Ogata, H. et al. (Eds.) (2015). Proceedings of the 23rd International Conference on Computers in Education. China: Asia-Pacific Society for Computers in Education

Learning Style Verification with use of Questionnaire and Page Flip History

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Abstract: The authors verified learners' learning styles with use of learning style questionnaires and page flip history of materials. First, page-flip detection function of material slides on learners' PCs was developed. This function also transfers the result to a dedicated LRS (Learning Record Store) server automatically. From this fine-grained learning activity log, student's learning styles were classified. Second, the authors estimated learners' learning styles with use of widely used learning style questionnaires. The authors verified these two types of learning styles for 100 subjects (research participant) in real 4 units of 2 classes. As a result, a student who "rushes up ladder" during a certain time period was significantly relevant to "Global" learning style tendency rather than "Sequential" one.

Keywords: Learning analytics, page flip, learning style

1. Introduction

1.1 Digitization of Education

Introduction and utilization of digital devices and learning materials have been common in various countries. KERIS (2015) in Korea started investigation and experiment in 2008, and finished implementation throughout the country until the end of 2014. Also China, Singapore, Philippines, India and other Asian countries are carrying investigation and experimental introduction forward. In Europe, England, France, Germany, Spain and other countries are under investigation and experiment. In US, some states including California, Washington and Utah are planning to deliver digital textbooks or complementary devices. In Japan, MEXT (Ministry of Education, Culture, Sports, Science and Technology) (2011) published a roadmap called "The Vision for ICT in Education", which were planning to introduce digital textbooks countrywide until 2020. Also, an experimental project was deployed from 2011 to 2013. It was a joint project between MEXT and MIC (Ministry of Internal Affairs and Communication) to introduce ICT and digital learning materials to selected 20 schools. Final report of this project (in Japanese) is available through MEXT (2015). At the same time, MEXT and MIC started experimental development projects of Digital Textbooks in 2013. In these projects, MEXT is focusing ePub3, while MIC is HTML5. These projects will continue in 2015.

On the other hand, various standardization organizations and communities are trying to specify standard file formats and specifications for Digital Textbooks. IEEE (2015) initiated Actionable Data Book Project in 2011, and published some research papers. Also, CEN (European Committee for Standardization) (2015) and IMS Global Learning Consortium (2015a) began eTernity Project and ICE Project in 2012 and 2013, respectively.

Among them, ISO/IEC JTC1/SC36 (2015), a subcommittee of ISO dedicated to e-learning technical specifications, started e-Textbook Project in September 2012 meeting at Busan, Korea. It is investigating related standardization activities, issued a set of questionnaires of Digital Textbooks to standardization communities, and arranged future issues in a document in 2014 meeting.

The latest and the most active one is called EDUPUB project. It is an alliance of IDPF (International Digital Publishing Forum) (2015), IMS (2015b), and W3C (2015), which specified ePub3 format for Digital Books. The first workshop of EDUPUB was held in October 2013 at Boston,

USA, while succeeding ones in February 2014 at Salt Lake City, USA, in June 2014 at Oslo, Norway, in September 2014 at Tokyo, Japan, and in February 2015 at Phoenix, USA.

1.2 Learning Analytics

Learning analytics (LA) has become a major area in learning science and learning technology research in the trend on digitization of education. Ferguson (2012) described a definition of Learning Analytics as follows: "Learning analytics is 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." A trend of digitization of learning, education and training can be divided into three categories. First one is an adoption of digital learning resources, e.g. LMS-based digital material delivery and client PC-based digital textbooks/ references/ dictionaries. Second is an application of digital environment for learning activities, e.g. interactive learning environment, group or peer-to-peer communication environment for discussion or information sharing, and various active learning supporting tools. The first is considered to be an upper stream of learning, whereas the second one is to be a midstream of learning. Compared to them, LA is considered to be a downstream process of learning. It means collection, analysis, and utilization of learning activity log data.

The learning activity log data has been collected and analyzed since hundreds years ago, even in age of paper-based learning environment. In 2000s, LMS (Learning Management System) based learning environments have been spread. At this period, many types of learning activity logs have been collected in these LMSs and analyzed. These data came from instruction-based activities, e.g. class participations, material views, and answers to quizzes. Also they included active learning-based ones, e.g. enrollments, utterances, interim and final products of group activities. In 2010s, usage of laptop or tablet PCs has been common in K-12 education in various countries. In this environment, various fine-grained learner related information have been available for Learning Analytics, e.g. page flip, learners' actions, eye-track, voice and environmental sound, GPS information, and even heartbeat with use of PC-equipped camera. In future, many types of physiological data like blood pressure and sweating will be available with use of wearable devices. This trend is summarized in Figure 1.

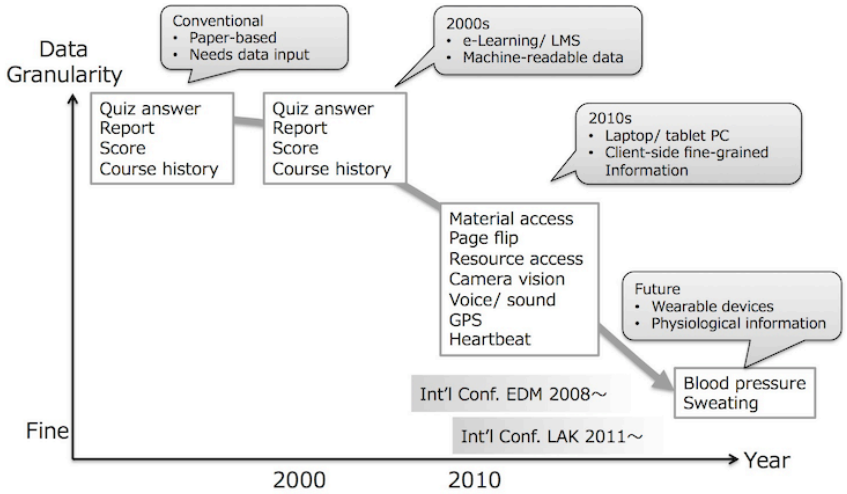


Figure 1. Trend of Learning Activity Data

There are many types of research-based information resources for Learning Analytics. An academic journal called Journal of Learning Analytics is published from SOLAR (Society for Learning Analytics Research) (SOLAR, 2015). Also, two types of International Conferences: Learning Analytics and Knowledge (LAK) and Educational Data Mining (EDM). LAK publishes proceedings from Long et al. (2011) through Baron et al. (2015). Also EDM publishes proceedings since Baker (2008) through Santos (2015). As a general survey, Shum (2012) classifies 5 types of LA activities: (1) analysis dashboard of LMS or VLE, (2) predictive analysis, (3) adaptive learning analytics, (4) social network analysis, and (5) discourse analysis. Especially for active learning and collaborative learning, Shum and Ferguson (2012) shows some LA goal and future issues of these

activities. Up to date discussion and information are available on Google Groups on Learning Analytics (2015).

Standardization organization of ISO/IEC JTC1/SC36 has started WG8, devoted to Learning Analytics in June 2015. In the WG8 meeting in Rouen France, an overall framework of Learning Analytics was discussed. Figure 2 is based on this discussion, and includes some expansion.

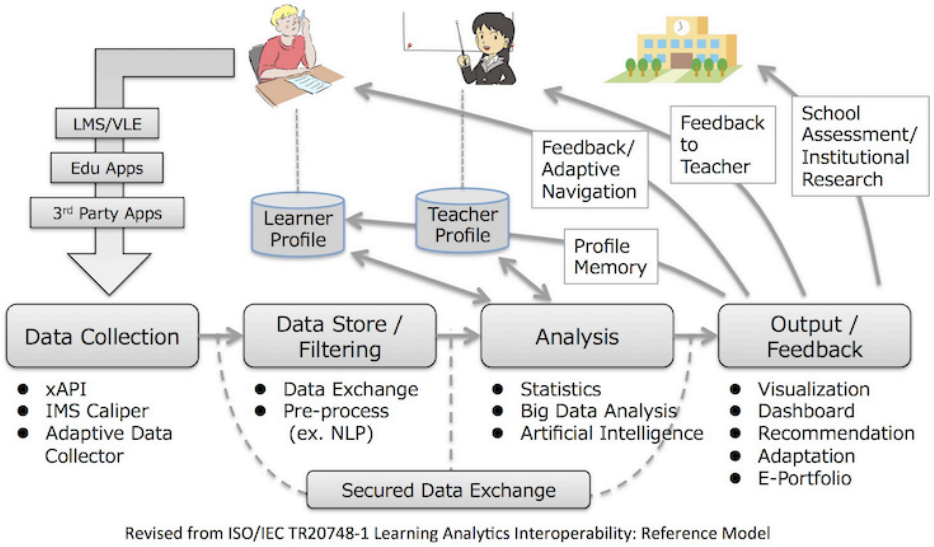


Figure 2. Overall Framework of Learning Analytics

There are major 4 steps: (1) data collection, (2) data store/ filtering, (3) analysis, and (4) output/ feedback. In the first step of data collection, learning activity data is collected with use of LMS, VLE (Virtual Learning Environment), education application or 3rd party application programs that are used by learners.

1.3 Learning Styles

There are theories that each person can be classified according to their style of learning. Often, it is used term cognitive style instead of learning style. Cognitive style is included under the term learning style, and it is defined as an individual's consistent approach to organizing and processing information during learning (Messick, 1984). Researches on the learning style started in 1970s, and various theories or models have been proposed on the field of educational psychology or cognitive science. Riding (1997) reviewed and organized these theories of learning styles, and pointed out two fundamental and independent dimensions of cognitive styles; the Wholist-Analytic dimension and the Verbal-Imargery dimension.

Table 1. The two dimensions of cognitive style (Riding, 1997)

Wholist-Analytic dimension: This dimension describes the habitual way in which an individual organizes and structures information.	Wholists	People who will retain a global or overall view of information
	Analytics	People who will deconstruct information to its component parts
Verbal-Imargery dimension: This dimension reflects an individual's habitual mode of representation of information in memory during thinking.	Verbalisers	People who consider the information they read, see or listen to, in words or verbal associations
	Imagers	People who read, listen to or consider information, experience fluent spontaneous and pictorial mental pictures

Taki (2005) argued that though e-Learning has the advantage allowing for learners' individual differences, today's design methods of e-Learning materials are based on Instructional Design paradigms which maintain the traditional "One-size- fits-all" approach; that is, one type of material designed for all. The advantage of e-learning that Taki pointed out is as follows; e-learning can generate and provide an appropriate learning environment according to learners' interests and abilities, or allow them to control the order and pace of learning. Taki prepared four types of e-learning materials based on Riding's four types of cognitive styles (Wholist-Verbalisers, Wholist-Imagers, Analytic-Verbalisers, and Analytic -Imagers). The reported results indicate that e−Learning materials with a suitable design regarding the cognitive styles bring higher learning performance.

There are various types of questionnaires or inventories that include Riding's two dimensions of cognitive style. Felder (1995) reviewed theories of learning styles and organized them into these four dimensions:

(1) Active-Reflective (Kolb, 1981, 1985),
(2) Sensing-Intuitive (Jung, 1971) (Myers, 1985),
(3) Visual-Verbal (Dale, 1969) (Oxford, 1993), and
(4) Sequential-Global (Kirby, 1988) (Pask, 1988) (Marton, 1988).

Among Felder's four dimensions, dimension(3) is equivalent for Riding's Verbal-Imargery dimension and dimension(4) is equivalent for Wholist-Analytic dimension.

Soloman (2005) proposed a questionnaire based on Felder (1995), named Index of Learning Styles Questionnaire (ILSQ). ILSQ has advantages below.

- This set of questionnaires is publicly available, while some inventories are commercial.
- The method is publicly available to calculate or estimate one's learning style.
- Number of questions is relatively few (44), while some inventories supplies near 100 questions.

1.4 Research Questions

Among various data in Learning Analytics, one of the authors Tamura (2015) focused on "page flip" information of e-textbook, and visualized page transition history of each learners. Page flip information or page transition history is the information when and in what order the learners flip the page. This page flip information could not available from paper-based textbooks or other materials, and therefore teachers using paper-based textbooks conduct lessons on the assumption that their learners follow the teacher. However, if teachers use digital textbooks on client PCs, page flip history of each learner can be visualized by equipping function to collect page flip information. Even in the age of LMS, theoretically it was available. However, its granularity was mainly "HTML file-wise", not page-wise.

Page flip history may show characteristic shapes or features that reflect various factors: such as learner's academic ability, motivation, difficulty level of the class, environment of classroom. The examples of features of page flip history and learning styles that may be relate to are as follows:

A) Glance all materials during a certain time period – Global style
B) History along with progress of the class – Sequential style

Among various factors, the authors focused on learning style in this research, and attempt to model features of page flip history and learning styles that may be relate to. As stated 1.3, one's learning style is usually estimated by using paper-based questionnaires or inventories. However, considering estimation of learners' learning style in real classroom, it imposes workload to use paper-based questionnaires on both teachers and learners. If their learning styles can be estimated automatically from their page flip actions, this workload of questionnaires or inventories can be decreased.

2. Experiment

2.1 Learning Analytics Data Acquisition Scheme

The authors developed a function to collect page flip information in real classrooms. One of the authors already developed a similar function on EPUB reading system (Tamura, 2015). This time, instead of EPUB based textbook, the target was moved to PowerPoint slide transition, because the author's classes mainly utilizes these slides in the lectures. The proposed scheme includes functions below.

A) Make input student's ID and memorize it
B) Fetch an action to move to another slide automatically
C) Transmit information (Unit ID, date & time, A), and B)) to a server automatically
D) A server to save transmitted information C). It is so called LRS (Learning Record Store)

One of the authors (Yamazaki) developed functions A), B) and C) in JavaScript. Also, PowerPoint slides were converted into JPEG and HTML files manually. For these HTML files, the other author (Horikoshi) added functions A), B) and C) manually.

Subjects access the materials from the link on LMS, and page flip information is sent to LRS when each subject change pages. The items stored in LRS are as below:

- Actor: student's ID
- Verb: lunched/ experienced
- Page: page number
- Date: date and times

In general, there are majorly two community standards to specify data format and protocol to transmit Learning Analytics data; ADL xAPI (ADL, 2015) and IMS Caliper (IMS, 2015c). xAPI data format is very flexible to represent any types of learning activities. However, because the format is based on JSON, there needs translation from simple set of 4 types of data into xAPI format. xAPI is good for anonymous client-server data transfer. At first the authors tried to implement a function C) based on xAPI, however we changed it into simple comma-separated string afterward, because the this experiment deal with only the above five items (actor, verb, title, page, date), and only dedicated clients and a server.

2.2 Learning Style Estimation

The authors utilized ILSQ (Soloman, 2005). As showed in 1.3, ILSQ originally has four dimensions. Among these dimensions, the authors focused on (3) visual-verbal and (4) sequential-global. There are two reasons for this selection. First, only these two dimensions correspond to Riding's two dimensions of cognitive style. Second, the authors hypothesized that features of page flip history related to these two dimensions observe easily from learner's page flip history. The authors translated ILSQ into Japanese and imported into Google Form.

2.3 Target Classes, Units, and Subjects

The authors set the two target classes. Both classes were held in Sophia University, Japan, and one of the authors was in charge. Target classes, initial number of students, and target units were as follows.

Class "Information literacy" (100 level): 90 students
    Unit "Journal search", on May 18, 2015 (abbr: IL518)
    Unit "Numerical data", on June 1, 2015 (abbr: IL601)
Class "Learning technology" (300 level): 80 students
    Unit "Instructional design", on May 19, 2015 (abbr: LT519)
    Unit "Test and Feedback", on May 26, 2015 (abbr: LT526)

The first Information Literacy class was entry level for 1st year students, so contents were rather easy. In contrast, Learning Technology was for 3rd year students, so contents were relatively difficult.

2.4 Procedure

Lecture slides, usually on PowerPoint, were converted into the target data described in section 2.1 beforehand. In the classes, one of the authors (Tamura) held lectures as usual, while page flip information are collected and transmitted into a dedicated server automatically. After the classes, all

subjects were requested to answer ILSQ questionnaire in Google Form described in Section 2.2. This result was downloaded and used to estimate their learning styles.

3. Result

3.1 Numbers of Acquired Data

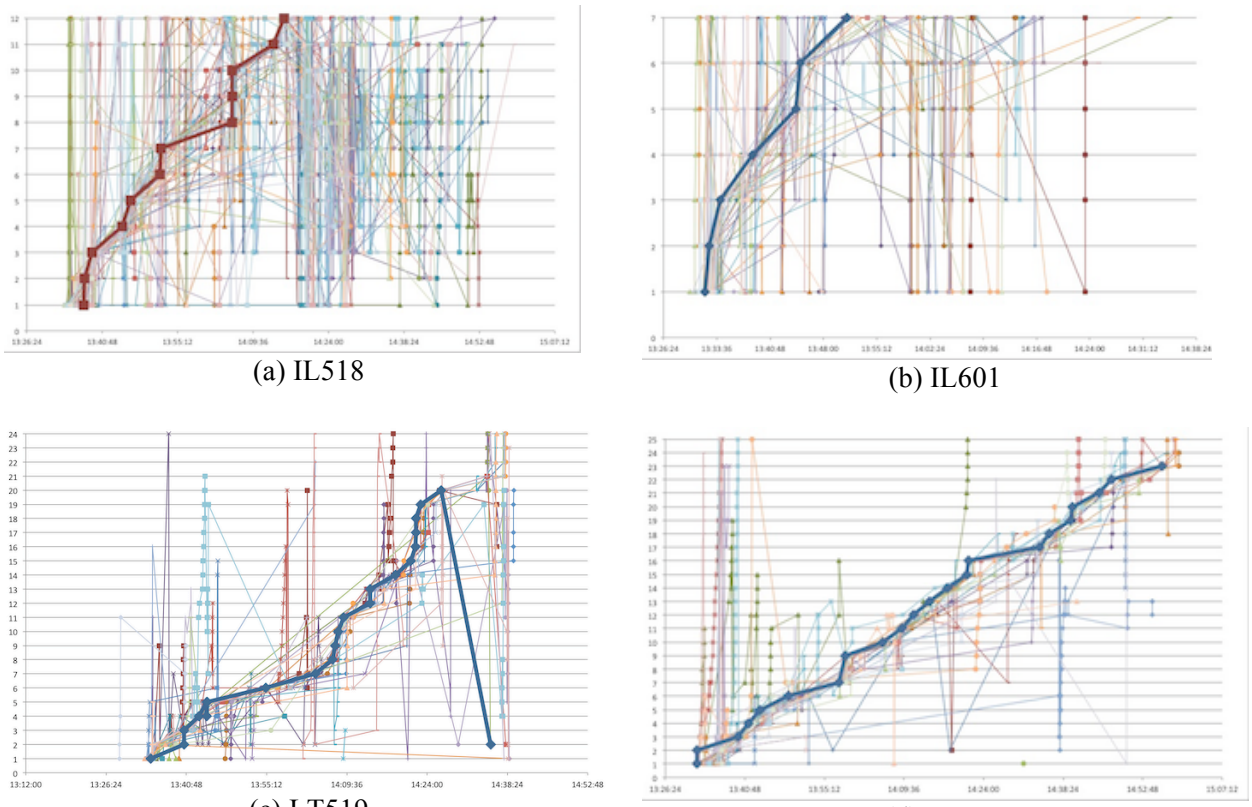
Numbers of subjects that succeeded to collect data is shown in Table 1. Not all subjects answered ILSQ, and not all ILSQ-answered subjects used the target materials described in section 2.1. The following analysis focuses on the subjects both to use the target materials and also to answer ILSQ.

Table 2. Numbers of collected data

Unit ID	LA data	ILSQ	Both
IL518	71	74	62
IL601	64	74	59
LT519	37	40	23
LT526	34	40	24

3.2 Page Flip History

Visualized page flip histories of teachers and all subjects are shown in Figure 3. In these figures, vertical axis shows slide page number and horizontal axis shows time (maximum of 90 minutes). A thick line shows a history of a teacher, other thin lines show subjects'.



(a) IL518 (b) IL601

(c) LT519 (d) LT526

Figure 3: Page flip history of 4 units

As observed from Figure 3, lines of (a) and (b) are scattering, but (c) and (d) are relatively closer to teacher's line. This difference suggests that (a) and (b) (Information Literacy classes) is relatively

easy to understand so subjects view slides that are not lectured at that time, while (c) and (d) are relatively difficult to understand so subjects concentrate on viewing slides currently lectured.

Quantitatively, this difference is shown in the sum totals of standard deviation of each unit. The result is shown in Table 2. Since total numbers of slides depend on the units, divided results are shown in row 4. From the result, IL518 and IL601 units shows bigger number of standard deviation than LT519 and LT526.

Table 3. Standard Deviation of 4 Units

Unit ID	SD	slides	SD/slides
IL518	2.933	12	0.244
IL601	2.004	7	0.286
LT519	4.401	24	0.183
LT526	4.604	25	0.184

3.3 Cluster Analysis

The original research question was to verify that Questionnaire-based learning style estimation matches the classification of page flip history or not. In order to do it, the authors adopted cluster analysis for page flip histories. First, the authors classified them with use of hierarchical cluster analysis to determine adequate cluster numbers. A cluster dendrogram of unit IL518 is shown in Figure 4. Second, they were divided into six or seven clusters by nonhierarchical cluster analysis.

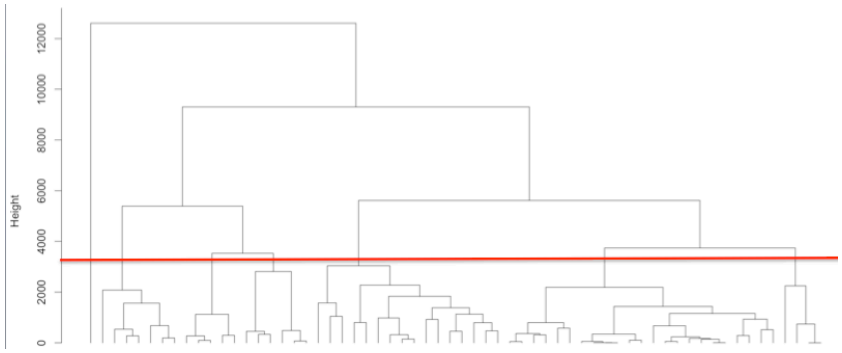
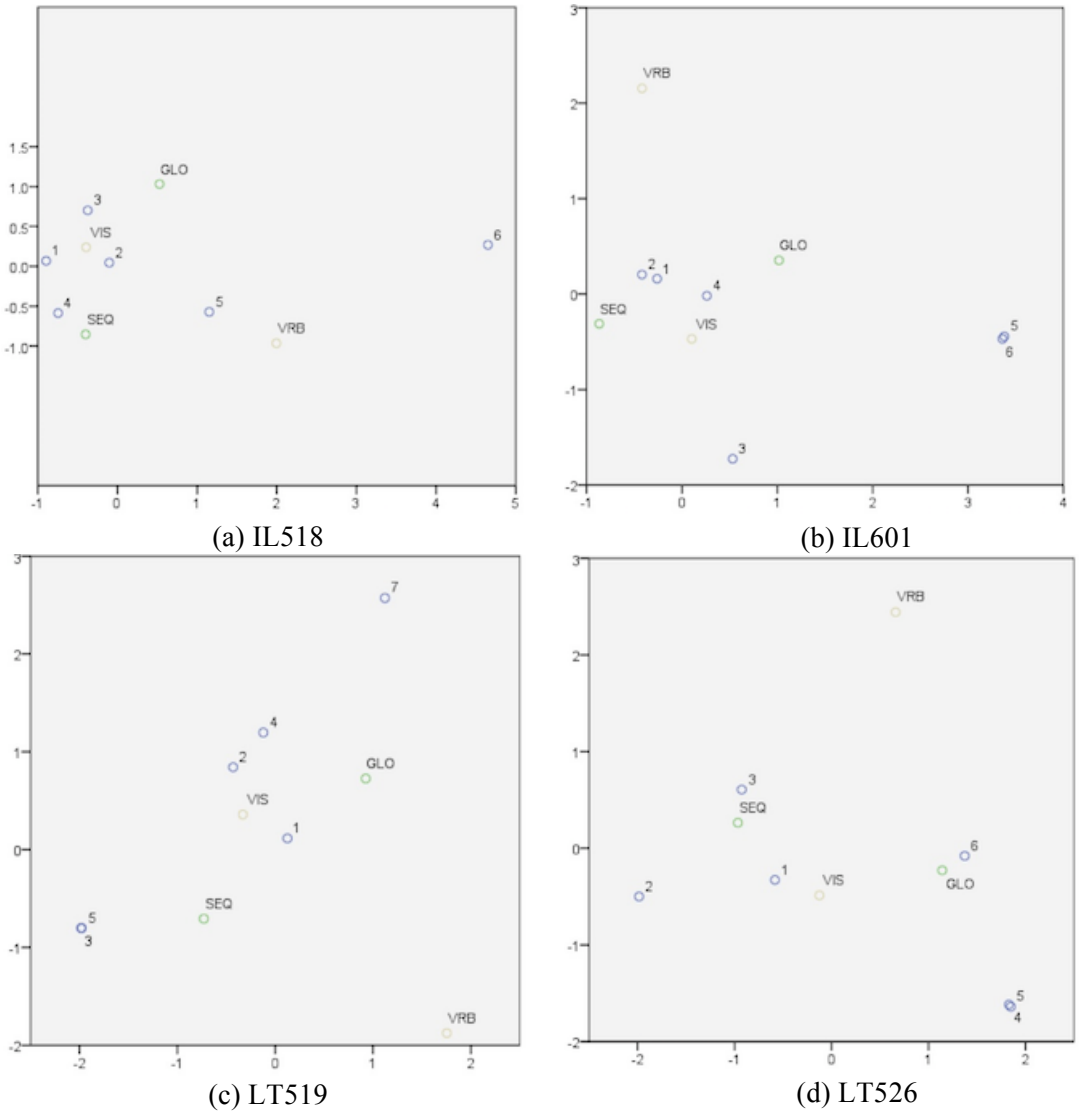


Figure 4. Cluster Dendrogram of Unit IL518

3.4 Multiple Correspondence Analysis

Based on cluster analysis in section 3.3 and learning style estimation on ILSQ in section 2.2, the authors checks correspondence between clusters and visual-verbal / global-sequential styles. The result is shown in Figure 5. In the figure, number 1 to 7 shows cluster numbers, while global as GLO, sequential as SEQ, visual as VIS, and verbal as VRB. From (a) to (d) in Figure 6, there was no significant correspondence between cluster number and learning styles. Quantitatively, as a result of chi-square tests of independence based on cross-tabulations, only one unit IL518 showed significant correspondence (χ^2 (5)=13.311, p=0.021) only in visual-verbal learning styles.



(a) IL518 (b) IL601

(c) LT519 (d) LT526

Figure 5. Result of Multiple Correspondence Analysis

3.5 Style estimation based on manual "Ladder" detection

In the multiple correspondence analysis in the section 3.4, there found no significant correspondence. The authors supposed this reason that the cluster analysis described in the section 3.3 had its own limit: it just classified the target data but did not identify "semantic" feature of the data.

In order to identify this semantic feature in page flip history, the authors used the hypothesis as stated 1.4: "Global learning style learners will glance all materials during a certain time period". Based on this hypothesis, the authors divided all subjects' page flip history into 2 groups manually. The target group's history included shapes to "rush up ladders" during a certain time period, while the control group's history did not. After that, the authors examined a cross-tabulation of these TG/CG and Global/Sequential learning styles. The result of chi-square test of independence based on the cross-tabulation showed significant correspondence ($\chi^2(1)=6.827$, $p=0.009$). It shows that the TG ("rush up ladder") significantly includes Global learning style, while the CG does not. In other words, there is significant association between Global style and the feature of page flip history that glance all materials during a certain time period.

4. Discussion

The authors first classified subjects with use of automatic cluster analysis. However, as shown in Figure 5, there were no significant correspondence between these clusters and ILSQ-based learning style estimation. On the other hand, the process described in section 3.5 found a significant correspondence when the authors detected "rush up ladders" manually. Currently, this "partial characteristics" detection is not available with use of general cluster analysis method , because the cluster analysis method treats one data set as a whole. In this sense, we need another method to identify a partial characteristic like "rushing up ladders". It might be some methods like feature extraction algorithm, or be refinement of cluster analysis method.

5. Conclusion, Future Works

The authors verified learners' learning styles with use of learning style questionnaires and page flip history of materials. The first approach was to classify learners with use of automatic cluster analysis, but the authors could not find any significant correspondence between clusters and learning styles. With use of the second approach, to distinguish learners with "rushing up ladder" characteristics, the authors found significant correspondence with "Global" learning style tendency.

There are some future works related in this paper.

- As described in section 4, there needs a method to identify a partial characteristic like "rushing up ladders". It might be some methods like feature extraction algorithm, or be refinement of cluster analysis method.
- ILSQ, described in section 2.2 in order to estimate learning style, has features to estimate other styles of active-reflective and sensing-intuitive, rather than global-sequential, and visual-verbal in this paper. Then there are still other hypotheses for these other learning styles.
- There might be some other factors to characterize page flip history, like difficulty of learning contents, teaching styles and strategies of instructors and units, etc.
- Page flip history might be used for "formative evaluation" of learning materials. For example, if page flip history of a learner includes a zig-zag manner, these parts of learning materials might have some problems: to be too difficult or assigned in wrong sequence. There can be variety of hypotheses like them.

Acknowledgements

This work was supported by JSPS KAKENHI Grant Number 26282059.

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