Reproducibility of Findings from Educational Big Data: A Preliminary Study

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ABSTRACT
In this paper, we examined whether previous findings on educational big data consisting of e-book logs from a given academic course can be reproduced with different data from other academic courses. The previous findings showed that (1) students who attained consistently good achievement more frequently browsed different e-books and their pages than low achievers and that (2) this difference was found only for logs of preparation for course sessions (preview), not for reviewing material (review). Preliminarily, we analyzed e-book logs from four courses. The results were reproduced in only one course and only partially, that is, (1) high achievers more frequently changed e-books than low achievers (2) for preview. This finding suggests that to allow effective usage of learning and teaching analyses, we need to carefully construct an educational environment to ensure reproducibility.

CCS Concepts
• **Applied computing~Education** • **Applied computing~E-learning** • *Applied computing~Distance learning*

Keywords
E-book; Educational big data; reproducibility.

1. INTRODUCTION
In recent years, many countries have implemented and begun assessment of information and communication technology (ICT)–based education and learning materials in schools, especially of electronic textbooks, called e-(text) books [3]. The present study focuses on one aspect of e-book use in an educational environment, that is, the digital footprints of students, which can be aggregated into educational big data. We can use such data to examine student performance patterns [1] to help teachers revise courses [2].

To improve teaching and learning, Kyushu University introduced a single platform learning system (M2B). An e-book system (BookLooper) of it enables students to browse e-book materials before/during/after lectures, anywhere and anytime, using their PC or smartphone; At the end of 2015 it collected approximately 5,320,000 log from approximately 20,000 students. We utilize this educational big data in our research, including analysis of browsing patterns against quiz scores [e.g., 6], investigation of effective learning behavior [e.g., 4. 7], and predictive modeling [e.g., 5].

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2. RESEARCH QUESTION
Ensuring generality and reproducibility of analyses is important for big data analytics, especially if for practical usage in the education environment. For example, findings obtained from the logs of an academic course should be reproducible in other courses. To address this issue as a preliminary step, we examined our previous findings regarding logs of a course from educational big data [4] using data from other courses. We [4] used e-book logs to investigate characteristics of the learning behavior of high and low achievers enrolled in an Information Science course in Kyushu University. We categorized e-book logs as follows: if a log was recorded before a class session in which the same e-book was used as a textbook, it was a *preview* log, and if after, a *review* log. We reported that (1) students who attained consistently good achievement more frequently switched between different e-books and different pages within e-books than low achievers, but that (2) this difference was found only for preview logs, not review logs, and also that (3) there was no significant difference in duration of browsing between high and low achievers. In the present study, we investigate whether these results were reproduced in other teachers' Information Science courses using the same e-books as textbooks as in the original course studied in [4].

3. METHODS
Preliminarily, we analyzed logs from four Information Science courses (from 2015.04.13 to 2015.07.30). The objective of these courses was the same (i.e., understanding fundamentals of ICT), and they used the same series of e-books as textbooks. Table 1 shows details of the courses, all of which were taught by teachers other than the teacher in [4]. We analyzed all of the logs from students who attended the courses. The numbers of logs per course are shown in Table 1. In the same way as [4], we calculated the following three measurements per hour per student, based on the e-book logs. *Change:* how many times a student changed e-books. *Page flip:* how many pages of the e-book a student flipped. *Duration:* how many seconds a student browsed a given e-book for.

Table 1. Details of the courses

	Course ID			
	1	2	3	4
# of sessions	14	14	15	15
# of used e-books	12	12	14	15
# of students	29	48	120	44
# of logs	43,788	38,720	207,106	54,725

Table 2. Proportion of grades

Grade	Course ID			
	1	2	3	4
A	45	65	73	43
B	21	23	20	45
C	14	10	3	5
D	17	2	1	5
F	3	0	3	2

We summed each of these for preview and review for each student. The students were categorized into five groups according to their grades in the course: A (excellent), B, C, D, and F (failure). Table 2 breaks down grades proportionally by course.

4. RESULTS

All statistical analyses were conducted using the Statistical Packages for the Social Sciences (SPSS; version 23; IBM). To examine whether the previous findings were reproducible in each of the additional courses and to identify any differences between the courses, we carried out three-way mixed-design ANOVA with course (4) and grade (5) as between factors and preview/review (2) as a within factor. This analysis was performed for each measurement. If the previous findings were to be replicated, a difference between high and low achievers was expected only for preview, that is, a significant interaction between grade and preview/review was expected.

The results show that only change had a significant three-way interaction, $F(11, 222) = 2.09$, $p = .022$, not page flip or duration, $F(11, 222) = 0.79$, $p = .653$; $F(11, 222) = 1.75$, $p = .064$. Figure 1 shows average change frequency for all students across the four courses. For each, two-way ANOVAs with grade (5) as a between factor and preview/review (2) as a within factor were carried out. Course 1 shows a significant interaction between grade and preview/review, $F(4, 24) = 3.14$, $p = .033$, but the other courses do not, Course 2: $F(3, 44) = 2{,}52$, $p = .070$; 3: $F(4, 115) = 1.87$, $p = .121$; 4: $F(4, 39) = 0.37$, $p = .828$. For Course 1, multiple comparisons with Bonferroni correction showed for preview, the group with A grades showed significantly more frequent changes than the D group ($p < .05$). In contrast, for review, there was no significant difference among the groups for Course 1.

5. DISCUSSION

In the present study, we examined whether the previous findings for e-book change frequency in one academic course were reproducible in other academic courses. Results (1) and (2) were partially replicated: the high achievers (group A) more frequently changed their e-books than the low achievers (group D) only for preview, not review. However, this difference was found only in Course 1, not Course 2, 3, or 4. The reason the findings were only partially reproduced could be explained by several factors. For example, as shown in the breakdown by grade (Table 2), grading criteria were not consistent throughout the courses, and so characteristics of "high achievers" and "low achievers" may be different among the courses. That might produce large discrepancies within each group, reflected in the large standard deviations in the results (Figure 1).

6. CONCLUSION

Our results suggest that for effective application of learning and teaching analyses of educational big data, we need to carefully set the educational environment. Employing rubrics may be one way of doing so.

7. ACKNOWLEDGMENTS

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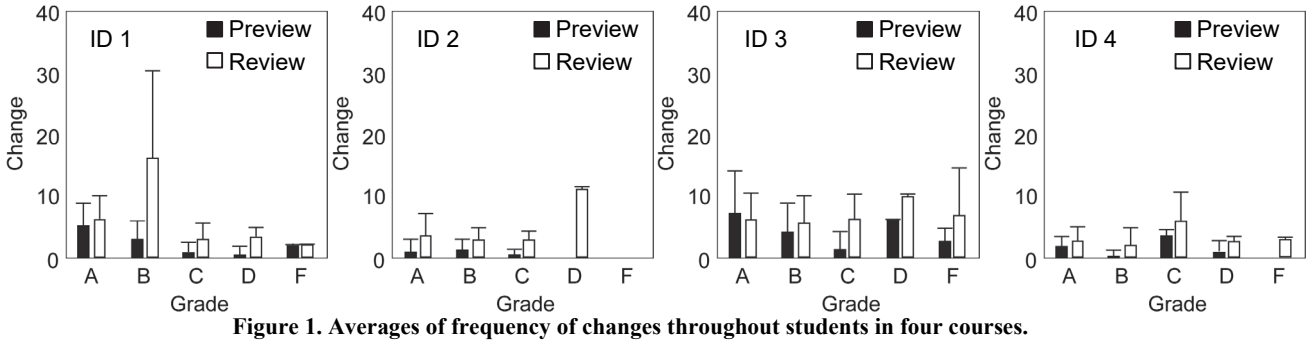

Figure 1. Averages of frequency of changes throughout students in four courses.