Factors investigation of learning behaviors affecting learning performance and self-regulated learning

Li Chen
Graduate School of Human-Environment Studies
Kyushu University
Fukuoka, Japan
chenli@mark-lab.net

Yoshiko Goda
Research Center for Instructional Systems
Kumamoto University
Kumamoto, Japan
ygoda@kumamoto-u.ac.jp

Atsushi Shimada
Faculty of Information Science and Electrical Engineering
Kyushu University
Fukuoka, Japan
atsushi@limu.ait.kyushu-u.ac.jp

Masanori Yamada
Faculty of Arts and Science
Kyushu University
Fukuoka, Japan
mark@mark-lab.net

***Abstract*—This study examined the factors of learning behaviors that predict university students' learning outcomes including learning performance and self-regulated learning awareness improvement in a higher education institution in Japan. Stepwise multiple regression analyses were conducted with a sample of 70 freshman university students. The results revealed that the learning behavior of changing pages using functional tools (bookmarks, markers), which are related to rehearsal strategies, are helpful for learning outcomes. In addition, the effects of learning behaviors on learning outcomes vary and are related with the different levels of content.**

Keywords—learning analytics, learning behavior, self-regulated learning, learning performance

I. INTRODUCTION

Self-regulated learning (SRL) is considered a critical factor in students' learning process and environment. Furthermore, it is believed to help effectively achieve learning goals such as test scores or skills in learning, and ultimately in self-instruction in future learning [1]. SRL is a self-directed process and closely related with cognitive and metacognitive strategies and motivation [2]. As technology advances, data collection methods have become diverse and convenient, especially for situations in which it is difficult to observe or record learning processes. For example, the Learning Analytics (LA) approach enables collecting and analyzing test scores and questionnaire data, as well as learning logs that can indicate learning behaviors. This promising approach provides a new direction for analyzing and exploring the effects of students' learning behaviors on their learning performance and learning awareness such as SRL.

II. LITERATURE REVIEW

A. *Self-regulated Learning and Learning Analytics*

As one component of strategic learning, SRL strategies are related with learners' actions and processes in terms of metacognition and motivation aspects, and directed by the acquisition of information or skills including learners' agency, purpose, and perceptions (Zimmerman, 1989; Tobias and Everson, 2009; Weinstein, Acee, Jung, 2011). As important aspects of SRL, cognitive learning strategies and metacognition involving the abilities to plan, monitor, regulate, and evaluate one's own learning are considered effective in regulating learning [3][4][5].

Planning activities include learning cognitive strategies such as dividing major goals into several manageable ones or managing time efficiently, asking oneself questions before reading the material, and analyzing tasks before performing them [3]. Monitoring activities includes observing and recording one's learning behaviors and tracking how learning strategies are used during the learning process [3][6]. Monitoring is considered important in SRL in terms of helping learners identify the sufficiency and deficiency of their learning processes and adjust learning strategies or choose better learning behaviors for the next phase [7]. Regulation activities involve revising deficient learning strategies such as by summarizing the learning contents or re-reading texts they do not understand well, adjusting the pace, or reviewing other related references based on monitoring activities and results [3][8]. The aim of evaluating activities is to make a judgment on the quality of the learning process and performance to determine whether the learning strategies applied are effective [9].

Monitoring is considered the intermediate phase between planning and evaluation. In the monitoring phase, learners focus on observing and recording behaviors according to the criteria set in the planning phase, and compare the results of this observation with the criteria in the evaluation phase [6].

Students' SRL activities and processes are generally measured through two major methods: observation of learners' performance and self-reports [4]. However, some challenges remain in measuring learners' SRL using these two methods. For example, it is difficult to develop effective and efficient methods to assess the use of cognitive strategies and metacognition, considering the labor-consuming complexity of observation and recording processes; limitation of observable numbers of participants; and accuracy of responses in learners' self-reports, which relies on learners' self-awareness and perception [4][10][11].

Thus, LA is considered a promising method to record learners' learning behaviors and processes. For example, the operations of learners on systems or their interaction through computers can be collected as learning logs to show how they conduct or change their cognitive learning strategies [4]. Here, the LA approach is adopted to help monitor and measure learners' learning behaviors and processes, and ultimately improve their SRL skills.

B. Learning Analytics and Learning Behaviors

As a growing field, the LA approach is considered a promising way by which to understand and improve learning by connecting data analysis with learning design and academic practices, and exploring effective tools and methods during the process [12][13]. Many studies have used LA to collect and analyze data on learners' learning behaviors and process, and related these data to cognitive learning strategies, learning performance, and learning awareness. For example, Oshima et al. [14] proposed a mixed-methods approach to measure the interaction among learners by quantitatively analyzing key points of discourse exchanges and exploring dialogical patterns through discourse analysis. Van Leeuwen [15] confirmed that the LA approach was effective in aggregating information to an understandable and manageable level, and supporting teachers in diagnosing students' progress and situations.

During individual learning and lectures at school, the learning strategies students use are often related with learning performance [16][17][18]. Therefore, it is important to understand students' individual learning and thinking behaviors, and how they use learning strategies. The LA approach is accepted as an effective way to collect and analyze academic data on learning behavior, which are considered factors of strategy, and to clarify the relationships with or effects on learners' learning performance. For example, Gašević et al. [17] collected and analyzed students' learning strategies according to self-report data concerning the learning process and trace data related to preparation activities before the lecture. They found that deep learning strategies promoted learning performance. From a broader perspective of the relationships between learning behavior data and learning performance, Bazelais et al. [19] examined the relationship between students' high school scores with their learning performance in a pre-university program using data of 9,877 students in a physics course. They confirmed that prior high school performance achievement was a strong predictor of college performance.

In higher education, the increased use of technology enables collecting data from various resources. For example, students' learning logs can be collected from the Learning Management System (LMS) and defined as their online behaviors. In previous research, many online behavior variables were collected and defined as students' frequency and duration of online participation, such as number of logins, link or materials accessed, the duration spent, page hits, discussion posts, and discussion reads [20][21]. In addition to learning activities in LMS, previous studies have also analyzed learning behaviors for operating e-book reader systems to clarify students' reading and thinking processes. For example, by using functional tools of e-book reader systems such as highlighting, bookmarks, and a keyword search, students can choose and use their learning strategies when reading learning materials [16][18][22]. Yamada et al. [23] investigated the relationships between the learning log, learning performance, and concept map use with cognitive learning strategy. Onoue et al [24] developed a learning analytics platform that visualizes concept map construction models. By collecting and analyzing these kinds of learning logs, students' learning behaviors using different strategies can be clarified.

The studies cited above indicate that measuring learners' learning behaviors is important and useful in understanding their cognitive learning processes and strategies, and in supporting the development of their SRL skills. However, considering the difficulties in the method and process of measuring learning processes, especially when dealing with a large number of students such as in higher education, LA is a helpful method to analyze learning behaviors and explore the effect of behaviors on several learning outcomes. In this study, we set three research questions (RQ):

RQ 1: What are the effects of learning behaviors on students' learning performance in a higher information technology course?

RQ 2: What are the effects of learning behaviors on students' SRL awareness in a higher information technology course?

RQ 3: What are the different effects of learning behaviors on students' learning performance and SRL awareness based on different types of course contents?

III. Methodology

A. Participants and the course

This study was conducted in an eight-week information technology course, namely "Cybersecurity Fundamentals." The participants were 70 freshman university students.

The time of 1 lecture per week was 90 minutes. During the course, students study primary cybersecurity issues including basic technologies, laws, and ethics.

Before each lecture, the teacher distributed the learning materials on the BookRoll system, which was used as a digital learning material reader. Students were asked to preview the learning materials in advance before each lecture. During the lesson, students were also required to bring their laptop to class, and access the learning materials on their own devices.

Students can use some functions of the BookRoll system while viewing the materials including the *Marker function* to highlight the contents on a page or *Annotation function* to add annotations, *Bookmark function* to post bookmarks within the materials, and *Search function* to search learning materials using keywords [25]. All students' operations in using these functions can be recorded and collected as learning logs, and used to represent their cognitive learning strategies in terms of reading learning materials. In the last ten minutes of each lecture, students took the comprehension test on the current contents.

B. Data collection

Data were collected using three methods: tests, questionnaires, and learning logs. The test for each lecture counted 10 marks, which represented learners' learning performance. The final test score used in this study was the sum of eight tests (80 full marks), and the assessment for their attendance and assignment submission (20 full marks).

Before and after the course, the Motivated Strategies and Learning Questionnaire (MSLQ) was administered as a pre- and post-questionnaire. The MSLQ is a self-reporting instrument developed by Pintrich and DeGroot [2] consisting of five factors: self-efficacy (SE), intrinsic value (IV), cognitive strategies (CS), self-regulation (SR), and test anxiety (TA). Moreover, in SRL, it is important to recognize when one's learning needs revision and when and how to ask others for help and support [4]. In this course, students were expected to seek help and support from others if they had difficulties with learning, especially during the learning time and activities outside the lecture. Thus, an additional factor, help seeking (HS) from Wolters et al. [26], was added to Pintrich and DeGroot's MSLQ questionnaire. The MSLQ questionnaire in this study contained 47 items rated on a Likert scale ranging from 1 (Strongly disagree) to 7 (Strongly agree). The differences between the responses on the pre-post MSLQ questionnaires were calculated, and the difference in the values of all factors summed up and used to present students' change in SRL awareness.

The third data collection method was learning logs, which recorded students' operations when they read the learning materials on the BookRoll system. In this study, we collected and analyzed 13 types of learning logs including the frequency of the following operations:

Turning to the next page (*Next*); turning to the previous page (*Prev*); jumping to a specific page (*Jump_Page*); searching for keywords (*Search*); clicking the provided links (*Clk_Link*); adding or deleting markers (*Add_Mk* and *Del_Mk*); adding, deleting bookmarks, or jumping to a bookmark (*Add_Bm*, *Del_Bm*, *Jump_Bm*); and adding, changing, or deleting annotations (*Add_Ant*, *Chg_Ant*, *Del_Ant*). These learning logs presented how students read the learning materials using certain cognitive learning strategies. The logs of the operations of opening and closing the BookRoll system were also collected, but not analyzed for the learning process. In this study, we collected 263,285 logs of students' learning behaviors on the BookRoll system.

C. Variables and data analysis

A stepwise multiple regression analysis was conducted to measure the impact of the learning behaviors of reading digital learning materials on students' learning performance and learning awareness.

The abovementioned 13 types of learning behaviors were used as independent variables to predict 2 dependent variables of learning outcomes, which were the final test scores and changes in the MSLQ.

Furthermore, we analyzed the different effect of learning behaviors in each lecture on students' test scores and SRL awareness improvement to examine the effect change in the conditions of different learning contents.

Concerning multicollinearity, the Variance Inflation Factor (VIF) values were checked. In this study, the VIF values ranged from 1.003 to 4.379, indicating no problems in terms of multicollinearity.

IV. Results and Discussion

A. Descriptive data and correlation analysis of variables

Table I presents the descriptive data of the two dependent variables, namely final test score and differences in the MSLQ, and 13 learning behaviors as the independent variables.

B. Effects of learning behaviors on learning performance and SRL awareness improvement

TABLE I. DESCRIPTIVE DATA OF FINAL SCORES, DIFFERENCES OF MSLQ, AND LEARNING BEHAVIORS

Variable	Average	SD	Minimum	Maximum
Final score	95.97	5.40	65	100
Differences in the MSLQ	10.36	31.58	-92	122
Next	1431.83	546.89	530	3529
Prev	664.60	359.60	135	1680
Jump_Page	71.87	63.75	20	457
Search	57.11	67.85	0	457
Clk_Link	.37	.97	0	6
Add_Mk	176.60	161.19	11	995
Del_Mk	27.10	29.42	0	144
Add_Ant	16.59	22.12	0	94
Chg_Ant	2.50	6.14	0	41
Del_Ant	.39	.75	0	4
Add_Bm	20.11	28.86	0	176
Jump_Bm	16.67	36.22	0	265
Del_Bm	2.59	3.64	0	24

RQ 1: What are the effects of learning behaviors on students' learning performance in a higher information technology course?

A stepwise multiple regression was conducted to determine which of the independent variables predicted students' final scores and changes in the MSLQ. When the final test score was used as the dependent variable, the independent variables *Jump_Bm* (β = .224, p = .059) and *Prev* (β = .257, p = .031) accounted for 7.4% of the variance of test scores: $F(2, 67) = 3.758$, p = .028. The results are shown in Table II. The regression coefficients indicate that the test score increases along with an increase in the learning behaviors of turning to the previous page or jumping to a bookmark.

TABLE II. RESULTS OF REGRESSION ANALYSIS PREDICTING TEST SCORES WITH LEARNING BEHAVIORS (N=70)

Variable	B	SE B	β	t
Prev	.004	.002	.257	2.197^{*}
Jump_Bm	.033	.017	.224	$1.919^{\dagger}$

R^2 = .101, Adjusted R^2 = .074, $^{*}p < .05$, $^{\dagger}p < .1$

As one learning strategy, the behavior of turning to the previous page means students were repeating the reading and learning of certain content, which can be associated with rehearsal strategies [27]. According to Weinstein et al., students are expected to use active rehearsal learning strategies involving cognitive processes to improve their learning. For example, they may use tools (e.g., flash cards or highlighting) to memorize or understand the learning content, rather than passive rehearsal strategies such as simple repetition. In this study, since we found that *Prev* and *Jump_Bm* behavior could predict students' test scores, that students' use of active rehearsal strategies with the bookmarks tools positively affected learning performance.

RQ 2: What are the effects of learning behaviors on students' SRL awareness in a higher information technology course?

When change in the MSLQ was the dependent variable, the independent variables *Next* (β = .604, p = .011), *Prev* (β = - .505, p = .032), and *Jump_Bm* (β = .199, p = .092) remained significant for the full model. These three variables accounted for 8.1% of the variance of the dependent variable changes in the MSLQ: $F(3, 66) = 3.037$, $p = .035$. The results are shown in Table III. The regression coefficients indicated that an increase in the learning behaviors of turning to the next page or jumping to a bookmark promoted students' SRL awareness. However, the SRL awareness of students who turned to the previous page more frequently tended to decrease.

TABLE III. RESULTS OF REGRESSION ANALYSIS PREDICTING SRL AWARENESS IMPROVEMENT WITH LEARNING BEHAVIORS (N=70)

Variable	B	SE B	*β*	*T*
Next	.035	.013	.604	2.606^{*}
Prev	- .044	.020	- .505	-2.185^{*}
Jump_Bm	.174	.102	.199	$1.707^{\dagger}$

R^2 = .121, Adjusted R^2 = .081, $^{*}p < .05$, $^{\dagger}p < .1$

In SRL, it is important for students to regulate their learning, including by revising present strategies or choosing new ones based on the monitoring of results [3]. The behavior of jumping to the pages where students added bookmarks mean they were aware of the type of information they wanted to know. Therefore, the functional tools of bookmarks would contribute to improving SRL awareness. Despite the positive effect of *Prev* behavior on learning performance, this behavior adversely affected SRL awareness improvement. It is considered that although students used rehearsal strategies with functional tools like bookmarks to improve their test performance, they were still lacking in some SRL factors such as self-efficacy for the self-perception of one's ability to accomplish a task, intrinsic goal orientation concerning goals or orientation to the course for reasons such as challenges or curiosity, or other factors. However, in this study, we only examined the predictors of general SRL awareness improvement, not specific SRL factors, which will be considered in our future work.

C. Effects of learning behaviors in each lecture on learning performance and SRL awareness improvement

RQ 3: What are the different effects of learning behaviors on students' learning performance and SRL awareness based on different types of course contents?

To determine whether the different effect of learning behaviors on learning outcomes was related to the course contents, we calculated the number of learning behaviors in each lecture and investigated the effect of these behaviors on learning performance and awareness. Therefore, the sum of the number of learning behaviors in each lecture was set as the independent variable. The independent variables were *Lecture1* (total logs during lecture 1)–*Lecture8* (total logs during lecture 8). The descriptive data of the independent variables are presented in Table IV.

TABLE IV. DESCRIPTIVE DATA OF LEARNING BEHAVIORS IN EACH LECTURE

Variable	N	Average	SD	Minimum	Maximum
Lecture1	70	473.34	209.05	166	1118
Lecture2	70	340.26	148.12	115	963
Lecture3	70	347.40	180.62	0	921
Lecture4	70	258.14	126.75	43	547
Lecture5	70	313.63	163.79	49	829
Lecture6	70	136.80	72.04	1	363
Lecture7	70	239.21	129.84	0	603
Lecture8	70	323.79	195.07	21	1081

When the final test score was set as the dependent variable, the total learning logs only during lecture 7 met the criteria for entry into the model (Table V). The variable *Lecture7* (β = .275, p = .021) accounted for 6.2% of the variance of the model: $F(1, 68) = 5.558$, $p = .028$. This result indicated that in lecture 7, students' frequent operations for reading learning materials improved learning performance. The topic of lecture 7 was the important issue of "Copyright." It is not difficult to understand the full content of this topic if students wanted to obtain high scores. Therefore, the learning behaviors related to cognitive strategies were important to use in predicting learning performance.

TABLE V. RESULTS OF REGRESSION ANALYSIS PREDICTING TEST SCORES WITH THE SUM OF LEARNING BEHAVIORS IN EACH LECTURE (N=70)

Variable	B	SE B	*β*	*t*
Lecture7	.011	.005	.275	2.357^{*}

R^2 = .076, Adjusted R^2 = .062, $^{*}p < .05$

To determine what indicators affect learning performance in terms of the learning contents of related knowledge about laws and ethics rather than technology, we analyzed the effect of specific learning behaviors in lecture 7 on students' test scores. The names of the independent variables were set as "learning behavior_7," for example, *Next_7*, *Prev_7*. As presented in Table VI, *Del_Mk_7* (β = .271, p = .023) was the only significant predictor for test scores, accounting for 6.0% of the variance of the model: $F(1, 68) = 5.395$, $p = .023$. According to the regression coefficients, the learning behavior of deleting markers helped to obtain high scores.

TABLE VI. RESULTS OF REGRESSION ANALYSIS PREDICTING TEST SCORES WITH LEARNING BEHAVIORS OF LECTURE 7 (N=70)

Variable	B	SE B	*β*	*t*
Del_Mk_7	.387	.166	.271	2.323^{*}

R^2 = .074, Adjusted R^2 = .060, $^{*}p < .05$

In this course, students were required to highlight the contents they did not understand or consider important, and delete markers if they could understand or change their ideas. Therefore, it can be inferred that if students made more efforts to understand the contents they had problems with, their learning performance would benefit more.

Furthermore, the effects of the learning behaviors in each lecture on students' SRL awareness improvement were also examined to determine whether the contents of the course influenced the results. First, the total number of learning behaviors in each lecture was used as the independent variable. As the results in Table VII show, the learning behaviors of

Lecture3 (β = - .344, p = .010) and *Lecture6* (β = .470, p = .001) were two predictors in the improvement of SRL awareness, accounting for 14.7% of the variance of the dependent variable changes in the MSLQ: $F(2, 67) = 6.926$, p = .002.

TABLE VII. RESULTS OF REGRESSION ANALYSIS PREDICTING SRL AWARENESS IMPROVEMENT WITH THE SUM OF LEARNING BEHAVIORS IN EACH LECTURE (N=70)

Variable	B	SE B	*β*	*t*
Lecture3	-.060	.023	-.344	-2.645**
Lecture6	.206	.057	.470	3.612***

R^2 = .171, Adjusted R^2 = .147, ***p < .001, **p < .01

The topic of lecture 3 was "Smartphone Security Settings," the content of which was similar to that in lecture 2. Furthermore, it was easy for students to understand since they were already familiar with the content of lecture 2. Thus, students could obtain high scores without much effort in this lecture. The negative regression coefficient proved this inference. The topic of lecture 6 was "Knowing about Laws," which had a similar level of difficulty in terms of content. Therefore, students could only obtain good scores by learning and understanding the material well through effective cognitive learning strategies. For example, they could spend more time reading, repeatedly read the materials, or use functionality tools to help them with reading. To determine which cognitive learning strategies were effective in these two topics in the information technology course, we further investigated the effect of the specific learning behaviors in lectures 3 and 6.

The independent variables were the learning behaviors of these two lectures, which were set as "learning behaviors_3(6)" (for example, *Next_3*, *Prev_6*). The results are provided in Table VIII. *Next_3* (β = - .248, p = .061), *Clk_Link_3* (β = .222, p = .051), and *Next_6* (β = .440, p = .001) accounted for 16.9% of the variance of the model: $F(3, 66) = 5.692$, p = .002.

TABLE VIII. RESULTS OF REGRESSION ANALYSIS PREDICTING SRL AWARENESS IMPROVEMENT WITH LEARNING BEHAVIORS IN LECTURES 3 AND 6 (N=70)

Variable	B	SE B	*β*	*t*
Next_3	-.074	.039	-.248	-1.905†
Clk_Link_3	26.32 3	13.262	.222	1.985†
Next_6	.381	.111	.440	3.421**

R^2 = .206, Adjusted R^2 = .169, **p < .01, †p < .1

As mentioned, the content of lecture 3 was easy for students to understand, meaning they understood without learning the materials very hard or repeating them by reading frequently. Thus, students who did well in SRL could efficiently regulate their learning and did not need to spend more time or effort reading the lecture 3 materials [3][8]. That was the reason inferred here to explain the negative effect on *Next_3* behaviors on SRL awareness. The predictor *Clk_Link_3* positively affected SRL awareness improvement, indicating the effectiveness of providing students with resources or references, which make them aware of what to do next [28], even when the contents are easy to understand.

Regarding lecture 6, only *Next_6* demonstrated a significant positive effect on SRL awareness. Considering the difficult contents in this lecture, students performed more changing pages behavior, indicating their frequent access to the learning materials, because they were aware of the degree of familiarity with the contents. This process is considered helpful in improving SRL awareness.

The path diagram of the specific learning behavior factors predicting learning performance and SRL awareness improvement is shown in Fig. 1.

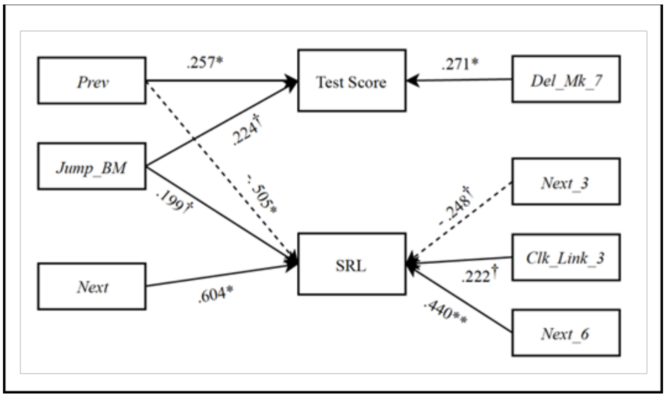

Fig. 1. Results of the multiple regression analysis

V. CONCLUSION AND FUTURE WORK

In this study, we examined the effects of learning behaviors on learning performance and SRL awareness improvement in an eight-week information technology course in higher education. The BookRoll system was used for the duration of the course to collect learning logs on the operations of learning materials.

To identify the predictors of learning performance and SRL awareness improvement, a stepwise regression analysis was performed in this study.

The results indicated that the behaviors of turning to previous pages, which related to rehearsal strategies, with the usage of the bookmark tool positively affected learning performance in the course. Although use of the bookmark tool also positively affected SRL awareness improvement, the behavior of turning to the next page had a negative effect.

To determine whether these results were influenced by the contents of each lecture, we also investigated the effects of learning behaviors in each lecture on learning performance and SRL awareness improvement. The results showed that in lectures with difficult content to understand and memorize (lectures 6 and 7), the functional tools like markers and additional resources provided were useful in promoting learning performance and SRL awareness. On the other hand, in the lecture with easy content to understand (lecture 3), the behavior of turning to the next page, which is related to a simple repetition strategy, negatively affected SRL.

Based on these results, rehearsal strategies, especially those using the functional tools of the BookRoll system, are considered useful in knowledge and SRL awareness acquisition. When designing a lesson with easy contents for students to understand and memorize, providing additional resources and references is helpful for them to regulate their learning, rather than asking them to use simple repetition reading strategies. However, when designing difficult or complex contents, active rehearsal strategies are still recommended.

In addition to collecting and analyzing learning data and learning activities, it is also important to provide feedback to teachers and students [28][29]. For example, in Shimada et al.'s [29] research, real time analytics graphs based on the results of the LA were provided to teachers to help them grasp students' status in class. Therefore, providing teachers and students with feedback based on the LA results and displaying this feedback in a more intuitive and understandable way is important.

In this study, we conducted our experiment on only one course over an eight-week period, raising concerns regarding the reproducibility of results for other courses. Thus, future work could investigate other courses with more participants.

ACKNOWLEDGMENT

This work was supported by a JST AIP, Grant No. JPMJCR19U1, Japan.

REFERENCES

[1] B. J. Zimmerman, "Becoming a Self-Regulated Learner: An Overview," Theor. Pract., vol. 41, no. 2, pp. 64–70, 2002.

[2] P. R. Pintrich and E. V. DeGroot, "Motivational and self-regulated learning components of classroom academic performance," J. Educ. Psychol., vol. 82, pp. 33–40, 1990.

[3] B. K. Hofer, S. L. Yu, and P. R. Pintrich, "Teaching college students to be self-regulated learners," in Self-regulated Learning: From Teaching to Self-reflective Practice, D. H. Schunk and B. J. Zimmerman, Eds. New York, NY, US: Guilford Publications, pp. 57–85, 1998.

[4] S. Tobias and H. T. Everson, "The importance of knowing what you know: A knowledge monitoring framework for studying metacognition in education," in Handbook of Metacognition in Education, D. J. Hacker, J. Dunlosky, and A. C. Graesser, Eds. New York, NY, US: Routledge, pp. 107–127, 2009.

[5] S. Tobias and H. T. Everson, "Knowing What You Know and What You Don't: Further Research on Metacognitive Knowledge Monitoring," Research Report no. 2002–3, College Entrance Examination Board, 2002.

[6] P. J. Belfiore and R. S. Hornyak, "Operant theory and application to self-monitoring in adolescents," in Self-regulated Learning: From Teaching to Self-reflective Practice, D. H. Schunk and B. J. Zimmerman, Eds. New York, NY, US: Guilford Publications, pp. 184–202, 1998.

[7] P. H. Winne and D. B. Stockley, "Computing technologies as sites for developing self-regulated learning," in Self-regulated Learning: From Teaching to Self-reflective Practice, D. H. Schunk and B. J. Zimmerman, Eds. New York, NY, US: Guilford Publications, pp. 106–136, 1998.

[8] K. W. Thiede, T. D. Griffin, and J. Wiley, "Metacognitive monitoring during and after reading," in Handbook of Metacognition in Education, D. J. Hacker, J. Dunlosky, and A. C. Graesser, Eds. New York, NY, US: Routledge, pp. 85–106, 2009.

[9] B. J. Zimmerman, "A social cognitive view of self-regulated academic learning," J. Educ. Psychol., vol. 81, no. 3, 329, 1989.

[10] P. H. Winne and J. C. Nesbit, "Supporting self-regulated learning with cognitive tools," in Handbook of Metacognition in Education, D. J. Hacker, J. Dunlosky, and A. C. Graesser, Eds. New York, NY, US: Routledge, pp. 259–277, 2009.

[11] P. Winne, and R. Azevedo, "Metacognition," In The Cambridge Handbook of the Learning Sciences, R. Sawyer, Ed. Cambridge: Cambridge University Press, pp. 63–87, 2014.

[12] R. L. Dunbar, M. J. Dingel, and X. Prat-Resina, "Connecting analytics and curriculum design: Process and outcomes of building a tool to browse data relevant to course designers," J. Learn. Analytics., vol. 1, no. 3, pp. 223–243, 2014.

[13] D. Hernández-Leo, R. Martinez-Maldonado, A. Pardo, J. A. Muñoz-Cristóbal, and M. J. Rodríguez-Triana, "Analytics for learning design: A layered framework and tools," *Brit.* J. Educ. Technol., vol. 50, no. 1, pp. 139–152, 2019.

[14] J. Oshima, R. Oshima, and W. Fujita, "A mixed-methods approach to analyze shared epistemic agency in jigsaw instruction at multiple scales of temporality," J. Learn. Analytics., vol. 5, no. 1, pp. 10–24, 2018.

[15] A. Van Leeuwen, "Learning analytics to support teachers during synchronous CSCL: Balancing between overview and overload," J. Learn. Analytics., vol. 2, no. 2, pp. 138–162, 2015.

[16] L. Chen et al., "Relationships between collaborative problem solving, learning performance and learning behavior in science education," in Proc. 2018 IEEE Int. Conf. Teach., Assess., Learn. Engineer. (TALE), Wollongong, NSW, Australia, pp. 17–24, 2018.

[17] D. Gašević, J. Jovanović, A. Pardo, and S. Dawson, "Detecting learning strategies with analytics: Links with self-reported measures and academic performance," J. Learn. Analytics., vol. 4, no. 2, pp. 113–128, 2017.

[18] M. Yamada, A. Shimada, F. Okubo, M. M. Oi, K. Kojima, and H. Ogata, "Learning analytics of the relationships among self-regulated learning, learning behaviors, and learning performance," Res. Pract. Technol. Enhance. Learn., vol. 12, no. 13, 2017.

[19] P. Bazelais, D. J. Lemay, and T. Doleck, "Examining the link between prior achievement in secondary education and performance in college: Using data from pre-university physics courses," J. Form. Design. Learn., vol. 2, no. 2, pp. 114–120, 2018.

[20] L. V. Morris, C. Finnegan, and S. S. Wu, "Tracking student behavior, persistence, and achievement in online courses," Internet Higher Edu., vol. 8, no. 3, pp. 221–231, 2005.

[21] C. Ramos and E. Yudko, "Hits" (not "Discussion Posts") predict student success in online courses: A double cross-validation study," Comput. Educ., vol. 50, no. 4, pp. 1174–1182, 2008.

[22] M. Oi, F. Okubo, A. Shimada, C. Yin, and H. Ogata, "Analysis of preview and review patterns in undergraduates' e-book logs," In the 23rd Int. Conf. Comput. Educ. (ICCE 2015), paper presented at Hangzhou, China, pp. 166–171, 2015.

[23] M. Yamada, A. Shimada, M. Oi, Y. Taniguchi, and S. Konomi, "BR-Map: Concept Map System Using e-Book logs," Proc. CELDA 2018, pp. 248–255, 2018.

[24] A. Onoue, M. Yamada, A. Shimada, T. Minematsu, and R. Taniguchi, "The integrated knowledge map for surveying students' learning," Proc. SITE 2019, pp. 1092–1100, 2019.

[25] H. Ogata et al., "M2B System: A digital learning platform for traditional classrooms in university," in Proc. 7th Int. Learn. Analytics Knowl. Conf. (LAK 2017), Simon Fraser University, Vancouver, Canada. SoLAR, pp. 155–162, 2017.

[26] C. A. Wolters, P. R. Pintrich, and S. A. Karabenick, "Assessing academic self-regulated learning," in What Do Children Need to Flourish? K. A. Moore and L. H. Lippman, Eds. The Search Institute Series on Developmentally Attentive Community and Society, vol. 3, Springer, Boston, MA, 2005.

[27] C. E. Weinstein, T. W. Acee, and J. Jung, "Self-regulation and learning strategies," New Direct. Teach. Learn., vol. 2011, no. 126, pp. 45–53, 2011.

[28] L. D. Roberts, J. A. Howell, and K. Seaman, "Give me a customizable dashboard: Personalized learning analytics dashboards in higher education," Technol. Knowl. Learn., vol. 22, no. 3, pp. 317–333, 2017.

[29] A. Shimada, S. I. Konomi, and H. Ogata, "Real-time learning analytics system for improvement of on-site lectures," Interact. Technol. Smart. Educ., vol. 15, no. 4, pp. 314–331, 2018.