

Effects of Pairing Methods Based on Digital Textbook Logs and Learner Artifacts in Conceptual Modeling Exercises

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ABSTRACT

This paper describes the effects of a pairing method based on digital textbook logs and learners' artifacts in conceptual modeling exercises. The authors developed a digital textbook system called Smart E-Textbook Application (SEA) and a conceptual modeling tool called KIFU 3.0 to collect conceptual modeling activity logs in exercises. This study proposes a method that makes pairs of learners for group work by considering the characteristics of the artifacts created by them and digital textbook logs. An initial evaluation was conducted to evaluate the learning effects of the proposed pairing method compared to the random pairing method. From its results, this study found the discussion patterns and digital textbook browsing status in the maximum value of improvement and deterioration points of learners' artifacts in the conceptual modeling.

KEYWORDS

Conceptual Modeling, Cooperative/Collaborative Learning, Digital Textbooks, ICT Technologies, Learning Analytics, Pair Work, Paring Algorithm, Software Development

INTRODUCTION

From the beginning of 2020, educational sites were forced to conduct online lessons due to COVID19. Lectures and exercises were conducted using various digital technologies, such as Zoom and Microsoft Teams. In addition, digital textbook systems have been introduced into schools and universities to improve education and learning by collecting and analyzing educational big data. Many educational researchers have focused on analyzing the digital textbook logs in order to enhance teaching and learning (Mohammad et al., 2018; Mouri et al., 2016 and 2018; Shimada et al., 2017; Ogata et al., 2017).

Exercises are also being conducted after teaching lectures, such as database design in computer science departments. Conceptual modeling activities are inevitable when designing a database as they help grasp a whole system, such as relations among entities and an attribute in an entity. Tanaka et al. (2016) developed a conceptual modeling tool called KIFU 3.0 to support such activities. By using

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the system, learners can create entities, attributes, and relations based on system requirements. In addition, the system can collect operation logs such as “Create,” “Edit,” “Save,” and “Undo.” They reported that the system is useful in carrying out conceptual modeling activities, but the problem of the differences in the understanding levels among the learners tends to increase. To solve the problem regarding the differences in the understanding levels among the learners, many researchers have focused on introducing group work to exercises (Lage et al., 2000; Mori et al., 2009). Ike et al. (2018) proposed a pairing algorithm in the group work of the conceptual modeling activity using operation logs collected in KIfU 3.0. Although they showed that the heterogeneous pairing method with different characteristics is effective for enhancing learning effects, the following aspects are yet to be explored: (1) proposing an effective pairing method based on both digital textbook logs and conceptual modeling activity logs and (2) verifying the effects of (1).

A pairing method utilizing digital textbook logs and conceptual modeling activity logs is proposed for this study. An experiment was conducted to measure the effectiveness of the proposed pairing method in comparison with the random pairing method.

LITERATURE REVIEWS

Research Related to Digital Textbook Systems For Learning Analytics

In recent years, digital textbook systems have been introduced to schools and universities in many countries. Most pilot studies on digital textbook systems focused on learning effects and educational digitalization by introducing a digital textbook system. In the field of educational big data and learning analytics, researchers have focused on analyzing and visualizing digital textbook logs to improve teaching and learning. The research team of Ogata et al. tackled introducing digital textbooks at the university level and analyzed digital textbook logs (Ogata et al., 2015; Mouri et al., 2021; Majumdar et al., 2021). The purposes of this research are as follows: Analyzing and visualizing digital textbook logs to improve learning materials (Mouri, Yin, & Uosaki, 2018; Mouri & Yin, 2017) and identifying students who are likely to fail or drop out (Okubo & Yamashita et al., 2017). Based on the results of the analysis, the method can find the points to be improved in the digital textbooks. By giving the visualization results to teachers and students, the latter could change their learning to obtain better learning achievements.

As shown above, quite a few studies have been conducted to improve learning and education by analyzing large volumes of digital textbook logs. However, to date, these studies have not focused on visualizing and analyzing both digital textbook logs and learning logs in exercises in order to support learning and education. In lectures and exercises, it is necessary to analyze their learning data to improve learning and teaching (Mouri et al., 2018). Therefore, this study introduces how to support collaborative learning by utilizing both digital textbook logs and learning logs in exercises.

Research Related to Computer Modeling Education And Collaborative Learning

Conceptual modeling (CM) is an important technique in database design. Education of the technique is a challenge for computer science departments in higher education institutions. In conceptual modeling education, researchers have improved learners’ artifacts in ER modeling (Suraweera and Mitrovic, 2004; Kung et al., 2008). Suraweera and Mitrovic developed a learning environment for Entity-Relationship (ER) modeling called KERMIT. KERMIT can monitor learners’ artifacts in ER modeling and provide feedback for each learner through an agent. The feedback includes suggestions of actions that the learners should take next and the indications of errors in their artifacts. Kung et al. conducted an empirical comparison of learners’ performance between the top-down and bottom-up approaches in a conceptual data modeling exercise.

They conducted an experimental exercise in which the participants made ER models using the specified methods. They analyzed the results by focusing on the differences in the participants’

error rates. However, these studies did not consider the data collection of the making processes in conceptual modeling. To collect data on the making processes in conceptual modeling, Tanaka et al. (2016) developed a system called KIFU (Tanaka et al., 2016). It provides an environment for learners to express their thinking while reflecting on the processes. They succeeded in collecting data on learners' thinking associated with artifact-making processes. According to the results of the artifact analysis for each learner, the differences in understanding levels among the learners tended to increase.

To solve the increasing differences in understanding levels among the learners, Ike et al. (2018) applied collaborative learning to exercises in conceptual modeling. Collaborative learning is defined as a situation in which two or more people learn or attempt to learn something together (Uosaki et al., 2019; Yin and Uosaki, 2017). In previous works on collaborative learning, most researchers reported that cooperative action works more strongly in heterogeneous groups than in homogeneous groups. To create heterogeneous groups, researchers have proposed grouping methods. For example, Paredes et al. (2010) proposed a grouping method based on learners' learning styles. The method uses the Felder-Silverman learning style model (FSLSM) to obtain the characteristics of each learner. FSLSM is defined as a learning style in a four-dimensional model: (1) active/reflective, (2) visual/verbal, (3) sensing/intuitive, and (4) sequential/global. Learning style is determined based on the results of a questionnaire, which consisted of 44 items. However, this grouping method does not consider the degree of learners' understanding. Ike et al. (2018) measured learners' understanding degree by analyzing the artifacts created by each learner and proposed a pairing method based on the analysis results. The pairing method tended to promote modification of the artifacts made by the learners, but deterioration of the artifacts also occurred in the peer review process. For this reason, they considered that the learners could not determine which opinion of the pair was correct because they were novice learners of conceptual modeling. In addition, they did not consider learning data collected in lectures to create heterogeneous pairs. The originality of this study is that it proposes a pairing method that utilizes not only conceptual modeling activity logs but also digital textbook logs in lectures or out-of-class. Our proposed method prioritizes to group the learners who have acquired basic knowledge in the lecture and cannot make artifacts based on the basic knowledge. That is, there is a possibility that the learner can modify the artifact with a little support. Therefore, by collecting both the lecture log and the exercise log, it is possible to grasp the learners who have a high possibility of improvement.

CONSTRUCTING A DIGITAL TEXTBOOK SYSTEM WITH A CONCEPTUAL MODELING SYSTEM

Digital Textbook System: Smart E-Textbook Application

To introduce digital textbooks into universities, this study previously developed a digital textbook system called the smart e-textbook application (SEA). SEA extends functions based on our previous digital textbook system named AETEL (Kiyota et al., 2016) and various functions such as grouping texts and objects in slide layout (Suzuki et al., 2019) and dashboard (Lkhagvasuren et al., 2016; Liu et al., 2020). Based on this system, this study integrated the digital textbook system with a conceptual modeling system. This section describes the function of SEA and the details of digital textbook logs.

Digital Textbook Reader

Figure 1 shows the interface of the digital textbook reader. Learners can read the digital textbooks on their web browsers at any time and place. Seven buttons are available on the digital textbook reader: next, back, bookmark, highlight, memo, search, and close. For example, clicking on the bookmark button saves the current page as a favorite for easier future access. When a learner encounters important words, phrases, or sentences, they are highlighted in red. Whereas unfamiliar words, phrases, or sentences are highlighted in yellow. Using different colors allows our system to analyze different user intentions behind highlights. When the memo button is clicked in a digital textbook, learners

can post a note about the target words. Additionally, they can also search the page numbers of the target word in the digital textbook by clicking on the search button.

Log data from SEA

SEA can collect log data for the pairing method. Table 1 shows the sample log data collected in SEA. There are many types of operations in logs, for example, OPEN means that the learner opened the

Figure 1. Digital Textbook Reader interface

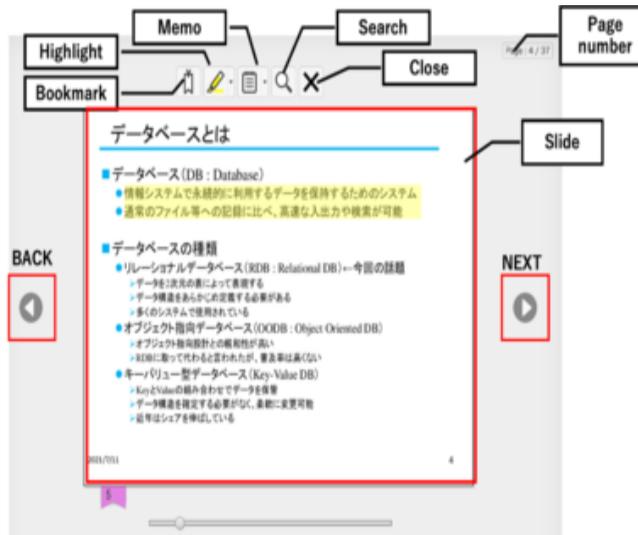


Table 1. Sample log data collected in SEA

USERID	E-book ID	Title (e-book)	Operation	Page	Operation date
XXXX01	0000KFG01	Conceptual Modeling	OPEN	1	2021/07/10 13:10:10
XXXX01	0000KFG01	Conceptual Modeling	NEXT	1	2021/07/10 13:10:15
XXXX01	0000KFG01	Conceptual Modeling	NEXT	2	2021/07/10 13:10:20
XXXX01	0000KFG01	Conceptual Modeling	BACK	3	2021/07/10 13:10:35
XXXX01	0000KFG01	Conceptual Modeling	ADD MEMO	2	2021/07/10 13:11:02
XXXX01	0000KFG01	Conceptual Modeling	ADD BOOKMARK	2	2021/07/10 13:11:10
XXXX01	0000KFG01	Conceptual Modeling	ADD HIGHLIGHT	2	2021/07/10 13:11:25
XXXX01	0000KFG01	Conceptual Modeling	SEARCH	2	2021/07/10 13:11:30
XXXX01	0000KFG01	Conceptual Modeling	NEXT	3	2021/07/10 13:11:35
XXXX02	0000KFG02	Programing language	OPEN	1	2021/07/14 13:10:00

textbook in SEA, and NEXT means that the learner clicked the next button to move to the subsequent page as shown in Figure 2. Furthermore, SEA can collect operation logs such as “bookmark,” “highlight,” “memo” and “search.” Using these log data, we can calculate how much time each learner spent browsing each page in the digital textbook.

Conceptual Modeling System: KIFU

A previous study on conceptual modeling (Tanaka et al., 2018) developed a UML class diagram editor, KIFU 2.0, to collect data on learners’ thinking during their artifact-making processes. Based on this system, they developed KIFU 3.0 to collect data on artifact-making processes. KIFU 3.0 was implemented using Google Web Toolkit (GWT), which is a Web application framework for Java. It also uses MySQL as a database to accumulate the log data. This section describes the function of KIFU 3.0 and the details of the log of artifact making processes.

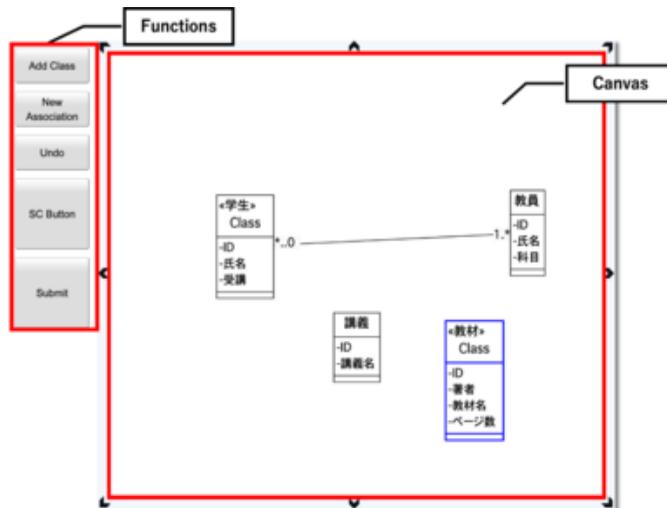
The Interface of KIFU 3.0

Figure 2 shows the interface of KIFU 3.0.

The interface has the following functions:

- (1) Canvas: A learner makes a diagram on the canvas. The learner can open a context menu by right clicking on the canvas, and the learner can add/remove/edit the diagram elements using the menu. KIFU 3.0 can record the log data each time the learner operates the canvas.
- (2) Add class: By clicking on the add class button, the learner can add a new class on the canvas.

Figure 2. Interface of KIFU



When the learner clicks the button, a new class appears under the mouse cursor. The learner can move the new class to any location on the canvas using the mouse, and drop it at the location by clicking on the canvas.

- (3) New Association: By using a new association button, the learner can add a new relation between two classes in the diagram. There are two ways to create a new relationship. One is that the learner clicks the button, and selects two classes by clicking on them. In the other method, the learner

selects a class, clicks the button, and selects another class. In either case, a new relationship appears between them.

- (4) Undo: The learner can cancel the previous operation on his/her artifact by clicking the button. In that case, KIfU 3.0 logs an “Undo” and restores the state of his/her artifact before the previous operation instead of deleting the previous operation.
- (5) Submit: The learners can submit the diagram to their teacher by clicking on the button. KIfU 3.0 records a “Submit” log with the latest state of the learner’s artifact in the same way as the Save operation.

Log Data from KIfU 3.0

The system can collect the log data of learners’ operations on their diagrams. Table 2 shows a sample of the log data. Target type refers to the type of the edit target; Event type refers to the type of event: “Start,” “Create,” “Edit,” “Remove,” “Place,” “Undo,” “Save,” and “Submit”; and Target Id refers to the id of the target element in the artifact. In addition, before edit and after edit refer to the target object strings before and after the edit, respectively, and Timestamp refers to the time when the event occurred. For example, the event in the top row of Table 1 logs an operation where the name of a class “Class8” was changed to “Stock”. Therefore, the values of ‘Before edit’ and ‘After edit’ are “Class8” and “Stock,” respectively. In KIfU 3.0, the initial default name of a class consists of the string “Class” followed by an integer. KIfU 3.0 generates the “Create” log when the default name is changed to any original name by a user. Hence, the value of ‘Event type’ of the log in Table 2 is “Create.”

Proposed Pairing Algorithm

This study proposes a pairing algorithm that utilizes both digital textbook logs and conceptual modeling activity logs. To (1) understand the degree of each learner in the lecture and (2) measure

Table 2. Sample log data collected in KIfU 3.0

Target type	Event type	Target Id	Before edit	After edit	Operation date
Class Name	Create	2	Class8	Stock	2021/07/11 13:10:20
Class	Place	2	152,124	315,282	2021/07/11 13:10:31
Attribute	Remove	1	-numberOfStock	(none)	2021/07/11 13:11:10
Class Name	Edit	2	Stock	Items	2021/07/11 13:12:32

the characteristics of the artifacts created by each learner in the conceptual modeling exercise, we created three matrices: understanding the degree matrix, feature matrix, and hamming matrix.

(A) Understanding the degree matrix:

Table 3 shows an example of the browsing status matrix. For a browsing status matrix A , each row of A represents the browsing status vector of a page browsed by a learner. Hence, each component of matrix A represents whether a learner has each browsing status. More specifically, a component $A_{i,j}$ of the matrix A represents (the learner that has $A_{i,j}$ is 1, which means that the he/she browsed the page j):

$$A_{i,j} = \begin{cases} 1 & (\text{if learner } i \text{ browses page } j) \\ 0 & (\text{otherwise}) \end{cases}$$

Table 3. An example of browsing status matrix

	Page 1	Page 2	Page 3	Page 4	Page 5
Learner A	1	1	1	1	1
Learner B	1	1	1	1	0
Learner C	1	1	1	1	1
Learner D	1	1	1	1	1
Learner E	1	0	0	0	0

Table 4 shows an example of a quiz matrix. For a quiz matrix B , each row of B represents a quiz vector of a question number answered by a learner. For example, Q1(Page 2) in Table 4 means that the question in the quiz was created by a teacher based on the contents of the page number 2 in the digital textbook. In other words, the contents of page number 2 correspond to Q1. Each component of the matrix B represents whether a learner correctly has each answer or not. More specifically, a component $B_{i,j}$ of the matrix B represents (learner i that has $B_{i,j}$ is 1 means that he/she correctly answered the question in the quiz):

$$B_{i,j} = \begin{cases} 1 & (\text{if learner } i \text{ correctly answered } j) \\ 0 & (\text{otherwise}) \end{cases}$$

We measure the degree of understanding of each learner based on the browsing status matrix

Table 4. An example of quiz status matrix

	Q1(Page 1)	Q2(Page 2)	Q3(Page 3)	Q4(Page 4)	Q5(Page 5)
Learner A	1	1	1	1	1
Learner B	1	0	1	1	1
Learner C	1	1	1	1	1
Learner D	0	0	0	0	0
Learner E	0	0	1	0	0

and quiz status matrix. Table 5 shows an example of an understanding degree matrix. To understand the degree matrix, we calculate the UD between vectors A_i and B_j for learners i (j is the page number correspond to the question). For example, the UD between $\nu_i = (A_{i,1}, A_{i,2} \dots A_{i,n})$ and $\nu_j = (B_{j,1}, B_{j,2} \dots B_{j,n})$ is defined as:

$$UD(\nu_i, \nu_j) = A_{i,1} \wedge B_{j,1}$$

(B) Artifact feature matrix

Table 5 shows an example of an artifact feature matrix. For an artifact feature matrix C , each

Table 5. An example of understanding the degree matrix

	UD 1	UD 2	UD 3	UD 4	UD 5
Learner A	1	1	1	1	1
Learner B	1	0	1	1	0
Learner C	1	1	1	1	1
Learner D	0	0	0	0	0
Learner E	0	0	0	0	0

row of C represents a feature vector of an artifact created by a learner. Hence, each component of the matrix C represents whether a learner's artifact has each feature or not. More specifically, a component $C_{i,j}$ of matrix C represents:

$$C_{i,j} = \begin{cases} 1 & (\text{if artifact by learner } i \text{ has feature } j) \\ 0 & (\text{otherwise}) \end{cases}$$

(C) Priority pair matrix

Table 5. An example of an artifact feature matrix

	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5
Learner A	1	0	1	1	0
Learner B	1	0	0	1	0
Learner C	1	1	0	0	1
Learner D	0	0	1	1	1
Learner E	1	0	1	0	1

This study calculates the priority pair (PP) based on each matrix $UD(\nu_i, \nu_j)$ and $C_{i,j}$. For example, the PP between $\mu_i = (\mu_{i,1}, \mu_{i,2} \dots \mu_{i,n})$ and $\mu_j = (\mu_{j,1}, \mu_{j,2} \dots \mu_{j,n})$ is defined as:

$$PP(\mu_i, \mu_j) = \sum_{l=1}^n C_{i,l} \wedge C_{j,l} \quad (\text{if } UD(\nu_i, \nu_l) \text{ is 1 and } C_{i,l} \text{ is 0})$$

Learner i with $C_{i,j} = 0$ means that he/she do not has the feature in the artifact. Therefore, learner i that has $UD(\nu_i, \nu_j) = 1$ and $C_{i,j} = 0$ has acquired basic knowledge in the lecture, but cannot make artifacts based on basic knowledge. In other words, there is a possibility that the learner i can modify the artifact with little support compared to other conditions such as “ $A_{i,j} = 1$ and $B_{i,j} = 0$ ” and “ $A_{i,j} = 0$ and $B_{i,j} = 1$ ”. Table 6 shows the priority pair matrix obtained from the feature matrix shown in Tables 4 and 5.

(D) Hamming matrix

For an artifact feature matrix, we calculate the Hamming distance (HD) between an arbitrary pair of feature vectors ν_i and ν_j for learners i and j . For example, the HD between $\nu_i = ($

Table 6. An example of a priority pair matrix

	Learner A	Learner B	Learner C	Learner D	Learner E
Learner A	0	0	2	1	1
Learner B	1	0	0	1	1
Learner C	2	1	0	2	1
Learner D	0	0	0	0	0
Learner E	0	0	0	0	0

$\nu_{i,1}, \nu_{i,2} \dots \nu_{i,n}$) and $\nu_j = (\nu_{j,1}, \nu_{j,2} \dots \nu_{j,n})$ is defined as:

$$HD(\nu_i, \nu_j) = \sum_{l=1}^n \nu_{i,l} \oplus \nu_{j,l}$$

Table 7. An example of a hamming matrix

	Learner A	Learner B	Learner C	Learner D	Learner E
Learner A	0	1	4	2	1
Learner B	1	0	3	1	0
Learner C	4	3	0	2	1
Learner D	2	0	2	0	2
Learner E	1	0	1	2	0

The Hamming matrix is a square matrix whose (i,j) component is HD (ν_i, ν_j). Table 7 shows the Hamming matrix obtained from the artifact feature matrix shown in Table 4.

Based on these matrices, this study proposes a priority algorithm with the following steps.

Step 1: Select the pair corresponding to the maximum component in the priority pair matrix. If there are multiple pairs whose corresponding components have the same maximum value, the exceptions apply.

Step 2: This step deletes the row and column components in the priority pair and hamming matrix that correspond to the selected pair in Step 1.

Step 3: If there are remaining elements in the priority pair matrix, return to Step 1.

Exception 1: Among the pairs with the same value in the priority matrix, the pair corresponding to the maximum component in the Hamming matrix is selected. If there are multiple pairs whose corresponding components have the same maximum value, the exception 2 is applied.

Exception 2: Among the pairs that have the same maximum hamming distance, the pair of learners i and j whose average value $M_{i,j}$ is minimum is selected. Here, each v in the formula is the component that should be deleted in Step 2, where $M_{i,j}$ is defined as:

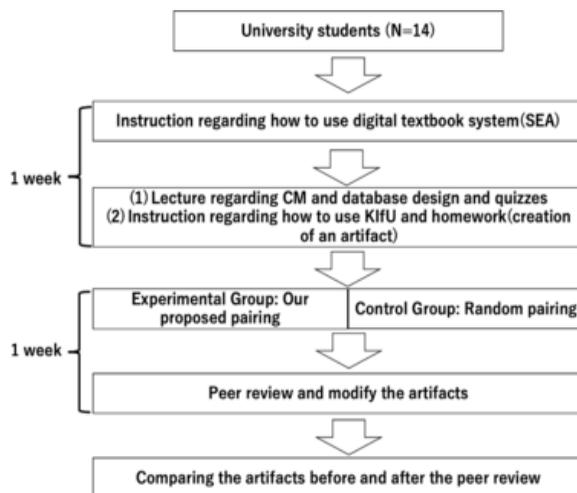
$$M_{i,j} = \frac{\sum_{k=1}^m (V_{i,k} + V_{j,k} + V_{k,i} + V_{k,j}) - V_{i,j} - V_{j,i} - V_{i,i} - V_{j,j}}{4m - 4}$$

EVALUATION DESIGN

Subjects

The experiment was conducted for a conceptual modeling education via online using Zoom (cloud-based video conferencing service) and gather town. The gather town is a social platform that allows learners to communicate with each other in a virtual space using an avatar. The subjects were 14 students from two-university laboratories in Japan.

Figure 3. Experimental procedure



Experimental Procedure

Figure 3 shows the experimental procedure.

In the first week, the teacher uploaded the digital textbooks on the server before the evaluation experiment. First, the teacher explained how to use the digital textbooks. Next, the teacher conducted the lecture regarding conceptual modeling and database design by teaching how to use KIfU 3.0 for an hour and the participants took the quizzes regarding the lecture for 30 min. The quizzes consisted of 15 questions regarding conceptual modeling and database design. They were created by teachers based on the content of the digital textbooks in the conceptual modeling and database design. In addition, the participants were required to make an artifact using KIfU 3.0 based on a system requirement until the next peer review after one week. Based on the results of the artifacts, the participants were divided into an experimental group and a control group. Table 8 shows the results for the artifacts in each group.

Table 8. Results of artifacts (before peer review)

	N	Mean (max 55)	SD	p-value
Experimental Group	8	42.5	4.87	P > 0.05
Control Group	6	42.8	5.45	

The means and the standard deviations were 42.5 and 4.87, respectively, for the experimental group and 42.8 and 5.45 for the control group. To test the normality of the data of the results, we used the Shapiro-Wilk test (Shapiro & Wilk, 1965). The test results showed the normality ($p \leq 0.05$). The F-test showed no significant difference between the two groups ($p > 0.05$). Therefore, this study adopted a t-test assuming equal variances. The t-test showed no significant difference between the two groups ($p > 0.05$), which means that the participants of the two groups had equivalent skills in conceptual modeling.

After the grouping, we divided the EG participants into four pairs using the proposed method, while those in the CG were randomly divided into three. We asked the participants in both groups to conduct peer reviews on the artifacts created in homework for 30 min. A peer review by a pair means discussing their artifacts by individually to check for unexpected elements, lack of elements, and reasons for existing elements. At the same time, we required them to modify their artifacts based on the peer review process. In the next section, we analyzed the changes in the artifacts before and after the pair work.

Experimental Results

Table 9 shows the results of the artifact after peer review in each group.

The means and the standard deviations were 42.8 and 5.75, respectively, for the experimental group, and 45.6 and 3.44 for the control group. The t-test showed no significant difference between the two groups ($p > 0.05$).

Table 9. Results of artifacts (after peer review)

	N	Mean (max 55)	SD	p-value
Experimental Group	8	42.8	5.75	P > 0.05
Control Group	6	45.6	3.44	

Table 10 shows the scores before and after peer review, improvement points (IP), and deterioration points (DP) of the features of the artifacts created by the participants in the EG. The total of IP and DP were 13 and 10, respectively. Table 11 shows the scores before and after peer review, IP and DP of the features of the artifacts created by the CG participants. The total of IP and DP were 18 and 0, respectively.

Table 10. Scores of learners' Artifacts before and after the pair work with IP and DP (EG)

Pair	User number	Score (before)	Score (after)	IP	DP
1	No.6	44	42	1	3
	No.8	40	39	0	1
2	No.5	36	40	4	0
	No.12	41	40	0	1
3	No.3	46	49	3	0
	No.4	53	55	2	0
4	No.7	39	42	3	0
	No.10	41	36	0	5

Table 11. Scores of learners' Artifacts before and after the pair work with IP and DP (CG)

Pair	User number	Score (before)	Score (after)	IP	DP
5	No.2	50	50	0	0
	No.13	33	41	8	0
6	No.1	48	48	0	0
	No.14	43	49	6	0
7	No.11	42	43	1	0
	No.9	41	43	2	0

DISCUSSION

Comparing the number of IP of EG with CG, the former was lesser than CG. In addition, comparing the number of DPs of EG with CG, the former was higher than CG. As shown in Table 10, pair 2 showed that the number of IP in EG was greater than in other pairs. In addition, pair 4 showed that the number of DPs in EG was greater than in others. Contrarily, as shown in Table 11, pair 5 showed that the number of IP in CG was greater than in other pairs. To find explanations, we investigated two methods: (1) analysis of digital textbook logs during peer work and (2) interviews with each participant.

Figures 4 and 5 show the matrix of browsing status in EG and CG, whether the participants browsed which page in the digital textbook. The red indicates that the learner browsed the page and

the blue indicates that the learner did not browse the page. The vertical axis shows each participant and the horizontal axis shows each page in the digital textbook.

Figure 4. Browsing status of each participant in the digital textbook in EG

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37		
Pair 1	User No.6	Blue																																						
	User No.8	Blue																																						
Pair 2	User No.5	Blue																																						
	User No.12	Blue																																						
Pair 3	User No.3	Blue																																						
	User No.4	Blue																																						
Pair 4	User No.7	Blue																																						
	User No.10	Blue																																						

Figure 5. Browsing status of each participant in the digital textbook in CG

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37		
Pair 5	User No.2	Blue																																						
	User No.13	Blue																																						
Pair 6	User No.1	Blue																																						
	User No.14	Blue																																						
Pair 7	User No.11	Blue																																						
	User No.9	Blue																																						

As shown in Figure 4, the browsing status of pairs 1,2 and 3 found that they conducted the pair work while reading exercise pages (exercise pages are from pages number 33 to 36). In addition, they browsed not only the exercise pages but also other pages. We can guess that the participants browsed target pages regarding them when they could not understand the keywords and the content during pair work. However, comparing pair 4 (user No.7 and No.10) with others, the browsing status was poor because they did not browse all exercise pages; they mostly did not browse other pages except exercise pages.

As shown in Figure 5, the users No.1 and No.2 browsed various pages unlike the browsing status of users No.13 and 14 in the same pair. In addition, IPs of the users No.13 and No.14 increased, but IPs and DPs of the users No.1 and 2 did not changed. Based on the results, we can guess that users No.13 and No.14 who have poor artifacts (the learner who rarely browsed digital textbooks during pair work) blindly accepted the opinions of the users 1 and 2 who have good artifacts (the learner who browsed various pages of digital textbooks during pair work). Consequently, they did not check the contents in the digital textbook after modifying their artifacts during peer work.

An interview was conducted on how to discuss the artifacts during pair work; three interview transcripts were obtained as follows.

Q1. Please tell me the content and flow of the discussion.

- A1. We showed the artifacts each other and the learning process of creation, and then discussed the different parts of each other's artifacts.
- Q2. Please tell us in detail what you discussed.
- A2. First, we found different parts of each other's artifacts (something was missing or had different names), and then we talked about the reasons and whether to correct them.
- Q3. How did you decide whether to modify it?
- A3. We modified the parts in the artifacts that we thought clearly wrong and did not modify if we did not know whether it is correct or wrong each other.

Participants in EG and CG with high IP commented "We modified the parts in the artifacts that thought clearly wrong and did not modify if we did not know whether it is correct or wrong each other." Pair 4 with high DP commented "After discussion about each other's artifact, we modified the different part between each other's artifacts." We can assume that user No.10 changed his/her artifact based on the different parts (wrong parts) of user No.7 artifact.

From answer to question 3 and Figure 5 in CG, it can be inferred that user No 2 explained "We modified the parts in the artifacts that we thought clearly wrong" while showing user No13 the page of the digital textbook that describes the underlying content. As the reason why their artifacts in the pair 5 was not deteriorated, they commented that "left the parts that came to the conclusion that they did not agree with each other". Considering these findings, our future work is described in the next section.

CONCLUSION AND FUTURE WORK

This paper described a pairing method based on digital textbook logs and learners' artifacts in conceptual modeling exercises. Our proposed pairing method was calculated based on two conditions: (1) understanding the degree of each learner in the lecture and (2) the characteristics of the artifacts created by each learner in the conceptual modeling exercise. To measure (1) and (2), we developed a digital textbook system called Smart E-textbook Application (SEA) and a conceptual modeling tool called KIFU 3.0 to collect conceptual modeling activity logs in exercises.

The initial evaluation was conducted to evaluate the learning effects of our proposed pairing method compared with the random pairing method. As mentioned in the "Experimental Results" section, the t-test showed that there was no significant difference between the two groups ($p > 0.05$). We conducted digital textbook log's analysis and interviews to investigate discussion details and digital textbook browsing status in the maximum value of IP and DP in EG and CG.

The results found that learners with high IP not only browse the exercise pages but also other pages during pair work. In addition, they commented "We modified parts in the artifacts that we think that it is wrong and did not modify if we did not know whether it is correct or incorrect".) and a conceptual modeling tool called KIFU 3.0 to collect conceptual modeling activity logs in exercises.

In addition, we consider that collecting and analyzing video data during the peer work is important because this evaluation could not grasp discussion situations during peer work. We believe that there is a possibility that finding active or passive learner by conducting emotional analysis based on the collected video data. Moreover, it might be able to find effective method of intervention by analyzing the relationships between the found active / passive learner and learning performance.

Based on these findings, we will develop an AI-based system that can intervene the following the browsing status of each learner's digital textbook during pair work in real time. In addition, it is necessary to consider how to discuss artifacts in the conceptual modeling during pair work. Therefore, we plan to collect and analyze learners' voice and face information using microphones and web cameras to grasp more details of the situation and discuss the artifacts in the conceptual modeling during pair work.

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