Educational Technology International
2017, Vol. 18, No. 2, 73-99

Interaction of Learning Motivation with Dashboard Intervention and Its Effect on Learning Achievement*

Jeonghyun Kim, Ewha Womans University
Yeonjeong Park, Honam University
Dami Huh, Ewha Womans University
Il-Hyun Jo**, Ewha Womans University
Korea

The learning analytics dashboard (LAD) is a supporting tool for teaching and learning in its personalized, automatic, and visual aspects. While several studies have focused on the effect of using dashboard on learning achievement, there is a research gap concerning the impacts of learners' characteristics on it. Accordingly, this study attempted to verify the differences in learning achievement depending on learning motivation level (high vs. low) and dashboard intervention (use vs. non-use). The final participants were 231 university students enrolled in a basic statistics course. As a research design, a 2 x 2 factorial design was employed. The results showed that learning achievement varied with dashboard intervention and the interaction effect was significant between learning motivation and dashboard intervention. The results imply that the impact of LAD may vary depending on learner characteristics. Consequently, this study suggests that the dashboard interventions should be offered after careful consideration of individual students' differences, particularly their learning motivation.

Keywords: Learning analytics, Learning motivation, Learning achievement, Dashboard

---

* This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2015S1A5B6036244).
** Department of Educational Technology, College of Education, Ewha Womans Univ.
ijo@ewha.ac.kr

Introduction

One of the research trends in learning analytics is to develop application tools that support teaching and learning. Among the diverse tools, using a dashboard has been reviewed positively for several reasons. First, it recycles the vast amounts of messy aggregated data that learners leave during their learning progress in a way that assists their learning. Second, it provides customized feedback to individual students. Consequently, if the tool were considered useful to students, it would work as an educational intervention and could even prevent students' drop-out or facilitate their learning. Third, it is mostly real-time and automatically updated. With this feature, learners could get some help for learning by viewing a current and historical state of learners or a course. Fourth, it is social in given the information to compare activities of each learner with their peers'. Finally, it is visual and intuitive, by definition, with the most important information needed to achieve goals. Usually, dashboard aims to give at-a-glance summaries of the status with key indicators on a single computer screen (Few, 2013).

It was known as the dashboard could have four views (learner, educator, researcher, and institutional) and could be used in diverse learning environments (traditional face-to-face teaching, online learning, or blended learning settings) (Siemens et al., 2011). Especially in terms of learners, the learning dashboards can improve learners' self-knowledge and social awareness of other colleagues' learning status and activity. Self-knowledge is a fundamental value to foster one's insights, increase self-control (O'Donoghue & Rabin, 2003), and promote positive behavior (Seligman & Darley, 1977). Displaying information by a dashboard ranging from a descriptive summary of the learner record to the achievement or the drop-out prediction in various learning contexts has been proven to be effective (Ali, Hatala, Gašević, & Jovanović, 2012; Arnold & Pistilli, 2012; Dollár & Steif, 2012; Grann & Bushway, 2014).

However, whether these advantages of a dashboard apply equally to all learners is yet unclear. As Corrin & de Barba (2015) highlighted, students may differently interpret feedbacks delivered by the dashboard due to an inability to understand the visualized information or connect them to their learning strategies. In a similar vein, we doubted that different characteristics of learners would impact the interpretation of dashboard and further usage patterns. Learner characteristic has been reported to influence learner behavior, and given its wide range of properties, dashboard intervention may not be limited by only technological issues. As previous studies have focused on the verification of dashboard usefulness and did not assess differences in the effects of dashboard depending on learner characteristics, it would be meaningful to investigate the underlying mechanisms between dashboard intervention and learning achievement from learner characteristics aspects.

As an important learner characteristic, this study focused on learning motivation, which is a psychological and internal construct possessed to differing degrees by learners. Students' learning motivation, one of the most important factors in their learning achievement, has been dealt activity in the field of learning analytics as well. However, previous dashboard research has focused on whether the dashboard brings a change in the behavior of learners or whether learners are motivated through the provision of a dashboard, and the importance of motivation that learners already have has been overlooked. Given that providing an intervention to meet the characteristics of diverse learners leads to their active responses, considering individual differences in conducting learning intervention seems to be necessary and related research must be followed.

Therefore, in this study, we focused on the learner's motivation as a psychological trait and hypothesized that the effect of dashboard, as measured by students' learning achievement, would vary depending on their learning motivation. We provided a dashboard in actual learning situation and compared the difference in learning achievement of learners according to learning motivation levels and dashboard use or not. In this context, this study was a correlational research to enable the researchers to evaluate the relationships and effects among the variables.

The research questions are as follows:

Research Question 1. In online learning situation, does learning achievement vary with dashboard intervention?

Research Question 2. In online learning situation, the relationship between learning achievement and dashboard intervention is different at different levels of learning motivation?

Related Research

Dashboard in learning analytics

Learning analytics (LA) is defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Long, 2011, p.34). Verbert, Manouselis, Drachsler, & Duval (2012) analyzed several previous studies, and based on which, they classified the objectives of learning analytics into the following six parts:

- predicting learner performance and modeling learners,
- suggesting relevant learning resources,
- increasing reflection and awareness,
- enhancing social learning environments,
- detecting undesirable learner behaviors, and
- detecting affects of learners.

These objectives are closely related to each other rather than acting alone, and the main goal of LA is to produce actionable intelligence to improve learning processes and the environment for learners, educators and decision makers (Ferguson, 2012).

The volume and scope of available data related to learning have provided an important impetus to the development of LA (Siemens, 2013). As many learners are engaging learning from diverse online sources such as Google, Wikipedia or YouTube these days, richer data trails are created so that researchers could incorporate this large amount of data for more in-depth study of learning (Chatti, Dyckhoff, Schroeder, & Thüs, 2012). Plus, the development of affordable sensors capturing physiological responses has expanded the scope of LA so that researchers could get some insights into learning and learners (Spann, Schaeffer & Siemens, 2017).

As the scope of data widens, the very important challenge for LA research and practice is how to give stakeholders the insights effectively. One of the widely used methods is using visual representations and interaction techniques since it exploits human perception to make people understand data intuitively (Poon et al., 2017). For this reason, dashboard, "a rich computer interface with charts, reports, visual indicators, and alert mechanisms that are consolidated into a dynamic and relevant information platform" (Malik, 2005, p. ix), has been widely adopted in many researches as an intervention tool. Through dashboards, learners can compare their own learning progress with that of their peers, of previous learners who registered for the class in former semesters, and with the objectives established by themselves (Siemens, Gasevic, Haythornthwaite, Dawson, Shum, Ferguson, & Baker, 2011). Such information can contribute to learners' awareness, self-reflection, and ultimately induce new meaning or change behaviors (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). It could also support teacher's awareness of the state of their learners and classes intuitively and provide a foundation to facilitate adaptive educational interventions (Rodríguez-Triana et al., 2017).

There is a growing number of empirical evidence suggesting the effectiveness of using dashboards in LA research. Santos, Verbert, Govaerts, & Duval (2013) deployed the 'StepUp!' tool, and emphasized its usability and usefulness based on learners' evaluation results. Although they acknowledged the need for further critical evaluations, the research showed the potential impact of the learning analytics dashboard on learners' behavior. RioPACE (Progress and Course Engagement) is another example of such an application. It is an early alert system that provides specific information on students as warning levels and allows instructors to provide timely educational interventions based on learners' log-in frequency, site engagement, and pace (Smith, Lange, & Huston, 2012). Although the faculty-designed intervention which instructors and staff reach students via telephone did not make significant differences in success rates, the result showed the students given this direct intervention had more success than the others who didn't.

In recent years, with growing interest in collaborative learning and social learning analytics, practices that use visualization tools in online team learning situations to facilitate cooperation and interaction between learners are continually being reported (e.g. Hernández-García, González-González, Jiménez-Zarco, & Chaparro-Peláez, 2015; Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015). Additionally, research into the effectiveness of such visual applications in the mobile learning environment is underway (e.g. Melero, Hernández-Leo, Sun, Santos, & Blat, 2015).

Although most previous studies confirmed usefulness of dashboards, learners' psychological differences in dashboard intervention has been a largely unexplored topic. Since learners' characteristics are so diverse, some educational interventions might serve well but others poorly without their good intentions (Maier, Wolf & Randler, 2016). Thus, it has been found that considering individual differences in educational intervention and identifying the beneficiary of the intervention or vice versa are important. In this context, we explore the effects of learner characteristics on dashboard intervention, particularly learning motivation, and assess the underlying mechanisms among learning motivation, dashboard intervention and learning achievement.

Motivation in dashboard

The characteristics of learners are individual differences in knowledge, attitude, and preference in the progress of processing information, constructing meaning, and applying to new situations (Jonassen & Grabowski, 1993). These are known as influencing learning performance and among others, motivation has been considered as one of the most influential factors for learning outcomes. Schiefele & Rheinberg (1997) described the influence of motivation as the persistence and frequency of learning activities, mode of performed learning activities, and the motivational and functional states of the learner during learning. A learner with higher motivation pays more attention to learning outcome, and such attention leads to enhanced achievement (Zimmerman & Kitsantas, 1999). Although there have been several theoretical perspectives on motivation (e.g., competence motivation, mastery motivation, achievement motivation, etc.), there also has been agreement that motivation is the main force to sustain goal directed behavior (Pintrich & Schunk 2002) and individual differences in motivation are associated with learning outcomes (Amrai, Motlagh, Zalani, & Parhon, 2011; Broussard & Garrison, 2004).

Sustaining students' motivation or providing a personalized intervention depending on it are also important in LA, and the dashboard has been researched as a representative tool for this purpose. Learning on LMS, the learning environment of most learning analytics studies, is a self-regulated process and motivation works as a crucial factor for successful self-regulation (de Barba, Kennedy, & Ainley, 2016). Therefore, the dashboard in learning analytics has been developed for the way that increase students' learning motivation or their participation through monitoring their learning progress and adjusting their strategies to attain these goals. Although previous LA studies have verified the effects of dashboard in terms of the usefulness, but little has been known about the individual differences between the learners. (e.g. Arnold & Pistilli, 2012; Kerly et al., 2008; Kobsa, Dimitrova, & Boyle, 2005). In other words, learning outcomes brought by the application of dashboards have been covered, but interaction effects, caused by the differences of learners' motivation have not been covered that much. When dashboard use is not forced, by comparing dashboard users with non-users in two learning motivation groups (high vs. low), it is possible to explore how the motivation gap impacts the relationship between dashboard intervention and learning achievement, and lay a groundwork for developing more personalized intervention.

Unlike most previous studies to focus on the effect of intervention itself, this study began in question that dashboard would be equally helpful to all students. Some instructional interventions may be less effective or even harmful to some individuals (Cronbach & Snow, 1977), and we can assume that learners with different levels of learning motivation would express different reactions or academic results following application of the same educational intervention. Therefore, we investigated the interaction effect between learning motivation and dashboard intervention under the assumption that the effect of dashboard intervention would vary depending on the level of learners' motivation. Through this research, we expect to examine the relationship between motivation and dashboard intervention better, and provide insight into the more optimal dashboard intervention.

Methods

Study design and settings

The advantage of this kind of research, a correlational design research which the study followed, is that it is possible to provide us a natural perspective to research questions (Field & Hole, 2002). The purpose of our research was to investigate the differences of motivation or achievement between the learners who used dashboard and who used not. The study was conducted in real learning situation, not under controlled conditions, and the dashboard was presented as an option in the class.

A total of 318 students' data, who took the online course entitled "Management Statistics" in the spring (188 students) and fall (130 students) semesters of 2014, was used for study. The course was a 100% online course opened in a women's university located in South Korea. But there was an offline orientation at the beginning of the semester, and to proceed them more fairly, midterm and final examinations were conducted in class. As a full online course, students were required to have access to the virtual learning environment, called Cyber Campus, to watch video lectures in accordance with the progress in class, to take online quizzes, and to submit individual tasks for successful course completion.

The provided contents, professor, semester period, and elements of evaluation were identical during the two semesters, but depending on the semester, the impact on the final score was slightly different. The impact on the final score of the spring semester course was weighted as follows: virtual attendance (5%), individual tasks (10%), quiz (10%), midterm examination (30%) and final examination (45%). The fall semester course's impact on the final score was weighted as follows: virtual attendance (5%), individual tasks (10%), midterm examination (35%) and final examination (50%). Because the midterm and final examination scores were a large portion of the total score and our dashboard was provided after midterm, final examination score was the most appropriate method to examine the student's achievement with dashboard effectiveness. For this reason, we converted each learner's final examination score to the standard scoring and used it as an indicator of learning achievement.

Research procedure and collected data

The research process was as follows. First, at the beginning of each semester, students' learning motivation was measured by Motivated Strategies for Learning Questionnaire (MSLQ). The survey was translated into Korean using a back-translation procedure. MSLQ is a well-known self-report instrument developed to assess college student' motivational orientations and their use of different learning strategies (Pintrich, Smith, García, & McKeachie, 1993). It includes two sections, a motivation section (31 items) and a learning strategies section (50 items), and we used all 31 items included in the motivation section. The items were about students' goals and value beliefs for a course. One of the features of a dashboard that we developed was to provide learners with information about their level of participation in their learning activities compared with their peers'. The purpose was to facilitate learners' learning motivation and ultimately lead them to real action for better achievement. Therefore, MSLQ, the survey made for understanding learners' self-regulated learning ability with sub-factors of motivation and learning strategy, was in line with the context of this study. Several studies using the Korean version have shown its reliability with an alpha coefficient of at least .867 (Park & Sung, 2012; Park, 2010); in our study, the alpha coefficient of the items was .79. Responses were measured on a 5-point Likert-type response scale ranging from 1 (not at all) to 5 (strongly agree).

Second, immediately after the midterm examination (on week 7), the learning analytics dashboard (LAD, from here in we use this term for the dashboard that we design and develop), was given to students as an option. LAD is a newly developed tool by the authors to support learners to present the state of their learning progress and classes. It utilized multiple visual representations and interaction techniques so that learners could grasp the information intuitively. It was developed in four steps: 1) First, to find key elements of the dashboard, literature review of journal articles and proceedings published between 2005 and 2013 was done. We followed what Verbert et al., (2013) suggested to select nine representative sample dashboards, and set four criteria for comparison: a) intended goals and target users, b) data-extraction and mining, c) visualization, and d) evaluation. 2) Second, universal design and development steps were implemented: a) needs assessment, b) rapid prototyping, c) usability test, and d) findings. Moreover, our design work was based on a series of previous studies (Jo, Ha, & Park, 2015; Park & Jo, 2014; Park & Jo, 2015) and thus the included information were products of these previous studies. 3) Third, the rapid prototyping process was followed. 4) Finally, the last evaluation was conducted with a pilot test and two surveys. After all these steps, modified version of LAD was made and used for this study.

One of the features learners wanted was to provide visualizations of students' learning traces and their peers at the same time. Students could check the average

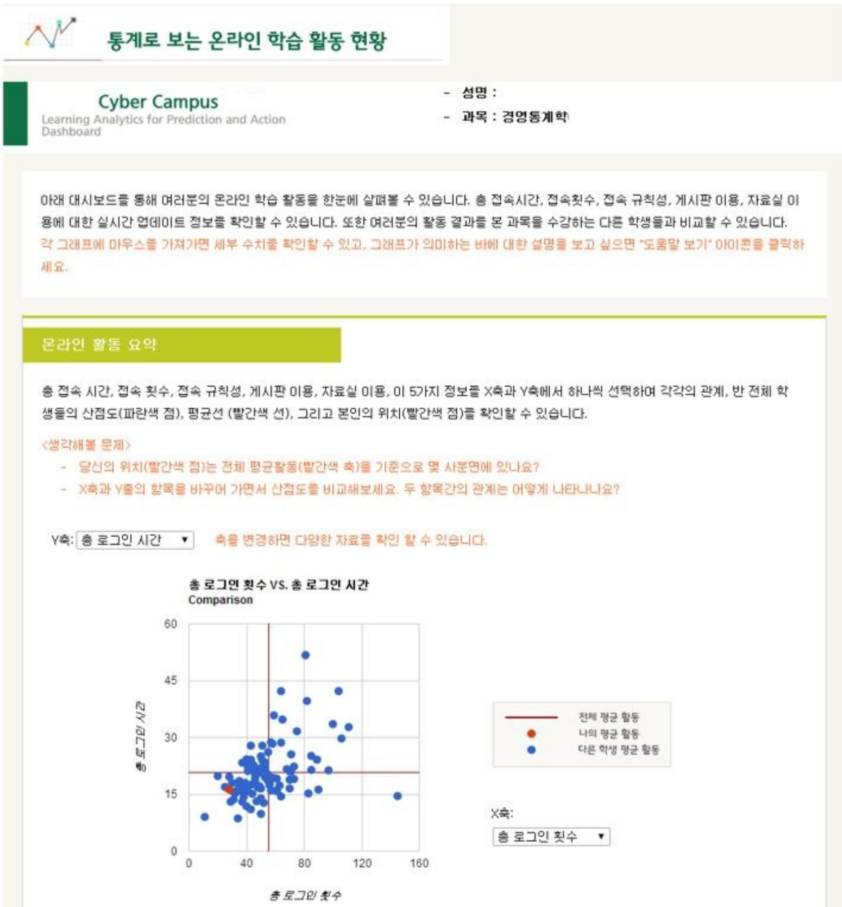

Figure 1. Screenshot of LAD

trends of peers apart from their own online activities by using the LAD. The way of showing the behavior of others is known to be effective in leading people's actions in a positive direction (Kahneman, 2011). The information presented on the LAD was divided into the two categories: 1) LMS access (i.e. total log-in time, total log-in frequency, log-in regularity), 2) usage of discussion or repository board (i.e. time spent on board, frequency on board, log-in regularity on board). Figure 1 shows a screen shot of LAD. At the top of the learning page, the icon "Learning analytics" was provided after the midterm examination. By clicking that icon, learners were connected to the LAD screen whenever they want.

Finally, web log files to investigate whether learners used the dashboard and the final examination scores to assess learners' learning achievement were extracted from the LMS after the semester was over. Second, as an indicator of the dashboard intervention, the sum of the number of times each student opened LAD was calculated based on the web log files recorded on the LMS, and was coded to the dummy variable (0, 1) which shows learners' dashboard use (or not). Finally, the final examination score converted to the standard scoring was used to measure students' learning achievement. The final examination items included multiple choice and short answer questions, such as interpretation of the results of statistical analysis.

In this study, learners' participation was voluntary and researchers made it clear that participation decision would not influence evaluation and grading. As a result, the number of distributed questionnaires was 318, but 77 responses were not included in our analysis due to missing answers, disagree to participation, or obvious careless responding (e.g. midpoint responding). And the responses of three students who did not take the final examination and seven students who showed the median learning motivation score were also excluded, as the study used a median-split procedure to generate high and low motivation groups. After removing all the above cases, the final sample contained 231 students and the response rate of the survey was 73% (231 of 318). The participants were 100%

female, and were from a variety of majors, such as business administration, architectural engineering, psychology, law, Chinese language, and literature. They were evenly distributed from the first to the fourth grade.

Statistical analysis

The analysis was performed with a 2 x 2 factorial design. One independent variable was learning motivation with one level low score (under the median) and the other level high score (above the median). The other independent variable was dashboard use or not with one level being unused and the other level used cases. R programming was used to generate the results of analysis. Each test was performed at a significance level of 0.05.

Results

Since the data were collected during the spring and fall semesters, and the dependent variable was the learning achievement (the final examination score), a t-test was performed to identify a significant difference in the final examination scores between the two semesters. The t-test showed that the difference in the final examination scores was not significant ($t=.677$, $p > .05$) so that both datasets were used.

Table 1 shows descriptive statistics of the entire study population. However, since students were grouped into two categories based on the learning motivation level (i.e. high and low) using a median-split procedure, the mean scores were 3.76 and 3.21 and the numbers of students were 114 and 117, respectively. Only 118 students were grouped into dashboard use. Frequency of use ranged from 1 to 25.

Table 2 shows the means and standard deviations of students with high and low motivation, and between students who did and did not use dashboard. Students with high motivation (mean = 69.33, SD = 17.94) showed higher final examination

Table 1. Descriptive statistics of the entire study population

	Minimum	Maximum	Mean	Std Dev	n
Learning motivation	2.58	4.61	3.48	0.33	231
Dashboard intervention	0	25	1.18	2.54	231

scores than their counterparts (mean = 57.09, SD = 22.96). Also, the dashboard use students (mean = 67.23, SD = 19.68) showed higher final examination scores than the dashboard non-use students (mean = 58.85, SD = 22.52). The dashboard use students with high motivation showed the highest scores (mean = 70.63, SD = 17.67), and the dashboard non-use students with low motivation showed the lowest scores (mean = 49.50, SD = 22.73). Levene's test of homogeneity to test for equality of variances showed that the error variance of the final score was equal across groups, $F(3, 227) = 2.606$, $p > .05$.

Table 2. Means and standard deviations of the variables

		Learning motivation		
		Low motivation	High motivation	Total
Dashboard non-use student	Mean	49.50	68.04	58.85
	Std Dev	22.73	18.27	22.52
	n	56	57	113
Dashboard use student	Mean	64.05	70.63	67.23
	Std Dev	21.04	17.67	19.68
	n	61	57	118
Total	Mean	57.09	69.33	63.13
	Std Dev	22.96	17.94	21.48
	n	117	114	231

To investigate whether learning motivation and dashboard use or non-use are related to learning achievement, a 2 (learning motivation: high vs. low) x 2 (dashboard use or not: use vs. non-use) factorial design was used. The main effects of learning motivation and dashboard intervention were statistically significant for learning achievement, $F(1, 230) = 22.67$, $p < .05$ and $F(1, 230) = 10.56$, $p < .05$, respectively (Table 3). Therefore, learning motivation and dashboard use or non-use had positive impacts on learning achievement. Above all, the interaction effect (learning motivation x dashboard intervention) was significant for learning achievement. As seen in Figure 2, the graph of the students with high motivation showed a larger intercept than the students with low motivation. But the slope was steeper when the learning motivation was low. That is, LAD had a positive effect on the learning achievement of both the groups, but there was a significant difference in the degree of the effect. If students had low learning motivation, dashboard intervention had a strong impact on learning achievement. However, it had no significant effect on their counterparts. In other words, if the learning motivation level was not considered, the students using dashboard generally showed better learning achievement. However, when learning motivation level was considered, dashboard intervention had a strong impact on the learning achievement only of students with low learning motivation. Figure 2 shows the interaction effects.

Table 3. Tests of between-subjects effects

Source	Sum of squares	df	Mean square	F	Sig.
Learning motivation	9098.70	1	9098.70	22.67	0.00
Dashboard intervention	4239.71	1	4239.71	10.56	0.00
Learning motivation x Dashboard intervention	2060.43	1	2060.43	5.13	0.02
Error	91128.05	227	401.45		
Total	106162.10	230			

$p < .05$.

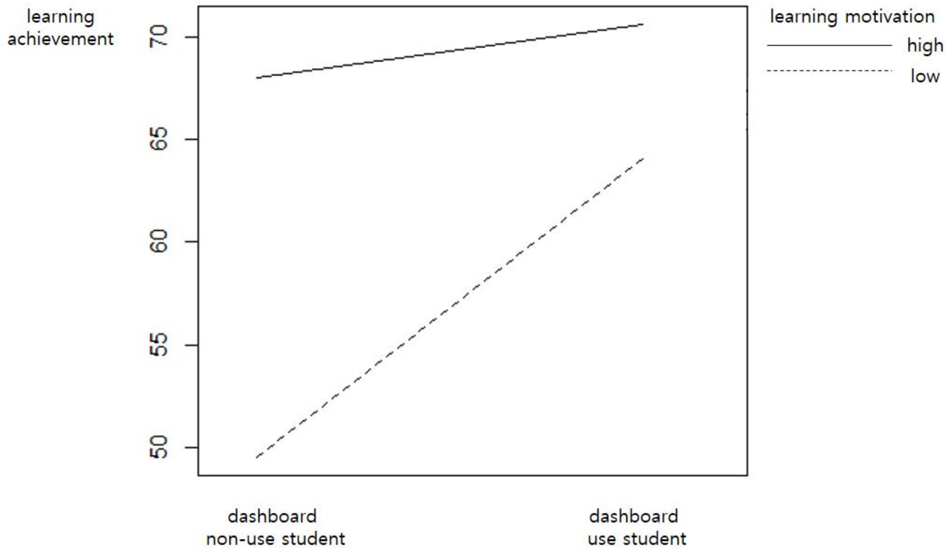

Figure 2. 2 x 2 Interaction on the final examination score

Discussion

In this study, we investigated the relationship among learning motivation, dashboard intervention and learning achievement and laid a groundwork for insights into the more optimal dashboard intervention. Results also showed that learning achievement varied with learning motivation, which has been consistently proven through previous studies, but we do not discuss it further here. In this section, we focused on the discussions whether learning achievement varies with dashboard intervention and whether the relationship between learning achievement and dashboard intervention is different at different levels of learning motivation.

First, learning achievement varied with dashboard intervention. Students who used dashboard showed higher learning achievement than the counterparts. It can be related to the fact that dashboard is known to provide learners with insights into the learning progress and contribute to learner's self-reflection and self-awareness (Grann & Bushway, 2014; Verbert et al., 2013). In case of the Course Signals research at Purdue University, which included surveys, focus groups, and interviews to assess the usability of the system, 74% of students responded that the system was informative and positively affected their learning motivation (Arnold & Pistilli, 2012). These characteristics were also evident in this study, and resulted in a gap in learning achievement. However, only few studies as to the dashboard effect have been conducted in real education settings, and most studies on the effectiveness or the perceived usefulness of the dashboard were carried out in the laboratory environment (e.g. Kerly et al., 2007; Kobsa, Dimitrova, & Boyle, 2005). Moreover, the conclusion about the usefulness of the dashboard on learning outcomes was not consistent among the previous ones. That is why Verbert et al. (2013) pointed out that only Course Signals research (Arnold & Pistilli, 2012) verified the impact of dashboard on learning. They argued that longitudinal studies of the dashboard in learning analytics field are required to assess the contribution of the dashboard to learners' behavior change and ultimate teaching-learning progress. For this context, more studies in a variety of learning environments and contexts to explore the relationship between dashboard intervention and learning achievement are needed.

Most of all, the interaction effect (learning motivation x dashboard intervention) was significant. This finding provides a new perspective and suggests the need for caution in exploring dashboard intervention. That is, although a dashboard is known for its multiple strengths, its effects may vary depending on learners' motivation level. However, when we consider that previous studies did not report consistent results about the effect of dashboard intervention, the factors which could influence the relationship between learning motivation and learning achievement should be explored more in depth to examine the dynamics of learners' motivation and effectiveness of using a dashboard on learning achievement much clearer. First, the types of contents, included in the dashboard, can affect the relationship between the dashboard intervention and learning achievement. In this study, information provided by LAD, such as learning traces of peers, may rather serve as unnecessary noise that prevents the concentration on study to learners with high motivation. That is, because the learners with high motivation are already well equipped for success in the course, the information they needed may have been the things helping them to reflect their own goals. Corrin & de Barba (2014) reported the research which examined the dashboard providing information on learners' assessment and engagement. In their study, the students with above the average performance were satisfied with their achievement status, despite it being below the goal established in advance. Moreover, in their another study (Corrin & de Barba, 2015), although the results of a survey and interview on how learners interpret the information presented on the dashboard indicated that the provision of class average on the dashboard showed a positive influence for most students, for some students, that information was also a factor to provide a distraction to the goal. Therefore, it is necessary to investigate the interaction between the contents provided in the dashboard and the level of learning motivation in depth before generalizing the results of this study.

The possibility that the comprehension of the information can be varied depending on the type of information or the way it is provided should also be explored more in detail. The data presented in the dashboard should be designed in a way that learners can intuitively understand and feel that it meets their interests or needs. In LAD, the information was presented by graphs that incorporate different types of data, and dashboard usage was dependent on the learners' willingness to use it. This way of information provision may influence the interest or willingness of the learners, and thus may have affected the learners' motivation to use the dashboard or the extent of the use.

In summary, this study is significant in that it proved the effectiveness of the dashboard intervention. However, because what content would be presented or how to provide it can work on the relationship between learning motivation and learning achievement, related research should be expanded to confirm the effectiveness of the dashboard intervention and the relationship between the two.

Limitations and further studies

This study provided a dashboard which has been proven its usefulness through the previous studies and aimed to identify the relationship among learning motivation, dashboard intervention, and learning achievement. Although verifying the effect of the dashboard in the real learning environment was the important significance of the study, but there were insufficient aspects to involve detailed experimental designs such as laboratory research. Moreover, due to the characteristics of the field application research, whose data can be collected only with the institutional approval and cooperation, there were also some limitations in terms of data collection.

Some suggestions for further research are as follows: First, despite various psychological characteristics of learners, this study tried to verify the interaction effect of dashboard intervention within the boundary of learning motivation. Although not investigated in this study, various learner characteristics would likely lead to the similar result. Furthermore, learning motivation itself can be also influenced by the various characteristics. Therefore, in conducting further research, to involve more psychological characteristics of learners and to confirm whether learning motivation is influenced by these characteristics should be proceeded.

Second, the research to look at the interaction between learning motivation and the formats of the dashboard intervention such as the amount of information, the type of data, and the graphic type may also provide meaningful implications to identify the effectiveness of dashboard intervention. The research as to the information visualization of dashboard intervention should be followed.

Third, follow-up studies including different types of variables can be suggested. For example, learning motivation can be considered as a continuous variable so that the effect of learning motivation on dashboard intervention can be conceived. Moreover, supplementing additional variables, such as dashboard usage time, log data or learning motivation after dashboard intervention, would be also helpful to reveal the mechanism underlying the effect of dashboard intervention more in depth.

Fourth, there is a need to study practical guidelines for applying learning analytics intervention to the field. Pressler (2014) insisted the "silo-ed" nature of most institutions make learning analytics practices difficult to proceed in an efficient way. Furthermore, the issues such as privacy, non-discrimination and the presumption of innocence, which are inherently involved in the characteristics of LA, act as a big challenge in applying the LA intervention to the field. We also went through serious consultations with the institution that owns the data and the course instructor. However, the guidelines for implementing LA intervention are not found, and this makes field application research more difficult.

Finally, widened scope of data and advanced analytics techniques can be utilized for the research. As data collection and analysis technologies have developed, it has become possible to consider the possibility of tailoring the learning progress of individual students. Since motivational and psychological traits are essential factors in personalized learning process (Lonn, Aguilar, & Teasley, 2015), these developments will facilitate accurate measurements of the psychological state of students. In this study, learning motivation was measured via self-report. Although self-report methods could provide insights on their own, but the aim of LA, providing timely intervention driven from real-time data is difficult to be achieved with these techniques. As several attempts to understand users' emotion and cognitive status through psychophysiological measures have been successful (Dirican & Göktürk, 2011; Brouwer, Zander, Van Erp, Korteling, & Bronkhorst, 2015), measuring learning motivation more objectively and developing more elaborate description models seem feasible. Therefore, we suggest considering the possibility of using data from multiple sources.

The results of this study should be interpreted with caution because it investigated the effect of dashboard intervention only according to whether learners used a dashboard or not; the extent of use was not considered. Additionally, this investigation only focused on learning motivation among various psychological traits. However, despite its limitations, this study has its meaning in that it showed the effect of dashboard on learning achievement and verified the mechanism underlying the effect of the interactions between dashboard intervention and learning motivation. Moreover, it suggested the role of learner characteristics for dashboard intervention. Since the psychological characteristics of learners are complex, conducting instructional intervention is challenging. However, although learner characteristics are convoluted, there would be indeed key indicators to predict learners' achievement, and identifying such key indicators of achievement will be the only way to facilitate improvement of learning quality.

References

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.

Amrai, K., Motlagh, S. E., Zalani, H. A., & Parhon, H. (2011). The relationship between academic motivation and academic achievement students. *Procedia-Social and Behavioral Sciences, 15*, 399-402.

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at purdue: Using learning analytics to increase student success. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge,* 267-270.

Broussard, S. C., & Garrison, M. (2004). The relationship between classroom motivation and academic achievement in elementary-school-aged children. *Family and Consumer Sciences Research Journal, 33*(2), 106-120.

Brouwer, A. M., Zander, T. O., van Erp, J. B., Korteling, J. E., & Bronkhorst, A. W. (2015). Using neurophysiological signals that reflect cognitive or affective state: Six recommendations to avoid common pitfalls. *Frontiers in Neuroscience, 9*, 136. doi:10.3389/fnins.2015.00136 [doi]

Card, S. K., Mackinlay, J. D., & Shneiderman, B. (1999). *Readings in information visualization: Using vision to think* Morgan Kaufmann.

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*(5-6), 318-331.

Corrin, L., & de Barba, P. (2014). Exploring students' interpretation of feedback delivered through learning analytics dashboards. *Proceedings of the Ascilite 2014 Conference,* 629-633.

Corrin, L., & de Barba, P. (2015). How do students interpret feedback delivered via dashboards? *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge,* 430-431.

Cronbach, L. J., & Snow, R. E. (1977). *Aptitudes and instructional methods: A handbook* *for research on interactions*. Irvington.

Dirican, A. C., & Göktürk, M. (2011). Psychophysiological measures of human cognitive states applied in human computer interaction. *Procedia Computer Science, 3*, 1361-1367.

Dollár, A., & Steif, P. S. (2012). Web-based statics course with learning dashboard for instructors. *Proceedings of Computers and Advanced Technology in Education (CATE 2012),*

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

Field, A., & Hole, G. (2002). *How to design and report experiments* Sage.

Grann, J., & Bushway, D. (2014). Competency map: Visualizing student learning to promote student success. *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge,* 168-172.

Hernández-García, Á., González-González, I., Jiménez-Zarco, A. I., & Chaparro-Peláez, J. (2015). Applying social learning analytics to message boards in online distance learning: A case study. *Computers in Human Behavior, 47*, 68-80.

Jo, I. H., Ha, K., & Park, Y. (2015). Measuring Information Perception in Learning Analytics Dashboard: Use of Eye-Tracking System. *The Journal of Educational Information and Media, 21*(3), 441-469.

Jonassen, D., & Grabowski, B. (1993). Individual differences and instruction. New York: Allen & Bacon.

Kahneman, D. (2011). *Thinking, fast and slow* Macmillan.

Kerly, A., Ellis, R., & Bull, S. (2008). CALMsystem: A conversational agent for learner modelling. *Knowledge-Based Systems, 21*(3), 238-246.

Kosba, E., Dimitrova, V., & Boyle, R. (2005). Using student and group models to support teachers in web-based distance education. *International Conference on User Modeling,* 124-133.

Lievens, F., Coetsier, P., De Fruyt, F., & De Maeseneer, J. (2002). Medical students' personality characteristics and academic performance: A five-factor model perspective. *Medical Education, 36*(11), 1050-1056.

Lonn, S., Aguilar, S. J., & Teasley, S. D. (2015). Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. *Computers in Human Behavior, 47*, 90-97.

Maier, U., Wolf, N., & Randler, C. (2016). Effects of a computer-assisted formative assessment intervention based on multiple-tier diagnostic items and different feedback types. *Computers* & *Education, 95*, 85-98.

Malik, S. (2005). *Enterprise dashboards: Design and best practices for IT* John Wiley & Sons.

Melero, J., Hernández-Leo, D., Sun, J., Santos, P., & Blat, J. (2015). How was the activity? A visualization support for a case of location-based learning design. *British Journal of Educational Technology, 46*(2), 317-329.

O'Connor, M. C., & Paunonen, S. V. (2007). Big five personality predictors of post-secondary academic performance. *Personality and Individual Differences, 43*(5), 971-990.

O'Donoghue, T., & Rabin, M. (2003). Self-awareness and self-control, time and decision: Economic and psychological perspectives on intertemporal choice.

Park, Y., & Jo, I. H. (2015). Development of the Learning Analytics Dashboard to Support Students' Learning Performance. *J. UCS, 21*(1), 110-133.

Park, Y., & Jo, I. H. (2014). Design and Application of Visual Dashboard Based on Learning Analytics. *The Journal of Educational Information and Media, 20*(2), 191-216.

Pintrich, P. R. (2003). A motivational science perspective on the role of student motivation in learning and teaching contexts. *Journal of Educational Psychology, 95*(4), 667.

Pintrich, P. R, & Schunk, D. (2002). Motivation in education: Theory, research, and application. *Columbus, OH: Merrill Prentice Hall.*

Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the motivated strategies for learning questionnaire

(MSLQ). *Educational and Psychological Measurement, 53*(3), 801-813.

Poon, L. K., Kong, S., Yau, T. S., Wong, M., & Ling, M. H. (2017). Learning analytics for monitoring students participation online: Visualizing navigational patterns on learning management system. *International Conference on Blended Learning,* 166-176.

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin, 135*, 322.

Pressler, E. J. (2014). Logging in to learning analytics. *Current Issues in Emerging eLearning, 1*(1), 6.

Rodríguez-Triana, M. J., Martínez-Monés, A., Asensio-Pérez, J. I., & Dimitriadis, Y. (2015). Scripting and monitoring meet each other: Aligning learning analytics and learning design to support teachers in orchestrating CSCL situations. *British Journal of Educational Technology, 46*(2), 330-343.

Rodríguez-Triana, M. J., Prieto, L. P., Vozniuk, A., Boroujeni, M. S., Schwendimann, B. A., Holzer, A., & Gillet, D. (2017). Monitoring, awareness and reflection in blended technology enhanced learning: A systematic review. *International Journal of Technology Enhanced Learning, 9*(2-3), 126-150.

Schiefele, U., & Rheinberg, F. (1997). Motivation and knowledge acquisition: Searching for mediating processes.

Seligman, C., & Darley, J. M. (1977). Feedback as a means of decreasing residential energy consumption. *Journal of Applied Psychology, 62*(4), 363.

Shin, M. (1998). Promoting students' self-regulation ability: Guidelines for instructional design. *Educational Technology, 38*(1), 38-44.

Siemens, G., Gasevic, D., Haythornthwaite, C., Dawson, S. P., Shum, S., Ferguson, R., Baker, R. (2011). Open learning analytics: An integrated & modularized platform.

Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 30.

Smith, V. C., Lange, A., & Huston, D. R. (2012). Predictive modeling to forecast student outcomes and drive effective interventions in online community college courses. *Journal of Asynchronous Learning Networks, 16*(3), 51-61.

Spann, C. A., Schaeffer, J., & Siemens, G. (2017). Expanding the scope of learning analytics data: Preliminary findings on attention and self-regulation using wearable technology. *Proceedings of the Seventh International Learning Analytics* & *Knowledge Conference,* 203-207.

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

Verbert, K., Govaerts, S., Duval, E., Santos, J. L., Van Assche, F., Parra, G., & Klerkx, J. (2014). Learning dashboards: An overview and future research opportunities. *Personal and Ubiquitous Computing, 18*(6), 1499-1514.

Verbert, K., Manouselis, N., Drachsler, H., & Duval, E. (2012). Dataset-driven research to support learning and knowledge analytics. *Journal of Educational Technology* & *Society, 15*(3), 133.

Zimmerman, B. J., & Kitsantas, A. (1999). Acquiring writing revision skill: Shifting from process to outcome self-regulatory goals. *Journal of Educational Psychology, 91*(2), 241.

Jeonghyun KIM
Postdoctoral researcher, Educational Research Institute, College of Education, Ewha Womans University.
Interests: Learning Analytics, Social Network Analysis, Human Resource Development, Mobile and Smart Learning
E-mail: naralight@naver.com

Yeonjeong PARK
Assistant Professor, Dept. of Early Childhood Education (Dedicated Professor, Institute of Teaching and Learning), Honam University.
Interests: Mobile and Smart Learning, Socio-cultural Aspects of Learning, Learning and Academic Analytics, Higher Education
E-mail: ypark@honam.ac.kr

Dami HUH
Master Student, Dept. of Educational Technology, College of Education, Ewha Womans University.
Interests: Learning Analytics, MOOCs, Social Network Analysis, Data Visualization, Human Resource Development
E-mail: supremed14@ewhain.net

Il-Hyun JO
Professor, Dept. of Educational Technology, College of Education, Ewha Womans University.
Interests: Learning Analytics, Social Network Analysis, Knowledge Management, Human Resource Development, Mobile-based Informal Learning in Workplace
E-mail: ijo@ewha.ac.kr

Received: August 24, 2017 / Peer review completed: October 04, 2017 / Accepted: October 05, 2017