Development and Evaluation of Learning Analytics Dashboards to Support Online Discussion Activities

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ABSTRACT: Online discussion plays an increasingly significant role in asynchronous online learning environments. While previous attempts have been made to develop learning analytics dashboards to facilitate such discussions, most of these dashboards have been designed without reference to data or visualization techniques that have been proven to make online discussions more effective. This study identified the difficulties and inconveniences experienced by learners in online discussion activities and generated a set of visual design guidelines for overcoming them. Applying these guidelines, a set of learning analytics dashboards were developed and evaluated. The study was conducted according to prototyping methodology, which yielded five prototype dashboards that display information on participation, interaction, discussion content keywords, discussion message types, and the distribution of debate opinions, respectively. The developed dashboards were then revised and refined in a three-step process: (1) expert validation to verify that the dashboards complied with the visual guidelines and provided learners with the information they needed; (2) tests to identify usability problems, collect qualitative and quantitative data, and determine participant satisfaction; and (3) user experience evaluations to determine how learners and instructors perceived their interactions with the dashboards. Practical and empirical discussions are provided based on the results, which offer a valuable base of user experience data that can be used in future studies.

Keywords: Visual dashboard, Prototype development, Online discussion, Learning analytics, Prototyping methodology

1. Introduction

Online discussions are learning activities commonly used in online learning environments, such as MOOCs or flipped learning. Asynchronous online discussions are useful for analyzing and reflecting on discussion content, because they allow learners to repeatedly check for discussion opinions (Hara, Bonk, & Angeli, 2000) with no constraints of time or space, unlike traditional face-to-face class discussions (Harasim, 1993). Such conversations take place on online forum bulletin boards, where text-based discussion accumulates over time. As such, learners are required to exert a large amount of effort to understand the discussion's overall flow and respond appropriately (Wise, Zhao, & Hausknecht, 2013). Thus, discussion forums are difficult to understand and manage when a large number of students are discussing ideas (Vieira, Parsons, & Byrd, 2018).

Researchers have previously adopted a learning analytics perspective to analyze and visualize discussion activities in a dashboard format so as to support learners' understanding and monitoring of online discussion activities. There is evidence that dashboards may promote learning by providing learners with opportunities to monitor and reflect on their learning process (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). However, most dashboards are designed through ad-hoc processes rather than in consultation with the results of rigorous research. Moreover, the lack of research on appropriate visualization techniques for each data type leads to the creation of ineffective dashboards (Verbert et al., 2019), and many learning dashboards are implemented without conducting usability tests on learners (Bodily & Verbert, 2017). A successful implementation of learning analytics dashboards requires considering learners' needs (Ifenthaler, 2017).

Against this background, this study sought to develop learning analytics dashboards applicable to online discussions by exploring the educationally meaningful information in online discussion activities and applying research-based guidelines to visualize it in the most effective way. Our chosen learning analytics dashboards were revised and validated four ways using expert reviews, expert validations, usability tests, and user experience evaluations. The results of this study offer practical and empirical paths forward for the development of visual dashboards for online discussion activities.

2. Literature review

2.1. Online discussion and visual feedback information

Rapport (1991) defined online discussions as interactions in which learners exchange text-based messages in a virtual space in a many-to-many format. Discussion forums have been widely applied and have many benefits as a teaching and learning tool for both blended and online courses in numerous disciplines (An, Shin, & Lim, 2009). Compared to face-to-face contexts, online discussion environments can encourage wider learner participation because there are no time or space constraints (Buckley, 2011; Harasim, 2000). Furthermore, learners can improve their critical thinking skills and generate new knowledge through collaborations with other learners (Weinberger & Fischer, 2006; Hew & Cheung, 2011). Online discussion forums also allow learners to gather and organize relevant data on a particular topic before contributing to the discussion (Hara et al., 2000).

Despite these educational benefits, online discussion activities have certain educational limitations that must be overcome. For example, learners may have difficulty with behavioral regulation during participation activities, or with understanding the meaning or detailed aspects of written messages (Kehrwald, 2008). To avoid such pitfalls, previous research has adopted a learning analytics approach, seeking to help learners better understand discussion activities by visually representing a range of results.

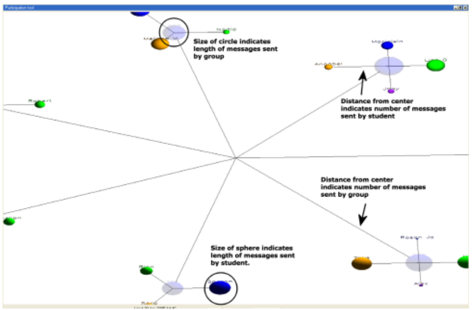
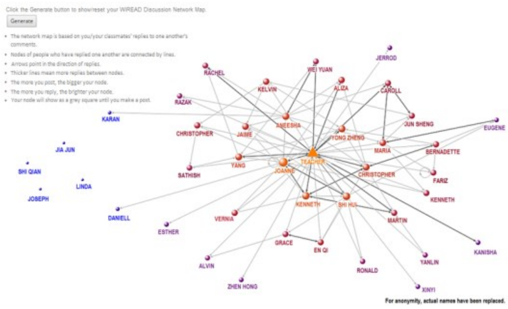
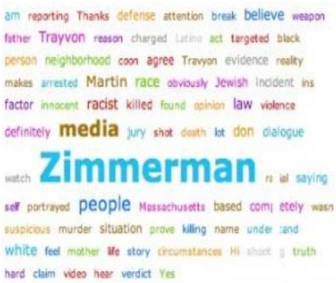
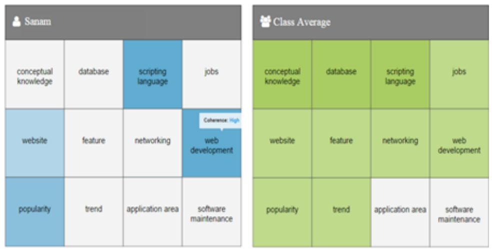
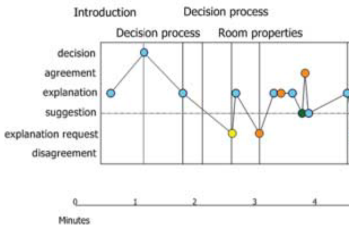
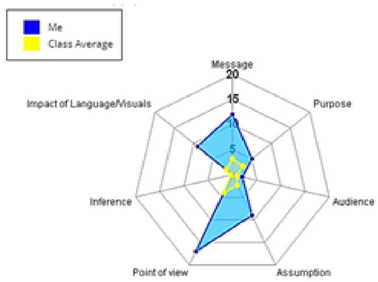
Following this approach, learners receive feedback on discussion activities through visualizations of the results of their participation, interaction, and discussion content analysis in individual or team discussions. Such visual feedback on the learning process and outcomes enables learners to objectively monitor their learning activities and understand the current state of the interactions among peer learners (Ferguson, 2012). When learning data is related to learning objectives and is able to track learners' progress, meaningful visual feedback can be created to enhance desired learning behaviors according to a process model (Verbert et al., 2013). As a result, learners may gain a better overview of discussion activities (*awareness*), reflect on their own activities (*self-reflection*), find their deficiencies (*sensemaking*), and change their learning behavior to compensate for these deficiencies (*impact*). To provide visual feedback on online discussion activities, it is important to identify the information that learners and instructors require (Yau, 2013). Due to the nature of online learning environments, however, some information is more difficult for learners and instructors to obtain than in face-to-face discussion activities. Table 1 shows the characteristics of online discussion activities proposed in previous research, learners' difficulties in online discussion forums, and the items that should be presented as visual feedback information.

Table 1. Visual feedback information focusing on the difficulties in online discussion

Characteristics of online discussion environments	Difficulties in online discussion	Visual feedback information
Independent	• Difficulty in making an objective self-evaluation of how to engage actively in discussion activities	(1) Online discussion participation (Hatala, Beheshitha, & Gasevic, 2016; Tan, Koh, Jonathan, & Yang, 2017)
Text-based conversations	• Difficulty in understanding interactions among learners • Difficulty in understanding the overall discussion	(2) Interaction among learners (Dawson, Bakharia, & Heathcote, 2010) (3) Keywords (Ali, Hatala, Gašević, & Jovanović, 2012) (4) Message types (Pallotta & Delmonte, 2011)

Since each student accesses the platform asynchronously and participates in online discussion activities independently, it is difficult for learners to observe other learners' discussion activities and so make objective self-assessments regarding their relative level of active participation. Yet, this participation as a basic learning behavior is the most important predictor of the educational effectiveness of online discussion (Jin, Yoo, & Kim, 2015). As seen in Table 2, previous studies have visualized individual learners' participation levels in online discussions either over time or in comparison with other learners. For example, Govaerts, Verbert, Duval, and Pardo (2012) assessed learners' participation over time, represented as a line graph, allowing each individual to compare their participation with other learners. By contrast, Jin et al. (2015) represented the participation levels of individual learners and teams using ten color codes, making it easier for them to grasp their participation information at a glance.

Table 2. Learning analytics dashboards on visual feedback information

Visual information	Online discussion dashboards	
Participation	Individual learner participation by date (Govaerts et al., 2012) 	Individual and team participation using ten color codes (Jin et al., 2015) 
Interaction	Interaction between teams (Janssen, Erkens, Kanselaar, & Jaspers, 2007) 	Interaction between individuals (Tan et al., 2017) 
Keywords	Frequency of words used by learners (Murray, 2014) 	Relevance between keywords suggested by instructors and words written by learners (Hatala et al., 2016) 
Message types	Learners' opinion analysis according to argumentative categories (Pallotta & Delmonte, 2011) 	Type of message selected by learners (Tan et al., 2017) 

Since online discussion activities are usually text-based conversations that accumulate messages in a bulletin board format, it is often difficult to grasp the relationships of interaction among learners. In this regard, some studies have provided visualizations of these interactions among individual learners and teams (Janssen, Erkens, Kanselaar, & Jaspers, 2007; Tan et al., 2017), representing activities related to writing their own opinions, reading the opinions of others, and posting comments or replies. Visual feedback on learner interactions can improve participants' presence and co-presence in online discussions by helping students clearly recognize their own and other learners' discussion activities (Lambropoulos, Faulkner, & Culwin, 2012). Sociograms composed of nodes and links are widely used to visualize these interactions. Expressing the learner as a node and the relationship among learners as a link, they can easily provide information on who is leading the discussion and who is being excluded.

Additional studies have extracted and presented keywords or analyzed the types of messages written by learners to help them better understand discussion topics and opinions. In these, key or common words used by learners are represented in word clouds (Murray, 2014) or by visualizing the semantic relationships between words (Sack, 2000). For example, Hatala et al. (2016) determined keywords related to the discussion topic and presented the degree to which those keywords were used to suit the content of the learners' discussion opinions, using four color-coded levels. In terms of analysis, Pallotta and Delmonte (2011) evaluated and visualized the types of messages written by learners over time according to argumentative categories, while Tan et al. (2017) offered learners seven critical lenses, required that they select one to write about, and portrayed the results in a radial graph.

2.2. Visual design guidelines for learning analytics dashboards

Visual design guidelines are essential for the effective design and development of learning analytics dashboards for online discussion forums. They can serve as a tool for determining how and what to visualize in online discussion activities (Yau, 2013). Learning analytics dashboards provide a visual representation of the learning process, giving both learners and instructors an interactive aggregation of individual and group goals, tasks, connections and achievements in real time (Alabi, Code, & Irvine, 2013). These dashboards enhance learning by providing feedback, especially behavioral process-oriented feedback to support students' learning regulation (Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2020). The visual design guideline presented in this study considers the relationship between visual dashboard design and learning analytics to provide process-oriented feedback that supports behavioral regulation in online discussion activities. Previous studies proposed visual guidelines for presenting the results of learning analytics that can be summarized as traceability, comparability, implicity, and overview plus detail.

Traceability refers to visualizing and portraying analysis results in the order that learning activities continuously occur, covering past discussion activities and forecasting future activities. Comparability means that a learner can compare his/her relative position with other learners' performance levels. Visualizations of online discussion activity results, based on learning analytics, areprovided in the form of a dashboard. As such, it is necessary to supply a large amount of information in a limited space. Implicity refers to elimination of unnecessary elements from the physical, visual, and cognitive aspects of information, and expressing meaningful information in abbreviated forms (Lohr, 2007). Overview plus detail involves providing detailed information as part of the discussion activity's full overview (Shneiderman, 1996).

In this study, these visual design guidelines used in previous studies to develop learning analytics dashboards were analyzed according to visual feedback information (see Table 3). Our dashboards were then developed in accordance with these guidelines.

Table 3. Visual design guidelines according to visual feedback information types

	Traceability	Comparability	Implicity	Overview+Details
Participation	Visualize learner participation levels according to the allocated discussion time period for a particular topic (Bakharia et al., 2016)	Provide the average and highest levels of participation to allow learners to compare their participation with their peers (Beheshitha, Hatala, Gašević, & Joksimović, 2016)	Visualize participation levels using color symbols (e.g., green for good, yellow for fair, and red for poor) (Wise et al., 2013)	Provide levels of team participation and all learner participation, and make the details visible by selection (Erickson & Kellogg, 2003)
Interaction	Visualize interaction levels between learners over time (Schneider, Passant, & Decker, 2012)	Be able to compare the level of interaction between learners (Mochizuki et al., 2007)	Visualize interaction levels using visual elements, such as location, size, color, and brightness (Hara et al., 2000)	Use a sociogram to allow for comparisons of interaction patterns within and among teams (Erickson & Kellogg, 2003)

Keywords	Make it possible to see changes in frequently mentioned keywords over time (Yi, Kang, Stasko, & Jacko, 2007)	Present the extent to which keywords are mentioned in the discussion to allow for comparisons with other learners (Mochizuki et al., 2007)	Simplify the central word using the word cloud technique (Siemens & Baker, 2012)	Visualize the degree to which students mention keywords (Teplovs, 2008) and the overall distribution of keywords in the discussion
Message types	Visualize the distribution of message types by discussion topics (Bakharia et al., 2016)	Present a distribution of message types that can be compared to the average of other learners (Tan et al., 2017)	Visualize the distribution of message types in the form of a radial graph (Ferguson, 2012)	Provide message types for all learners, and if one has selected each type, make related opinions available for viewing
Pros/cons message types	Visualize the distribution of pros and con opinions over time	Make it easy to compare the pro and con opinions on the discussion topic (Teplov, 2008)	Mark the pros and cons with different symbols or colors	Provide message types (pro and con) for all learners, and if one has selected each type, make related opinions available for viewing

Based on the above guidelines, the specific research questions were as follows:

- What are the appropriate learning analytics dashboards for online discussion activities that correspond with the aforementioned visual feedback information?
- How do learners and instructors perceive online discussion dashboards?

3. Research method

Lantz (1985) defined prototyping methodology as a "system development methodology based on building and using a model of a system for designing, implementing, testing and installing the system" (p. 1). In this methodology, after a succinct statement of objectives and goals, development is conducted using parallel processes through which prototype designs are created. The prototyping process requires having the system's definitions, an opportunity to use and test the prototype, and software that allows the rapid building and modification of the prototype (Tripp & Bichelmeyer, 1990). Often, the initial prototype emphasizes only the visual aspects of the final product, because these are less costly and demanding to build. After overall format decisions have been made, an executable prototype may be constructed to determine the product's usability (Jones & Richey, 2000). This process can be used to verify a product's form, fit, and function. It also has a strong impact on productivity, that is, means getting a product from concept to prototype to reality (Kamrani & Nasr, 2010). Following this methodology, we designed, developed, reviewed, and revised several learning analytics dashboards in parallel, using an iterative process. Figure 1 shows the specific sequence used in this study for each dashboard.

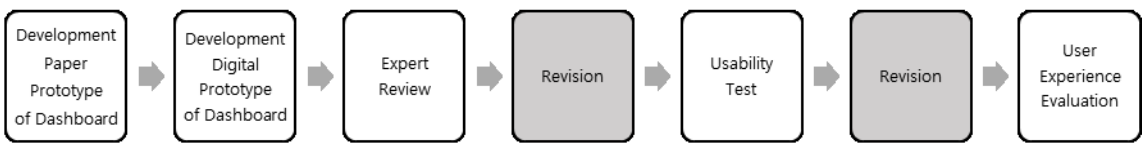


Figure 1. The study procedures

4. Initial visual learning analytics dashboards for online discussions

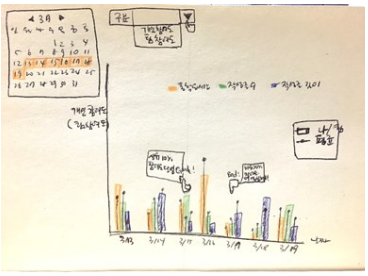
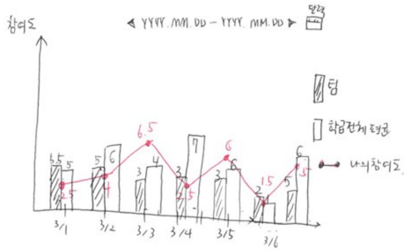
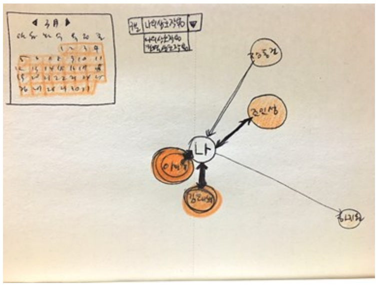
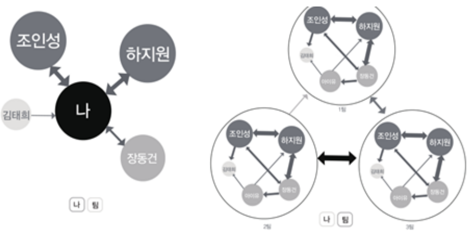
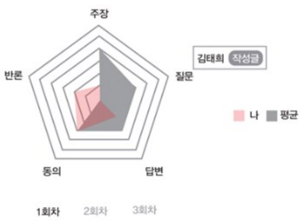
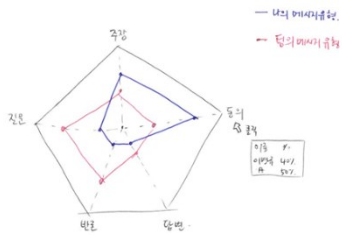
4.1. Participants and procedures

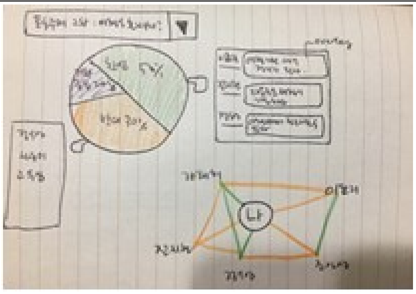
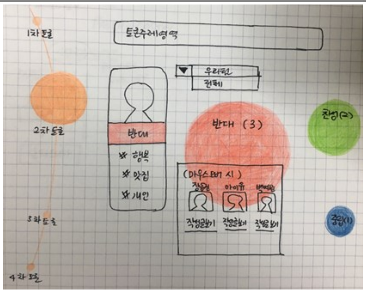
Six designers were invited to design paper prototypes for the learning analytics dashboards. Paper prototyping is widely used for designing, testing, and refining user interfaces, allowing designers to stay focused on users, while requiring little or no programming skills on the part of the designers (Rudd, Stern, & Isensee, 1996). The participants were three instructional designers, two web designers, and a computer programmer. They were provided with a fictional scenario and design guidelines, including the goal of the dashboards for online discussion activities and design specifications in an online format. The design process started with a request to develop these dashboards, and it then defined the target users, presented their persona, and offered examples of how to use the dashboards. Each designer created five types of learning analytics dashboards: participation, interaction, keywords, discussion message types, and debate (pros/cons) message types.

4.2. Paper prototypes

Although the designers were asked to develop paper prototypes, two used a digital form due to the convenience of computer authoring tools. Table 4 shows some of the final paper prototypes, chosen after the expert reviewing stage.

Table 4. A selection of paper prototypes developed by the six designers

Visual information	Examples of paper prototypes	
Participation		
Interaction		
Keywords		
Message types		

Pros/cons message types		

4.3. First digital prototypes

A learning analytics dashboard, the most widely used intervention strategy in learning analytics, is a visual display that provides information presenting students' learning processes and behavior patterns (Jo, 2012). We designed and developed the first digital prototypes of the learning analytics dashboards to support individuals' self-reflective learning based on case studies (Yoo & Jin, 2017), theoretical reviews on self-regulating in the learning analytics approach (Sung, Jin, & Yoo, 2016), and learning theories, such as cognitive theory, cognitive-behaviorism, and social constructivism. The visual guidelines were applied to the five learning analytics dashboards, designed as follows (Figure 2).

The *participation dashboard* represents learners' participation in a particular discussion topic alongside the average participation levels of the team and the entire class. Based on Bandura (1991), it enables self-evaluation through intrinsic reinforcement, as self-regulation denotes the ways in which an individual may influence their external environment through self-observation and self-judgment. By applying the traceability guideline, when a specific period is selected, the participation level in that period is displayed as a bar graph, allowing learners to see their participation level on a specific date. After comparability implementation, a learner could compare the participation levels of all classmates, the team, and him/herself (traffic-light colored circles and line graph). The individual participation value is displayed in each circle: green means excellent, yellow is good, and red is a warning.

The *interaction dashboard* allows learners to identify the interaction levels among learners and teams by discussion topic. It represents connectivism in that it depends on building networks of information and supports a social constructivist pedagogy by proposing social discussion forums where learners can connect with others and exchange information (Khalil & Ebner, 2016). Here, the traceability guideline assesses and displays interaction patterns over a defined period, and the comparability guideline allows for interaction comparisons between the team and the whole class. The implicity guideline was followed by displaying interaction level differences through color, brightness, and size (a longer and thicker line corresponds to a higher interaction level). Learners can understand inter-team and interpersonal interactions through the overview plus detail guideline.

The keywords and message types dashboards are informed by the cognitive-behaviorist model, which involves providing students with guided learning and feedback (Khalil & Ebner, 2016). Through the *keywords dashboard*, learners can not only identify frequently used keywords over a certain period, but also discover who has used them often and compare them with their own frequently used terms. By applying the four visual design guidelines, the keywords can be identified for each discussion topic and the degree to which a keyword is mentioned can be compared using circle sizes. These circles are located near the keywords and appear larger as the keywords are mentioned more frequently. The green circle represents "Me" and the colors (green, orange, or blue) indicate the different teams.

The *message types dashboard* helps learners identify the type of messages used in discussion topics. Previous research has distinguished different message types by analyzing the content of online discussions. Many researchers have drawn on Henri's (1992) discussion analytical model, using message analysis frameworks based on the type of discussion. The analytical model used in this study followed the recommendations of Cho, Park, Kim, Suk, and Lee (2015) to divide message types into five categories: statement, agreement, argument, question, and answer. To facilitate message type comparisons, their distribution is visualized as a radial graph. "My message type" is represented in orange, and team message types are in blue. When each message type is clicked, learners can see a list of relevant posts and read each post.

The *pros and cons dashboard* helps the learners see how many people are on each side of a debate-style forum discussion, who wrote pros and cons, and what they wrote. Previous studies revealed that providing a pros and cons dashboard has a positive effect on satisfaction in discussion activities, according to students' writing efficacy and social comparative motivations (Jin & Yoo, 2019). In this dashboard, learners can see the number distributions of the pros and cons, and the ratio by debate topic. The pros were represented as blue and the cons as red. When learners click "pros" or "cons," they can view a list of learner names that have given their opinion and read them.

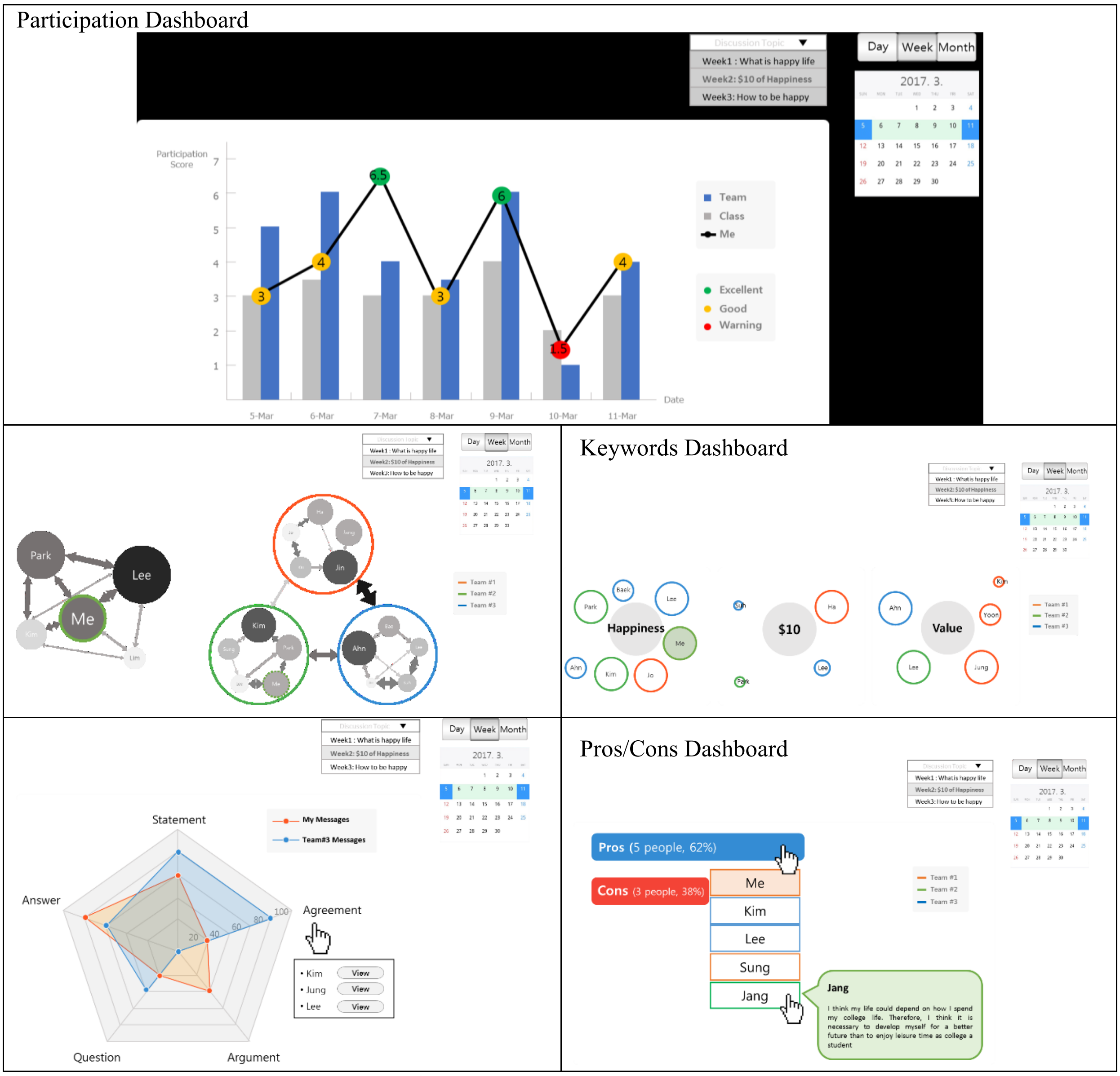


Figure 2. First version of digital prototypes

5. Revision and validations of learning analytics dashboards

5.1. Expert review participants and procedure

The expert review was conducted by six experts, who were recruited for their theoretical and practical experience in educational technology or learning analytics. The experts were introduced to the purpose of this research, the visual design guidelines, and the learning analytics dashboards. We conducted semi-structured interviews to determine which was the most incomprehensible prototype, and what were the strengths and weaknesses of each. We also asked participants their opinions and suggestions to improve the dashboards. Their reviews and comments were collected and analyzed for each dashboard type.

5.2. Expert review results

The experts' comments on each learning analytics dashboard are presented in Table 5. We reflected on the expert reviews and assessed the learning theories and visual design guidelines of previous studies to revise the learning analytics dashboards.

Table 5. Expert review results

Category	Answers
Participation dashboard	The line graph in the participation dashboard seems to indicate the changes in participation, but it would be better to delete it, because these changes are not the focus of this visualization (Expert A). The participant scores should not be directly presented as a specific number. Instead, they should be provided only when a learner wishes (Expert F).
Interaction dashboard	The interaction dashboard was not easy to understand. The interaction levels could be sufficiently expressed through the arrows' different thickness levels and colors (Expert C).
Keyword dashboard	The circles indicating "Me," displayed in green, were not visible and we recommend that they should be displayed in red for emphasis (Experts D & F).
Pros/Cons dashboard	The pros and cons distributions would be better represented as a pie chart in which the sum of the two (pros and cons) equals 100% (Expert F).

5.3. Participants and usability test procedure

We conducted a usability test with 20 graduate learners majoring in educational technology at university A and five instructors. Of the six experts who participated in the expert review, five also participated in the usability test, with the exception of Expert F. Usability is usually considered to be a user's ability to successfully carry out a task with a product, and the usability test serves to improve a tested product's use (Dumas & Redish, 1999). Our test consisted of five scales: accessibility (2 items; $\alpha = .85$), usefulness (4 items; $\alpha = .95$), satisfaction (2 items; $\alpha = .83$), aesthetics (2 items; $\alpha = .73$), and intention of use (2 items; $\alpha = .82$) (Lund, 2001; Nokelainen, 2006). The Table 6 provides an example of a representative questionnaire.

Table 6. Usability test questionnaire

Category	Questionnaire
Accessibility	I can get the information what I want to know using the learning analytics dashboard.
Usefulness	It is easy to use.
Satisfaction	The information obtained from the learning analytics dashboard is valuable.
Aesthetic	I think the learning analytics dashboard is attractive.
Intention of use	I would recommend it to a friend.

Using a five-point Likert scale, the participants were asked to reflect on how they felt looking at the static dashboard image. Semi-structured interviews were also conducted to gather participants' additional comments on the dashboards. The interview questions, used if the previously determined answers were inconclusive, were based on the following three questions: which dashboard was the most understandable, which was the most incomprehensible, and what were the strengths and weaknesses of each dashboard? In this process, we employed a stimulated recall interview, which is useful in helping users recall specific moments during the test (Park & Jo, 2015).

5.4. Usability test results

Table 7 shows the results of the usability test. The users' perceptions of the dashboards were generally positive. Both learners and instructors responded that the learning analytics dashboards were useful for obtaining information, easy to use, save time, and that they would recommend them to friends. Table 8 presents the interview results.

After the instructor and learner interviews, expert reviews were performed again. Expert B recommended removing the date options, because most discussion activities are provided to learners by topic rather than by date. Experts C and E suggested fixing the positions of the circle representing each team in the keywords dashboard, because it was difficult to recognize at a glance where each team is positioned.

Table 7. Usability test results

Category	Students		Instructors	
	M	*SD*	*M*	*SD*
Accessibility	4.23	0.77	4.50	0.53
Usefulness	4.45	0.63	4.45	0.52
Satisfaction	4.00	0.72	4.40	0.70
Aesthetics	4.23	0.53	4.50	0.53
Intention of use	4.25	0.71	4.50	0.53

Table 8. Usability interview results

Category	Answers
Participation dashboard	• It seems unnecessary to express individual participation with a line graph, because it is already shown as a circle (Instructor B).
Interaction dashboard	• The fact that information on the interactions of the whole class and the team is provided simultaneously is confusing (Instructor A). • Understanding what the visualization elements meant was time-consuming. I was confused by the simultaneous appearance of interpersonal and team interactions on the same screen (Student A). • It is difficult to understand what the size of the circle representing an individual meant. If it represents participation, it seems to conflict with the interaction (Instructor C). • Too many colors were applied to the dashboard, making it difficult to grasp at a glance what each color represented (Student C).
Keyword dashboard	• The interaction dashboard provides information for both teams and individuals, but the keyword dashboard provides only one. I would like these to be separate here as well (Student A). • It was very complicated to visualize the extent of all learners' messages in the class (Student B).

5.5. Final version of the learning analytics dashboards

At this stage, the learning analytics dashboards were revised to reflect the research participants' opinions, gathered through expert reviews and usability tests. Figures 3, 4, 5, 6, and 7 presents the final revised versions.

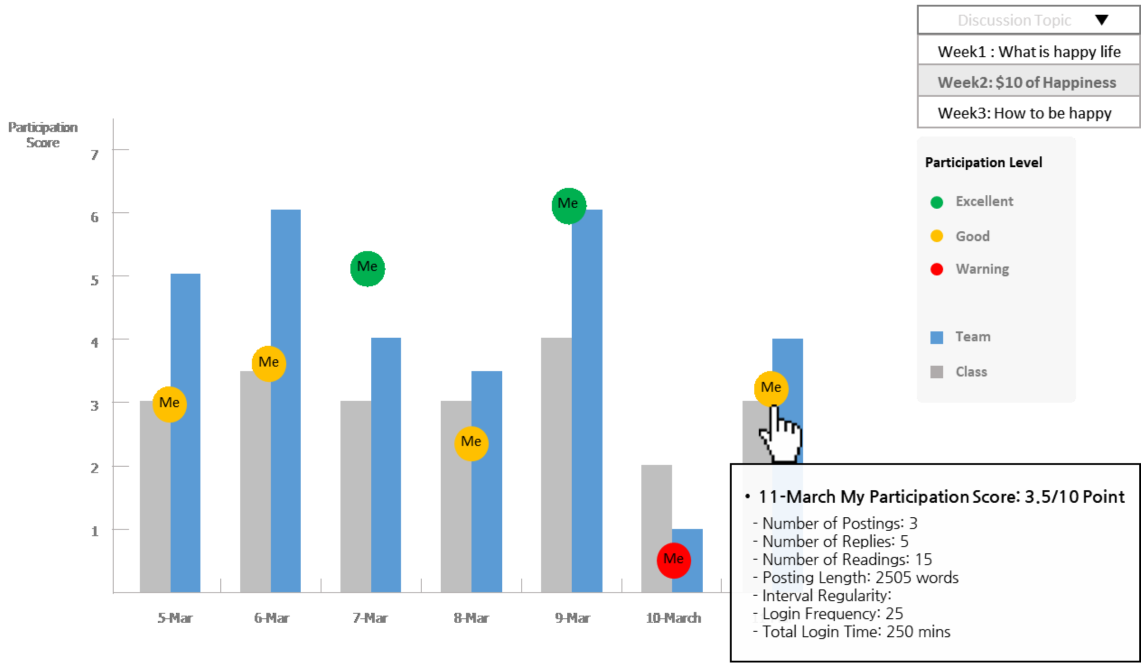


Figure 3. Final revised version of the Participation Dashboard

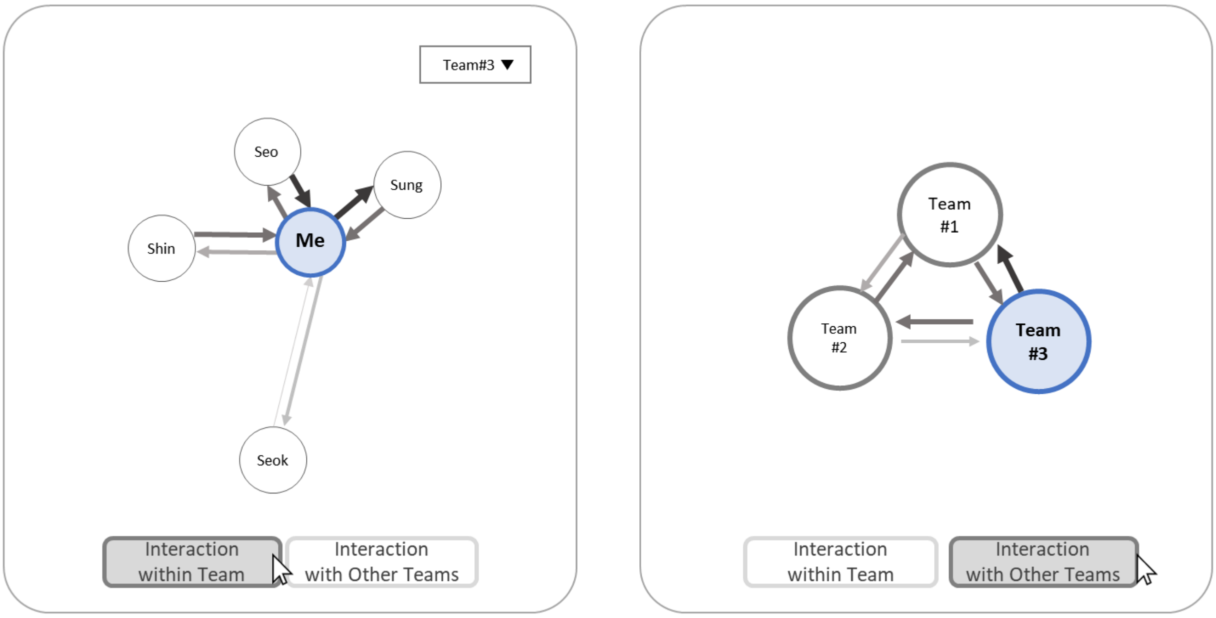


Figure 4. Final revised version of the Interaction Dashboard

The following discussion enumerates the significant changes we made from the first version of the learning analytics dashboards.

First, we applied the traceability principle and provided two options for selecting discussion topics and data, which allowed the learners to reflect on their previous discussion activities. We deleted the date selection, retaining only the discussion topic selection option, because too many options can confuse the users.

For the participation dashboard, we deleted the line graph because instructor B indicated that individual participation is already shown as a circle (Figure 3). The individual participation score was removed and it presented as a separate pop-up window that appears when a user hovers the mouse cursor over the circle. When a learner hovers over the graph, the score displays on the graph.

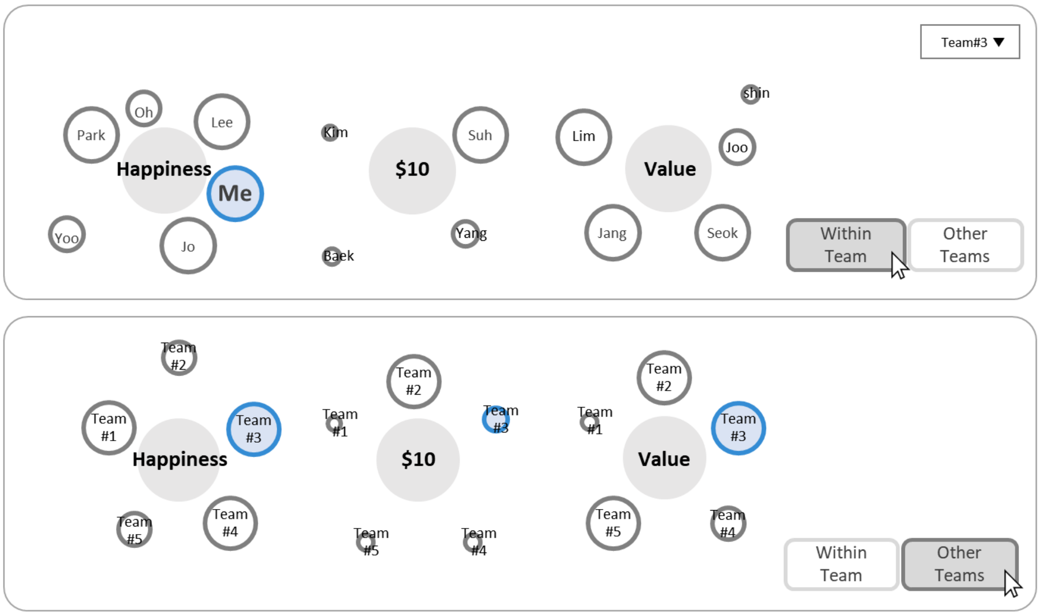


Figure 5. Final revised version of the Keywords Dashboard

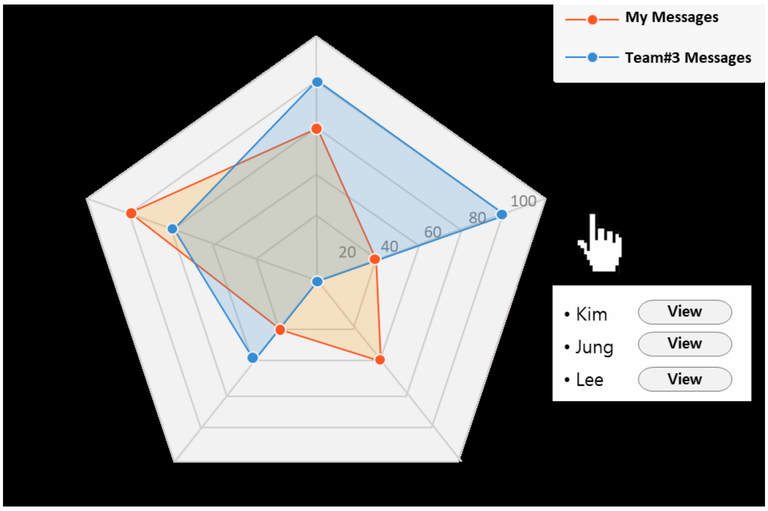


Figure 6. Final revised version of the Message Types Dashboard

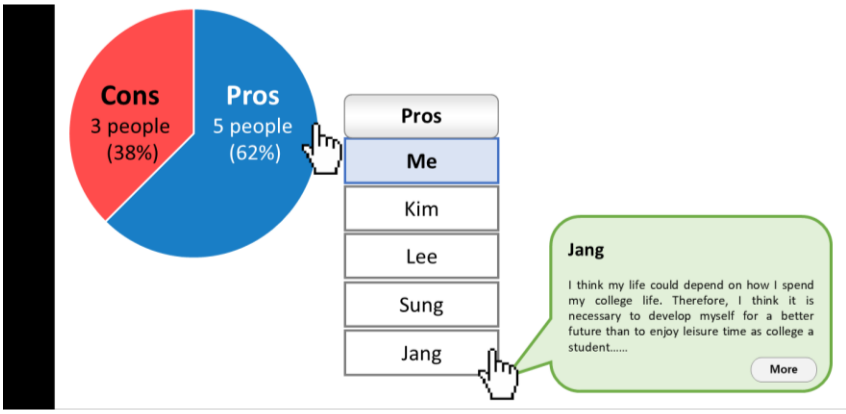


Figure 7. Final revised version of Pros/Cons Dashboard

In the first version of the interaction dashboard, different colors were used for each team, but these were simplified and only the colors of "my team" were highlighted in the final version (Figure 4). The interaction level was represented by the thickness and color of the arrows, and the interactions between teams were depicted more simply. In addition, the "interaction within team" and the "interaction with other teams" screens were divided so that each would be displayed only when the learner selects them, since it appeared to be confusing to have both visualizations on one screen.

Keyword frequency was visualized within and across teams, and a team's spatial position was fixed in order to maintain the integrity of the interaction dashboard (Figure 5). The message types dashboard helps learners identify the type of messages used in discussion topics. To facilitate message type comparisons, a radical graph shows the distributions of message types (Figure 6). For pros/cons dashboard, the bar graph was changed to a chart, which made it easier to see what percentage of pros and cons constituted the total 100% of the opinions (Figure 7).

We conducted expert validations to ensure the learning analytics dashboards' reliability. The experts were presented with the final versions of the dashboards, and were asked to evaluate whether the instructors' and learners' feedback was well-applied to the final version. The expert validation results were calculated using a content validity index (Chang, Gardner, Duffield, & Ramis, 2010). The agreement for all items was found to be 100%. Hence, each dashboard was found to be suitable for achieving the respective design purpose.

6. User experience evaluations of the learning analytics dashboards

6.1. Participants and procedures

After the learning analytics dashboards were created, we conducted a user experience evaluation that would reflects a broader perspective, assessing the individual's entire interaction with a product as well as his/her thoughts, feelings, and perceptions (Albert & Tullis, 2013). The participants comprised 31 graduate learners majoring in educational technology at university B and five instructors who participated in the usability test. We used the user experience questionnaires and data analysis tool developed by Laugwitz, Held, and Schrepp (2008; www.ueq-online.org) and included 26 items pertaining to the following scales: attractiveness (6 items; $\alpha = .86$), perspicuity (4 items; $\alpha = .70$), efficiency (4 items; $\alpha = .57$), dependability (4 items; $\alpha = .77$), stimulation (4 items; $\alpha = .84$), and novelty (4 items; $\alpha = .63$). The items are scaled from -3, the most negative answer, to +3, the most positive answer. This study sought to evaluate the relative quality of a user's experience through a benchmark analysis.

6.2. User experience evaluation results

A benchmarking analysis was conducted to compare these results with the user experience results for other products. Figure 8 shows the results of a benchmarking analysis of the learning analytics dashboards, both learners and instructors had a mostly positive impression of the dashboards for all the categories. The learners' overall impressions of the final versions were almost average. The novelty was excellent, efficiency and stimulation were good, perspicuity was above average, and attractiveness and dependability were below average. The instructors' impressions were excellent except for attractiveness. Both the instructors and the learners recognized the learning analytics dashboards as being very creative and innovative (novelty). They also confirmed that the dashboards were efficient in helping them understand the discussion activities and that they were motivated to use them (efficacy and simulation). In addition, their level of familiarity with the dashboards was confirmed to be above average (perspicuity). As their perceptions of dependability were relatively low, there is room for improvements that would allow users to have more control over their interactions with the dashboards (dependability).

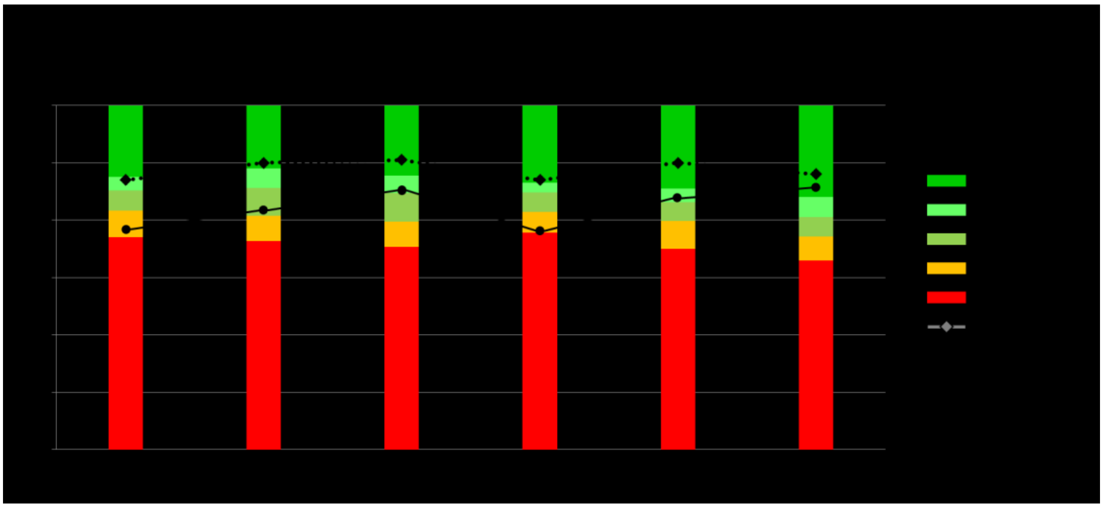


Figure 8. Benchmarking analysis results

Table 9. Results of user experience interviews

Category	Answers
Familiarity	The participation dashboard was the most familiar, probably because the bar graph is a familiar to me (Student A).
Participation engagement	The participation dashboard helps me understand the participation levels of an entire class, a team, and my own. I think it can be a stimulus for the next discussion and I would like to use it again (Student D).
Quality of discussion	I worry about the discussion message's quality if unnecessary or meaningless dialogue is included at the participation level (Instructor D).

Regarding the user experience interviews, we posed semi-structured interview questions that included participants' previous experience using learning analytics dashboards and their feelings about the experience of each dashboard. Table 9 presents a summary of the user experience interviews.

7. Discussion

7.1. Contributions to practice

The learning analytics dashboards developed in this study can serve as a guide regarding *what* to visualize in online discussion activities and *how* to do so. Yau (2013) argued that one must determine what users want to know before deciding which visualization technique to use, in order to take advantage of the appropriate visualization techniques for the required information. In other words, to develop an effective dashboard for online discussion activities, it is important to identity what information learners and instructors want to know. This study identified the following five kinds of information as useful in online discussion environments: participation, interaction, keywords, discussion message types, and distributions of pros and cons in a debate format. Our development of visual design guidelines and five types of dashboards has evident practical implications for future researchers interested in developing learning analytics dashboards for discussion activities.

The dashboards developed in this study presents learners with qualitative information on discussion contents and quantitative participation information regarding online discussion activitie. Furthermore, the content on learning activities can be classified into quantitative information on "how much is learned" and qualitative information on "what to learn" (Mayer, 2011). Previous research on dashboard development has mostly visualized quantitative information by analyzing learning log data. We placed a particular emphasis on the importance of qualitative analysis, because fragmented information, such as the number of postings and responses in online discussion activities, does not provide sufficient information for learners to reflect on their discussion activities (Malheiro, Morgado, & Mendes, 2008).

Recent research has found that applying learning analytics to learning activities can improve students' levels of engagement, which can in turn play an essential role in a self-regulated learning environments (Lai & Hwang, 2016). The learning analytics dashboards presented in this study can provide learners with feedback on their cognitive and social engagement in online discussion activities. Cognitive engagement refers to "the learner's psychological investment in and effort directed toward learning, understanding, or mastering the knowledge, skills, or crafts that academic work is intended to promote" (Newman, Wehlage, & Lamborn, 1992, p. 12). Social engagement denotes the process of communicating within a discussion environment in an online community. It is expected that, by providing learners with social engagement information, the learning analytics dashboards will promote a sense of cohesion and group-belonging in learners during online discussion activities, thereby alleviating feelings of isolation or alienation in online learning environments.

7.2 Empirical contributions

This study has implications for identifying the cognitive, emotional, and social problems that learners and instructors experience during online discussion activities. We included a user experience evaluation of the learning analytics dashboards to describe the interactions between a user and a product (Albert & Tullis, 2013). The results of this evaluation show lower scores for learners than for instructors. It was confirmed that most learners were using these kinds of learning analytics dashboards for the first time. Therefore, they may have felt that most dashboards were useful, but a few (e.g., the interaction dashboard) may have been unfamiliar or relatively less dependable. By contrast, the instructors, whose prior experience in online discussion activities was brought to bear on the operation and evaluation of the learning analytics dashboards, made very positive assessments of all the scales (perspicuity, efficiency, dependability, stimulation, and novelty). This result suggests an improvement plan from the viewpoint of various users, and indicates that learners should be informed about the use of prototypes in educational environments.

Schrepp, Hinderks, and Thomaschewski (2014) provided a benchmarking data set for user experience evaluations of various new systems or services, and a basis for analyzing the evaluation results. However, their benchmarking dataset did not include the user experience evaluation results of dashboards based on learning analytics. From this point of view, the data collected in this study can serve as a base that can be used to compare user experience evaluations in future studies that develop learning analytics dashboards.

7.3 Limitations and future research

Despite the extensive processes of this research, the study has certain limitations. First, it is necessary to implement the learning analytics dashboards developed in this study within an online learning system and investigate their educational effects. This study provides conceptual modeling and visualization techniques according to five types of visualization objects on discussion activities. In order to implement this in e-learning systems, computational modeling should be done using learning log data, learner creation data, and instructor creation data from e-learning environments. Further research should be conducted to analyze whether the learning analytics dashboards implemented in an online discussion learning system are effective in achieving educational objectives. In the future, it will be useful to apply quantitative evaluation methods, such as eye tracking and physiological response measurement. Second, only 20 learners from a specific university class and five instructors participated in the usability test in this study, which limits the generalizability of our usability test results. Finally, this study did not consider the possibility of providing interventions for learners' individual differences. As such, for the next phase of designing and developing learning analytics dashboards, individual differences in achievement levels need to be considered (Park & Jo, 2015).

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References

Albert, W., & Tullis, T. (2013). *Measuring the user experience: Collecting, analyzing, and presenting usability metrics*. Waltham, MA: Elsevier Inc.

Ali, L., Hatala, M., Gašević, D., & Jovanović, J. (2012). A Qualitative evaluation of evolution of a learning analytics tool. *Computers & Education*, *58*(1), 470-489.

Alabi, H., Code, J., & Irvine, V. (2013). Visualizing learning analytics: Designing a roadmap for success. In *Proceedings of EdMedia+ Innovate Learning* (pp. 951-959). Waynesville, NC.

An, H., Shin, S., & Lim, K. (2009). The Effects of different instructor facilitation approaches on students' interactions during asynchronous online discussions. *Computers & Education*, *53*(3), 749-760.

Bakharia, A., Corrin, L., de Barba, P., Kennedy, G., Gašević, D., Mulder, R., Williams, D., Dawson, S., & Lockyer, L. (2016). A Conceptual framework linking learning design with learning analytics. In *Proceedings of the 6th International Learning Analytics & Knowledge Conference* (pp. 329-338). New York, NY: ACM.

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes, 50*(2), 248-287.

Beheshitha, S. S., Hatala, M., Gašević, D., & Joksimović, S. (2016). The Role of achievement goal orientations when studying effect of learning analytics visualizations. In *Proceedings of the 6th International Learning Analytics & Knowledge Conference* (pp. 54-63). New York, NY: ACM.

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.

Buckley, F. (2011). Online discussion forums. *European Political Science, 10*(3), 402-415.

Chang, A. M., Gardner, G. E., Duffield, C., & Ramis, M. A. (2010). A Delphi study to validate an advanced practice nursing tool. *Journal of Advanced Nursing, 66*(10), 2320-2330.

Cho, Y., Park, H., Kim, J., Suk, Y., & Lee, S. (2015). Exploring roles of feedback to facilitate online discussion. *Asian Journal of Education, 16*(2), 289-313.

Dawson, S., Bakharia, A., & Heathcote, E. (2010). SNAPP: Realising the affordances of real-time SNA within networked learning environments. In *Proceedings of the Seventh International Conference on Networked Learning 2010* (pp. 125-133). Lancaster, UK: Lancaster University.

Dumas, J. S., & Redish, J. (1999). *A Practical guide to usability testing.* Portland, OR: Intellect books.

Erickson, T., & Kellogg, W. A. (2003). Social translucence: Using minimalist visualisations of social activity to support collective interaction. In K. Höök, D. Benyon, & A. J. Munro (Eds.), *Designing Information Spaces: The Social Navigation Approach* (pp. 17-41). London, UK: Springer.

Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, *4*(5-6), 304-317.

Govaerts, S., Verbert, K., Duval, E., & Pardo, A. (2012). The Student activity meter for awareness and self-reflection. In *Proceedings of CHI'12 Extended Abstracts on Human Factors in Computing Systems* (pp. 869-884). New York, NY: ACM.

Hara, N., Bonk, C. J., & Angeli, C. (2000). Content analysis of online discussion in an applied educational psychology course. *Instructional Science*, *28*(2), 115-152.

Harasim, L. (2000). Shift happens: Online education as a new paradigm in learning. *The Internet and Higher Education, 3*(1-2), 41-61.

Harasim, L. (1993). *Global networks: Computers and international communication*. Cambridge, MA: MIT Press.

Hatala, M., Beheshitha, S. S., & Gasevic, D. (2016). Associations between students' approaches to learning and learning analytics visualizations. In *Proceedings of the LAK 2016 Workshop on Learning Analytics for Learners* (pp. 3-10). Aachen, Germany: RWTH Aachen University.

Henri, F. (1992). Computer conferencing and content analysis. In A. R. Kaye (Ed.), *Collaborative Learning through Computer Conferencing* (pp. 117-136). Berlin, Germany: Springer.

Hew, K. F., & Cheung, W. S. (2011). Higher-level knowledge construction in asynchronous online discussions: An Analysis of group size, duration of online discussion, and student facilitation techniques. *Instructional Science, 39*(3), 303-319.

Ifenthaler, D. (2017). Are higher education institutions prepared for learning analytics? *TechTrends, 61*(4), 366-371.

Janssen, J., Erkens, G., Kanselaar, G., & Jaspers, J. (2007). Visualization of participation: Does it contribute to successful computer-supported collaborative learning? *Computers & Education*, *49*(4), 1037-1065.

Jin, S., Yoo, M., & Kim, T. (2015). Design of a dashboard for enhancing e-learning participation and interaction. *Journal of Educational Technology, 31*(2), 191-221.

Jin, S., & Yoo, M. (2019). The Effect of an online debate dashboard on students' satisfaction and perception. *Journal of Learner-Centered Curriculum and Instruction, 19*(7), 41-61.

Jo, I. (2012). On the LAPA (Learning Analytics for Prediction & Action) model suggested. In *Proceedings of the Future Research Seminar* (pp.1-6). Seoul, Korea: Korea Society of Knowledge Management.

Jones, T. S., & Richey, R. C. (2000). Rapid prototyping methodology in action: A Developmental study. *Educational Technology Research and Development, 48*(2), 63-80.

Kamrani, A. K., & Nasr, E. A. (2010). *Engineering design and rapid prototyping.* New York, NY: Springer.

Kehrwald, B. (2008). Understanding social presence in text-based online learning environments. *Distance Education, 29*(1), 89-106.

Khalil, M., & Ebner, M. (2016). What massive open online course (MOOC) stakeholders can learn from learning analytics? In M. Spector, B. Lockee, & M. Childress (Eds.), *Learning, Design, and Technology: An International Compendium of Theory, Research, Practice, and Policy* (pp. 1-30). Cham, Switzerland: Springer.

Lai, C. L., & Hwang, G. J. (2016). A Self-regulated flipped classroom approach to improving students' learning performance in a mathematics course. *Computers & Education, 100*, 126-140.

Lambropoulos, N., Faulkner, X., & Culwin, F. (2012). Supporting social awareness in collaborative e-learning. *British Journal of Educational Technology, 43*(2), 295-306.

Lantz, K. E. (1985). *The Prototyping methodology.* Englewood Cliffs, NJ: Prentice Hall.

Laugwitz, B., Held, T., & Schrepp, M. (2008). Construction and evaluation of a user experience questionnaire. In *Symposium of the Austrian HCI and Usability Engineering Group* (pp. 63-76). Berlin, Germany: Springer.

Lohr, L. L. (2007). *Creating graphics for learning and performance: Lessons in visual literacy.* Upper Saddle River, NJ: Prentice Hall.

Lund, A. M. (2001). Measuring usability with the use questionnaire. *Usability Interface, 8*(2), 3-6.

Malheiro, S., Morgado, L., & Mendes, A. (2008). Analysis of engaged online collaborative discourse: A Methodological approach. In A. J. Mendes, I. Pereira, & R. Costa (Eds.), *Computers and Education: Towards Educational Change and Innovation* (pp. 33-43). London, UK: Springer.

Mayer, R. E. (2011). *Applying the science of learning*. Boston, MA: Pearson/Allyn & Bacon.

Mochizuki, T., Kato, H., Fujitani, S., Yaegashi, K., Hisamatsu, S., Nagata, T., Nakahara, J., Nishimori, T., & Suzuki, M. (2007). Promotion of self-assessment for learners in online discussion using the visualization software. In N. Lambropoulos,

& P. Zaphiris (Eds.), *User-centered design of online learning communities* (pp. 365-397). Hershey, PA: Information Science Publishing.

Murray, T. (2014). Supporting deeper deliberative dialogue through awareness tools. In *Proceedings of the 2014 Build Peace Conference* (pp. 1-8). Cambridge, MA: MIT Media Lab.

Newman, E. M., Wehlage, G. G., & Lamborn, S. D. (1992). Taking students seriously. In F. E. Newmann (Ed.), *Student engagement and achievement in American secondary schools* (pp. 40-61). New York, NY: Teachers College Press.

Nokelainen, P. (2006). An Empirical assessment of pedagogical usability criteria for digital learning material with elementary school students. *Educational Technology & Society, 9*(2), 178-197.

Pallotta, V., & Delmonte, R. (2011). Automatic argumentative analysis for interaction mining. *Argument & Computation, 2*(2-3), 77-106.

Park, Y., & Jo, I. H. (2015). Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science, 21*(1), 110-133.

Rapport, M. (1991). *Computer mediated communication: Bulletin boards, computer conferencing, electronic mail, information retrieval.* San Francisco, CA: Wiley & Sons.

Rudd, J., Stern, K., & Isensee, S. (1996). Low vs. high-fidelity prototyping debate. *Interactions*, *3*(1), 76-85.

Sack, W. (2000). Conversation map: An Interface for very large-scale conversations. *Journal of Management Information Systems, 17*(3), 73-92.

Schneider, J., Passant, A., & Decker, S. (2012). Deletion discussions in Wikipedia: Decision factors and outcomes. In *Proceedings of the Eighth Annual International Symposium on Wikis and Open Collaboration* (pp. 1-10). New York, NY: ACM.

Schrepp, M., Hinderks, A., & Thomaschewski, J. (2014). Applying the user experience questionnaire (UEQ) in different evaluation scenarios. In *International Conference of Design, User Experience, and Usability* (pp. 383-392). Cham, Switzerland: Springer.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S., & Kirschner, P. A. (2020). Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior, 107,* 105512. doi:10.1016/j.chb.2018.05.004

Shneiderman, B. (1996). The Eyes have it: A Task by data type taxonomy for information visualizations. In *Proceedings of the 1996 IEEE Symposium on Visual Languages* (pp. 336-343). IEEE. doi:10.1109/VL.1996.545307

Siemens, G., & Baker, R. S. (2012). Learning analytics and educational data mining: Towards communication and collaboration. In *Proceedings of the 2nd International Learning Analytics & Knowledge Conference* (pp. 252-254). New York, NY: ACM.

Sung, E., Jin, S., & Yoo, M. (2016). Exploring learning data for supporting self-directed learning in the perspective of learning analytics. *Journal of Educational Technology, 22*(3), 487-533.

Tan, J. P. L., Koh, E., Jonathan, C. R., & 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.

Teplovs, C. (2008). The Knowledge space visualizer: A Tool for visualizing online discourse. In *Proceedings of the Eighth International Conference of the Learning Sciences* (pp. 1-12). Utrecht, Netherlands: International Society of the Learning Sciences.

Tripp, S. D., & Bichelmeyer, B. (1990). Rapid prototyping: An Alternative instructional design strategy. *Educational Technology Research & Development, 38*(1), 31-44.

Verbert, K., De Croon, R., De Laet, T., Broos, T., Millecamp, M., Ochoa, X., Bodily, R., Kay, J., Drachsler, H., & Conati, C. (2019). VISLA: Visual approaches to learning analytics. In *Proceedings of the 9th International Learning Analytics & Knowledge Conference* (pp. 750-753). SoLAR.

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 57*(10), 1500-1509.

Vieira, C., Parsons, P., & Byrd, V. (2018). Visual learning analytics of educational data: A Systematic literature review and research agenda. *Computers & Education, 122*, 119-135.

Weinberger, A., & Fischer, F. (2006). A Framework to analyze argumentative knowledge construction in computer-supported collaborative learning. *Computers & Education, 46*(1), 71-95.

Wise, A. F., Zhao, Y., & Hausknecht, S. N. (2013). Learning analytics for online discussions: A Pedagogical model for intervention with embedded and extracted analytics. In *Proceedings of the 3rd International Learning Analytics & Knowledge Conference* (pp. 48-56). New York, NY: ACM.

Yau, N. (2013). *Data points: Visualization that means something.* Somerset, NJ: John Wiley & Sons.

Yi, J. S., Kang, Y., Stasko, J. T., & Jacko, J. A. (2007). Toward a deeper understanding of the role of interaction in information visualization. *IEEE Transactions on Visualization and Computer Graphics, 13*(6), 1224-1231.

Yoo, M., & Jin, S. (2017). An Analytic review of dashboard based on learning analysis for online discussion activities. *The Journal of Educational Information and Media, 23*(3), 465-497.