfere excessively with the learning process. In this regard, the system should first mirror the current learning situation objectively to induce autonomous reflection and control of the learners, rather than providing the complete level of support immediately (e.g., providing direct instructional guidance, visiting instructor to the group) as soon as some issues are detected. In addition, the interaction techniques of the system will be able to allow students to choose the preferred level of support autonomously.

While autonomy is important, however, excessive autonomy can hinder the effectiveness of learning (Jones & Issroff, 2005). Proper level of autonomy should be provided because learners lack the ability to monitor and regulate their current learning status (Azevedo et al., & Burkett, 2010). In particular, in the context of collaborative learning, when extreme level of autonomy is given, learners may have problems such as choosing an ineffective learning strategy or superficial participation in their collaboration (Lipponen, Rahikainen, Lallimo, & Hakkarainen, 2003). Therefore, the level of support should be differentiated according to the learner's level of competence in the task, and a high level of intervention (e.g., direct support of the instructor) should be required in certain situations. Because the instructor retains a crucial factor in the success of collaborative learning (Dillenbourg, 1999), the instructor can trigger timely interventions according to the current learning situation when the system is infeasible to determine the appropriate timing. Ironically, it can be helpful to provide the instructor with the control that is available as needed to ensure the learner's autonomy (Cohen, 1994).

4.1.4. Promoting participation and interaction

The fundamental and intuitive criterion is that a collaborative learning context is participatory in interaction (Dillenbourg, 1999). When a system supports collaborative learning, the system should promote interaction in their collaboration so that they coordinate and negotiate their roles and tasks in their collaboration (Cohen, 1994; DeChurch & Mesmer-Magnus, 2010). Successful collaborative problem-solving groups tend to be characterized by mutuality of exchanges among group members (Barron, 2000). In collaborative learning, learners construct new knowledge through interacting with peers, and they develop a plan to achieve common goals collaboratively (Malmberg, Järvelä, & Järvenoja, 2017). This interactivity makes collaborative learning active, increases engagement, and consequently influences learning performance (Blasco-Arcas et al., 2013). In particular, the amount of interaction is critical to achievement in collaborative learning where learners are solving ill-structured problems because various opinions are required to address the problems (Cohen, 1994). Therefore, the matter of how to promote interaction should be considered when designing and developing supporting tools to enhance group learning process and outcome in collaborative learning (Resta & Laferrière, 2007).

To facilitate the participation and interaction, a system should enhance group awareness and provide meta-level feedback together so that group members can reflect and regulate their learning process. Although the monitoring can help group members to be aware of their collaboration status, the awareness itself does not guarantee to improve competencies or group performance (Janssen, Erkens, & Kirschner, 2011; Jermann & Dillenbourg, 2008; Jivet, Scheffel, Drachsler, & Specht, 2017). For example, Jermann and Dillenbourg (2008) showed that a mirroring tool that displayed graphical representation of the group members' collaboration did not substantively affect the behavior of collaborative problem solving while a metacognitive tool that displayed a standard for desirable behaviors led to increased participation. On the other hand, Cho and colleagues (2015) provided meta-level feedback that led reflection about group collaboration with visualization of interactivity patterns, as a result, the amount of discussion participation and learner interaction increased significantly. Therefore, the system should provide not only graphical representation that allow learners to be aware of their collaboration status intuitively but also feedback that facilitate desirable interaction behaviors clearly.

To facilitate desirable interaction by providing feedback, the system can reinforce scaffolding for productive interactions by encompassing the interaction rules in the design of the system (Dillenbourg, 1999; Resta & Laferrière, 2007). The instructor usually specifies interaction rules for face-to-face collaboration to promote productive peer interaction. For example, in a collaborative argumentation activity, the instructor can introduce rules such as "every group member should give his or her argumentation," "leave a comment about other group member's argumentation before starting a group discussion." The system can continuously reinforce the interaction rules by sending feedbacks that notice the status of compliance with the rules. This notification can be done by selecting and monitoring proper indicators that represent the pattern of group interaction so that the system can determine whether the group keeps the interaction rules or not.

In addition, the interaction between learners and instructor also plays an important role (Blasco-Arcas et al., 2013). The instructor retains a crucial factor in the success of collaborative learning because he or she has an obligation to manage learning progress and to provide feedback and support to learners who ask for help (Dillenbourg, 1999). Learners have rights to ask for such help. However, in face-to-face learning, learners tend to avoid requesting help due to social pressures such as social prestige or popular reputation (Ryan, Pintrich, & Midgley, 2001). These social pressures can be more substantial in large-scale lectures where many learners are participating and can inhibit help-seeking behavior. Therefore, to encourage interaction between the instructor and the learner, the system can provide a specialized communication channel that allows students to ask for the help of the instructor with low social pressure.

The principles described above are not sharply divided and operate organically to achieve the intent and purpose of each principle. The next section describes the details of the system we have developed based on these principles.

4.2. Dashboard characteristics

Learning analytics dashboard developed for this study is an adaptive support system that provides real-time support for face-to-face collaborative argumentation. The system is especially useful for large-scale classes where a small number of instructors are hard to manage large number of groups adaptively according to the groups' current collaboration status.

The dashboard utilizes group process data collected from an online collaboration tool, Trello. This tool has a board-like user interface that allows students to organize and manage their group task synchronously. Students could create a new card (like a new posting on a discussion board), add a new comment, labels (representing what contents the card has) on the shared working space. All the actions are recorded in real-time as an activity data. The data is used for monitoring group collaboration through identifying important indicators that represent important learning status of individual and group regarding collaborative argumentation.

There are two types of dashboards: student and instructor dashboard. The student dashboard is to allow students to monitor their individual and group learning status, and to receive adaptive support according to their current learning status in real-time. The instructor dashboard is to help instructor understand the learning situation of the whole class, identify weak groups that are having difficulty in collaboration. It also has control functions that allow the instructor to determine when and what instructional guide or support are delivered manually. The detailed characteristics of these two dashboards are described in the following sub-sections.

4.2.1. Student dashboard

The student dashboard is developed as a HTML5-based dynamic web page. The dashboard consisted of two parts: a *learning phase guide* and *feedback*. The part of the learning phase guide shows the succinct task guide according to each activity phase. (the purple panel in Figure 4-1). It can be removed by tapping the close button in the panel. Another part of the feedback consisted of three sections: *Opinion counts*, *Participation and interaction*, and *argumentation labels* (the other three blue panels in Figure 4-1).

Each feedback section has two components: *visualization* and *message.* The visualization component is to allow students to identify their current collaboration status with ease. The message component describes the current learning status in more detail and delivers appropriate contents according to the status. Every message has a *Details* button for more detailed and direct instructional guides (see Figure 4-2), which allows students to decide autonomously whether they used the complete level of support or not. Each section is color coded using traffic-light colors (green, yellow, and red) by comparing the desired learning status. The detailed design of each feedback section will be described.

In addition, we implemented a *Help* button on the upper right of the student dashboard (See the purple button in Figure 4-1). Students may be burdened with asking for help from instructors, especially in large face-to-face classes because they get a lot of attention from many other students (Aleven, Stahl, Schworm, Fischer, & Wallace, 2003; Ryan et al., 2001). When the detailed feedback was not enough to improve the collaboration status, students could use the button to request the instructor to visit their group for additional help with lower burden. This button allowed students to autonomously decide and request the highest level of support, direct help from the instructor.

Each group's help request was displayed in the instructor's dashboard by highlighting the groups' actual position in the classroom.

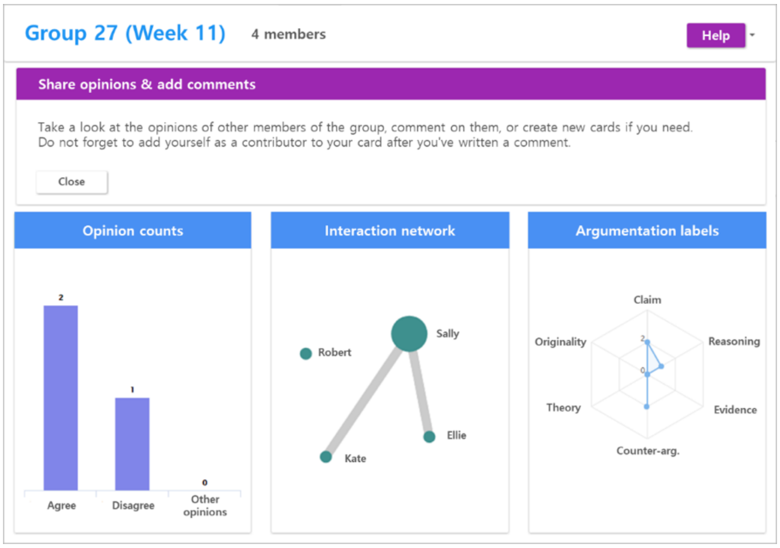

Figure 4-1. Default status of student dashboard

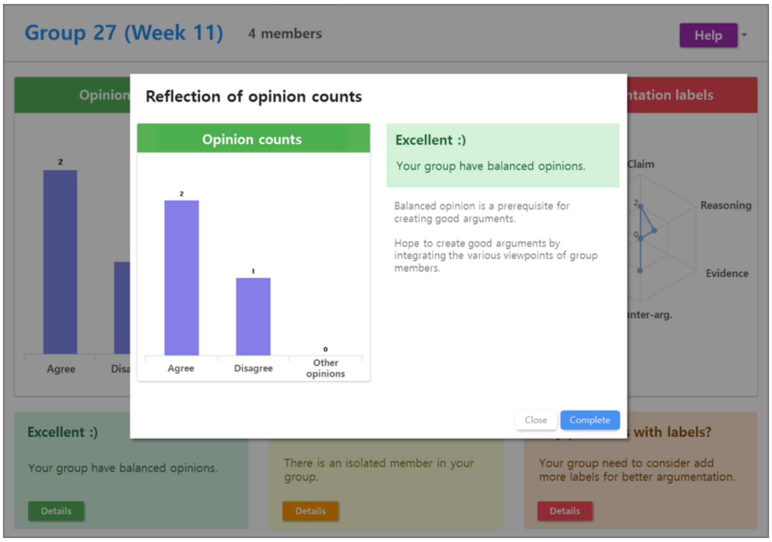

Figure 4-2. Student dashboard with higher level of feedback using additional pop-up window

Feedback section 1: Opinion counts

The opinion counts section is to guide group members to consider various opinions on the ill-structured problem so that they can produce a good group argumentation that includes various point-of-views. The desired learning status for this feedback section is the balanced distribution of opinions that have no more than one difference between the Agree and Disagree position. On the other hand, the worst learning status is the biased distribution that all opinions have the same position (see Figure 4-1). The rule sets for the color codes are summarized in Appendix A. The color theme was changed as results of comparison between the desired and the current learning situation with traffic-light color codes (see Figure 4-3).

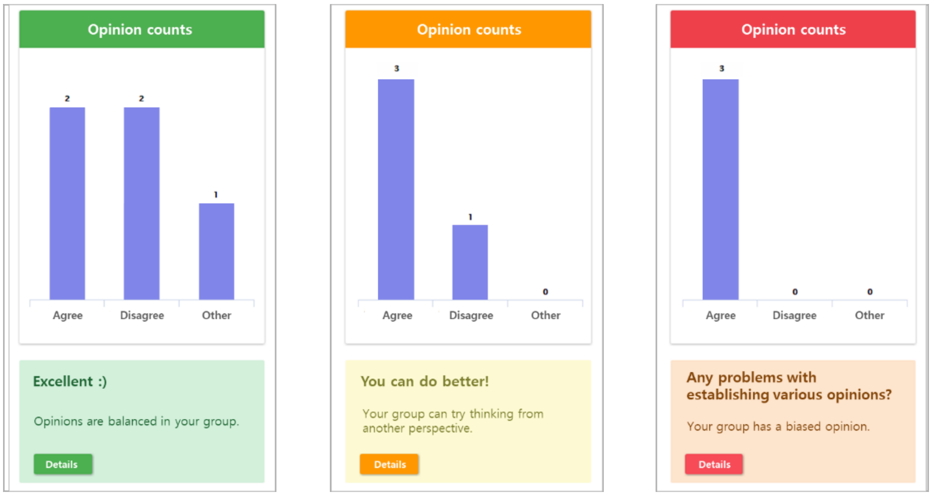

Figure 4-3. Three status of opinion counts section

Diverse opinions are helpful for learning gain in collaborative argumentation (Clark, D' Angelo, & Menekse, 2009; Nussbaum & Schraw, 2007; Weinberger & Fischer, 2006). When a group has diverse opinions on a discussion topic, the group can not only explore the various solutions for problem-solving but also consider counterarguments required in a convincing argument. To encourage groups to create diverse opinions, traffic-light labels in this section were determined by a balance between counts of opinions in the two positions, Agree and Disagree. When a group has opinions only on one position, a red label is used, so that the group needs to consider the other position. When a group has opinions both on the two position, the difference between the number of opinions on two positions was considered to determine the label's color as either green or yellow. When the difference is less than two, the group was considered to have a balanced opinion and a green label was used. The difference was allowed up to one because some groups had an odd number of members, three or five. If the difference is more than two, however, a yellow label was used to encourage the group to consider minority opinions. The pseudo-code for traffic-light labels in this section is in Appendix A.

A bar chart was presented to visualize the distribution of opinions among group members. Students were able to monitor the opinion distribution through the bar chart and be aware of whether their opinions were balanced or not during the class. For the autonomy of the learner, the system did not send a message at the first phase where students were writing individual argumentation (see Figure 4-1 default state of the student dashboard). The system waited for the group members to modify the existing arguments or add more arguments to make their opinions balanced by themselves. After the first phase of class, the system started to deliver feedback messages that have differentiated contents according to the current opinion distribution to guide unbalanced opinions to become balanced by providing several keywords according to the deficient point-of-view. The keywords were provided using a popup window that popped up when the *Details* button was tapped (see Figure 4-2), so that the students had the option to decide whether to use the higher level of support or not. The contents of the message and the color codes were continuously updated as the distribution changed. If the distribution of opinions did not improve until the third learning phase, the system provided explicit examples, rather than the keywords, for the deficient position to make the distribution balanced, and suggested the group to ask the instructor's support.

Section 2: Participation and interaction

The interactivity section is to encourage students to participate in group activity and communicate with each other actively so that they can create an integrated group argumentation that includes all members' ideas. There are two desired learning status in this section. In the first phase of the class, all group members were required to create their initial argumentation. After the first phase, they were required to comment on each other's argumentation to have no isolated initial argumentation in their group. It was considered the worst learning status if there were members who did not create initial argumentation in the first phase, or if there was no interaction between members after the first phase. This section also used the traffic-light color codes according to the current learning status (see Figure 4-4).

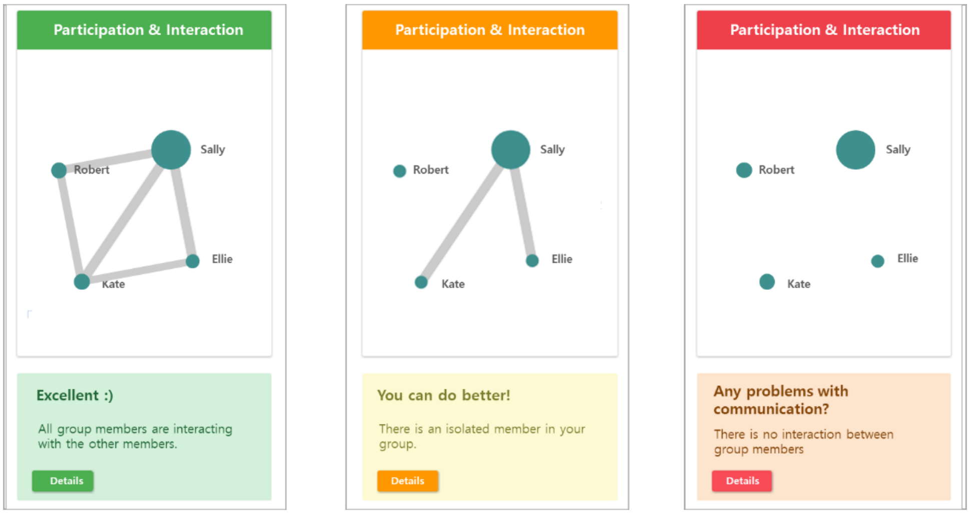

Figure 4-4. Three status of interactivity section

In the first phase of class, the traffic-light labels for this section were determined by considering group member's participation. Participation is particularly important and necessary for successful collaborative learning (Dillenbourg, 1999; Jonassen & Kim, 2010; Panitz, 1999; Renzi & Klobas, 2000). All group members need to participate through the whole problem-solving process. Because the students had limited learning time in the face-to-face classroom, they had to complete creating their initial opinions in the first phase for meaningfully participating in the following learning phases. Thus, the color label of this section was set as green when all group members created their own opinions, and as red when at least one group member did not. From the second phase, where opinion sharing was started, the group member's interaction was considered to determine the color of traffic-light labels. Group interaction is one of the most important requirements for successful collaboration (Blasco-Arcas et al., 2013; Cohen, 1994; Gress et al., 2010). When there was no interaction by commenting on each other's argument, the color label of this section was set as red. Even if there were a few interactions, the color was updated up to yellow when there was still some isolated member who had no interaction with other members. With no isolated members, the color was set as green. The pseudo-code to determine the color of traffic-light labels of this section is summarized in Appendix A.

A network graph is presented to show the participation and interaction status of the group. Each node represents the amount of participation for writing argumentation including individual and group, and each edge represents the amount of interaction by commenting between the members. Like the first feedback section, this section also has provided different level of support for student’s autonomy in managing their learning process. While students were writing their initial argumentation, they were just able to monitor their learning status without feedback messages. From the time when they started to share their argumentation, the system started to provide a feedback message to encourage all group members to complete their individual writing and participate in the sharing activity. When students started to integrate individual argumentations to group argumentation, the system started to provide a message regarding interaction to facilitate referring to the other members'opinion. The message in this section also included the *Details* button to provide more detailed instructional guide. The detailed guide encouraged students not to cling to perfect writing but to complete it, even at the level that included only central ideas, and provided simple examples along with an explanation that they can comment on the others' arguments in a way that presents conflicting opinions or complements.

Section 3: Argumentation elements

The argumentation elements section is to guide group members to consider the elements for good argumentation when they wrote their argumentation. The desired learning status in this section is that students considered not only the basic elements; claim, reasoning, evidence, and counter-argument but also all the other elements; theory and originality in their argumentation. The worst learning status is at least one element among the basic elements was not considered. Like the other feedback section, this section also used the traffic-light color codes (Figure 4-5).

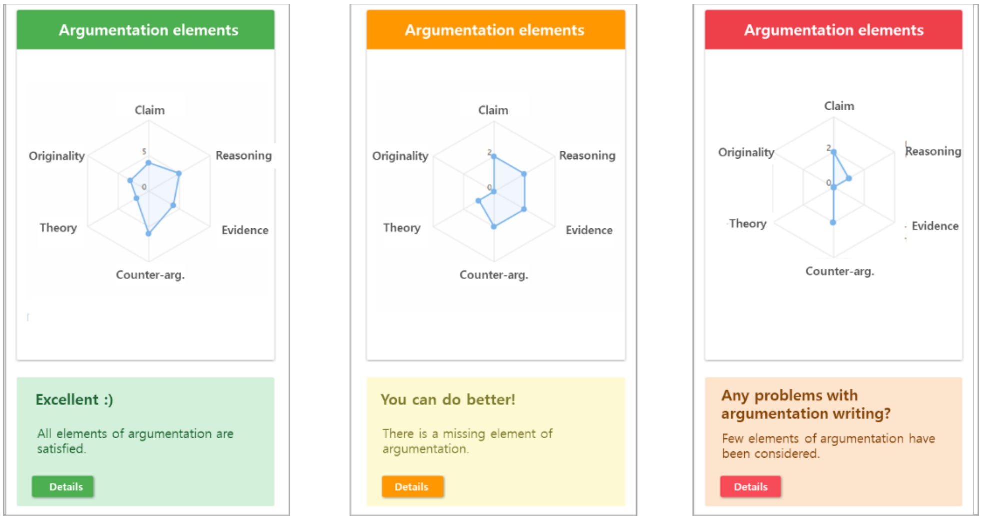

Figure 4-5. Three status of argumentation elements section

The traffic-light labels for this section were preferentially determined by use of primary argumentation elements. *Claim, reasoning, evidence*, and *counterargument*, were deemed as the primary elements that should be considered for argumentative writing because good argumentations require explicit claims, appropriate reasoning with objective evidence, and considering counter-arguments (Noroozi et al., 2012; Toulmin, 2003). If any of the primary elements were missing among the all the writings within a group, the dashboard turned on a red light in this section regardless of considering secondary argumentation elements. The secondary elements were *theory* and *originality*. Theoretical backgrounds can not only make the argument more convincing but also let students have opportunities to deepen their understanding of the pedagogical theories learned in class while applying the theories to real problems

(Jonassen & Cho, 2011). In addition, originality needed to be considered to encourage students to make their own unique arguments rather than the usual ones that can easily be found from the Internet. When a group considered all the argumentation elements in both primary and secondary the color label was set to green. Otherwise, if a group missed one of the secondary elements, while all the primary elements were used, the color label is set to yellow. In Appendix A, the pseudo-code for this section' s color labels is summarized.

A radar chart is presented to show the usage of each argumentation element that was considered in the group' s all argumentation writings. As with the other sections, this section also encouraged students to reflect and improve their learning process autonomously through monitoring rather than the direct instructional guide. The contents of the guide gradually became detailed with color-coded messages. In the first and second phases of class, the high level of support given by the Details button provided an operational definition of the missing element and guided to consider the element additionally. From the third phase of class, the guide became more direct and provided a simple example of the missing element.

4.2.2. Instructor dashboard

In face-to-face collaborative learning, comprehensive judgment and response of the instructors with empirical knowledge and expertise play an important role (Cohen, 1994; Van Leeuwen et al., 2015; Webb, 2009), so we developed a dashboard for the instructor as well as the students.

The instructor dashboard was also developed as a dynamic web page that was updated in real-time and displayed the current collaboration status of the whole class (see Figure 4-6). By using this dashboard, the instructor could easily and quickly identify which groups were having difficulty in collaboration or needing extra support. Each group’ s collaboration status was organized into six blocks consisting of three rows and two columns, and the set of blocks was displayed at the physical location of the group in the classroom. The three blocks in the first column were synchronized with color-codes of the three sections in the student dashboard at the first phase of collaboration process. Likewise, the three blocks in the second column were for the collaboration status after the initial phase. By preserving the initial status and updating the following step’ s status in real-time in additional column, the instructor could detect not only the current situation but also the progress of the collaboration activities of each group. In addition, the instructor could easily visit and support the weak groups having yellow or red blocks by referring to the location in instructor dashboard. Furthermore, student’ s help requests were also highlighted in this dashboard. Figure 4-6 showed an example that group 6 and 14 requested instructor’ s help. When the instructor needed more detailed information about a group’s collaboration status, the instructor could access the student dashboard and Trello board by tapping the hyperlink included in the group’s name.

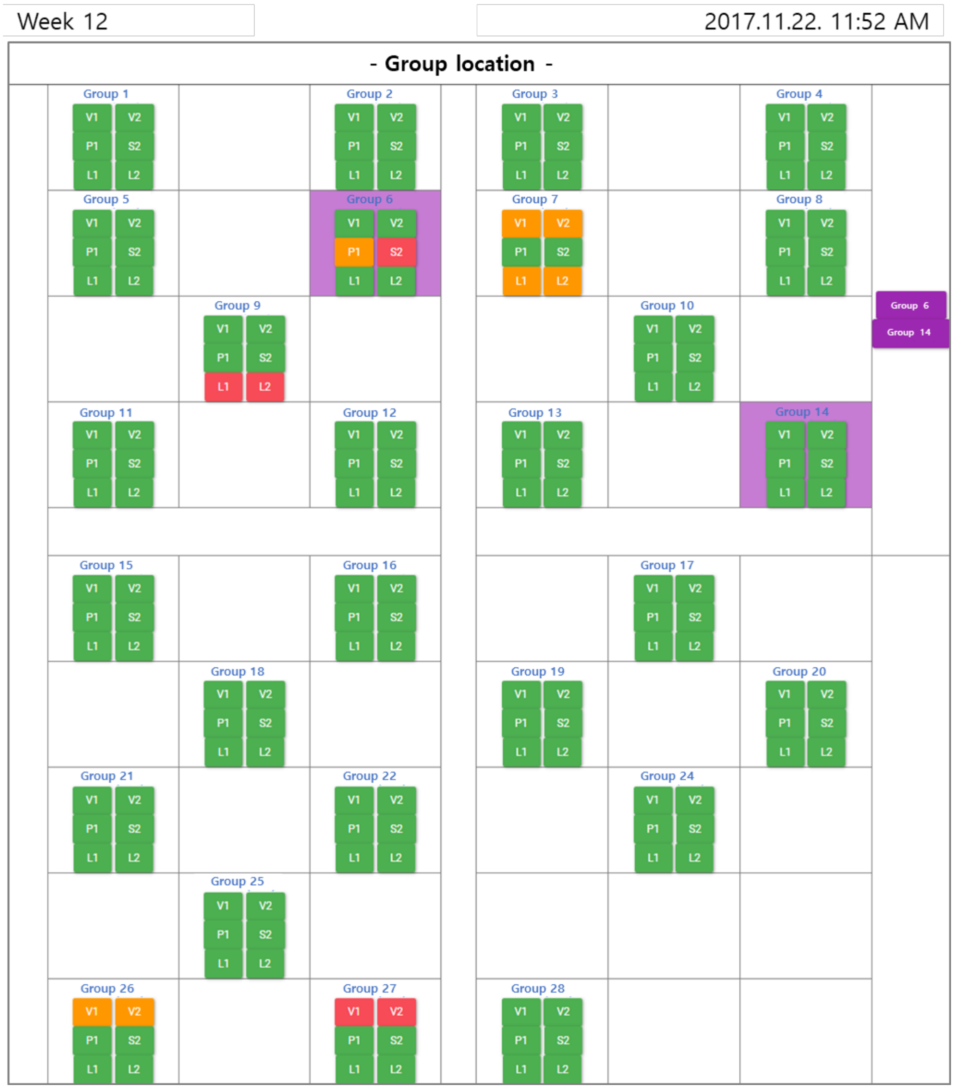

Figure 4-6. Instructor dashboard

4.3. Evaluation of the dashboard

To show the effectiveness of the dashboard system, we conducted an empirical experiment in a large face-to-face class where adaptive supports are difficult to be provided by a few instructors. We compared not only individuals' perceived learning process and outcome on collaborative argumentation but also groups' argumentation quality when the dashboard system was supported and when it was not. We also investigated the students' perceptions of the system with a survey, and advantages and limitations of the system with interviews.

4.3.1. Participants

In this experiment, 88 pre-service teachers (56 females, 32 males) participated in a series of four collaborative argumentation about educational issues over four weeks. The participants were undergraduate students enrolled in a course on "Introduction to the Study of Education." After the experiment, ten students (7 females, 3 males) voluntarily participated in post interviews. This research closely followed the Seoul National University IRB protocol (No. 1710/001-005) for recruiting the participants and implementing the procedure of this experiment.

4.3.2. Experiment context

The 88 participants were assigned to 22 heterogeneous groups considering their gender, major, and pre-experience of collaborative learning. This study was conducted for seven consecutive weeks (Figure 4-7). Before the data collection for this experiment, students had a practice period for three weeks to familiarize with the use of collaboration software and the collaborative argumentation activities.

The students were asked to bring their own devices such as laptop or smart phone to use the collaboration software, Trello, and the classroom provided free Wi-Fi access.

After the pre-training period, the participants were engaged in face-to-face collaborative argumentation classes for four weeks. In the first and second week of experiment, they only used the collaboration software for the group activities. In the third and fourth week, the dashboard system was implemented to provide adaptive support for face-to-face collaborative learning. Each group received a tablet PC (iPad mini) to use student dashboard.

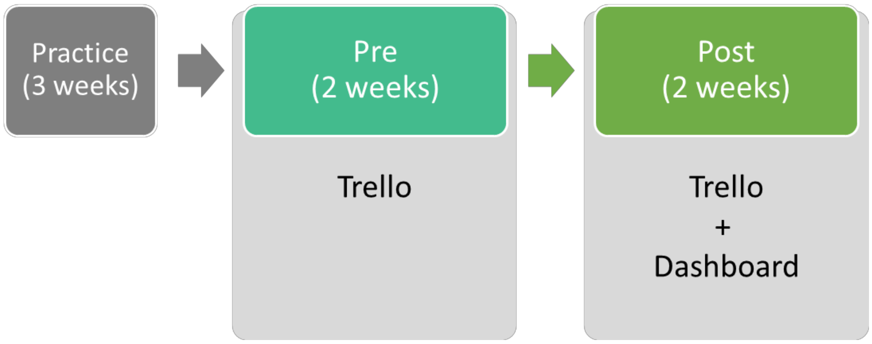

Figure 4-7. Timeline of the experiment

Collaborative argumentation classes were held once a week for 90 minutes over four consecutive weeks. At the beginning of the class, the instructor gave a short lecture that introduced ill-structured problem as the discussion topic for collaborative argumentation, and he provided example cases that the problem occurs with a guide of collaborative argumentation. The process of the collaborative argumentation consisted of the four following phases:

Figure 4-8. Students' in-class activities on a Trello board

- Individual writing of argumentation: each group member created a new card on their Trello board and wrote their individual argumentation regarding the ill-structured problem on the card (from Figure 4-8-a, b). They could add six types of labels to the card-claim, reason, evidence, counter-argument, theory, and originality - that were used as a checklist to improve the quality of their argumentations (see the color labels in Figure 4-8-c)

- Sharing and revising: group members read each other's cards and add comments to elaborate the argumentations (Figure 4-8-d)
- Group writing of argumentation: each group was asked to integrate their varied opinions into a single group argumentation as their group solution, and to submit the solution for the result of the group task (Figure 4-8-e)
- Reflection on collaborative argumentation: every group solution was shared through a public Trello board where all students could access. Students reflected their learning by referring to the other group's solutions.

When students used the dashboard system, they could monitor their collaboration status over the class. The instructor guided students to reflect their current collaboration status and plan to improve their collaboration based on the information their dashboard provided before moving on to the second and third step.

4.3.3. Measures

To investigate the changes in the group process, we used four variables; opinion balance, comments counts, network density, and counts of argumentation elements. Each variable extracted from the group process data collected by the collaboration tool, Trello. Opinion balance is defined as the negative absolute difference of the number of argumentation cards between Agree and Disagree. For example, when five group members create two argumentation cards on Agree position and the other three on the Disagree position, then the opinion balance of the group would be $-|3-2|=1$. As the number of argumentations between the two positions is balanced, the opinion balance will be close to zero. Comments count is the total number of comments sent and received between group members. Network density is a measure of the degree of interaction among group members. It is defined as the number of existing connections over the number of all possible connections among group members (Wasserman & Faust, 1994). When all group members interact with all peers, the value of this variable is one. Counts of argumentation elements are usage counts of the six elements for good argumentation on all of the argumentation cards on group Trello board.

The group achievement was assessed by evaluating the group solutions that were submitted as the results of the group task. Two researchers independently evaluated the quality of solutions with a rubric that had been developed based on the previous studies (Jonassen & Cho, 2011; Nussbaum & Schraw, 2007). There were six categories in our rubric: Claim (Are the claims expressed clearly and consistently in their argumentation?), Reason (Are the adequate supporting reasons provided in their argumentation?), evidence (Are the objective and concrete evidences supporting the reasons presented in their argumentation?), counterargument (Are the counterarguments considered and rebutted in their argumentation?), theory (Are the pedagogical theories are applied to back up their argumentation?), and originality (Are the novel perspectives and unique claims presented in their argumentation?). Each category of the rubric was rated from 0 to 2 points (Poor: 0, Fair: 1, Good: 2). The inter-rater reliability was 0.521 and all differences were resolved through discussion between two researchers.

Student perception of learning process was surveyed at the end of every class over four weeks. The survey contained a total of 23 items that were developed based on previous researches (Dewiyanti, Brand-Gruwel, Jochems, & Broers, 2007; DiDonato, 2013; Michinov & Michinov, 2009) using 5-point Likert scales (see Table 4-1). Internal consistency of each sub-category ranges .677 ~ .913.

At the end of the last class, student perception of the dashboard system was surveyed. The survey contained of 12 items about usefulness, usability, and attitude of the system using 5-point Likert scales based on the study of Park and Nam (2012) (see Table 4-2). Internal consistency of each sub-category ranges .811 ~ .945.

Table 4-1. Survey items for investigating the perception of learning process and outcome

Category	Sub-category	Item example	Number of items	Cronbach's alpha
Perceived learning process	Situational interest	I enjoyed participating in the collaborative argumentation activities.	4	.821 ~ .869
	Participation	Every group member actively expressed their own opinion.	3	.843 ~ .913
	Interaction	My group members exchanged questions that helped promote each other's thought.	3	.677 ~ .823
	Group regulation	My group members worked together to make up for the shortcomings of our group task.	3	.679 ~ .752
	Group conflict†	There was(were) group member(s) who often confront me in my group	3	.718 ~ .888
Perceived learning outcome	Perceived learning outcomes	I have achieved the learning objects through the collaborative learning.	4	.697 ~ .853
	Perceived performance	My group has successfully completed our task.	3	.771 ~ .885

Note. †: Reverse item.

Table 4-2. Survey items for investigating the perception the dashboard system

Category	Item example	Number of items	Cronbach's alpha
Usefulness	The dashboard system helped us monitor and improve our collaboration activities.	4	.945
Usability	I could use the dashboard system without much efforts.	4	.811
Attitude	I like to use the dashboard system for collaborative learning again.	4	.912

4.3.4. Evaluation results

Group learning process

The group process in collaborative learning was analyzed by conducting paired t-test with the online activity data. The results are summarized in Table 4-3. As used the dashboard system, opinion balance, which was defined as the negative absolute difference between the number of agree and disagree opinions, significantly decreased (t (21) = 4.174, $p < 0.001$), and the number of comments exchanged with peers significantly increased (t (21) = 6.527, $p < 0.001$). In addition, the use of all the six argumentation elements significantly increased (Claim, t (21) = 3.792, $p < 0.01$; Reason, t (21) = 4.469, $p < 0.001$; Evidence, t (21) = 5.369, $p < 0.001$; Counter argumentation, t (21) = 3.705, $p < 0.01$; Theory, t (21) = 6.019, $p < 0.001$; Originality, t (21) = 3.705, $p < 0.01$).

Group learning outcome

The group achievement was analyzed by paired t-test with the evaluation of each group's solution (see Table 4-4). The group achievement was significantly improved when the collaboration groups used the dashboard system (t (21) = 7.241, p < 0.001).

Student perception of learning

We conducted paired t-test analysis to compare the student perception before and after the dashboard system provided (see Table 4-5). As three students did not response the survey, a total of 85 students' survey data was analyzed. In the learning process, situational interest (t (84) = 2.773, p < .01), participation (t (84) = 3.352, p < .01), productive interaction (t (84) = 3.778, p < .001), and group regulation (t (84) = 7.868, p < .001) showed significant differences. All variables in the learning outcomes showed significant; perceived learning outcomes (t (84) = 4.268, p < .001), perceived performance (t (84) = 4.593, p < .001).

Student perception of the dashboard system

Students' perception of the system was generally positive. Students responded that the system was useful (Usefulness: M = 3.929, SD = .968), usable (Usability: M = 4.034, SD = .718) and worthy of use it (Attitude: M = 3.907, SD = .958).

Table 4-4. Results of t-test and descriptive statistics for comparing group process (n = 22)

Variables		Pre		Post		t
		Mean	SD	Mean	SD	
Opinion balance		-1.886	0.755	-0.864	0.743	4.174***
Comments counts		5.182	2.621	9.818	2.575	6.527***
Network density		0.716	0.342	0.950	0.147	2.889**
Counts of argumentation elements	Claim	3.864	0.889	4.659	0.793	3.792**
	Reason	2.818	1.129	4.114	0.899	4.469***
	Evidence	2.045	1.143	3.455	0.975	5.369***
	Counter argumentation	1.909	0.921	2.818	0.839	3.705**
	Theory	1.000	0.845	2.432	0.849	6.019***
	Originality	1.909	0.921	2.818	0.839	3.705**

Note. ** $p < .01$, *** $p < .001$

Table 4-3. Results of t-test and descriptive statistics for comparing group achievement (n = 22)

Variables	Pre		Post		t
	Mean	SD	Mean	SD	
Group achievement	7.932	1.365	10.136	1.136	7.241***

Note. *** $p < .001$

Table 4-5. Results of t-test and descriptive statistics for comparing student perception of learning (n = 85)

Variables		Pre		Post		t (84)
		Mean	SD	Mean	SD	
Learning process	Situational interest	4.033	.569	4.193	. 636	2.773**
	Participation	4.245	.597	4.443	.493	3.352**
	Productive interaction	4.233	.533	4.455	.457	3.778***
	Group regulation	3.653	.631	4.169	.575	7.868***
	Group conflict	1.435	.510	1.346	.492	-1.471
Learning outcome	Perceived learning outcomes	3.835	.584	4.057	.633	4.268***
	Perceived performance	3.939	.494	4.155	.524	4.593***

Note. ** $p < .01$, *** $p < .001$

Interviews

We conducted post-interviews to understand how the dashboard system influenced on the group process. The interviewees responded that the system was helpful to facilitate group reflection. They said because their collaboration status was summarized with simple visualization and text on the dashboard, they could grasp their unperceived weak points and discuss how to improve their group activity in detail. They said the information delivered by the dashboard could be used to encourage some passive members to participate in group collaboration. Because the information was objective, not subjective, they could persuade them without emotional burden. In addition, some groups started to discuss about their roles before starting group activity when they used the dashboard. Because they already know how to receive the green feedback, they coordinated their roles in creating initial argumentations to make balanced argumentation, built their own strategies to use all the elements of argumentation. Consequently, the dashboard system seemed to support collaborative learning by enhancing group participation, interaction, and coordination.

On the other hand, a few interviewees pointed out limitations of the system. First, they said they had difficulties in trusting the feedback because it was based on simple counting that could be easily faked by themselves. In addition, they felt uncomfortable when using the dashboard because they felt like they were under surveillance of the system. They responded that even if the dashboard would provide some useful feedback, but they did not pay much attention to the dashboard because they did not want to care the surveillance.

4.4. Discussion

The purpose of this study is to design and implement learning analytics dashboards that provide adaptive supports for face-to-face collaborative learning based on the theoretical background: monitoring, adaptiveness, autonomy, and interactivity. The impact of the dashboards on the group process and achievement was evaluated in a real classroom setting. Student perceptions of learning processes and outcomes were also surveyed. The results showed that the group process, group achievement, and student's perception of learning improved significantly by using the dashboards. In addition, students showed a positive perception of the system. In this section, some issues involved in this study are to be discussed.

The dashboards in this study helped to improve the learning process and achievement of the group. In a collaborative argument, the diversity of opinions has a significant impact on the outcome (Clark et al., 2009; Nussbaum & Schraw, 2007). Because the dashboards scaffold to make a balanced distribution of opinions, groups started to create additional cards with insufficient point-of-view or coordinated the roles of Agree and Disagree. This change indicates that the group members considered various positions for the integrated group solution. In addition, as the system was used, the number of comments and the network density in each group significantly increased. Interaction is a critical indicator of the success of collaborative learning (Cohen, 1994; Dillenbourg, 1999; McAlister, Ravenscroft, & Scanlon, 2004). For instance, to comment to the other peers, group members would need to review the other group members' argumentation carefully. The increased network density means that these careful reviews were done among more groups, which implies that this increased interaction could lead to productive face-to-face interaction. Lastly, the usage of argumentation elements was also significantly increased. The increased use of the elements provided like checklists means that students tried to include more elements when writing their argumentation. These collaboration changes that resulted from the use of dashboards can have a positive impact on the group's integrated outcomes so that the group can attain better achievement.

A positive change in student perception of learning was also confirmed. The students responded that they were more interested in the learning situation, more actively participating in the collaboration, interacting with other peers and regulating the activities of the group. We could not confirm a significant decrease in group conflict. It seems to be because group conflict was not high from the first and second week, so that had enough room to decrease significantly. However, interviews showed that the dashboards could reduce emotional conflict when group members coordinate their roles and encourage participation. Perceived learning outcomes and performance were also significantly improved. This improvement of the perception of learning indicates that the dashboard positively changed the students' overall perception of learning.

Those improvements seemed to appear because the dashboard system was integrated into the learning context closely. In order for a system to be effective, intended learning activities are needed, which use the information presented by the system (Jonassen & Rohrer-Murphy, 1999). Our dashboard presented adaptive instructional feedback based on the key indicators and baselines determined by the learning content and activities of the collaborative argumentation. Learning analytics is not for one size fits all (Gašević et al., 2016). So, the dashboards based on learning analytics should be developed considering not only fundamental design principles but also the characteristics of the target learning context.

One of the most important requirements for this study was how to collect in-class activity data during a class. We thus explored many technologies for the data collection and reviewed previous studies that used digital technology in face-to-face classes. We have found that the advancement of mobile technology has led to several prior studies using digital tools in face - to - face classrooms. They used various digital tools such as handheld device (Nussbaum et al., 2009; Zurita & Nussbaum, 2004), tabletop (Maldonado et al., 2012), digital pen (Huang, Su, Yang, & Liou, 2017), tablet PC (Volk et al., 2017). These tools were used to provide a shared working space and scaffold activities to enhance collaborative learning. However, we concerned that students might feel uncomfortable in using a digital tool during face-to-face interaction. Consequently, we have put a great deal of effort into intimately integrating the activities so that the use of the tool is not a constraint on face-to-face interaction.

Unlike our concerns, students were able to quickly adapt themselves to tool use during the three-week practice period. They used the tool as a new communication channel to share their current learning progress and materials to accomplish their group task without notable complaints. Even some groups used the tool for their final exam that was not related to this study. We were able to observe positive responses of some learners during the lesson. For example, they responded that the comments that were explicitly written in each argument led to more productive and in-depth face-to-face discussions. In addition, they said that because each member's writing was already written digitally in a shared workspace, it was convenient to gather the writings and share the final group solution with the whole class.

Above all, the most important advantage of using the digital tool was that we could collect online activity data without seriously harming face-to-face collaboration. The data allowed the students to monitor essential indicators that they had to be aware of and the instructor to understand the overall learning status of a large classroom. In addition, data utilization has also enabled us to achieve a research advantage that we could closely measure changes in the learning process. Although there is a limitation of data collection in some activity phase where the use of the tool is reduced (e.g., phase 3), we expect that this problem will be addressed by collecting multimodal data to capture the comprehensive learning process through advanced analysis for speech, action, or gesture (Blikstein & Worsley, 2016).

Although the students responded positively in terms of usability, availability, and attitude of the dashboard through the post-survey, a few interviews confirmed that they felt uncomfortable due to the feeling of being watched. We empathized that the dashboard is not for surveillance or evaluation but for providing appropriate help and support. However, it seems that students still feel burdened. It seems to be because a face-to-face class is a learning context having great teacher presence, and the instructor is also exposed to the actual monitoring of the learning situation through his dashboard. We also realized a few weird changes of a learning process where some students seemed to do gaming to trick the dashboard system for taking the green lights. Concerned with this side effect, we did not include comparisons or competitive factors in the dashboard information. For example, we considered including average values of the class in the first and the third chart of the student dashboard, but we finally excluded the relative comparison factors for reducing students' burden. However, in a case of a learning context where it is difficult to set absolute baselines for assessing learning status, the relative baselines have to be used. In this context, the system designer should consider not only overheating competition but also side effects such as boomerang effects.

One of the most commonly used visual factors in learning analytics dashboard is color (Demmans Epp & Bull, 2015). Among various ways of using color for dashboards, traffic-light labels have been widely used in many fields because users do not need pre-training or legends. For example, Course Signals (Arnold & Pistilli, 2012) provide students with feedback along with traffic signals to indicate how they are doing in each course; red signal indicates a high likelihood of being unsuccessful, whereas a green signal indicates a high likelihood of succeeding in the course. Charleer and colleagues (2018) also used traffic-light labels in their learning analytics dashboard, LISSA, to represent successful exams, tolerable grades, and failed courses. In other fields, traffic-light labels also were used to persuade users to change their behaviors such as promoting healthy food choices (e.g., Chen et al., 2017; Thorndike, Riis, Sonnenberg, & Levy, 2014) or encouraging energy-saving behaviors (e.g., Bartram, 2015; Strengers, 2011). In these studies, traffic-light labels can help users quickly identify the overall mood of feedback and persuade them to perform desired behaviors.

Despite the effectiveness of traffic-light labels, some ethical issues can be raised with the negative feedback using red color. For instance, Charleer and colleagues (2018) found that some student advisers are not likely to show a negative visual message in their counseling with students who have a very high number of red signals that represent remaining failed courses. The advisers thought that it was not a good idea to start an already negative situation with the negative feedback that had no possibility of positive interpretation. To avoid the ethical issues, we provided an archive button in each feedback message so that students can hide negative messages colored in red. In the context of this study, we implemented that mechanism because we can not delay the provision of negative feedback continuously during limited face-to-face learning time. However, if the learning context is highly sensitive to the issues due to these negative feedbacks, it will be necessary to reconsider the timing and coverage of feedback. One possible solution could be to use a function for requesting feedback that enables students to ask for feedback when they are ready to accept any feedback, including negative one. This function could reduce the issue of negative feedback as well as increase the willingness of the feedback by increasing the responsibility for the feedback (Winstone et al., 2017).

In this study, we found that our learning analytics dashboard improved both the learning process and outcome significantly by providing adaptive support based on in-class online activity data. We used a one-group pretest-posttest design to investigate if the dashboard could be meaningfully operated in a large class, rather than in a small lab environment. It was a realistic choice made in a situation where another large class could not be taken as a control group. However, due to the repeated measurements design, this study has limitations in interpreting the effects of the dashboard; we cannot rule out the possibility that the results are due to external factors such as familiarity with activities, tools, and group members or characteristics of group tasks. This study was conducted in the latter part of coursework. It is thus presumed that some of the familiarity-related external factors might have limited influence because students had sufficient time for getting used to the class activities and the use of an online collaboration tool. Nevertheless, since not all external factors still remain uncontrolled, rigorously controlled experimental studies should be followed in the future to confirm the effect of the dashboard. In addition, the effect of the dashboard also needs to be confirmed in other learning contexts such as K-12. Differences in learning context can lead to differences in required adaptive support. By investigating the effects of adaptive support and students' responses in a variety of learning contexts, we will be able to generalize our findings and obtain other insights to create a more effective learning analytics dashboard.

4.5. Summary

It is hardly feasible for a few instructors to monitor and support a large number of collaboration groups. In particular, when the role of instructors is required during face-to-face learning in a physical classroom, students are less likely to receive the necessary support from the instructors. We anticipated that this problem could be addressed by utilizing online activity data. By integrating an online collaboration tool into face-to-face learning activities, we could collect during-class online activity data that allowed students to monitor both individual and group activity. In addition, it was possible to provide collaboration groups with adaptive support based on their collaboration status identified by the data utilization. As a result, a positive change was confirmed in both learning processes and outcomes.

These results indicate that it is possible to collect high-quality activity data during class without interfering with learning activities, and the data can be utilized for generating and delivering effective feedback automatically during class in real-time. It also demonstrates that the data can be used to generate group-level feedback as well as individual-level through an aggregation process that converts individual activities into important learning indicators for collaboration group. These findings allow us to see the broader availability of online activity data.

Although the results confirmed the effects of student dashboard, the effectiveness of the instructor dashboard was not rigorously verified. The instructor dashboard has a variety of expected effects. First, the dashboard can be expected to promote more instructional support. By enabling the instructors to be aware of invisible or unnoticeable learning behaviors, it can allow them to understand the overall learning situation of a class effectively and efficiently. Consequently, they can be more supportive due to the more information of learning situation (Van Leeuwen et al., 2015). Second, the dashboard can promote student-centered learning. When the instructors can understand the learning situation of their classes more deeply, they can be confident that they can control the classes as their plans or intention (Cohen, 1994). Consequently, they can decrease direct supervising in their class and increase the opportunities that allow students to interact and work with peers. It is because the responsibility for classroom management is given to the instructors, so ironically, the controllability of the instructors yields the autonomy of the students. Future studies could investigate the effectiveness of instructor dashboard. In particular, the effectiveness would be more beneficial to the instructors who have little teaching experience or who have to manage a large number of collaboration groups alone.

The usability and availability of the *Help button*, which was included in the student dashboard, is likely to need more investigation. The button was used nine times in the first week when the dashboard was available, and only once in the following weeks. In the first week, it seemed that usage might be inflated temporarily due to so-called novelty effects. Most of the nine help requests were just simple questions to confirm their interpretation of the feedback displayed on their dashboard. It seems that the usage of the button sharply decreased as the dashboard became familiar and the novelty effects disappeared. Because this study was conducted at the end of the semester when students were well accustomed to collaborative learning, collaboration groups might have no need for the highest level of instructional support accompanied by instructor's visits. Further investigation is needed on how this *hotline* that facilitates interaction between instructor and students influences the learning process throughout the whole course.

We are interested to see how usage pattern of dashboard would change as the course progresses, if students use the dashboard for a longer period of time than they did in this study. One may suppose that some gaming behaviors may wane as they internalize the system’s good intentions and start to make better uses of their dashboards. Or alternatively, they may get used to its features and make less use of it. In any case, the question remains how the dashboard should be adapted to the changing student behavior throughout the course. Future research can address this agenda in terms of designing the strategies to visualize and present the information provided by the learning analytics dashboard.

Chapter 5. Real-time detection of at-risk groups in face-to-face CSCL

Collaborative learning plays an important role in developing deep understanding and solving authentic problems (Chi & Wylie, 2014). Educators have emphasized collaborative problem-solving skills are important for students to work and to live in this society. Many international organizations, including OECD and UNESCO, have mentioned collaboration as one of the key competencies for in the 21st century (Voogt & Roblin, 2012). In addition, PISA assessment included a ColPS (Collaborative Problem Solving) volume in PISA 2015 (OECD, 2017). However, there are many factors that hinder the effectiveness of collaborative learning (e.g., low participation and inactive interaction) (Kwon et al., 2014). For successful collaborative learning, it is crucial to detect groups that have difficulties in collaborating at the right time and provide them with appropriate instructional support (Nussbaum & Schraw, 2007). This chapter is about the investigation of detecting low-achieving groups in real-time with machine learning techniques by utilizing during-class online activity data collected with high time-granularity in computer-supported collaborative learning.

5.1. Important learning behaviors of group in collaborative argumentation

In collaborative learning, students participate in all phases of problem-solving to complete a common group task (Jonassen & Kim, 2010). However, when only some of the group members are entrusted with the group task or, conversely, when some group members are reluctant to participate in the task, the effectiveness of collaborative learning can be hindered. The active participation of group members is essential for improving learning performance in collaborative learning (Blasco-Arcas et al., 2013). Thus, the pattern of participation of group members in collaborative learning can have an impact on group achievement.

Interaction patterns among group members also have a crucial effect on group achievement. In particular, the patterns of interactions strongly influence the group' s learning outcome in the collaborative argumentation, which is the group-based activity implemented in this study. Collaborative argumentation involves taking positions, making claims, and supporting the claims by providing reasons and evidence (Chinn & Clark, 2013). In collaborative argumentation, each group member establishes individual argumentation at the initial phase of the activity, and all members then integrate their argumentations into one single group argumentation via peer interaction. It is difficult to expect a group to succeed in this activity when some group members do not establish their own initial argumentation, when the group members participate in the activity passively, or when some group members are isolated from the peer interaction. Therefore, it is important for group members not only to establish individual argumentation but also that to share and elaborate on each other's opinions for integration in the process of collaborative argumentation.

In order to produce good argumentations, students need to consider the essential elements: claim, data, warrant, backing, rebuttal, and qualifier (Toulmin, 2003). In addition, good argumentations typically have multiple sides considering counterarguments to productive integration (Nussbaum & Schraw, 2007). When students are aware of the essential elements, they will be able to write a higher quality of argumentation.

5.2. Method

5.2.1. Research context

A total of 88 pre-service teachers (56 females, 32 males) participated in this study for two weeks as part of their undergraduate coursework. They were assigned to 22 groups with three to five members each, considering a diverse mix of gender, major, and prior experience with collaborative learning in each group. They participated in a face-to-face collaborative argumentation task to solve an ill-structured problem of educational practices for 60 minutes once a week. They used the collaboration software, Trello (see Figure 5-1). This software has a board-like user interface, students can create a new card, like a post, on the board. They can communicate by adding comments on others' cards. These user activities that occur on the Trello board are applied and updated in real-time so that they can monitor other group members' activities efficiently.

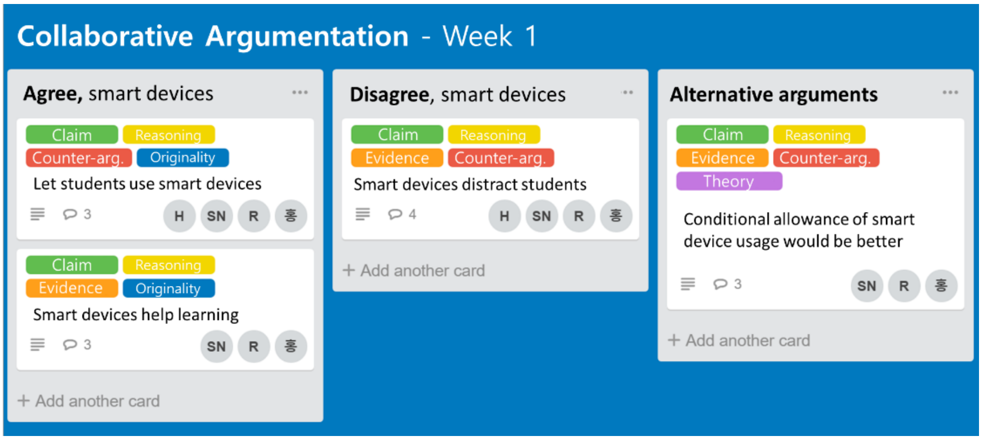

Figure 5-1. A screenshot of the collaboration tool (translated)

In class, the instructor provided a short lecture that introduced the learning topic for collaborative argumentation and guided the group activity. The process of the collaborative argumentation consisted of the four following phases: 1) Individual writing of argumentation (15 minutes), 2) Sharing and revision (15 minutes), 3) Group writing for integration of the individual argumentations (20 minutes), and 4) Reflection on collaborative argumentation (10 minutes). A series of labels – claim, reason, evidence, counter-argument, theory, and originality – was provided so that participants could use it as a checklist to improve the quality of argumentations (see the colored labels on each card in Figure 5-1). In addition, when participants shared their opinions, they added themselves as contributors on the cards with their comments. Collaboration groups submitted their integrated group argumentation during the last phase, and each group's argumentation was graded between 0 and 12 scores by two researchers (Cohen’s kappa 0.81~0.85).

5.2.2. Data collection and feature extraction

The collaboration tool provided high-quality activity data that recorded every learning behaviour in JSON (JavaScript Object Notation) format. The data was collected in one-minute time granularity. A total of 44 groups' in-class learning data was collected over two weeks. From the data, ten group activity features were extracted (see Table 5-1) that fall into three categories: participation, interaction, and quality of argumentation. Some of the features were normalized by the number of group members and scaled in each week's dataset to enhance the performance of the prediction model (marked as superscript † in Table 5-1).

5.2.3. Model prediction and feature importance

A random forest algorithm was used to bulid prediction model. This algorithm is a popular supervised machine learning technique that can be used for both classification and regression problems (James et al., 2013). It is a suitable algorithm for a context with a relatively small size of samples but a large number of predictors (Bureau et al., 2005). As its name implies, it builds many decision trees to make a forest using multiple bootstrap samples from the training data. In the case of classification problems, the predicted class of the random forest algorithm was decided by majority voting from the multiple decision trees' predictions. This decision-making mechanism makes the performance of the algorithm more stable.

Table 5-1. Group activity features of collaborative learning

Category	Feature	Definition
Participation	Total text length†	The total amount of text that group members write
	New card count†	The total number of action count for creating a new card on which to write an argumentation
	Update card count†	The total number of action count for updating argumentation on a card
	Average of action count	The average action count of group members
	Variance of action count	The Variance of action count among group members
Interaction	Comment card count†	The total number of action count for leaving comments on cards
	Contribution count†	The total number of action count for adding new contributors to cards
	Network density	The density of the interaction network of the group[①]
Quality of argumentation	Total label count†	The total number of action count for adding labels on cards
	Counter-argument label count†	The total number of action count for adding the counter-argument labels on cards

[①] The network density is defined as the number of existing connections over the number of all possible connections among group members (Ferguson & Shum, 2012).

In this study, 70% of the in-class group activity data was used as a training set to build our prediction model, and 30% as a test set to assess the model's performance. Low achievement groups were defined as groups that received the bottom 33% score of the group argumentation evaluation. Each week's achievement scores between the low and the other groups were significantly different (first week: $t(25) = 3.726$, $p < 0.01$, second week: $t(25) = 7.868$, $p < 0.01$). With this class label, prediction models were trained with during-class online activity data accumulated in every elapsed time during a class and assessed each model's accuracy.

Another advantage of the random forest algorithm is that it measures the relative importance of each predictor on the prediction and returns a rank list. This list is called *feature importance*. In this study, the feature importance was used to identify influential group learning behaviors that have a major impact on the group achievement in each phase of collaborative argumentation. The influential group learning behaviors were identified by the following steps. First, feature importance lists were obtained from the model of each elapsed time. Second, except for the top three features, the rest are excluded. Third, the remained features were aggregated by each phase. Lately, the frequencies of the remained group activity feature were calculated. A feature with a high frequency of appearance for each phase was considered an important group learning behavior.

5.3. Model performance and influential features

5.3.1. Prediction accuracy for each elapsed time set

Figure 5-2 shows the change in prediction accuracy at each elapsed time. During the first few minutes of group activity, the model was unable to perform the prediction because of a lack of collaboration tool usage. A few minutes later, when the participants started using the collaboration tool, the model showed a high accuracy of more than 75%. Because participants were merely writing individual argumentations in the first phase the usage of the tools was simple so that the data seemed to possess not enough information regarding learning activities. Therefore, the model did not show further improvement in accuracy during the first phase. As the class progressed, learning activities were diversified. The prediction accuracy improved up to 84.6% as participants began to share their argumentations by commenting and adding labels. This improvement occurred more frequently in the third phase where participants began to integrate their argumentations. The interesting point is that these performance gains are noticeable at the later part of each phase (see the orange dotted box in Figure 5-2). This seems to be because the model was able to make better predictions when the participants' activity information accumulated after some amount of time from the start of a new activity (Kim, Park, Yoon, & Jo, 2016). These results imply that the instructor can identify the expected low-achieving groups more accurately by using the prediction models before moving on to the next phase. This improvement can help in targeting groups that will require additional support for a subsequent phase. With this selective instructional support, the group will have the opportunity to overcome the shortcomings of the remain phases. This early detection of low-achievement groups can provide opportunities for at-risk groups to receive early support from the instructors (Van Leeuwen et al., 2015).

5.3.2. Influential features in each learning phase

Table 5-2 shows the influential group activity features in each phase based on feature importance. In the first phase, the most influential feature was the number of new cards that were created on which to write individual argumentation. It seems that the individual argumentation created at this phase played an important role as the foundation of the subsequent activity states (Kwon et al., 2014). It is interesting that the length of the text written by the group members was a common influential feature amongst all phases. Of course, the quantity of writing does not always guarantee its quality. However, considering the characteristics of the collaborative argumentation, the total length of written text seemed to represent how many initial ideas produced by group members remain and permeate into the integrated group argumentation (Nussbaum & Schraw, 2007). The Variance of action count and contribution count also had an impact on group achievement throughout the overall activity phases.

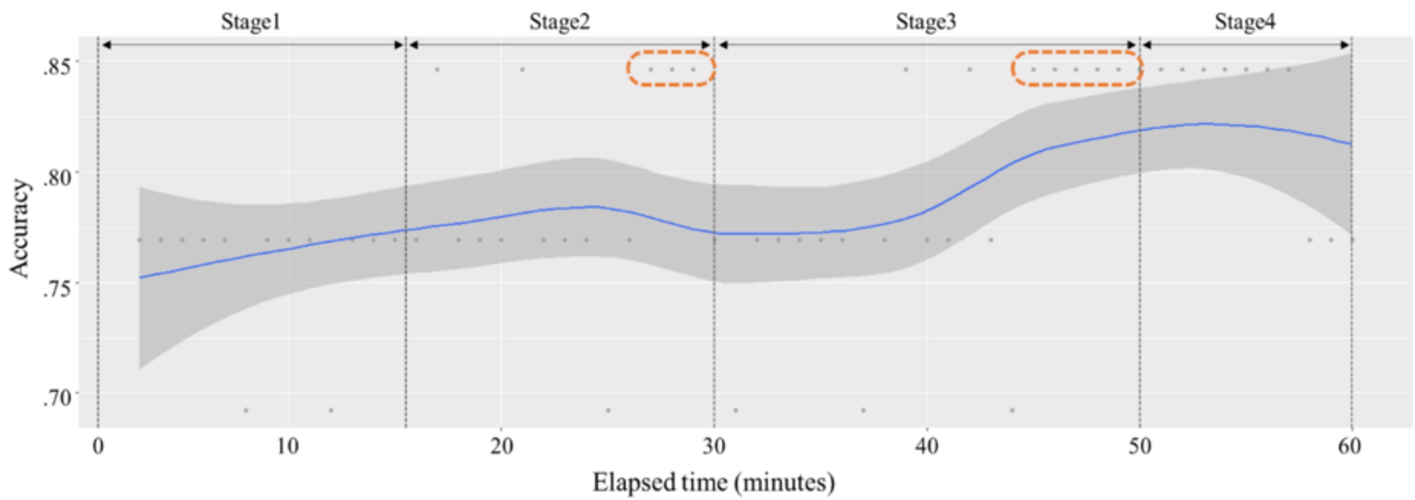

Figure 5-2. Prediction accuracy for each elapsed time from the beginning of face-to-face collaborative learning

In the second phase where group members started to share their ideas, the contribution count had a great effect on group achievement after the total text length. In the last phase, the contribution count had the greatest effect on group achievement. Based on the result, instructors can pay more attention to certain learning behaviors when they support at-risk groups depending on the phase of the class. For example, before moving on to the third phase, the instructor could visit predicted low-achieving groups and check whether the groups are writing a sufficient amount of text in their argumentations, or whether they are interacting actively to contribute each other's argumentation.

Table 5-2. Influential features in each phase

Phase	The first most frequent feature	The second most frequent feature	The third most frequent feature
1	New card count	Variance of action count	Total text length
2	Total text length	Contribution count	New card count
3	Total text length	Contribution count	Variance of action count
4	Contribution count	Total text length	Variance of action count

5.4. Discussion

The results show that we can detect at-risk groups during a class by utilizing the online activity and machine learning algorithm. Our prediction model created based on the data and algorithm achieved up to 84.6% accuracy during a class, and indicated important learning behaviours of group in each phase of class.

Although our model performed with high accuracy, we cannot expect any prediction algorithm to perform flawlessly with 100% accuracy (Box, 1979). All prediction algorithms inevitably have some errors. The prediction model of this study did not show perfect prediction performance either. Among the errors made by the model in predicting at-risk learners, what we should pay more attention to is negative false rather than positive false (Kim, Park, Yoon, & Jo, 2016; Marbouti et al., 2016). The negative false is an error that classifies at-risk students who need help indeed as not at-risk students. If an intervention is given based on this error, the students will be left behind because they cannot get the necessary support.

One possible alternative we can take to address the problem is using soft information that can be obtained from the prediction model. Many machine learning algorithms that perform classification tasks predict classes based on the probability (range 0 to 1) that each sample is classified into particular classes (James, Witten, Hastie, & Tibshirani, 2013, pp. 129 - 170). The algorithms use a specific threshold as a decision boundary (i.e., 0.5) to make a hard decision to classify each sample. If we use the probability, the soft information, before the hard decision, we can at least be able to counter the problem of errors that occurs near the decision boundary. For example, based on the need-to-support list ordered by the at-risk probability, instructors will be able to provide instructional support as much as their resource allows. It can have the similar effect as adjusting the threshold to minimize the errors of negative false. In addition, if the basic statistics of important features that have a significant impact on the at-risk probability are presented, as shown in this study, it may help instructors to adjust the decision boundary by understanding the overall learning status. Future research could continue to explore practical strategies for addressing this problem when the prediction models are used as an early warning system in real classrooms.

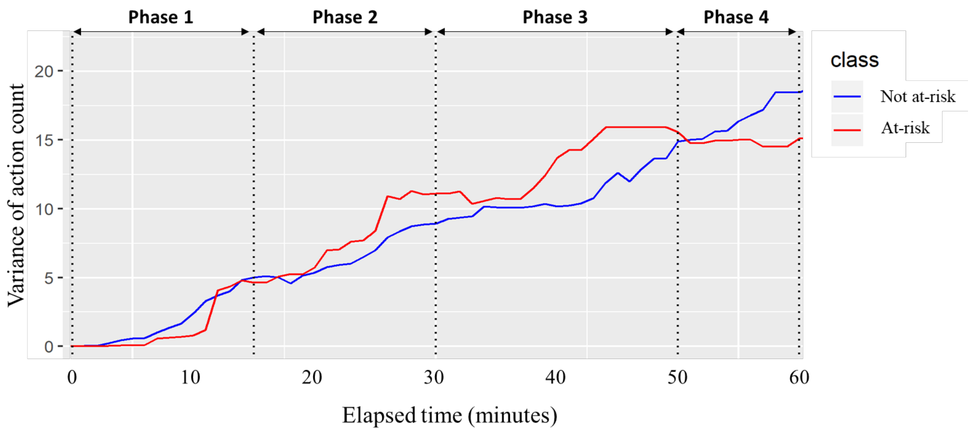

Figure 5-3. The change of the variance of action count during class

In the results of this study, it was possible to identify specific learning behaviors importantly influencing group achievement in each phase; however, it was hard to argue that each learning behavior has a consistent influence on the overall the class. For example, in the case of the variance of action count, it was found that the average of the count between at-risk and the not-at-risk groups showed an inconsistent change as the class progresses (see Figure 5-3). This inconsistent change is explainable when we consider the characteristics of learning activity that a few group members had to finalize and submit their group solution. In other words, unequal participation was natural at the end of the class, and consequently, the variance had to be increased. Although we can explain the change, the results can not provide a global guideline that instructors can use. Therefore, for the role of a practical guide, it is necessary to supplement this inconsistency with basic statistical information that informs the overall learning status of the class as we suggested.

The results of this study indicate that instructors can be helped to identify at-risk groups and can be informed specific learning behaviors requiring more attention during a class by using prediction models based on in-class online activity data. However, there are several limitations to this study. The main limitation is that the results do not tell the practical effects of the prediction model. To investigate the effects on instructor's teaching or student's learning, future research should further develop and confirm these initial findings by conducting empirical studies that apply prediction models to real classroom settings. Another limitation is due to the size of data we used for model training. Because we used relatively small data for training our prediction model (precisely, 70% of the 44 samples were used for the training), the model unavoidably suffers from the generalization issue such as overfitting. In order to more generalize the possibility of using predictive models based on machine learning algorithms, future research should be conducted with a larger number of samples.

5.5. Summary

In typical face-to-face collaborative learning, only a few instructors have a role to monitor and support many groups of students. In this study, a computer support tool was actively utilized in face-to-face collaborative learning, and the use of the during-class online activity data from the tool was investigated in order to detect student groups that are likely to underperform in real-time. The result shows that high accuracy can be achieved in detecting low-achieving groups during a class. In particular, the accuracy improvement shown at the later part of the phase indicates that it is possible to more accurately detect groups that need support at the transition of phases. In addition, the model reveals the influential group learning behaviors in each phase of class. In the first phase, establishing individual argumentation and Variance of action count had major impacts on group achievement. In later phases, the total amount of text and contributing the other group members' argumentation influenced group achievement. These results imply the possibility of constructing an early warning system that identifies groups that are likely to underperform in face-to-face collaborative learning at the right time and provides the instructional support that such groups need. In addition, this approach can allow instructors to focus more closely on some specific groups that need help.

With the development of technology, it is expected that during-class online activity data will become more widely available. These changes will allow instructors to collect more various and detailed information about student's learning, even in physical classrooms. The collected data can be summarized as essential information through a series of processes to help instructors provide students with appropriate instructional support. This study can be a guide for utilizing high-quality in-class activity data to implement face-to-face collaborative learning more efficiently and effectively. We hope that further research will investigate the impact of utilizing in-class activity data for students and instructors in various learning contexts such as K-12.

Chapter 6. Conclusion

As technology advances, educational data has become more abundant, and many attempts have been made to enhance learning by utilizing the data. Learning analytics is one of the methodologies to make use of the educational data. This methodology utilizes data to understand students and their learning processes to optimize their learning and the environment in which it occurs (Pardo, 2014). In this dissertation, the learning analytics method is applied to address issues of face-to-face collaborative learning by utilizing online activity data on students' learning behaviors recorded in an online system. First, student characteristics identified from the data were determined as important group heterogeneity that influenced group achievement significantly. Student groups could be formed in an efficient manner by automatically extracting important student characteristics from the data. In addition, the adaptive support provided by learning analytics dashboards has significantly improved both group's learning process and achievement. Because current learning status was monitored based on the data, appropriate feedback was provided accordingly; this led to the improvement. Last, the predictive model built based on the data was able to detect at-risk groups accurately during class. The model also revealed the important learning behaviors that can influence group achievement. The results of the three studies show that online activity data can be utilized to tackle the issues we face in face-to-face collaborative learning.

These results were able to be accomplished because the data was analyzed and utilized based on pedagogical theories and research evidence. Among the numerous learning behaviors that can be captured from the data, it is not easy to determine which ones are important. In this dissertation, theoretical backgrounds guided to point out important learning behaviors to address the issues by understanding students and their learning. For example, the student's academic characteristics identified from the data, namely opinion and engagement, were selected based on previous works which suggested that the heterogeneity of opinions and prior knowledge had a beneficial effect on group achievement. In the second study, opinion balance, participation, interaction, and use of argumentation elements were selected as relevant indicators representing current learning status under consideration of previous studies. The relevant indicators were used not only for designing adaptive feedback but for examining the effects of the dashboard system. Additionally, group activity features for building the predictive model of at-risk group detection were selected and extracted from the data considering research evidence. Since the features are representing meaningful learning behaviors of a group, the implications of the model could be discussed more clearly.

A greater emphasis should be put on analyzing and utilizing data based on theoretical backgrounds in face-to-face settings because data-driven approaches are hardly applicable, as big data is not a feasible option in such a setting. Compare to online environments, face-to-face settings can only allow a limited number of students and time to partake in learning. In other words, it is difficult to obtain a substantial number of samples and collect their activity data for a very long time. Given this restriction of face-to-face learning environments, one should be able to interpret the data from a theoretical ground despite its small size. Hence if one is to utilize data in a face-to-face learning environment, the interpretability of data with respect to literature and theories should be considered.

This dissertation has the following academic and practical contributions. First of all, it can be a guide for learning analytics research by presenting specific cases of how to take a learning analytics approach according to the educational context and needs. For an effective design of face-to-face collaborative learning, one can use the online activity data that details all possible student learning behaviors when the instructor is not present. When the data is available before the face-to-face class, relevant student characteristics can be captured from the data to construct productive heterogeneous groups. In addition, in terms of supporting face-to-face collaborative learning groups, time-resolution data is recommended to portray a group's dynamic learning status. High-quality data is used to understand the learning process because students' learning behaviors change by very short units (Nguyen, Huptych, &Rienties, 2018). With the data, it was demonstrated that visualization or machine learning techniques can be applied to improve learning processes as well as learning outcomes. The studies in this dissertation have their significance in the application of learning analytics based on educational theories and studies.

Second, this dissertation shows the possibility of solving practical issues in educational practice. Although education practitioners well recognize and understand the importance and necessity of collaborative learning, several issues have hindered the effectiveness and dissemination of collaborative learning. This dissertation presented specific methods and applications to address three issues in face-to-face collaborative learning: an efficient method for group formation, a dashboard system for adaptive support in a large classroom, and a predictive model for at-risk group detection. Each research provides solutions to resolve the problems reported in educational practices. By applying the results, it can be expected that the important issues in face-to-face collaborative learning may be addressed, and in consequence, the successful collaborative learning may be implemented in educational practices.

Third, the learning analytics approaches presented by this dissertation have high applicability in educational practices. It is because the three research results in this dissertation were obtained in a real classroom, rather than a laboratory setting. The research data was collected in a real learning context and was utilized to address the issues under the understandings of the context. This can lead to the promise of both applicability and effectiveness of the learning analytics approaches in the real-world classroom. In addition, it can be expected that the data utilization methodology would become implementable as the learning environments in which student learning-related data is available are expanded. With the development of information and communication technology, students are able to use various mobile technologies for their learning not only at home but also in the classroom (e.g., laptop and digital textbook). This increases the opportunities to capture student’ s learning behaviors with the use of data and utilize them for improving student’ s learning. The increased opportunities may promise the high possibility for applying the learning analytics approaches in the near future.

This dissertation shows that the practical issues of face-to-face collaborative learning can be addressed by utilizing online activity data. However, it has the following limitations. First, the utilization of data merely focuses on students' learning behaviors rather than their learning artifacts. The data collected from the online tools, edX and Trello, had records not only about student’ s online behaviors but about their learning artifacts such as opinion writing or comments. In this dissertation, however, only the learning behaviors were used for analysis. Although the research goals could be achieved by analyzing the behaviors, it would also be beneficial to use artifacts together to obtain a broader understanding of learning. Therefore, future research could continue to use the artifacts by employing various methodologies, such as natural language processing, to analyze them with a view to maximizing the utility of the data.

Second, the effect of three solutions suggested in this dissertation, efficient group formation, adaptive supporting system, and at-risk group detection, needs to be more thoroughly examined. Efficient group formation and adaptive supporting system have not been applied in the real classroom settings, and their effects have not been examined yet. Besides, though the effect of the adaptive supporting system was investigated using a time-series design, the compound effects may occur in the learning process. Therefore, the effects of the three suggested solutions need to be examined by employing nonequivalent groups design as well as time-series design. By measuring the effects over a period of time before and after the intervention in nonequivalent groups, it would be possible to provide the evidence for the effects of the interventions. This dissertation tried to address the issues by suggesting solutions utilizing online activity data; however, these limitations are needed to be more carefully investigated by further research.

This dissertation demonstrates interdisciplinary approaches to address practical issues; data science and machine learning techniques are applied in educational fields. As technology-enhanced learning environments are spreading out in various educational contexts, the technologies have potentials to be the key component for resolving problems in the classroom. The technologies can not only increase the efficiency and effectiveness in the learning process but also provide a new type of solutions which were not possible in the past. However, just applying the technology itself does not guarantee that the problems are solved; it needs to be guided by educational theories and studies. Then, the technology would be meaningfully used to resolve the educational problems and enhance learning. By presenting the cases of interdisciplinary approaches in educational practices where educational data can be utilized, this dissertation is expected to be basic research of the field of learning analytics.

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Appendix

Appendix A. Pseudo codes for traffic-light labels of student dashboard

Feedback section	Pseudo codes

Opinion counts	IF a group has at least one opinion in both agree and disagree position THEN
	    IF the absolute difference between the two positions less than two THEN
	        color label as "**Green**"
	    ELSE
	        color label as "**Yellow**"
	    ENDIF
	ELSE
	    color label as "**Red**"
	ENDIF

Participation and interaction	IF the class is in the phase THEN
	    IF all members create their own individual argumentations THEN
	        color label as "**Green**"
	    ELSE
	        color label as "**Red**"
	    ENDIF
	ELSE
	    IF at least one member has an interaction with another member THEN
	        IF there is no isolated member in the group THEN
	            color label as "**Green**"
	        ELSE
	            color label as "**Yellow**"
	    ELSE
	        color label as "**Red**"
	    ENDIF
	ENDIF

Argumentation elements	IF the group has Claim, Reasoning, Evidence, and Counter-arg. labels THEN
	    IF the group has all the six argumentation elements THEN
	        color label as "**Green**"
	    ELSE
	        color label as "**Yellow**"
	    ENDIF
	ELSE
	    color label as "**Red**"
	ENDIF