

What is Monitored and by Whom in Online Collaborative Learning?: Analysis of Monitoring Tools in Learner Dashboard

Ji Young LIM Jisoo CHOI Yoon Jin KIM Jeongin EUR Kyu Yon LIM*

Ewha Womans University
Korea

The purpose of this study is to draw implications for designing online tools to support monitoring in collaborative learning. For this purpose, eighteen research papers that explored learner dashboards and group awareness tools were analyzed. The driving questions for this analysis related to the information and outcomes that must be monitored, whose performance they represent, and who monitors the extent of learning. The analytical frameworks used for this study included the following: three modes of co-regulation in terms of who regulates whose learning (self-regulation in collaborative learning, other regulation, and socially shared regulation) and four categories of dashboard information to determine which information is monitored (information about preparation, participation, interaction, and achievements). As a result, five design implications for learner dashboards that support monitoring were posited: a) Monitoring tools for collaborative learning should support multiple targets: the individual learner, peers, and the entire group; b) When supporting personal monitoring, information about the individual and peers should be displayed simultaneously to allow direct comparison; c) Information on collaborative learning achievements should be provided in terms of the content of knowledge acquired rather than test scores; d) In addition to information related to interaction between learners, the interaction between learners and learning materials can also be provided; and e) Presentation of the same information to individuals or groups should be variable.

Keywords : Monitoring, Group awareness tool, Learner dashboard, Self-regulation, Co-regulation, Socially shared regulation, Collaborative learning

* Corresponding author: Department of Educational Technology, Ewha Womans University
klim@ewha.ac.kr

Research Background

Collaborative learning involves multiple learners sharing goals and building knowledge through interaction (Dillenbourg, 2002). By interacting with others, an individual's knowledge is distributed to peer learners and the group's shared knowledge is constructed and expanded (Stahl, 2000). However, the process of learning through collaboration is so complex that learners need to regulate not only their own learning and that of others but also the group's cognitive, behavioral, and affective states for the collaboration to be considered successful (Hadwin, Järvelä, & Miller, 2018). Regulatory mechanisms for collaboration were developed from self-regulated learning theories that emphasize the feedback loop evoked by monitoring (Winne, 2001). Accordingly, monitoring multitudinous aspects of collaboration is expected to help learners coordinate their collaboration processes.

When considering the online context of collaborative learning, the dynamic nature of group processes (McGrath, Arrow, & Berdahl, 2000) is significantly more complex because nonverbal or contextual information often cannot be delivered directly to the learners (McKenna & Bargh, 2000). Also, learners may have more difficulty when monitoring learning online compared to face-to-face collaborative learning. Suthers (2000) expressed the contradictory roles of technology for collaborative learning as medium and constraint. However, the online trace data generated by learners reveals multiple aspects of learning to be monitored with the help of analytical and visualization techniques (Sung, Jin, & Yoo, 2016).

One popular technology that supports monitoring for collaboration involves group awareness tools that enhance the perceptions of social and cognitive phenomena that take place during collaboration (Buder, 2011). The learner dashboard, a single display that aggregates multiple indicators about the learner, has also gained attention recently as a collaboration monitoring tool (Jin, 2019). Although it is difficult to find prior studies that claim that group awareness tools and learner dashboards have identical purposes, it is clear that both commonly support monitoring.

In this study, researchers examined learner dashboards, including group awareness tools, from the perspective of monitoring for online collaborative learning. In particular, we combined two different but closely related aspects for analysis, namely, the target to be monitored and the types of information required to support monitoring. These two aspects reflect the complex nature of the online collaborative learning process mentioned earlier, and they help identify the current status of monitoring tools that may serve as the foundation for future design.

Regarding the target of monitoring, we used the approach of “modes of regulations” suggested by Hadwin and colleagues (2018). They defined different modes of regulation in a collaborative learning context as follows: a) self-regulation (SR) refers to an individual’s metacognitive regulation in a joint task, b) co-regulation (CoR) refers to the regulation of other learners’ regulation processes, and c) socially shared regulation (SSR) is a group’s metacognitive and transactive regulation. This is particularly useful to understand whose learning was regulated and by whom, with focus primarily on agents in a group. Although this approach provided a theoretical framework for multi-dimensional aspects of regulation in collaborative learning, it was not clear if presenting information on all regulation modes at the same time would be effective. Given that little previous research has addressed this design issue, it was necessary to identify which modes of information were provided by the existing monitoring tools.

Regarding types of information, prior research about dashboards or group awareness tools has focused on the types of information presented by technology (e.g., Bodily & Verbert, 2017; Janssen & Bodemer, 2013). However, few studies have integrated the agent and information perspectives for monitoring collaborative learning. Considering the characteristics of collaborative learning that need to be monitored simultaneously with diverse aspects, it would be meaningful to identify the provided information with the monitoring target.

In sum, this study aimed to draw implications on what information to provide to promote three modes of monitoring by examining existing collaboration monitoring tools, including learner dashboards and group awareness tools. For this

purpose, three research questions were generated:

1. Which modes of monitoring (SR, CoR, SSR) are supported by monitoring tools?
2. What types of information are provided by the monitoring tools?
3. Which types of information are provided in each mode of monitoring (SR, CoR, SSR) by monitoring tools?

Literature Review

Monitoring mode based on regulation in collaborative learning

The study of regulation in collaborative learning stems from the theory of self-regulation that has provided explanations regarding how learners metacognitively, behaviorally, and motivationally regulate themselves (Zimmerman, 1990). The roles of social contexts surrounding a learner, such as parents or teachers, were considered the main factors influencing the development of self-regulation. For example, McCaslin and Hickey (2001) suggested co-regulation as a concept to describe the emergent regulation that arose when learners interacted with teachers or parents, after which co-regulation was internalized by learners to enable them to develop self-regulation.

As the theory expanded to the context of collaborative learning, substantial research interest pivoted to observe peers in a social context, and the role of the social context became more dynamic. According to Hadwin and colleagues (2018), regulation in collaboration occurs on three different levels: self-, co-, and socially shared regulation. These three concepts differ mainly in terms of who controls whom, and co-regulation is considered the most frequently occurring factor in collaboration compared to other levels of regulation. As McCaslin and Hickey (2001) initially suggested, co-regulation emerges when the learner interacts within a

social context, including teachers or parents. What remains distinguishable from McCaslin and Hickey's suggestion is that Hadwin and colleagues (2018) described co-regulation as something distributed among peers. The mechanism of co-regulation includes the regulation by oneself on oneself, another particular member, and the whole group, or regulation by the group on a specific group member or the whole group. Co-regulation is considered to be temporal (Hadwin et al., 2018; Malmberg, Järvelä, & Järvenoja, 2017). Since co-regulation is a very complex phenomenon that is difficult to capture, some researchers specify the subject and target of regulation and then suggest a term like "other" regulation. Other regulation is a specific form of co-regulation wherein the learner regulates another learner in a team (Lim, Lim, & Lee, 2018b; Rogat & Adams-Wiggins, 2014).

The other two concepts, namely self- and socially shared regulation, can be defined as relatively explicit regulatory mechanisms compared to co-regulation. Self-regulation is defined as a learner's metacognitive regulation directed to an individual's contribution to groups (DiDonato, 2013) as well as an individual's knowledge building (Lim, Lim, & Kim, 2017). Socially shared regulation involves regulation that is contributed and shared across group members; therefore, strategic metacognitive control over the group's learning occurs jointly as well (Hadwin et al., 2018; Malmberg et al., 2017).

As reviewed, expanding self-regulated learning theories to the context of collaborative learning does not simply mean more regulatory agents participating in learning. It shows us that learners confront different levels of regulation at the same time in such a manner that the cognitive load of each individual increases (Kirschner et al., 2018). Furthermore, group-level regulation is more complicated than individual-level regulation because interactions between learners are synergetic (Kim & Cho, 2018). When it comes to the feedback-loop concept of regulation, which is the core concept of self-regulation wherein monitoring prompts adjustments to regulatory strategies (Zimmerman, 1990), the process of regulation in collaborative learning becomes noticeably complicated. Regulatory adjustment

initiated by one learner may reciprocally generate other learners' individual- or group-level regulation. This occurs continuously during collaboration (Malmberg et al., 2017). Based on the aforementioned reasons, technologies like group awareness tools to support each regulatory level have been suggested.

While it is still difficult to find studies that consider different regulatory mechanisms carefully when designing dashboards, Sedrakyan, Malmberg, Verbert, Järvelä, and Kirschner (2018) published conceptual research about the design of dashboards based on self-regulated learning theory. They suggested that the learning process and outcome data need to be collected and provided at both the individual and group level. They presented examples of learning processes and outcomes that were addressed differently at the two levels. Although their conceptual framework and examples suggested dashboard designers what to consider in design in terms of regulatory levels and modes, a more detailed and systemic analysis focused on the visualization of varied regulatory modes in collaborative learning contexts is needed.

Types of information in monitoring technologies

Monitoring is a key mechanism of self-regulation which brings feedback loop in learning (Winne, 2001). Self-monitoring is an individual's mechanism of acquiring knowledge by setting goals along a personal learning path and checking their own progress toward them (Gravill & Compeau, 2008). As learners monitor their learning strategies, they react to feedback and adapt their learning behavior and approach (Zimmerman, 1990). All learners are not expected to monitor their individual learning processes equally well; therefore, technologies to support monitoring have been developed (e.g., Arnold & Pistilli, 2012; Bodemer, 2011). These technologies are divided into two types depending on the learning context: a) learner dashboards applicable to individual learning, and b) group awareness tools suitable for collaborative learning.

As monitoring tools, learner dashboards and group awareness tools help learners

understand and identify the learning process and their progress while guiding them with additional instructions and suggestions. However, the scope of monitoring information that each tool provides is different. Learner dashboards cover individual information with less emphasis on interactional information, while group awareness tools focus primarily on in-depth interaction. To date, very few studies have systemically reviewed existing group awareness tools to elaborate the social information category of learner dashboards. By examining the types of information that group awareness tools are designed to provide, we can provide suggestions to improve the design of learner dashboards from the perspective of collaborative learning.

Learner dashboards

Several studies reviewed existing learner dashboards and identified the information categories that they generally provide. Although different category names have been used, the definitions and types of information included in the categories are essentially the same. First, Schwendimann and colleagues (2016) reported that there are two purposes of learner dashboards, namely, monitoring the individual and “others.” Additionally, they suggested six indicators but did not provide detailed identification of each type. Learner indicators generally include learner characteristics. Action indicators include learning behaviors. Content indicators include learning materials that are used or produced. Result indicators include learning outcomes. Context indicators include the situations where learning took place. Finally, social-related indicators include ways in which learners interact with others.

Further, Bodily and Verbert (2017) suggested six data sources that are presented to learners by dashboards: resource use, assessment, social interaction, time spent, other sensors, and manually reported data. When comparing the data sources to Schwendimann and colleagues (2016), resource use is related to content indicators, assessment to result indicators, social interaction to social-related indicators, and

time spent to action indicators. Other sensors include logs of recorded data, such as mouse moves and physiological data. Manually reported data is information provided primarily by instructors.

Another category of dashboard information was suggested by Hundhausen, Olivares, and Carter (2017). They described five types of content to be presented on dashboards: data, information, critique, suggestion, and encouragement. Most of the information categories suggested in the previous two studies were included in data and information, and critiques were provided on the basis of both. Suggestions and encouragement included information to improve learning or to motivate learners to continue their studies.

Recently, Lim, Eun, Jung, and Park (2018a) reviewed relevant literature and dashboards. They qualitatively analyzed learner experiences through interview data and reported four categories: preparation, participation, interaction, and performance, as well as eleven subcategories of dashboard information. In each subcategory, the authors described detailed information and examples provided in existing dashboards.

One of the ideas shared in the aforementioned studies is that dashboard information is generally self-oriented with some specific sections that are social-oriented. Apart from the social-related indicators (Schwendimann et al., 2016), social interaction data sources (Bodily & Verbert, 2017), and social behavior data and information (Hundhausen et al., 2017), the scope of learning information in all other categories is limited to the individual. In other words, learning activities such as time spent, resource use, and outcome data can be collected from each individual even when social interaction does not occur. Conversely, social-oriented information can only be collected when learners interact with each other. In collaborative learning, however, learner interaction is difficult to reduce to one category. Multi-level regulations that take place during collaboration (Hadwin et al., 2018) make collaboration a multi-dimensional phenomenon. Therefore, the wider range of learner interaction information also needs to be collected and provided in the dashboard. Nevertheless, related literature and existing dashboard information

categories regarding social information cover only partial angles of interaction. Although the contents for social behavior from Hundhausen and colleagues (2017) cover participation level, content, and quality, other interaction levels are not considered in information collection and provision.

Group awareness tool

While both dashboards and group awareness tools provide monitoring, researchers who study collaboration have more frequently used the term group awareness (e.g., Janssen, Erkens, & Kirschner, 2011; Kreijns, Kirschner, & Jochems, 2002). Group awareness serves as an umbrella term representing the perception and understanding of both social and cognitive, and both observable (e.g., activities) and unobservable (e.g., knowledge or attitudes) phenomena that occur in the context of collaborative learning (Buder, 2011). While monitoring in the dashboard is expected to develop a feedback loop for learning, group awareness is expected to guide learning and enhance collaborative processes by facilitating perceptions and a deeper understanding of various aspects of collaboration (Bodemer & Dehler, 2011; Buder, 2011; Miller & Hadwin, 2015). This raises the question of why group awareness is more widely used to indicate monitoring in collaborative learning. One possible answer is that group awareness covers more than just monitoring. Buder (2011) explained group awareness as two phases, display and monitoring. In the display phase, the generation of information, such as assessment or narrative feedback, takes place. In the next phase, information is displayed for the purpose of monitoring. Information visualization is commonly conducted in this phase. However, considering that the existing group awareness tools focus more on providing support for monitoring than displaying (e.g., Kwon, Hong, & Laffey, 2013; Lin, Lai, Lai, & Chang, 2016), it is also likely that the complexity of group awareness is higher than monitoring in individual learning contexts because of the multiple levels of interaction.

Existing studies revealed that information about individuals and groups have

different effects on collaboration. For example, Kimmerle and Cress (2008) examined the effects of information about a team's participation in learning in three different conditions. In the first, the number of each participant's activities were separately provided to the group. In the second, the averaged activities of the group were provided to the group. The third condition was the control group where information was not provided. Findings showed that information about individuals significantly increased cooperative activities compared to the other two groups. They further examined the individual's self-presentation tendency—a motivation to give a certain impression to others—and then reported that group awareness tools could be used for the purposes of self-presenting, especially when information related to how a specific learner was progressing was provided to the group. Kimmerle and Cress's study suggested that group awareness tools that present two types of information about individuals and groups may be perceived differently to learners. In the study of Engelmann, Baumeister, Dingel, and Hesse (2010), it was found that group awareness was most effective when information about an individual was provided together with information about a group. Although more empirical studies are needed, previous studies have revealed that monitoring collaboration needs to be accomplished at different levels.

The classic understanding of group awareness encompasses individuals and collective interaction (Buder & Bodemer, 2008); therefore, it includes other- and group-level monitoring rather than self-monitoring. However, self-monitoring during collaboration can also be supported by group awareness tools. As Buder (2011) pointed out, comparability between the learner's own information to that of others is one of the key mechanisms that explain how group awareness tools function. Although comparisons do not always have positive effects on learning, being aware of the state of learning of peers may help learners understand their own progress. Furthermore, the co-regulation perspective expands the range of group awareness to self-monitoring. From the co-regulation perspective, Miller and Hadwin (2015) described three targets of monitoring in collaborative learning as myself, others (peers), and my team. Considering that socially shared entities are

established on the foundation of metacognition of self (Winne, Hadwin, & Perry, 2013), all three levels of monitoring are ultimately required for well-monitored collaboration.

We must then identify the kinds of information provided by group awareness tools. Carroll, Neale, Isenhour, Rosson, and McCrickard (2003) proposed three types of awareness: social, action, and activity. They described social awareness as recognizing the presence of collaborators and knowing who is nearby. Action awareness relates to timing, type, or frequency of collaborator's interactions, that is, knowing what is happening. Activity awareness is concerned with creations, changes, and modifications of tasks; in other words, recognition of how things are going. Although the early work of Carroll and colleagues (2003) described awareness systematically, they focused primarily on providing a conceptual framework to evaluate activity awareness in schools. A more widely accepted conceptual understanding is that there are two types of group awareness tools, cognitive and social (Bodemer, Janssen & Schnaubert, 2018). In cognitive group awareness tools, learning topics and metacognitive information can be provided. Then, in a social group awareness tool, sociobehavioral, emotional, and motivational information is available. Social interaction information in a learner dashboard as reviewed above is limited to sociobehavioral information of group awareness tools. However, further elaborated information categories for group awareness tools have yet to be proposed. It is also difficult to find the information category of group awareness tools that considers different levels of interaction.

Methods

Paper selection

A systematic literature review was performed to answer the research questions. First, journal articles about learner dashboards and group awareness tools within

the context of collaborative learning published from 2009 to 2019 were searched in the following academic databases: EBSCOhost, Web of Science, ScienceDirect, and RISS. The keywords used for searching were “collaborat* learn* dashboard,” “online discussion dashboard,” and “group awareness.” Initially, 254 articles were collected, and the authors reviewed every article to determine whether they met the following inclusion criteria: (a) articles describing a dashboard or group awareness tool; (b) articles describing detailed functions of a dashboard or group awareness tool; (c) dashboard and group awareness tools that were designed to support learners; and (d) the research contexts were related to the educational field. Even for some articles that met all of the inclusion criteria, 22 studies that were published in multiple journals were removed. Also, other conceptual or review papers were excluded for the following reasons: those that did not describe sufficient details of the dashboard or group awareness tool (26), reviews of group awareness tools designed specifically for teachers (2), studies not related to education, for example those related to business (32), medical (57), software engineering (90), ergonomics (1), environment (5), and articles that did not include detailed design components or functions (1). As a result of these exclusions, a total of 17 studies were selected for analysis. In addition, the snowball method was employed in order to ensure that we did not miss any important studies based on the original criteria. From this, a total of 18 articles were selected for analysis (see Appendix for the final list of selected articles).

Coding framework

Regarding research question 1, the information provided in each tool was analyzed according to the modes of monitoring following self-regulation in collaborative context scale developed by Lim and colleagues (2017): self-regulation in collaborative context, other regulation, and socially shared regulation monitoring (see Table 1).

Table 1. The framework used to code the monitoring modes

Self-regulation scale in collaborative context	Monitoring mode in group awareness tool	Definition
Self-regulation in a collaborative context	Self-monitoring	Observing the cognitive, behavioral, and motivational status of oneself
Other regulation	Other monitoring	Observing cognitive, behavioral, and motivational status of a designated team member
Socially shared regulation	Socially shared monitoring	Observing the cognitive, behavioral, and motivational status of the group

For example, if the group awareness tool provided information about the individual learner and each learner could monitor the learning status of oneself to facilitate collaborative learning, the tool was coded as self-monitoring. If the tool provided information about individual learners and they could monitor the learning status of a specific team member, the tool was coded as “other” monitoring. Finally, if the tool provided information about the group as a whole, the tool was coded as socially shared monitoring. Multiple coding was allowed when the tools provided more than two modes of monitoring.

To answer research questions 2 and 3, the categories of learning information reported in Lim and colleagues (2018a) were used. They analyzed relevant literature, existing dashboards, and learners’ dashboard experiences, after which they extracted four categories of information that were required in order to meet the various needs of online learners: learning preparation, learning participation, interaction, and learning outcomes (see Table 2). Although dashboards and group awareness tools tend to provide different types of information based on the differences of their learning contexts, the fundamental role remains the same; that is, to facilitate both individual and group learning in a collaborative learning context. Also, a cross-analysis was conducted to examine the types of information provided in each mode for research question 3.

Table 2. The analytical framework of monitoring information (Lim et al., 2018a)

Category	Definition	Subcategory	Definition
Preparation	□ Information provided to establish goals and plans before learning.	Diagnosis of learning	□ Information about determining future learning direction and level based on prior learning experiences, such as learner's course history, existing achievement level, etc.
		Learning plan	□ Information about planning learning schedules, such as primary learning activity and task submission schedule.
Participation	□ Information provided to examine and diagnose learner's investments of time and efforts.	Learning time	□ Information about monitoring time spent on learning, such as total learning hours, learning time of the day, etc.
		Frequency of activities	□ Information about monitoring the degree of participation in learning activities, such as log data, the number of postings, and comments.
		Feedback on learning participation	□ Information about encouraging participation in learning, such as answers to learner questions, and recommendations of learning strategies.
Interaction	□ Information provided to identify relationships and learner's position.	Interaction with instructor	□ Information about contacting instructors or teaching assistants, such as the number of contacts with instructors, and interaction patterns between learners and instructors.
		Interaction with peers	□ Information about contact with peers, such as interaction frequency among learners, and interaction patterns between learners.
		Interaction with learning materials	□ Information about the use of learning materials, such as the number of downloads, a recommendation of high-quality materials, etc.
Performance	□ Information provided to identify learning outcomes.	Level of learning achievement	□ Information about cognitive achievement as a result of learning activities, such as test score, and total scoring percentage.
		Level of plan attainment	□ Information about the degree of goal attainment and progress of learning, such as the recommended learning schedule and achievement rates of learning objectives.
		Emotional state	□ Information about emotions experienced in the learning process, such as recorded emotional state changes of learners.

All of the authors in this study participated in coding. Before analyzing the articles, authors predetermined the meaning of regulation modes, categories, and subcategories of information. More than two authors reviewed and analyzed each article, after which they discussed it to resolve potential disagreements until consensus was reached. A cross-check was then conducted with the other authors who did not participate in the initial analysis.

Analysis

The primary analytical method used for this study was frequency analysis. To examine research questions 1 and 2, multiple frequency analyses were conducted. The total number of codes counted for each category was divided by the total number of articles reviewed. Therefore, the sum of the percentage of categories exceeded 100%. To examine research question 3, cross-analyses were conducted; that is, the numbers of information types provided for each monitoring mode were counted. Given that quantitative analysis may have limited the interpretation of the results, we focused more on describing the information from each monitoring tool and identified them according to the monitoring mode.

Results

Monitoring modes

The monitoring modes supported in each tool were analyzed. Since multiple coding was allowed, the total number of modes counted was 36, and the total percentage was 200.0%. Ten of the eighteen supported self-monitoring (55.6%), fourteen supported other monitoring (77.8%), and twelve supported socially shared monitoring (66.7%). More precisely, six group awareness tools supported all

monitoring modes (A, D, G, K, L, and O). Four supported only self- and other monitoring modes (C, M, N, and R), while two supported other and socially shared monitoring (F and G). The remaining six supported only socially shared monitoring (B, E, H, and I) or other monitoring (P and Q).

Although it was difficult to identify which monitoring mode was predominantly supported by monitoring tools for collaboration, we found that more than half of the tools supported multiple monitoring modes. For example, Janssen and colleagues (2011; G) presented a group awareness tool called a participation tool (PT). They represented each member's participation as a network surrounding a task, thereby visualizing the number of sent messages as the size of each node and the amount of keystrokes as the distance of each node from the task. As the name of each member was written beside each node, learners could detect not only their own participation level (self-regulation) but also how a specific learner was participating intensively (other regulation). Further, all members in a group were represented in one network, and the group's overall participation level could also be visually identified (socially shared regulation).

Also, information for self-monitoring was always provided with the information for other monitoring (A, C, D, G, K, L, M, N, O, and R). For example, Bodemer (2011; A) and Erkens and Bodemer (2019; C) presented the amount of knowledge of each member. Also, Lin (2018) and Pifarre, Cobost, and Argelagos (2015; N) presented the level of participation of each member in a group separately. More specifically, Lin (2018) presented statistics of collaborative activities in each column and participants in each row so that the individual's participation level could be readily identified. Interestingly, the learning processes reported in the aforementioned studies included comparing oneself with other learners and to either adapt their learning accordingly or help others. Therefore, it may be inferred that providing information about the individual leads to comparisons with other learners.

Information provided for monitoring

The results of the frequency analysis of the information provided for monitoring are presented in Table 3. With multiple coding, 26 information categories were counted, yielding a percentage of 144.4%. Regarding subcategories, there were 29 frequency counts.

In terms of the amount of information provided, no noticeable difference was found among the four categories. The numbers of tools in each category were as follows: performance (8; 44.4%; A, D, H, I, K, P, Q, and R); interaction (7; 38.9%; B, D, F, J, K, M, and N); Learning preparation (6; 33.3%; C, E, F, J, K, and O); and learning participation (5; 27.8%; F, G, K, L, and N).

Performance information was mainly provided as a knowledge level, as seen in the number of the subcategory. Seven monitoring tools (38.9%; A, D, I, K, P, Q, and R) provided the level of learning achievement. Although the initial coding framework suggested examples of learning performance information as scores, only two monitoring tools used scores resulting from the test (K and P). Instead of test scores, for example, Schreiber and Engelmann (2010; Q) presented a digital concept map illustrating the knowledge structure of an individual learner, peer learners, and the whole group.

Bodemer (2011; A) showed the learners' answers. Erkens, Bodemer, and Hoppe (2016; D) regarded knowledge levels as the extent of the topic and represented them in a bar chart (number of words). Zufferey, Bodemer, Buder, and Hesse (2010; R) used the score as a knowledge level index that, however, was a self-assessment of the knowledge.

Next, an interesting result was found in the interaction category. Although it is not surprising that four (F, J, K, and M) out of seven monitoring tools provided information about the interaction between learners, four (B, D, F, and N) out of seven presented information on the interaction between learners and learning materials. For example, Buder, Schwind, Rudat, and Bodemer (2015; B) indicated whether the learners had read the posts using different colors. Erkens, Bodemer,

and Hoppe, (2016; D) provided the frequently addressed topic list of a whole group so that learners could compare the group’s learning materials and topic list to that of the learner’s own. Iandoli, Quinto, De Liddo, and Shum (2014; F) alerted learners to the characteristics of a conversation and its stage by differentiating the type of links. Pifarré, Cobos, and Argelagós (2014; N) presented the documents with the number of times each document had been annotated.

Table 3. The numbers and percentages of information provided in group awareness tools

Category	n	Percentage	Subcategory	n	Percentage
Preparation	6	33.3%	Diagnosis of learning	3	16.7%
			Learning plan	3	16.7%
			Learning time	1	5.6%
Participation	5	27.8%	Frequency of activities	5	27.8%
			Feedback on learning participation	0	0.0%
			Interaction with instructors	0	0.0%
Interaction	7	38.9%	Interaction with peers	4	22.2%
			Interaction with learning materials	4	22.2%
			Level of learning achievement	7	38.9%
Performance	8	44.4%	Level of plan attainment	1	5.6%
			Emotional state	1	5.6%
			Total	26	144.4%

Monitoring information for each regulation mode

After separately analyzing monitoring modes and information types, a cross-analysis was conducted. The analysis showed no noticeable difference in the amount of information provided by each monitoring mode. That is, the difference was too minimal to interpret as a meaningful finding. Nevertheless, there was consistency in the pattern of the amount of information provided for the three monitoring modes. For example, there was comparatively less information

provided for self-monitoring compared to other-monitoring or socially shared monitoring. Information about the learner's own learning preparation was provided by only three (C, K, and O), while five provided information about the learning preparation of specific learners in a group (C, F, J, K, and O) or the group as a whole (E, F, J, K, and O). Similar patterns were found for the other three information categories. Results are shown in Table 4.

Table 4. The number of tools providing information for each mode

	Preparation	Participation	Interaction	Performance
Self-monitoring	3	4	4	4
Other monitoring	5	5	6	6
Socially shared monitoring	5	4	5	5

Table 5. The number of tools providing information in terms of subcategories

	Preparation			Participation			Interaction			Performance		
	a	b	c	d	e	f	g	h	i	j	k	
Self-monitoring	2	1	1	4	0	0	2	2	4	0	0	
Other monitoring	3	2	1	5	0	0	4	3	6	0	0	
Socially-shared monitoring	2	3	1	4	0	0	3	3	4	1	1	

Note. a: Diagnosis of learning, b: Learning plan, c: Learning time, d: Frequency of activities, e: Feedback on the learning participation, f: Interaction with instructors, g: Interaction with peers, h: Interaction with learning materials, i: Level of learning achievement, j: Level of plan attainment, k: Emotional state

Regarding subcategories of information, only particular types of information had been provided for self-monitoring, other monitoring, and socially shared monitoring. For example, neither feedback on learning participation nor interaction with instructors were provided in any of the three monitoring modes. The results are described in Table 5.

Finally, we looked more closely at the information provided in each tool to find

commonalities and differences among the monitoring modes. We found that the way in which information was provided was different depending on the level, namely, individual (self-monitoring and other monitoring) or group (socially shared monitoring). For example, when Lin and colleagues (2016; K) provided information about interaction with peers, they adopted two methods to present the information. First, the number and percentages of help-seeking behaviors of each learner were presented in a table with the learners' names placed one per row. The number of number and corresponding percentages were placed in columns. As the display of names in the table led learners to monitor each peer separately, we categorized these as information for self-monitoring as well as other monitoring. On the other hand, Lin and colleagues visualized information about help-seeking behavior as a network structure throughout the group. The network was not formed merely to express the frequency that certain learners sought help, rather it provided information about the overall patterns of interaction history within the group.

It was clear that not every tool supporting socially shared monitoring provided visualized information. Except for one case that paired two learners as a group (A), seven monitoring tools (B, D, E, H, I, J, and L) combined or averaged the scores of individual learners into a single value. The other four monitoring tools visualized information about the group in a method that could reveal the relationships between learners. For example, Puhl, Tsovaltzi, and Weinberger (2015; O) presented a four quadrant representing each learner as a node. Iandoli and colleagues (2014; F), Janssen and colleagues (2011; G), and Lin and colleagues (2016; K) visualized networks consisting of learners.

Discussion

This study examined technologies that support collaboration monitoring in order to identify the information that must be provided when designing monitoring tools, as well as to determine to whom the information pertains and to whom it should be

available. We reviewed papers on learner dashboards (portal technology that supports monitoring by providing information related to learning) and group awareness tools (data gathering and reporting technology designed to provide information about collaboration). Two frameworks were used to review the papers: first, a framework that categorized the various regulation mechanisms that occur during collaborative learning; and second, a framework that demonstrated the monitoring information required by learners. In general, the results showed that the number of tools supporting each monitoring mode and the learning information provided were not noticeably different. However, the following findings related to each research question have been made, with each suggesting how monitoring tools for collaborative learning should be designed.

For the first research question, we found that 12 out of 18 tools supported more than two monitoring modes. Since collaborative learning consists of highly complex activities and does not guarantee successful learning (Kuhn, 2015), students must try to continuously regulate multitudinous participants while collaborating. For this reason, it can be inferred from the results that the monitoring tools for collaborative learning must be designed to support not only one but multiple monitoring modes. We also revealed that tools supporting self-monitoring also provide information for monitoring others. One possible explanation for this result can be found in the social comparison theory, introduced by Festinger (1954), in which people have a desire to evaluate their abilities or opinions. Part of this is the attempt to compare themselves to others even when there are no objective criteria for evaluation. Considering that the purpose of monitoring is to make real-time judgments on learning in the moment (Flavell, 1979), designs should allow information for self-monitoring to be provided alongside that of other monitoring to allow learners to compare themselves to others during collaborative activities.

For the second research question, information about learning performance is provided as a representation of acquired knowledge, for example, as a concept map rather than a score. It is worth noting that the outcomes of collaborative learning are rarely if ever measured or summarized simply as test scores. Enyedy and

Stevens (2016) suggested four dimensions characterizing analytical methods to study collaboration. They explained performance on a test after a collaboration session as distal outcome and interaction itself as a proximal outcome. They also posited that collaboration itself could be the desired outcome. Enyedy and Stevens's (2016) interpretations show us that the learning outcomes of collaboration can take various forms and are not limited to a single test score. Therefore, the pedagogical perspective of collaboration needs to be considered when designing monitoring tools that represent the outcomes of collaborative learning.

Second, information related to interaction with learning materials was provided as frequently as information about peer interaction. This is partly because the provision of information about interaction with learning materials may reduce the extra load of collaborative learning situations (Bodemer, 2011). Since information on interaction with learning materials shows not only a learner's but also the peers' interactions with materials, this can improve the learner's awareness of contextual information that contributes to monitoring peers in the end. Besides, the interaction of learners with learning material should be carefully reviewed according to the definition or essence of the material (Dado & Bodemer, 2017). Learning material includes a variety of subject matter that is produced during the process of meaning-making (Bernard et al., 2009). This means that learning material is not only limited to materials given by teachers but also covers a more broad range of tools, objects, and elements known as knowledge artifacts used in the process of learning. Knowledge artifacts, such as a topic of discussion or even a simple annotation on a short piece of informational text, can be defined as learning material. As more learners collaborate, the base of available knowledge artifacts expands. Therefore, it can be suggested that many types of learning material, both core and supplemental, should be considered for inclusion in collaboration monitoring tools.

For the final research question, there were no significant differences in the number of information categories provided for self, other, and socially shared monitoring. However, dissimilarities were found in the ways information was

presented. Depending on the level of the monitoring mode (individual or group), the information was either provided in a form suitable for the identification of a specific peer learner (individual-level) or in a format representing the structure of an entire group (group-level). Simply merging or aggregating an individual's data to compute a group's updated value can minimize or conceal the particular pattern of learning within a group. Therefore, the monitoring mode level must be considered when designing differential presentations of information for monitoring tools.

Further implications based on the limitations of existing monitoring tools include the following: First, the amount of information in each category is unbalanced. For example, there are no tools that support feedback on learning participation. Also, information on the level of plan attainment and emotional states are supported only once in each of the two monitoring tools and only for socially shared monitoring. Therefore, more monitoring tools need to incorporate this information into their designs for updated versions. Second, the needs of target users who will receive monitoring support must be given greater consideration. Among the papers we reviewed, it was difficult to find studies that gave specific explanations for why they chose to provide certain information for an individual learner, other learners, or the entire group. As monitoring for collaborative learning generally involves comparative information, further investigation is required to identify how learners perceive certain types of information and how that information can affect the self-, other, and socially shared regulation of learners. Although comparative information can help learners evaluate their progress and current state in order to determine areas where they can improve their academic performance, this information can easily be misinterpreted (Jivet, Scheffel, Drachslar, & Specht, 2017) or considered negatively by learners (Smith, 2000; Tan, Koh, Jonathan, & Yang, 2017).

Despite the findings and implications drawn from this study, the uniqueness of each monitoring tool should be further defined. As this study used a quantitative approach, this may have limited the interpretation of each case's traits and values (Ezzy, 2013). In order to understand the unique positive and negative aspects of each monitoring tool, we suggest qualitative analysis for further studies.

Despite these limitations, the significance of this study lies in the design implications based on its theoretical background. We expect that the suggestions offered throughout this study can provide instructional designers with alternative methods to explore online collaboration based on emerging frameworks that explain and elaborate regulatory mechanisms during collaboration. As the complexity of interaction during online collaboration is greater than face-to-face collaboration (McGrath et al., 2000; Suthers, 2000), decisions regarding the types of information provided for monitoring should be made based on an appropriate framework that best describes the dynamic nature of collaboration.

Acknowledgement This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2017R1A2B4002606).

References

- Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd international conference on learning analytics and knowledge*(Vancouver, Canada).
- Bernard, R. M., Abrami, P. C., Borokhovski, E., Wade, C. A., Tamim, R. M., Surkes, M. A., & Bethel, E. C. (2009). A meta-analysis of three types of interaction treatments in distance education. *Review of Educational Research*, 79(3), 1243–1289.
- Bodemer, D. (2011). Tacit guidance for collaborative multimedia learning. *Computers in Human Behavior*, 27(3), 1079-1086.
- Bodemer, D., & Dehler, J. (2011). Group awareness in CSCL environments. *Computers in Human Behavior*, 27(3), 1043-1045.
- Bodemer, D., Janssen, J., & Schnaubert, L. (2018). Group awareness tools for computer-supported collaborative learning. In F. Fischer, C. E. Hmelo-Silver, S. R. Goldman, & P. Reimann (Eds.), *International handbook of the Learning Sciences*(pp. 351-358). New York: Routledge.
- Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies*, 10(4), 405-418.
- Buder, J. (2011). Group awareness tools for learning: Current and future directions. *Computers in Human Behavior*, 27(3), 1114-1117.
- Buder, J., & Bodemer, D. (2008). Supporting controversial CSCL discussions with augmented group awareness tools. *International Journal of Computer-Supported Collaborative Learning*, 3(2), 123-139.
- Buder, J., Schwind, C., Rudat, A., & Bodemer, D. (2015). Selective reading of large online forum discussions: The impact of rating visualizations on navigation and learning. *Computers in Human Behavior*, 44, 191-201.
- Carroll, J. M., Neale, D. C., Isenhour, P. L., Rosson, M. B., & McCrickard, D. S.

- (2003). Notification and awareness: synchronizing task-oriented collaborative activity. *International Journal of Human-Computer Studies*, 58(5), 605-632.
- Dado, M., & Bodemer, D. (2017). A review of methodological applications of social network analysis in computer-supported collaborative learning. *Educational Research Review*, 22, 159–180.
- DiDonato, N. C. (2013). Effective self-and co-regulation in collaborative learning groups: An analysis of how students regulate problem-solving of authentic interdisciplinary tasks. *Instructional Science*, 41(1), 25-47.
- Dillenbourg, P. (2002). Over-scripting CSCL: The risks of blending collaborative learning with instructional design. In P. A. Kirschner (Ed.), *Three worlds of CSCL. Can we support CSCL?* (pp. 61-91). Heerlen: Open Universiteit Nederland.
- Engelmann, T., Baumeister, A., Dingel, A., & Hesse, F. W. (2010). The added value of communication in a CSCL-scenario compared to just having access to the partners' knowledge and information. In *Proceedings of the 4th international conference on concept mapping* (Pamplona, Spain).
- Enyedy, N., & Stevens, R. (2016). Analyzing collaboration. In R. K. Sawyer (Ed.). *The Cambridge handbook of the Learning Sciences* (2nd ed.), (pp. 191-212). New York, NY: Cambridge University Press.
- Erkens, M., & Bodemer, D. (2019). Improving collaborative learning: Guiding knowledge exchange through the provision of information about learning partners and learning contents. *Computers & Education*, 128, 452-472.
- Erkens, M., Bodemer, D., & Hoppe, H. U. (2016). Improving collaborative learning in the classroom: Text mining based grouping and representing. *International Journal of Computer-Supported Collaborative Learning*, 11(4), 387-415.
- Ezzy, D. (2013). *Qualitative analysis-Practice and innovation*. London: UK. Routledge.
- Festinger, L. (1954). A theory of social comparison processes. *Human Relations*, 7(2), 117-140.
- Flavell, J. H. (1979). Metacognition and cognitive monitoring: A new area of cognitive–developmental inquiry. *American Psychologist*, 34(10), 906.

- Gravill, J., & Compeau, D. (2008). Self-regulated learning strategies and software training. *Information & Management*, 45(5), 288-296.
- Hadwin, A., Järvelä, S., & Miller, M. (2018). Self-regulation, co-regulation, and shared regulation in collaborative learning environments. In D. H. Schunk., & J. A. Greene. (Eds.), *Handbook of Self-regulation of learning and performance (2nd ed.)*, (pp. 83-106). New York, NY: Routledge.
- Hundhausen, C. D., Olivares, D. M., & Carter, A. S. (2017). IDE-based learning analytics for computing education: a process model, critical review, and research agenda. *ACM Transactions on Computing Education (TOCE)*, 17(3), 11.
- Iandoli, L., Quinto, I., De Liddo, A., & Shum, S. B. (2014). Socially augmented argumentation tools: Rationale, design, and evaluation of a debate dashboard. *International Journal of Human-Computer Studies*, 72(3), 298-319.
- Janssen, J., Erkens, G., & Kirschner, P. A. (2011). Group awareness tools: It's what you do with it that matters. *Computers in Human Behavior*, 27(3), 1046-1058.
- Janssen, J., & Bodemer, D. (2013). Coordinated computer-supported collaborative learning: Awareness and awareness tools. *Educational Psychologist*, 48(1), 40-55.
- Jin, S. H. (2019). The effects of dashboard types and learner characteristics on educational effectiveness in an asynchronous online discussion. *Korean Journal of Educational Technology*, 35(2), 339-364.
- Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: pitfalls of learning analytics dashboards in the educational practice. In Proceedings of the 12th European Conference on Technology Enhanced Learning: Data driven approaches in digital education. (Tallinn, Estonia).
- Kimmerle, J., & Cress, U. (2008). Group awareness and self-presentation in computer-supported information exchange. *International Journal of Computer-Supported Collaborative Learning*, 3(1), 85-97.
- Kim, S-y., & Cho, K-l. (2018). The effects of social network centrality in collaborative interaction groups on group synergy and academic achievement. *Korean Journal of Educational Technology*, 34(3), 383-406.

- Kirschner, P. A., Sweller, J., Kirschner, F., & Zambrano, J. (2018). From cognitive load theory to collaborative cognitive load theory. *International Journal of Computer-Supported Collaborative Learning*, 13(2), 213-233.
- Kreijns, K., Kirschner, P. A., & Jochems, W. (2002). The sociability of computer-supported collaborative learning environments. *Educational Technology & Society*, 5(1), 8-22.
- Kuhn, D. (2015). Thinking together and alone. *Educational Researcher*, 44(1), 46-53.
- Kwon, K., Hong, R. Y., & Laffey, J. M. (2013). The educational impact of metacognitive group coordination in computer-supported collaborative learning. *Computers in Human Behavior*, 29(4), 1271-1281.
- Lim, K., Eun, J., Jung, Y., & Park, H. (2018a). An exploratory study on the information design of the online dashboard for learner-centered learning. *Journal of the Korean Association of Computer Education*, 21(3), 35-50.
- Lim, K. Y., Lim, J. Y., & Lee, J. H. (2018b). The development of an other-regulation scale for college students. *The Journal of Educational Studies*, 49(2), 1-26.
- Lim, K. Y., Lim, J. Y., & Kim, H. J. (2017). An exploratory study of self-regulation in a collaborative context scale for college students. *Korean Journal of Educational Technology*, 33(3), 567-598.
- Lin, J. W., Lai, Y. C., Lai, Y. C., & Chang, L. C. (2016). Fostering self-regulated learning in a blended environment using group awareness and peer assistance as external scaffolds. *Journal of Computer-Assisted Learning*, 32(1), 77-93.
- Malmberg, J., Järvelä, S., & Järvenoja, H. (2017). Capturing temporal and sequential patterns of self-, co-, and socially shared regulation in the context of collaborative learning. *Contemporary Educational Psychology*, 49, 160-174.
- McCaslin, M., & Hickey, D. T. (2001). Educational psychology, social constructivism, and educational practice: A case of emergent identity. *Educational Psychologist*, 36(2), 133-140.
- McGrath, J. E., Arrow, H., & Berdahl, J. L. (2000). The study of small groups, past,

- present, and future. *Personality and Social Psychology Review*, 4, 95-105.
- McKenna, K. Y. A., & Bargh, J. A. (2000). Plan 9 from cyberspace: The implications of the Internet for personality and social psychology. *Personality and Social Psychology Review*, 4, 57-75.
- Miller, M., & Hadwin, A. (2015). Scripting and awareness tools for regulating collaborative learning: Changing the landscape of support in CSCL. *Computers in Human Behavior*, 52, 573-588.
- Pifarré, M., Cobos, R., & Argelagós, E. (2014). Incidence of group awareness information on students' collaborative learning processes. *Journal of Computer Assisted Learning*, 30(4), 300-317.
- Puhl, T., Tsovaltzi, D., & Weinberger, A. (2015). Blending Facebook discussions into seminars for practicing argumentation. *Computers in Human Behavior*, 53, 605-616.
- Rogat, T. K., & Adams-Wiggins, K. R. (2014). Other-regulation in collaborative groups: Implications for regulation quality. *Instructional Science*, 42(6), 879-904.
- Schreiber, M., & Engelmann, T. (2010). Knowledge and information awareness for initiating transactive memory system processes of computer-supported collaborating ad hoc groups. *Computers in Human Behavior*, 26(6), 1701-1709.
- Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2016). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies*, 10(1), 30-41.
- Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (in press). Linking learning behavior analytics and learning science concepts: designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior*.
- Smith, R. H. (2000). Assimilative and contrastive emotional reactions to upward and downward social comparisons. In J. Suls & L. Wheeler (Eds.), *Handbook of social comparison: Theory and research* (pp.173-200). New York: Plenum.

- Stahl, G. (2000). A model of collaborative knowledge-building. In *Fourth international conference of the Learning Sciences* (Vol. 10, pp. 70–77). Mahwah, NJ: Erlbaum.
- Sung, E., Jin, S. H., & Yoo, M. (2016). Exploring learning data for supporting self-directed learning in the perspective of learning analytics. *Journal of Educational Technology*, 32(3), 487–533.
- Suthers, D. D. (2006). Technology affordances for intersubjective meaning making: A research agenda for CSCL. *International Journal of Computer-Supported Collaborative Learning*, 1, 315–337.
- Tan, J. P. L., Koh, E., Jonathan, C., & Yang, S. (2017). Learner dashboards a double-edged sword? Students' sense-making of a collaborative critical reading and learning analytics environment for fostering 21st-century literacies. *Journal of Learning Analytics*, 4(1), 117–140.
- Winne, P. H. (2001). Self-regulated learning viewed from models of information processing. In B. J. Zimmerman., & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives*, (2nd ed.), (pp. 153–189). Mahwah, New Jersey: Routledge.
- Winne, P. H., Hadwin, A. F., & Perry, N. E. (2013). Metacognition and computer-supported collaborative learning. In C. E. Hmelo-Silver., C. A. Chinn., C. K. K. Chan., & A. O'Donnell (Eds.), *The international handbook of collaborative learning* (pp. 462-479). New York, NY: Routledge.
- Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist*, 25(1), 3-17.
- Zufferey, J. D., Bodemer, D., Buder, J., & Hesse, F. W. (2010). Partner knowledge awareness in knowledge communication: Learning by adapting to the partner. *The Journal of Experimental Education*, 79(1), 102-125.

Appendix A. The list of articles reviewed

- A. Bodemer, D. (2011). Tacit guidance for collaborative multimedia learning. *Computers in Human Behavior*, 27(3), 1079-1086.
- B. Buder, J., Schwind, C., Rudat, A., & Bodemer, D. (2015). Selective reading of large online forum discussions: The impact of rating visualizations on navigation and learning. *Computers in Human Behavior*, 44, 191-201.
- C. Erkens, M., & Bodemer, D. (2019). Improving collaborative learning: Guiding knowledge exchange through the provision of information about learning partners and learning contents. *Computers & Education*, 128, 452-472.
- D. Erkens, M., Bodemer, D., & Hoppe, H. U. (2016). Improving collaborative learning in the classroom: Text mining based grouping and representing. *International Journal of Computer-Supported Collaborative Learning*, 11(4), 387-415.
- E. Hadwin, A. F., Bakhtiar, A., & Miller, M. (2018). Challenges in online collaboration: effects of scripting shared task perceptions. *International Journal of Computer-Supported Collaborative Learning*, 13(3), 301-329.
- F. Iandoli, L., Quinto, I., De Liddo, A., & Shum, S. B. (2014). Socially augmented argumentation tools: Rationale, design, and evaluation of a debate dashboard. *International Journal of Human-Computer Studies*, 72(3), 298-319.
- G. Janssen, J., Erkens, G., & Kirschner, P. A. (2011). Group awareness tools: It's what you do with it that matters. *Computers in Human Behavior*, 27(3), 1046-1058.
- H. Järvenoja, H., Järvelä, S., & Malmberg, J. (2017). Supporting groups' emotion and motivation regulation during collaborative learning. *Learning and Instruction*, 27, 1046-1058.
- I. Kwon, K., Hong, R. Y., & Laffey, J. M. (2013). The educational impact of metacognitive group coordination in computer-supported collaborative learning. *Computers in Human Behavior*, 29(4), 1271-1281.
- J. Lin, J. W. (2018). Effects of an online team project-based learning environment with group awareness and peer evaluation on socially shared regulation of

- learning and self-regulated learning. *Behaviour & Information Technology*, 37(5), 445-461.
- K. Lin, J. W., Lai, Y. C., Lai, Y. C., & Chang, L. C. (2016). Fostering self-regulated learning in a blended environment using group awareness and peer assistance as external scaffolds. *Journal of Computer Assisted Learning*, 32(1), 77-93.
- L. Liu, M., Liu, L., & Liu, L. (2018). Group awareness increases student engagement in online collaborative writing. *The Internet and Higher Education*, 38, 1-8.
- M. Phielix, C., Prins, F. J., Kirschner, P. A., Erkens, G., & Jaspers, J. (2011). Group awareness of social and cognitive performance in a CSCL environment: Effects of peer feedback and reflection tool. *Computers in Human Behavior*, 27(3), 1087-1102.
- N. Pifarré, M., Cobos, R., & Argelagós, E. (2014). Incidence of group awareness information on students' collaborative learning processes. *Journal of Computer Assisted Learning*, 30(4), 300-317.
- O. Puhl, T., Tsovaltzi, D., & Weinberger, A. (2015). Blending Facebook discussions into seminars for practicing argumentation. *Computers in Human Behavior*, 53, 605-616.
- P. Sangin, M., Molinari, G., Nüssli, M. A., & Dillenbourg, P. (2011). Facilitating peer knowledge modeling: Effects of a knowledge awareness tool on collaborative learning outcomes and processes. *Computers in Human Behavior*, 27(3), 1059-1067.
- Q. Schreiber, M., & Engelmann, T. (2010). Knowledge and information awareness for initiating transactive memory system processes of computer-supported collaborating ad hoc groups. *Computers in Human Behavior*, 26(6), 1701-1709.
- R. Zufferey, J. D., Bodemer, D., Buder, J., & Hesse, F. W. (2010). Partner knowledge awareness in knowledge communication: Learning by adapting to the partner. *The Journal of Experimental Education*, 79(1), 102-125.

What is Monitored and by Whom in Online Collaborative Learning?:
Analysis of Monitoring Tools in Learner Dashboard



Ji Young LIM

Doctoral candidate, Dept. of Educational Technology, College of Education, Ewha Womans University.

Interests: Computer-Supported Collaborative Learning, Co-regulation, Technology-enhanced Learning Design

E-mail: jylim.edu@ewhain.net

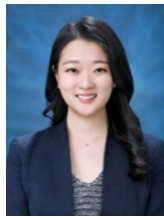


Jisoo CHOI

Graduate student, Dept. of Educational Technology, College of Education, Ewha Womans University.

Interests: Computer-Supported Collaborative Learning, Co-regulation, Technology-enhanced Learning Design, Personalized Learning

E-mail: jschoi96@ewhain.net



Yoon Jin KIM

Graduate student, Dept. of Educational Technology, College of Education, Ewha Womans University.

Interests: Computer-Supported Collaborative Learning, Self-regulation, Learning analytics, Data visualization

E-mail: yoonjin.kim@ewhain.net

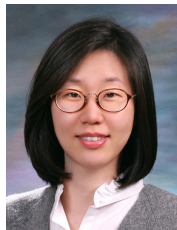


Jeongin EUR

Graduate student, Dept. of Educational Technology, College of Education, Ewha Womans University.

Interests: Computer-Supported Collaborative Learning, Co-regulation, Technology-enhanced Learning Design, Personalized Learning

E-mail: jeongineur@ewhain.net



Kyu Yon LIM

Associate professor, Dept. of Educational Technology, College of Education, Ewha Womans University.

Interests: Computer-Supported Collaborative Learning, Co-regulation, Technology-enhanced Learning Design

E-mail: klim@ewha.ac.kr

Received: September 10, 2019 / Peer review completed: October 2, 2019 / Accepted: October. 15, 2019