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Linking Real-World Experiences with Course Contents: A Text Mining Approach Toward Effective "*There and Back Again*"

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Abstract: In higher education, teachers sometimes urge students to apply what they have learned during class to real-life situations. However, interweaving real-world events with class activities, or the *There and Back Again* process, entails difficulty in relating dynamic experiences to the course contents. This study attempted to link both sides using text mining techniques on course data from a Japanese university. We extracted key phrases from four weekly assignments featuring students' real-world explorations. Then we measured the semantic similarity between each key phrase and each course content and linked the pairs with high similarity. For the linked pairs, we conducted data analyses. We also held a semi-structured interview with a course teacher regarding the interpretability of visualized data and its practical use. Consequently, we confirmed: 1) the links between the course contents and students' key phrases appeared differently in the weekly assignments, 2) notable links between specific course contents and key phrases were identified, and 3) the visualized data contained valuable insights for the teacher, but more fine-grained linking and integrated presentations were required. Despite several limitations, the results support the potential utilization of this approach for effective data-enhanced experiential learning.

Keywords: real-world learning, learning analytics, text mining, key phrase extraction, data-enhanced experiential learning

1. Introduction

Learning from real-world experience is a well-known approach in education. Theoretically, learning is known to be constructed through the transformation of experience (Kolb, 1984), which involves the integration of one's own thinking, feeling, perception, and behavor (A. Y. Kolb & D. A. Kolb, 2005). Thus, teachers, especially in higher education, sometimes intend to implement learning-by-doing or real-world activities in their learning designs, such as situated language learning, fieldwork, and pre-service training.

To make such experiences effective, it is common to employ a hybrid learning style comprising: raising awareness beforehand, tackling a hands-on experience, and reforming the understanding through reflection and conceptualization (Gibbs, 1988). In particular, we call such a learning process that features real-world experience as *There and Back Again*, inspired by a fantasy novel in which the main character leaves the homeland once, undergoes an uncertain journey, and then returns with plenty of takeaways (Tolkien, 1973).

However, it is difficult to know how conceptual knowledge cultivated in class was exercised in a real-world context. Worksheets and reflective writing are common approaches to align students' activities with their learning goals (Basten et al., 2014; Fernandez et al., 2015). However, these methods cannot suggest the exact connections between course contents and students' descriptions. In addition, it is even more difficult to relate numerous prior course contents.

Data-enhanced approaches that rely on text mining and learning analytics could overcome this issue. Data analysis of students' descriptions about their experiences, such as reflection papers and essays, could provide insights into their written thoughts and findings (Lebowitz et al., 2020). This would provide learners with tangible clues to recall both the prior course contents and their takeaways. It might also be helpful for teachers to understand their students' perspectives and improve their learning designs (Dawson, 2019). Nonetheless, previous studies have tended to analyze only the experiential side. In other words, holistic analyses of conceptual knowledge acquisition and real-world experiences are lacking.

To fill this gap, this study aims to reveal how prior course contents have been applied to students' real-world experiences by analyzing their outcomes from the *There and Back Again* process. Moreover, we examine a teacher's perspectives on the interpretability and practical use of visualized data. Accordingly, we set the following research questions:

- RQ1: To what extent did students' outcomes from real-world experiences involve prior course contents?
- RQ2: Which prior course contents were related to which part of the outcomes?
- RQ3: How does the teacher interpret visualized data?

2. Related Works

2.1 Experiential Learning Cycle

Theoretically, the *There and Back Again* process relies on the experiential learning cycle model. In light of the learning theories that emphasize interaction with the world (Dewey, 1938; Lewin, 1942), the model proposes a cyclic process of learning essentially consisting of concrete experience, reflective observations, abstract conceptualization, and active experimentation (Kolb, 1984; A. Y. Kolb & D. A. Kolb, 2013).

The model has assisted teachers in realizing effective real-world learning in practice, even when students enter unfamiliar circumstances. Especially, the cycle suggests that the pre- and post-activities play important roles in enhancing awareness and prior knowledge before a certain experience and also in deepening reflection afterward (Gibbs, 1988; Lee et al., 2020). Nonetheless, in the reflection phase, it is often challenging to draw clear connections regarding which prior knowledge was applied during an experience.

2.2 Assistance for Reflection and Conceptualization

Worksheets are a common aid in maintaining links between the topics covered in class and real-world experiences. The tool can provide a clear structure for an activity and guide learners while keeping their autonomy, even in a situation with a high degree of flexibility (Basten et al., 2014). This helps learners keep remain aware of what to learn throughout their learning process. However, manually reviewing the gains from an experience would be difficult, especially when there are affluent memos on a worksheet.

Taking time for reflective writing can be a further aid. It expects learners to describe and analyze own experiences by recalling their thoughts and feelings in a situation. Learners can obtain deeper insights and ideas by validating their basic assumptions or knowledge (Boud et al., 1985). This process leads to increased self-awareness of updating knowledge and skills (Fernandez et al., 2015). However, reflection requires cognitive efforts to relate events and one's own understandings. Thus, there will be a need for further assistance.

2.3 Data-Enhanced Experiential Learning

Learning analytics is an approach to improve teaching and learning by capturing, analyzing, visualizing, and reporting data about learners. (Dawson, 2019). Incorporating learning analytics into educational technologies enables data-enhanced pedagogical solutions. Regarding the difficulties above, two approaches can be introduced. One is by directly collecting the footprints of learning, or learning logs, from field activities and reminding them through visualization (Mouri et al., 2018; Perez-Colado et al., 2018). However, it is still unclear how to deal with complex learning scenarios (Pishtari et al., 2020) since prior studies have barely discussed holistic data analysis covering both classroom and field activities (Ishihara et al., 2024).

Text mining is another approach. Although text data, such as texts from reflective writings, would be an indirect footprint of an experience, it could contain rich descriptions influenced by course contents in certain out-of-class events. One possible way of clarifying the links from texts is to capture the co-occurrence of words (Lebowitz et al., 2020; Takamatsu et al., 2018). This technique can form groups of words by considering the frequency of word use and visualizing them as a network graph. Frequently used words will emerge as prominent nodes. However, this may not fit the context of our concern. Grouping occurs for the same words, whereas learners often avoid the repetitive use of the same words in writing. If there is a paraphrased description of a certain course content, it will never be linked to the course content because of the variation in expression.

The issue of variation in expression can be solved by key phrase extraction, a text mining technique that outputs key phrases from sentences by grouping similar words (Boudin, 2018). Additionally, measuring semantic similarity allows us to identify texts with similar meanings (Harispe et al., 2015). Given that the conceptual knowledge of course contents is expressed as words with similar meanings, these methods can capture desired links. To the best of our knowledge, no prior study has attempted such an approach. This study thus examines its feasibility in higher education.

3. Method

3.1 Data Collection

3.1.1 Learning Context

We obtained a dataset from the “Human Interface” course held in the fall semester at a Japanese university in 2023. The weekly course consisted of 12 classes, and 41 undergraduate students attended. The course employed *Moodle*, an online learning management system, and an online eBook reader called *BookRoll* (Flanagan & Ogata, 2018). By courtesy of the course teachers and prior agreement from the students, we were allowed to access the course data from the first week to the fifth week.

Every week, the students learned new topics about the human interface with a lecture material shown on *BookRoll*. Then, they tackled a writing assignment after each class, which required them to find and analyze several interfaces in living spaces by applying the ideas of the course contents. They were permitted to refer to the prior lecture materials on *BookRoll* at any time. The students submitted the weekly assignments via *Moodle* by the next class. These activities were aligned with the *There and Back Again* process, as shown in Figure 1.

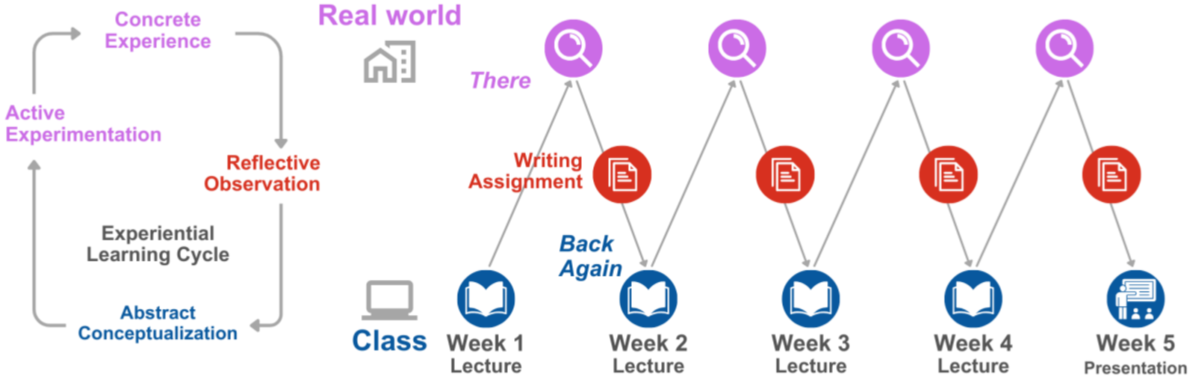

Figure 1. The *There and Back Again* process in the course period.

3.1.2 Dataset

We collected course contents from the lecture materials and also key phrases from the students' writing assignments from the first week to the fourth week. The fifth week, dedicated to the mid-term presentations, had neither lecture materials nor assignments. We adopted 25 course contents from the lecture material of the first week, assuming that they were supposed to be related to all the assignments. We regarded the title of each page as a course content, that is, the conceptual knowledge to be learned. However, the pages with a summary of the week and instructions for the assignment were omitted.

For key phrases that could represent students' application of knowledge, we collected the writing assignments from 17 students who completed all submissions from the first week to the fourth week and granted the use of their data for research purposes. As a result, 68 files were gathered. The file format was PDF. Most of the descriptions in the files were in Japanese, except for several technical terms and proper nouns that were in English.

To extract texts from the PDF files, we used the Python library called *PDFMiner*. We then used the following Python libraries for preprocessing on students' descriptions: *neologdn* for normalizing texts and also *spaCy* and *GiNZA* for tokenization and morphological analysis in Japanese. First, we set up the normalization criteria and executed them. Second, we detected and deleted person names using Named Entity Recognition, a text mining technique used to distinguish predefined categories, such as persons, organizations, and places. Third, we manually checked the preprocessed texts and refined the normalization criteria until no personal information was found. Consequently, we obtained the dataset presented in Table 1.

Table 1. *Dataset*

Category	Week	# of PDF files	# of course contents in material or tokens after preprocessing
Lecture material	1	1	25
Writing assignment	1	17	12,168 (Mean: 715.8, SD: 312.7)
	2	17	6,464 (Mean: 380.2, SD: 153.7)
	3	17	6,671 (Mean: 392.4, SD: 192.4)
	4	17	5,765 (Mean: 339.1, SD: 96.6)

SD: Standard deviation

3.2 Linking Key Phrases with Course Contents

3.2.1 Key Phrase Extraction

We extracted key phrases from the students' assignments using the multipartite rank model in the Python library called *pke*. Multipartite rank is a graph-based algorithm for identifying key phrases based on the co-occurrence relationship and position of words in a document (Boudin, 2018). Candidates for key phrases are selected from sequences of adjectives and nouns, and these are treated as nodes. Similar ones are regarded as a group. Each candidate node has directed edges to others in different groups. Incoming edges to candidates located at the beginning of the document are weighted more. The nodes with weighted incoming edges will be ranked higher, and the top *N* candidates will be output as key phrases. We extracted up to 10 key phrases from each assignment and finally obtained 679 key phrases.

3.2.2 Measuring Semantic Similarity

To capture the links between key phrases and course contents, we measured semantic similarity using *sentence_transformers*. It is a Python framework that allows us to vectorize texts dealing with more than 100 languages and measure cosine similarity. Cosine similarity is a well-known metric that quantifies the similarity of a pair of vectors (Harispe et al., 2015). We calculated the cosine similarity, ranging from -1 to 1, for all combinations of key phrases and the course contents. To find relevant course contents of the first lecture to key phrases from each assignment, we extracted the top five cosine similarity scores between the course contents and the key phrases. We eventually gathered 114 pairs that marked higher cosine similarity scores. These were considered as the links and their strengths.

3.3 Data Analysis

For RQ1, we examined how the course contents of the first lecture material were related to the key phrases from the assignments over four weeks. We summed up the cosine similarity scores for the course contents and then aggregated them per assignment. If a course content had cosine similarity scores for several key phrases, the sum of scores was given to the course content. In doing so, we identified highly associated course contents for each assignment.

For RQ2, we explored the notable links between the course contents and the key phrases in detail. We drew heatmaps to obtain an overview of the links with high and low scores in terms of each page of the lecture material and each student's assignments. If a student's five key phrases in an assignment were related to the same course content on a page, the heatmap gave the strongest color in the corresponding coordinate. In addition, we drew network graphs to grasp the details of specific links.

3.4 Semi-Structured Interview with a Teacher

For RQ3, concerning the teacher's perspective of the visualized data, we conducted a semi-structured interview with the teacher who led the lectures from the second week to the fifth week. The interviewee had several years of teaching experience and specialized in learning analytics. We inquired about the following: 1) the usual methods of evaluation for assignments that require applying course contents in a real-world context, 2) the interpretability of heatmaps and network graphs, and 3) the impressions of the use of data in practice.

The interviewee was not informed of the questions or visualizations in advance. Thus, before asking about the visualizations, we provided a brief explanation of what each element in the figures represents.

4. Results

4.1 Links Between the First Lecture and Assignments over Four Weeks

We identified five highly linked course contents in the first lecture material, as shown in Table 2 and Figure 2. The most prominent course content was "Design Principles." It was followed by other course contents: "Usability Principles," "User Experience Goals," "Interaction Paradigms," and "About Interaction Design." These results suggest that the two principles introduced in the first lecture had an impact on all assignments.

Table 2. *Top Five Course Contents Based on Sum of Cosine Similarity Scores*

Course contents (in English)	Assignment 1	Assignment 2	Assignment 3	Assignment 4	Total
デザイン原理 (Design Principles)	11.94	2.88	3.84	7.74	26.40
ユーザビリティ原理 (Usability Principles)	11.52	0.78	1.69	4.30	18.29
ユーザ体験目標 (User Experience Goals)	10.29	0.78	0.81	1.61	13.49
インタラクションパラダイム (Interaction Paradigms)	0.89	0.95	1.78	1.60	5.22
インタラクションデザインとは (About Interaction Design)	0.92	0.91	1.84	0.79	4.46

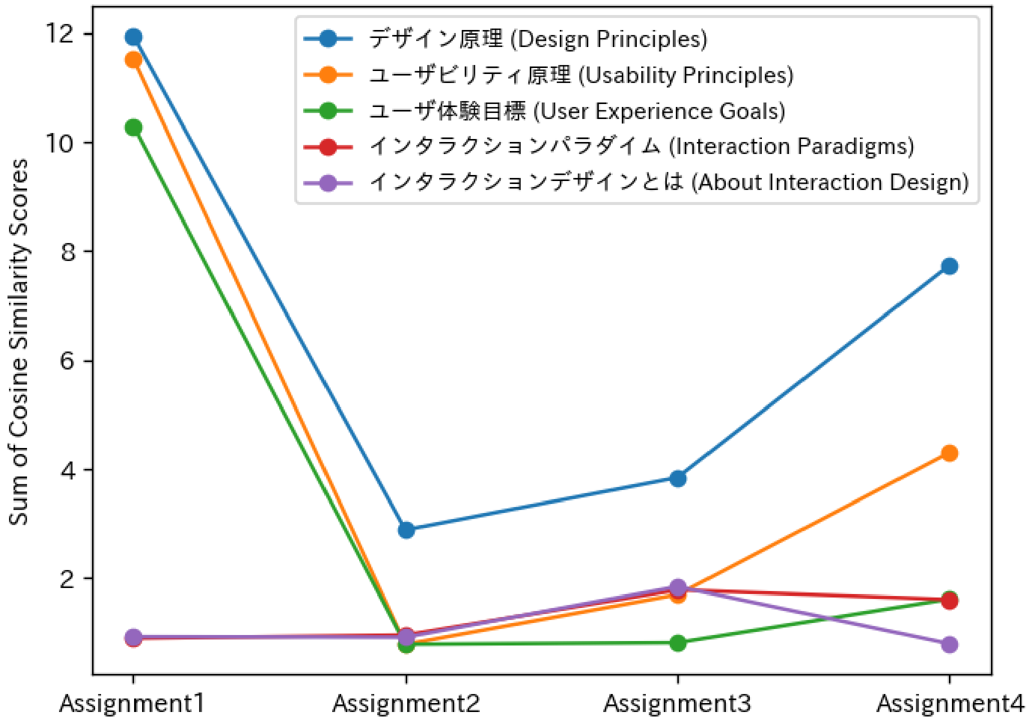

Figure 2. Sum of cosine similarity scores per assignment.

The top three course contents (blue, orange, and green lines in Figure 2) showed a tendency for the sum of cosine similarity scores to decrease once but increased afterward. The fourth and fifth places of the course contents (red and purple lines in Figure 2) showed another tendency to maintain their presence at a relatively low level.

4.2 Identifying Strong Links

In the heatmaps, specific pages of the lecture material emerged. In the leftmost heatmap in Figure 3 for Assignment 1, the column for page 22, of which the course content was "Usability Principles," indicated stronger links with the assignments of Students 15 and 17. For Assignment 2, the second heatmap from left, the colored area decreased. According to the heatmaps for Assignments 3 and 4, right half in Figure 3, the colored area increased. In the rightmost heatmap, we can identify page 9, of which the course content was "Design Principles," had higher scores, especially on the assignments of Students 8 and 9.

The tendency of the colored areas seems to align with the tendency of the top three course contents in Figure 2. The course contents of the first lecture strongly affected Assignment 1, but the impact decreased in Assignment 2, and then it gradually increased toward Assignment 4.

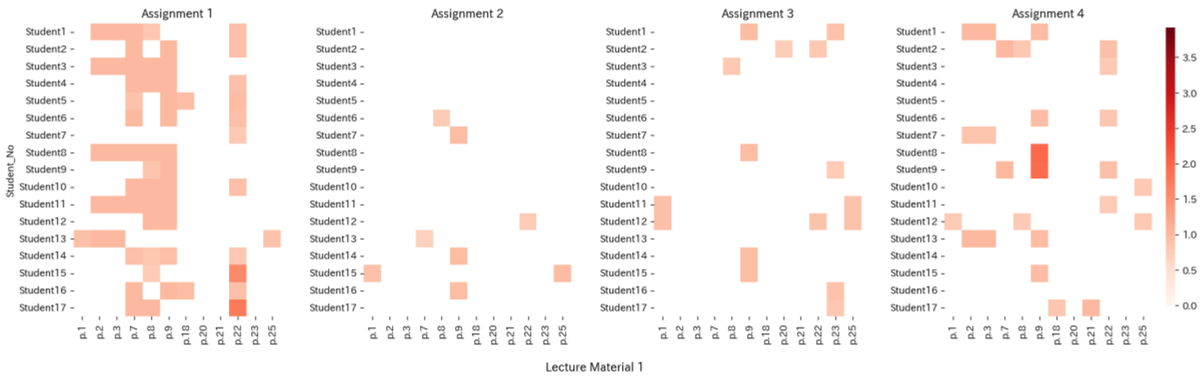

Figure 3. Strength of the links between assignments and pages of the lecture material.

Next, we dug deeper into the specific links. We built a network graph representing whole associations of the students, assignments, key phrases, course contents, the lecture material for the first week, and its pages, as shown in Figure 4 a. The node size and the edge thickness correspond to the frequency of the association. We particularly examined the relationship between the course contents of the first lecture and the key phrases derived from Assignment 4, the most distant in time.

As examples, we looked at Students 8 and 9 whose key phrases from Assignment 4 were notably linked to page 9 of the lecture material. As Figure 4 b depicted, the graph of Student 8 showed two red nodes for the key phrases “Design Principles” and “Design,” one blue node for the course content “Design Principles,” and one azure node for page 9 of the lecture material. This suggested that Student 8 argued about design and design principles in Assignment 4, which was influenced by the idea of course content on page 9.

In the graph of Student 9 in Figure 4 c, two clusters emerged. The left graph in Figure 4 c showed that the student discussed “Usability Goals,” and the key phrase was linked to “Usability Principles” on page 22 and “Usability Goals” on page 7 of the lecture material. Another cluster revealed that the student also argued “Design Principles” and “Design Problems” in Assignment 4, and these were linked to “Design Principles” on page 9. We can infer that the course contents on usability goals and design principles were applied to the students’ real-world exploration.

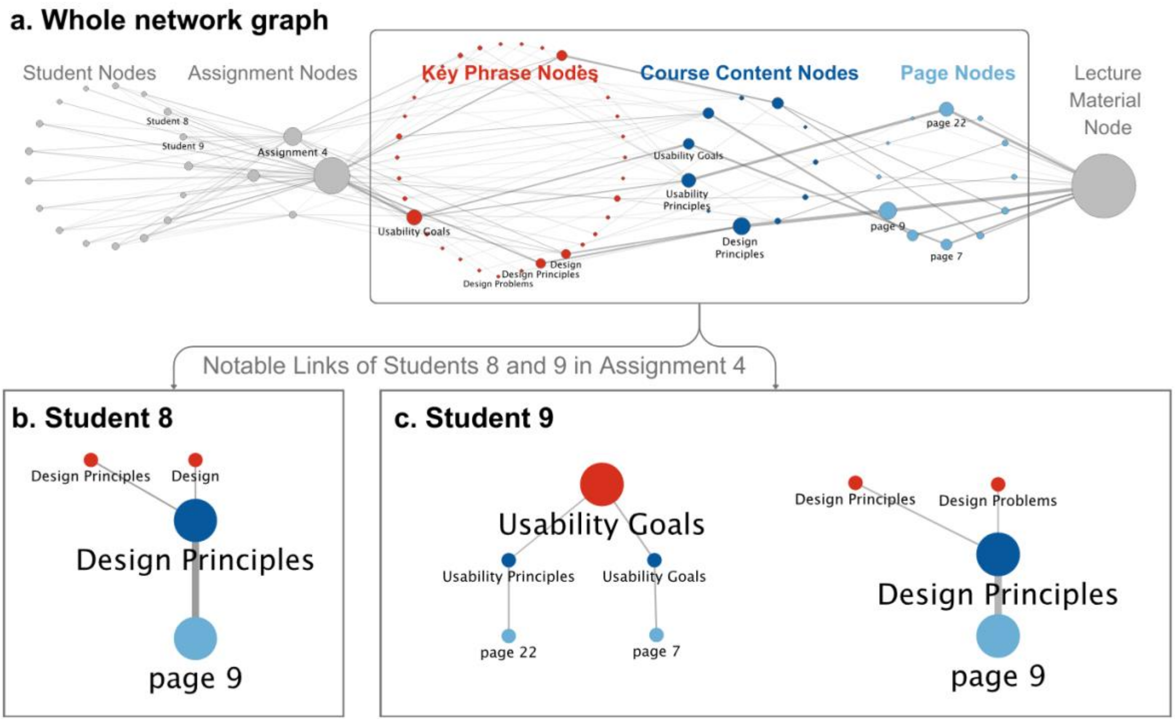

Figure 4. Whole associations and notable links of Students 8 and 9 in Assignment 4.

4.3 Teacher’s Perspective of the Data Visualization

In the interview, we first asked about the teacher’s usual methods of evaluation for writing assignments that urge students to apply course contents in a real-world context. The teacher uses a rubric that gives scores depending on achievement. For instance, the submission was completed on time, any course content introduced in the week was mentioned, and former course contents were additionally included. The teacher had no significant difficulty in the evaluation thanks to the rubric and also the students’ peer evaluation. However, the teacher expressed a concern about formative assessment: it would be challenging to provide adequate feedback if the argument in an assignment was insufficient.

With regard to the heatmaps, the teacher could find notable links by considering the colored area and the color intensity. For instance, the teacher specified the exact pages of the lecture material that had strong links to students' assignments. Moreover, the teacher recognized a macro-level tendency that suggested that the links decreased after Assignment 1 and then increased in the end. The teacher analyzed that this was because Assignment 4 urged students to apply any previous course contents, whereas other assignments required them to apply the course contents of the current week.

For the network graphs in Figures 4 b and 4 c, the teacher interpreted them as well as we reported above. After confirming that the teacher had insights from the visualized data, we asked the teacher to compare the graphs with the original PDF file for Student 9. The teacher acknowledged that, intuitively, the links in the graphs represented more or less the characteristics of the student's descriptions. However, the teacher pointed out that some of the course contents we used seemed too general. It meant that it should have included more detailed levels of course contents; for example, "Design Principles" can be broken down more, such as visibility, consistency, affordance, and so forth.

Through data interpretation, the teacher also acknowledged the potential use of visualizations. Nonetheless, the teacher demanded the integration of information because it would not be efficient to refer to different visualizations and interpret them individually.

5. Discussion

5.1 Overall Tendencies of the Links

Regarding RQ1, we examined to what extent students' writing assignments based on real-world experiences involved the course contents of the first week. The emerged top five course contents showed two kinds of tendencies. One is that the total similarity scores of the upper three course contents decreased in Assignment 2 and then increased toward Assignment 4. This may be influenced by the assignment instructions. According to the teacher, Assignments 1, 2, and 3 mainly expected students to apply the course contents within the week, whereas Assignment 4 anticipated exercising any prior course contents.

It is notable that the links to the course contents "Design Principles" and "Usability Principles" continued to emerge, even though when the assignment instructions did not clearly request to apply the course contents of the first week. Also, as tokens in Table 1 implied, the number of words in an assignment decreased over time, but these two course contents kept their presence. Such persistent links can be useful clues for reflection and conceptualization.

Another tendency concerning the fourth and fifth places of the course contents showed constant, but not very high, scores. These course contents, especially the fourth-place course content "Interaction Paradigms," may have a potential impact. If a teacher or a system reminds students of such semi-strong links during reflection, it could evoke their awareness of the course contents and motivate further explorations (Fernandez et al., 2015). However, the fifth-place course content, "About Interaction Design," seems too general. This may simply be linked due to its universal wording.

This time, we focused on students' writing assignments. However, our approach can produce synergy with mobile learning approaches that collect learning logs from field activities (Mouri et al., 2018; Perez-Colado et al., 2018). Accumulating students' fresh impressions and findings during real-world experiences through a mobile system would capture their applications of knowledge more precisely.

5.2 Identifying Notable Links

For RQ2, we identified specific course contents that had notable links with the students' assignments. The heatmaps revealed which pages of the lecture material were impactful on each student's assignment. This traceability could play an important role in easing students to go back and forth between their outcomes and specific pages of the lecture material. For teachers, data visualization could help recognize which course contents were well delivered or should have been emphasized more. In addition, the network graphs clarified how an individual's key phrases, the course contents, and lecture material pages were related.

Although we analyzed limited samples, in this direction, the connection between course contents and real-world experiences could be more tangible.

Nonetheless, this study had several technical limitations. First, the links extracted based on cosine similarity might capture only explicit applications of knowledge despite the fact that students' outputs may implicitly refer to course contents. Recent large language models potentially could contribute to the detection of subtle applications of knowledge with their capability for nuanced reasoning (Mahowald et al., 2024).

Second, the accuracy of the linking has not yet been assessed. Although the tendency in the heatmaps seemingly depicted each student's characteristics of knowledge application, the links might overlook the implicit applications of knowledge. Also, irrelevant links may have been included. Measuring cosine similarity for all combinations of key phrases and course contents may harm accuracy because of an increase in false-positive linking. Further studies should assess accuracy and improve it toward credible data-enhanced learning and teaching.

Moreover, this study did not automatically extract the course contents from the lecture materials. In practice, it is inefficient for teachers to prepare a structured data of course contents manually. For this purpose, we need an automated method that can automatically form structured knowledge items from various lecture materials (Takii et al., 2024).

5.3 Teacher's Perspective

Regarding RQ3, which explored the teacher's perception of data visualization, we observed that the teacher could interpret the figures well. It should be noted that the teacher is familiar with data interpretation as a researcher in the field of learning analytics. However, the presentation of the data should be sophisticated. Our visualization seemed disorganized due to the separate information. For improvement, wider stakeholder opinions and the principles of comprehensible data visualization should be considered.

Sophisticated data visualization could facilitate teachers' inferences of students' specific knowledge applications in real-world contexts. It could also tell teachers about well-delivered and weakly-delivered course contents for a better learning design (Dawson, 2019). Such a scenario would be applicable for various *There and Back Again* processes, such as situated language learning, fieldwork, and pre-service training.

6. Conclusion

This study addressed the issue of linking students' outcomes to course contents, particularly their descriptions based on real-world explorations. A text mining approach relying on key phrase extraction and semantic similarity measurement revealed notable links at a detailed level from a university course dataset. Visualized data could help teachers evaluate students' real-world activities. Despite several limitations, this approach is still worth developing. Ultimately, it will contribute to establishing a data-enhanced experiential learning cycle, an effective framework for learning through the *There and Back Again* process between conceptual knowledge and dynamic experiences.

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