

# SEQUENCE ANALYSIS IN DISTRIBUTED INTERACTIVE LEARNING ENVIRONMENTS: VISUALIZATION AND CLUSTERING OF EXPLORATORY BEHAVIOR

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## ABSTRACT

*Constructivist learning posits that learners should construct their own meaning and organization of knowledge through exploration. Web-based distributed interactive learning (DIL) environments are a type of information and communications technology that supports learners in exploring learning materials. Although educators can access learners' navigational paths on DIL websites, the exploratory nature of such paths cannot be efficiently analyzed. Educators cannot determine the effects of small improvements or adjustments on DIL websites. In this study, the navigational paths of learners using alternative versions of a DIL website were recorded and analyzed using integrated sequence analysis methods. Visualization and clustering of the sequences revealed five common navigational patterns, and associations between the navigational patterns and learning outcomes were also identified. The findings show how educators can understand and improve the design of DIL websites by performing a sequence analysis.*

*Keywords: distributed interactive learning environment, online learning, sequence analysis, constructivism*

## INTRODUCTION

With a constructivist perspective, learners should explore the world to construct their own meanings and ways to participate in any field (Duffy & Cunningham, 1996). The role of educators is to observe learners while they explore and provide guidance and encouragement when needed. According to Khalifa and Lam (2002), web-based distributed interactive learning (DIL) environments employ the Web “to support hypertext-based exploration in terms of learning process and outcome” (p. 350). The hyperlinked nature of the Web enables learners to explore materials according to their needs and progress through their learning. However, the remote nature of DIL prevents educators from directly observing learners' exploratory behavior. Basic statistics, such as visit duration and page count, can be generated

from most websites. However, these statistics present a very limited view of learner exploration. Exploration of a website is a journey that is unique to individual learners, whose navigational paths reflect the exploratory nature of their website visits. Each path represents a series of choices of which web pages to visit. The amount of data can easily become unmanageable when the number of learners increases, and examining the exploratory behavior of a group of learners can be difficult for educators when the group is relatively large. Without effective analytical tools, educators using DIL websites cannot track the learning activities of students.

Generally, educators are not professional website designers, and thus the DIL websites they work with may require adjusting. Educators must learn how minor modifications can assist

learners. In website design, a common practice called “A/B testing” is often used (Kohavi, Henne, & Sommerfield, 2007; Nielsen, 2005). Website owners who adopt A/B testing create slightly different versions of a website and observe how such differences affect visitor behavior. Educators who operate DIL websites can improve or adjust their websites by adopting A/B testing. However, a lack of analytical tools for transforming complex navigational data into an informative and manageable format raises obstacles for educators who adopt this mode of testing.

Analytical tools have been created for examining sequences. Sequence analysis is a collection of techniques aimed at understanding and analyzing data that are sequential in nature (Gabadinho, Ritschard, Müller, & Studer, 2011). Originating from research on genetic data, sequence analysis is fundamentally designed to handle a large number of sequences. Educators who own a DIL website can adopt sequence analysis in their daily practices. According to the constructivist view, learners construct their own structure and meaning by exploring, processing, and interpreting the world. In the current study, we focused on understanding learners’ exploratory behavior. Specifically, we examined how the user interface (UI) design of a DIL environment affects learners’ exploration under different task orientations and how sequence analysis can be employed to elucidate such behaviors. We focus on two areas of sequence analysis: visualization and clustering.

The results of this study would benefit DIL researchers and practitioners. Unlike distributed passive learning (DPL), in which learners passively receive materials from instructors (e.g., slides and study notes), learners navigate a web-based DIL environment to explore the learning materials. Navigational paths are highly informative, revealing what they experience and choose. However, following each path to identify common patterns can be a time-consuming and tedious task. With the assistance of relevant visualization techniques, educators can examine students’ exploratory behavior by visualizing a large number of navigational paths on human-readable charts. Clustering methods automatically identify common patterns, which can enable educators to focus on specific patterns. The result can also enable the educators and administrators of massive

open online courses (MOOCs) to understand students who may treat the material as modularized resources or edutainment (Zheng, Rosson, Shih, & Carroll, 2015). Furthermore, this study can also enrich the set of learning analytics tools available for higher education institutions (Ifenthaler, 2017; Klačnja-Milićević, Ivanović, & Budimac, 2017).

## LITERATURE REVIEW

### *Constructivist View of Learning*

Constructivism is one the two learning perspectives that are frequently debated by researchers; the other perspective is objectivism (Cooper, 1993; Duffy & Cunningham, 1996; Wilson 1997). According to the objectivist view, knowledge and meaning are determined by the structure of the reality (Cooper, 1993). Conversely, constructivists consider reality to be “out there” rather than inside the learner’s mind (Wilson, 1997). Learners construct symbols that represent reality and create meanings in their minds. Constructivism does not involve the transfer of objective reality from the instructor’s mind to that of the learner (Leidner & Jarvenpaa, 1995). Learners explore, interact, and discover various types of materials and environments to construct unique concepts, meanings, and representations of knowledge. The learner’s mind is regarded as a network of small processing units. Learning involves the process of constructing symbols through various experiences and interactions with the environment that are mapped or stored in interconnected small processing units. Knowledge is an activation of patterns of relationships and interactions between these units. The process of learning primarily involves continual adjustments in the relationships such that the appropriate representation of knowledge can be reconstructed at appropriate times.

### *Sequence Analysis*

In sequential data, each data item is a series of values or states. Because of this sequential nature, analysis is challenging. Sequence analysis was originally developed for clustering and visualizing sequences of molecules in DNA structures (Waterman, 1995). In social sciences, many data are sequential in nature. Researchers in life-course analysis have adopted sequence analysis in studying people’s change of status over a long period (Abbott & Tsay, 2000; Gabadinho et al., 2011). The course of life becomes an ordered sequence of statuses (e.g.,

“at school,” “at work,” and “retired”). Exploratory navigation of DIL websites is also sequential in nature and educators must understand the learners’ exploratory behavior as part of the constructive process. Therefore, sequence analysis should also be helpful to educators.

Two major approaches of sequence analysis are clustering and visualization techniques. Clustering refers to a set of methods that automatically group (i.e., cluster) data items (Gabadinho et al., 2011; Kaufman & Rousseeuw, 2005). This automatic process is based on metrics that measure similarities between data items. Optimal matching (OM) analysis is a method that is commonly used to calculate the similarity between sequences (Abbott & Tsay, 2000; Billari, 2001); it generates a measure of similarity between two sequences by calculating the minimum number of operations (i.e., insertions, deletions, and replacements) that are required to render two sequences identical. Partitional and agglomerative methods are the two main types of clustering techniques (Jain, Murty, & Flynn, 1999). Partitional methods form a large cluster with all sequences, which are progressively divided into smaller clusters based on similarity. By contrast, agglomerative methods involve forming initial clusters based on each sequence; subsequently, similar clusters are joined. The Ward method is one of the most widely used similarity measurements for clustering (Murtagh, 1985; Ward, 1963). Agglomerative methods produce clusters as well as a tree-like structure that documents the process of merging the clusters (i.e., which clusters were merged during the process).

Visualization techniques present sequence data in a graphical format. Different states or values in sequences are often represented by different colors. Various types of visualization present different aspects of sequence data. For example, a data set of sequence data can be presented with a single graph in which each row represents a sequence. TraMineR (Gabadinho et al., 2011) is a software package that was developed for sequence analysis. At a conference on sequence analysis, it was applied to topics such as family formation (Van Winkle, Fasang, & Raab, 2016) and youth career development (Rousset, Trouve, & Lawes, 2016).

Recent studies have enriched the area of learning analytics by introducing sequence analysis to educational contexts. Jovanović, Gašević,

Dawson, Pardo, and Mirriahi (2017) investigated learner behavior outside the classroom in a flipped classroom context. Flipped learning requires the active participation of learners inside and outside a classroom. The researchers used sequence analysis to cluster learner behavioral data to reveal different learning strategies. They analyzed data from the online preparation sessions of students with their scores in the course. Gašević Jovanović, Pardo, & Dawson (2017) studied students’ online preparation and traced students’ online preparation activities for lectures. With the clustering technique, the study identified learning strategies adopted by students and then associated the strategies with students. One significance of this study was a measurement of student approaches to learning and then cross-referencing that information with the learning strategies they used.

#### *User Interface Design in Web-Based Learning*

Motivating learners with web-based learning technologies has garnered the attention of researchers (Sánchez-Franco, Peral-Peral, & Villarejo-Ramos, 2014). The UI is a design aspect in websites for learning (Cho, Cheng, & Lai, 2009; Rivera-Nivar & Pomales-García, 2010). UI design for educational purposes is a complex task, and multiple design aspects must be considered (Sánchez-Franco et al., 2014). A visually appealing UI may attract the attention of students, and the usability of a UI enhances how they perceive the usefulness of a website. A UI design can adhere to a set of design principles (Feifer & Tazbaz, 1997), although when derived specifically in the context of web-based learning, such principles are extremely limited (Lohr, 2000).

Researchers of educational technologies have focused on UI design (Cates, 2002; Van Aalst, Van Der Mast, & Carey, 1995). In a case study of how UI designers work with experienced teachers in designing a UI for learning systems, Perry and Schnaid (2012) indicated that knowledge pertaining to the education and learning domain is essential for such design activities. The UI of a web-based learning system has been shown to influence learner usage motivation. In a survey administered among university students, Cho et al. (2009) showed that when students perceive the UI of e-learning to be more user-friendly, they perceive the system to be more useful, which indirectly enhances their intention to continue using it. Sánchez-Franco et

al. (2014) reported survey results showing that a UI with a fascinating and creative design enhanced learners' perceived usefulness of a learning system and indirectly enhanced their satisfaction with using it, ultimately increasing their willingness to continue using the system.

Researchers have attempted to enhance the UI design of e-learning systems. Rivera-Nivar and Pomales-García (2010) explored the feasibility of a universal UI for learners in various age groups. They manipulated four design modules in a web-based distance-learning system: (a) whether videos focused on the face or the body (half-shot) of the instructor, (b) whether the videos had a background, (c) the instructor's gender, and (d) the video size. The results revealed that when encountering modules that differed in design, younger and older learners differed in their behaviors regarding their sense of disorientation and satisfaction. The researchers concluded that accommodating users from different age groups with a single UI design is difficult. Their results also suggested that design modules influence learner information recall regarding the content.

#### *A/B Testing of UI Design*

A/B testing is a research method that involves comparing two versions of a design to determine which one performs more effectively (Hanington & Martin, 2012). This method is based on the concept of laboratory experiments in which one aspect of what participants experience is manipulated. With other aspects controlled, the difference in the results is interpreted to be contributed by the manipulation; accordingly, a cause-and-effect relationship can be inferred. The method is widely used in website design (Nielsen, 2005). For educators using DIL websites in their teaching practices, A/B testing can be adopted to identify alternative UI designs that help students learn more effectively.

#### **STUDYING LEARNER EXPLORATION ON DIL WEBSITES**

According to constructivist learning, learners must interact with the world and learning materials to construct their own method of adapting to a community of practice. Learner self-exploration is part of the learning process. The remote nature of DIL websites enables learners to explore learning materials at a time and in a space that they prefer. In the constructivist view, the role of educators is to facilitate learner exploration. However, the remote

nature of DIL websites prevents educators from observing learner exploration. Educators might be unaware of whether learners have visited and explored the DIL website. Basic statistics, such as the number of times learners have logged in and the duration of their sessions, can be collected from DIL websites. However, these data present a limited view of the learner's exploration. Exploration of a website involves opening various web pages in different parts of the website, and learners may differ in the order in which they explore parts of a DIL website. Statistics of page views and visit duration are limited indicators of the site-browsing behavior of learners. Understanding the exploratory behavior of learners on a DIL website may be difficult for educators. Consequently, learners with low motivation or those who are experiencing difficulty cannot be easily detected, rendering educators unable to respond to their students' needs and thereby reducing the effectiveness of DIL websites.

Sequence analysis is a method that can efficiently fill this gap. Recording the sequence in which learners visit web pages during a DIL website session provides insights into their exploratory style. Temporal information is preserved in terms of the order of the web pages they visit. Although the amount of data can be considered large as the number of learners increases, visualization techniques can assist educators in visually inspecting a large number of sequences. Clustering techniques help educators to identify common visit patterns among the sequences and enable a close inspection of similar patterns.

In its raw form, website visit data consists of an ordered series of records documenting the web pages visited by learners. Each record in a series can have many possible values (the same as the number of web pages on a DIL website), which are interpreted as possible states at certain points in a sequence. Sequence analysis becomes ineffective when the number of possible states is large (e.g., > 10). Sequence visualization techniques involve using colors to represent different states. Having too many possible states can introduce too many colors into the sequence visualization, which can cause the visualization to become overly complex and render it difficult to interpret. OM similarity measures, which are commonly used in clustering sequence analysis in the social sciences, are derived from the



number of insertions, deletions, and replacements required to make two sequences identical. If there are many possible states, then pairs of sequences can be matched only through a large number of operations. In other words, OM similarity measures tend to indicate that sequences differ substantially from each other, even when their constituent parts are of a similar nature (e.g., browsing similar but not identical web pages). Therefore, a coding scheme is required for converting the visited web pages into a finite set of states.

In the context of DIL websites, one option is coding the web page according to the major section in which it belongs on the website. On a typical website, web pages are organized in a hierarchical structure (i.e., a tree-like structure) comprising categories and subcategories (Garrett, 2010). Major categories are often referred to as major sections. In principle, web pages with similar content or of a similar nature are allocated into one major category. Furthermore, the number of major sections typically does not exceed ten. Therefore, coding web pages according to their corresponding major sections is an optimal coding scheme.

Our aim of performing a sequence analysis on navigational data on a DIL website is to assist educators in maintaining a DIL website to understand the exploratory behavior of learners. The type of coding scheme employed influences the types of exploratory behavior that can be examined. With this coding scheme, each major section, which is assigned a unique code, is represented with a color on a visualization of the sequences. The resulting visualization illustrates how learners explore and navigate various major sections on the website. In actual scenarios, educators may need to determine the types of exploratory behavior of interest. In the current study, coding by major sections was employed because of the relevance of the content in each major section.

Sequence analysis can also assist educators who can adopt A/B testing to improve a DIL website. They can modify certain aspects of a DIL website and study how changes influence the exploratory behavior of learners. In this study, we modified the UI of a DIL website by adding a description to hyperlinks presented on the pages. The additional description informs information seekers about the content of web pages linked by hyperlinks (Pirolli, 2007; Pirolli & Card, 1999). Tselios, Katsanos, &

Avouris, (2009) demonstrated that cues in website's UI design influence visitors' search performance and efficiency. The current study explores the effect of additional cues in the context of learning through sequence analysis. From the constructivist perspective, we were interested in determining whether and how the additional UI cues influenced the exploratory behavior of learners searching for specific information and those who were not.

This study is part of a research project concerning the effects of UI on learners' behavior and learning outcome on DIL websites (Ho & Yao, 2018).

## METHODS

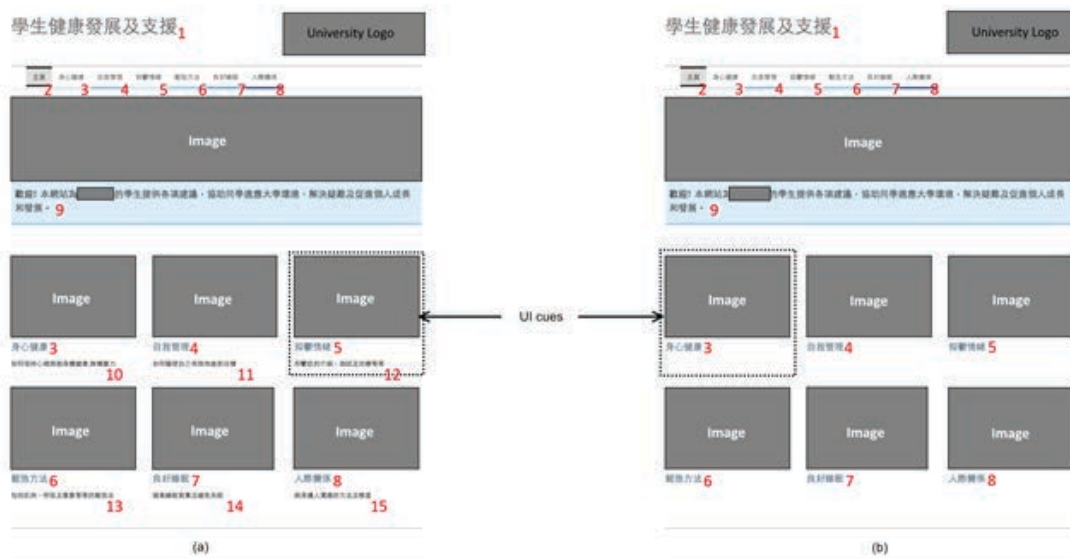
We conducted a laboratory experiment to examine the influence of additional UI cues of a DIL website about health tips under different information search conditions on exploratory behavior. In addition, the outcome of the learners' visits to the website was examined with a postvisit test on the content. A laboratory experiment was adopted as the method because it is more effective than other methods in controlling the search conditions. In addition, with a laboratory experiment, the postvisit test could be conducted immediately after the participants visit the DIL website. We adopted a 2 (search task condition: with versus without)  $\times$  2 (additional UI cues: with versus without) between-subject factorial design for our experiment in which the participants were asked to visit a website on healthy and balanced lifestyles. The participants were randomly assigned to one of the four experimental conditions. In contrast to within-subject design, a between-subject experimental design prevents participants from experiencing the same website content twice.

### *Participants*

With announcements in classes, we recruited 82 participants (mean age: 20.0 years, SD: 1.7 years) from a public university in Hong Kong; they were provided supermarket cash coupons valued at HK\$50 (approximately US\$6.04) as an incentive. Their average experience of using the Internet was 10.6 years (SD: 2.5). All the participants had experience using a DPL website to obtain course materials (e.g., slides) from instructors. At the beginning of each session, informed consent was obtained.

### *Stimulus Materials*

The major stimulus of the experiment was a website with educational materials on staying



English translation of the text – 1: Student health development and support 2: Homepage 3: Mental and physical health 4: Self-management 5: Depression 6: How to relax 7: Sleep well 8: Interpersonal relationships 9: Welcome! This website offers various kinds of advice to students of [university name], to help them adapt to university environment, solve problems, and facilitate personal growth and development. 10: How to keep a healthy mind and body, be immune to stress 11: How to make yourself to achieve goals effectively 12: Introduction to depression, e.g., diagnosis and treatment 13: Ways to relax, including muscular, breathing, and imaginative 14: To enhance sleeping quality and avoid insomnia 15: Methods and attitudes to communicate with others

Figure 1. Home Page Of The Website (A) With Additional UI Cues and (B) Without Additional UI Cues. The Number Labels in Red are Added for English Translation Annotation.

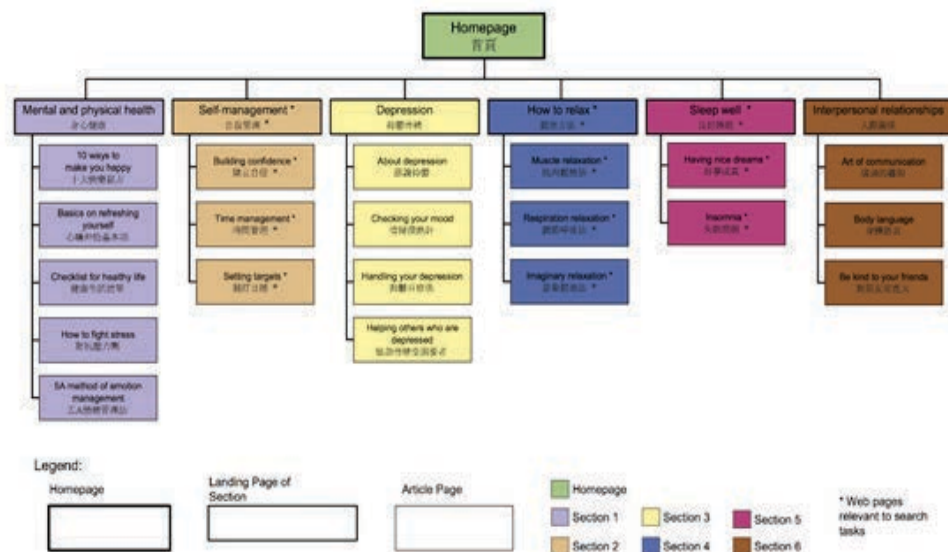


Figure 2. Site Map of the Structure of the Experimental Website

healthy, managing stress, and maintaining a social life. To motivate the student participants, the topic of health was chosen, and the content referred to student health issues. The title of the website also explicitly stated that it was designed for students (Figure 1). We manipulated the UI cues by attaching additional textual cues to each hyperlink. The

textual cues provided a description of the hyperlinked web page. Figure 1 depicts the variations of the two manipulations by showing the conditions with and without the additional UI cues.

The website contained 20 articles on how to attain a healthy and balanced lifestyle, each presented on a single web page. The website was devised with a dual-layered hierarchical information

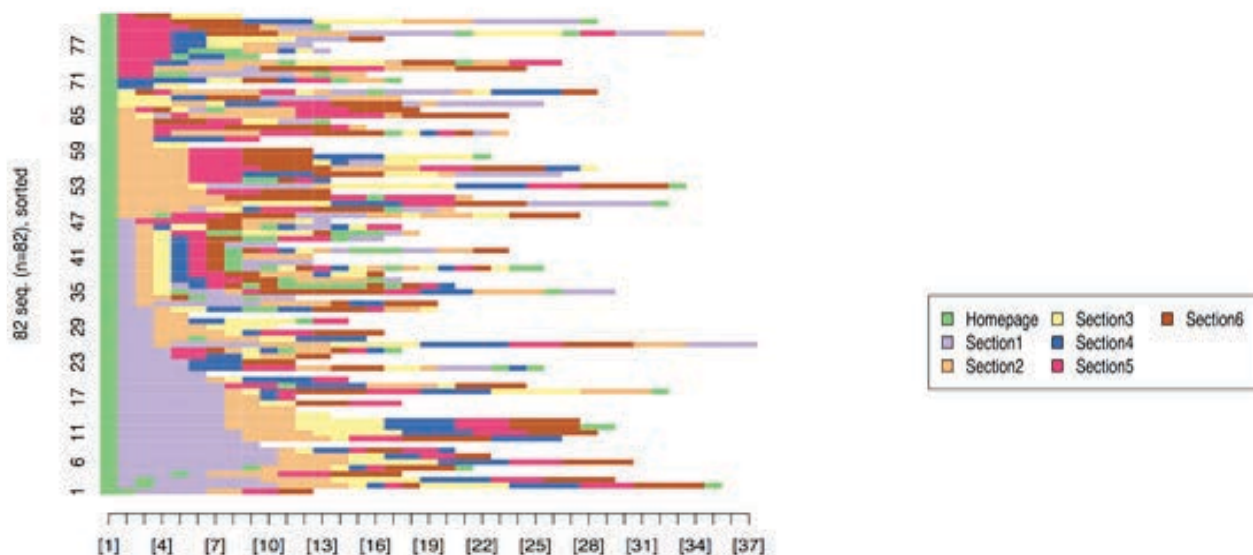


Figure 3. Visualization of All Sequences Showing the Navigation Patterns of the Learners. Each Row Represents a Sequence (One Navigation Path), and Each Cell Represents The Web Page Visited (Color-Coded)

(Garrett, 2010). The 20 web pages were grouped under six major sections. An overview page was available for each section. The home page presented an introduction and hyperlinks to the six overview pages. Figure 2 shows a site map depicting the website structure. The website was in Chinese.

#### *Dependent Measures*

The web pages visited by each participant were recorded as an ordered series by using a logging function in the software used in the experiment. Each visited web page was encoded into one of the following seven categories: Home page, Section 1, Section 2, Section 3, Section 4, Section 5, and Section 6. The section numbers were based on the order in which the major sections were presented on the primary navigation bar of the DIL website used in the experiment.

Assessing the learning outcomes entailed the following: After the participants visited the website, they were asked to complete a paper questionnaire containing three open-ended questions concerning the content of three of the six major sections (Sections 2, 5, and 6) on the website. The participants were asked to respond with as much detail as possible. The answers were graded against the content on the experimental website by two independent graders. We assessed the interrater reliability by using a two-way mixed consistency average-measures intraclass correlation coefficient (ICC) (McGraw & Wong, 1996) to evaluate the degree to which

the two graders were consistent in grading the responses. The resulting ICC was in the “excellent” range ( $ICC = 0.96$ ; Cicchetti, 1994), indicating that the two graders had a high degree of agreement and that any measurement errors introduced by the independent graders was negligible. Thus, the statistical power of the subsequent analysis was unlikely to be reduced substantially. For each participant, the average of the two scores given by the two graders was considered the final result.

#### *Procedure*

The experiment was conducted in a laboratory setting. Upon arrival, each participant was briefed on the procedure and then signed a consent form. Participants were then seated in front of a desktop computer with a 17-in. screen. The screen displayed the instructions, which consisted of a description of the scenario and an introduction to the website. The participants in the experiment with search task conditions were given three search tasks concerning the topics covered in three major sections (Sections 2, 5, and 6) of the experimental website. The participants in the experiment without search task conditions were asked to browse the website freely. Subsequently, the participants were shown the experimental website, which was viewed using Internet Explorer in full-screen mode. An “exit” hyperlink was positioned in the side margin of each web page. The participants were requested to click on the exit hyperlink once



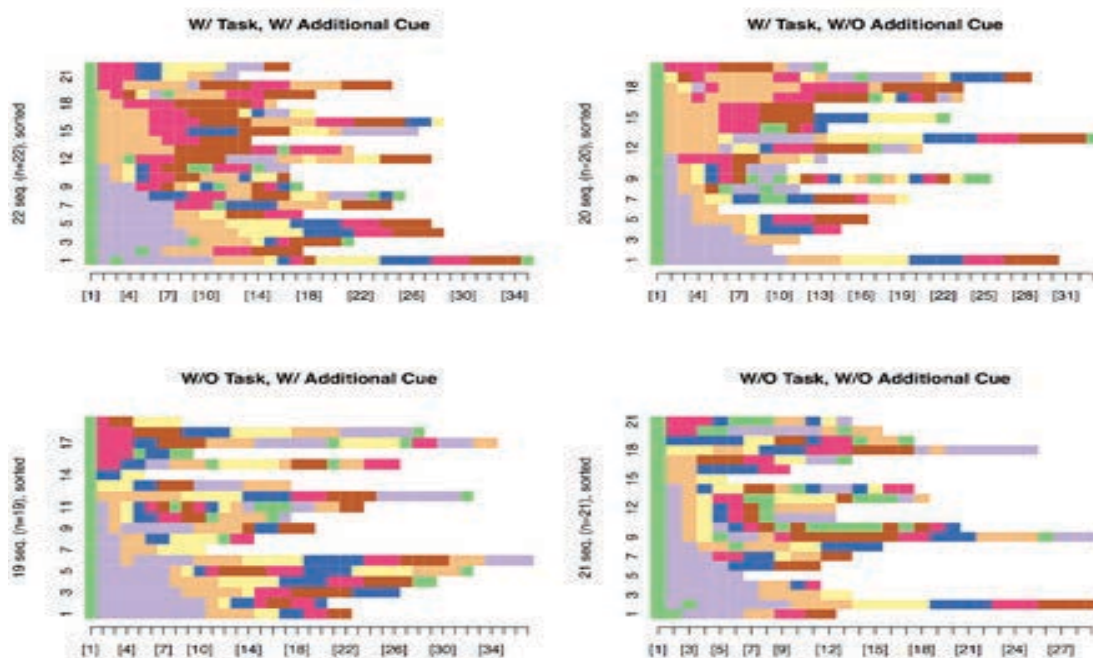


Figure 4. Visualization of the Sequences in the Four Experimental Conditions

they had completed their visit. They were able to continue visiting the website until they decided to finish when a paper questionnaire was administered to evaluate the learning outcomes. No time limit was set for responding to the questionnaire. Upon completing the questionnaire, each participant was debriefed.

## RESULTS

Visualization and clustering were performed in an R programming environment with the TraMinR software package (Gabadinho et al., 2011).

### *Visualization of Sequences*

Figure 3 depicts the exploratory behaviors of 82 participants; each row represents a sequence (one navigation path) of web pages visited by a participant, and each cell represents the web page visited (color-coded). Green represents the home page, and each other color represents a major section (purple as Section 1, tan as Section 2, yellow as Section 3, blue as section 4, pink as section 5, and brown as Section 6). The duration that the participants stayed on each web page was not considered because the focus was on their exploratory behavior across the major sections. In the visualization, all sequences start with a green cell because all participants started on

the home page of the experimental website. Green cells also appear in the middle and at the end of the sequences, indicating that the participants occasionally returned to the home page. A few sequences show that some participants visited the home page immediately before ending their visit.

Figure 4 shows the sequences grouped according to the four experimental conditions. In the two conditions with search tasks (the two charts at the top), Section 2 (tan), Section 5 (pink), and Section 6 (brown) are relatively popular. This accords with our expectations because the participants in these conditions were assigned specific search tasks related to the content in these three sections. The sections unrelated to the search tasks were also visited by the participants, showing that despite the participants being assigned specific search tasks for when they visited the website, they also explored the other sections that were unrelated to those tasks. In this group of participants, using the search tasks as a motivator to drive them to search the website encouraged them to visit not only the task-related sections but also the other sections on the website.

### *Clustering of Sequences*

The OM similarity measure was calculated among the 82 sequences. Subsequently, agglomerative clustering was performed using



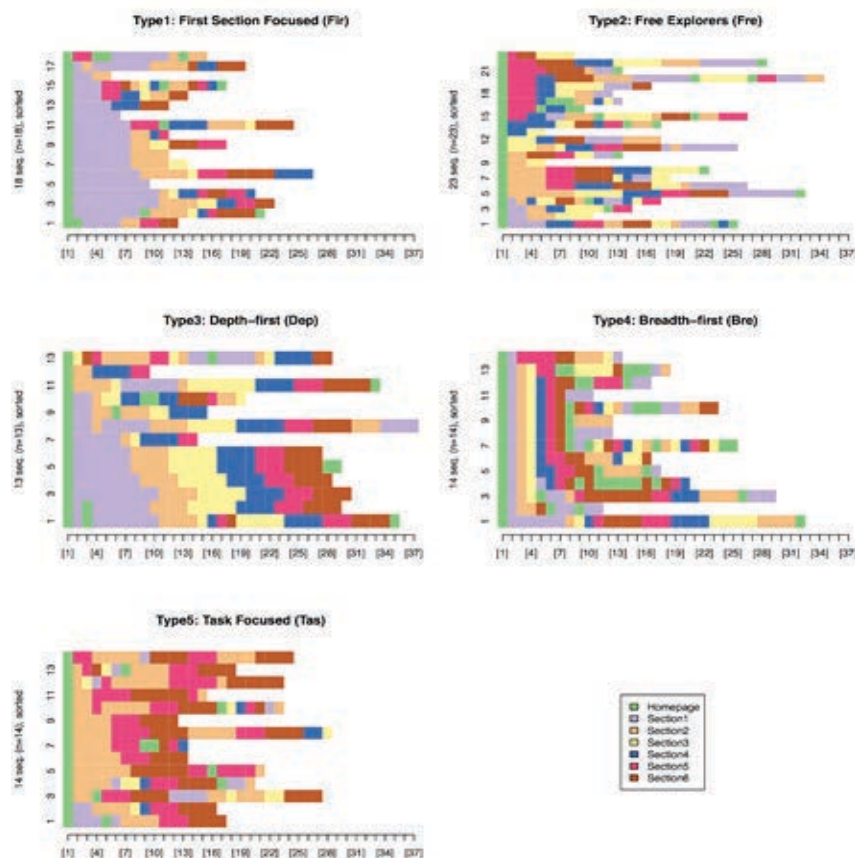


Figure 5. Visualization of the Five Clusters

Ward's method. Figure 5 shows a visualization of the five clusters derived from the analysis, the sizes of which range from 13 to 23. The cluster visualization facilitates visual inspection and interpretation. Cluster 1 contains 18 sequences. Purple cells appear mostly in the initial parts of these sequences. The participants visited several web pages in Section 1, and some of them subsequently visited other sections but only briefly. This pattern indicates that these participants appeared to focus on the first section during their sessions; therefore, this type of behavioral pattern was labelled "first-section focused" ("Fir" for short).

Cluster 2 contains 23 sequences. The visualization of this cluster shows different colors at the beginning of the sequences. The participants visited two to four web pages in these sections before moving on to the other sections, indicating that the participants in this pattern visited different sections without being led by the order of the website sections. Accordingly, they were labelled

"free explorers" ("Fre" for short).

Cluster 3 contains 13 sequences. The visualization of this cluster indicates that most participants visited four to six web pages in each major section following the order in which the sections were presented on the website, indicating that the participants in this cluster visited each section in sequence and inspected them thoroughly by opening a few pages in each section. Therefore, this behavioral pattern was labelled "depth-first" ("Dep" for short).

Cluster 4 contains 14 sequences. As indicated in the visualization, most of the sequences started with one web page from each major section and are in the order in which the major sections are presented on the website, indicating that the participants exhibiting this pattern briefly visited every section before moving on to the next section. This cluster was labelled as "breadth-first" ("Bre" for short).

The final cluster contains 14 sequences. The

Table 1. Descriptive Statistics of Memory Recall Stratified by Cluster

Cluster	Mean	Standard Deviation	N
1: Fir	8.528	4.8884	18
2: Fre	10.674	9.4852	23
3: Dep	14.846	13.2577	13
4: Bre	9.143	7.7768	14
5: Tas	19.821	8.2709	14
Total	12.165	9.6235	82

visualization shows that the participants focused primarily on the three major sections related to the search tasks (i.e., Sections 2, 5, and 6). Not many web pages other than these sections are visited. Therefore, this cluster was labelled as “task focused” (“Tas” for short).

#### *Memory Recall by Behavioral Type*

Memory recall was used as supplementary information to understand the clusters. This metric provides a view of the learning outcomes derived from the various behavioral styles identified using the clustering technique. Table 1 shows the descriptive statistics of memory recall stratified by the behavioral types (i.e., the clusters).

Kruskal-Wallis H test results revealed that a statistically significant difference in memory recall among the various behavioral patterns,  $\chi^2(4) = 15.175$ , with a mean rank memory recall of 34.75 for First Section Focus, 36.93 for Free Explorers, 44.38 for Depth First, 33.71 for Breadth First, and 62.79 for Task Focused. The participants in the Task Focused cluster exhibited the highest performance in the memory recall task. This accords with the

task focused exploration pattern. Subsequent Mann-Whitney tests indicated that the Task Focused cluster outperformed the First Section Focused cluster ( $U = 25.5$ ,  $p < .001$ ), Free Explorer Cluster ( $U = 67.5$ ,  $p = .003$ ), and Breadth First cluster ( $U = 32.5$ ,  $p = .003$ ).

The participants in the Depth First cluster had the second-highest average score in the memory recall task. Depth First behavior is associated with relatively more effective memory recall. However, the participants in the Depth First cluster attained the largest standard deviation among the clusters, possibly because, although they explored the major sections thoroughly, not all of them actively remember the content.

#### *Distribution Of Behavioral Types In Experimental Conditions*

Figure 6 shows the behavioral types stratified by the four experimental conditions. Between the two conditions without search tasks (the two charts at the bottom of the figure), no participant engaged in Task Focused behavior. This is consistent with

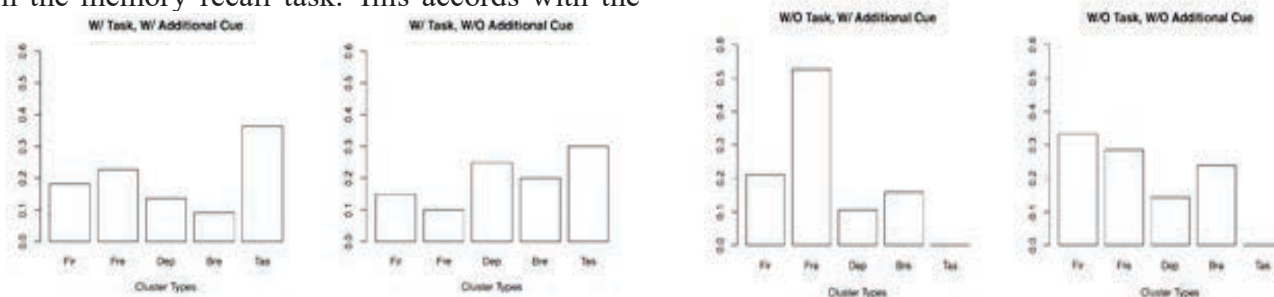


Figure 6. Cluster-Type Frequency Distribution Stratified By The Experimental Conditions

the corresponding experimental conditions because they were not assigned search tasks and had no reason to focus on only those three task-related sections. Comparing the two conditions without search tasks reveals that adding additional UI cues appeared to increase the percentage of participants in the Free Explorers cluster. Having additional UI cues encouraged the learners to explore different sections of the website without following the order in which they were presented. This indicates that educators could use additional UI cues to encourage learners to engage in nonlinear exploration when visiting this DIL website without any predefined search task.

The two charts illustrating the two conditions with search tasks show that Task Focused behavior is the most common behavioral pattern, which is consistent with the assigned search tasks. Comparing the two conditions with search tasks revealed that the percentages of Free Explorers and Task Focused behavior increased when additional UI cues were added. For educators, these results show that additional UI cues can encourage learners to be either more efficient or more thorough when performing search tasks.

## DISCUSSION

The current study illustrates an example of using sequence analysis in studying the exploratory patterns of users on a DIL website. Sequences were visualized for visual inspection of these behaviors from an overall perspective. A clustering method was employed to identify and categorize five exploratory patterns. Visualization of the five patterns facilitated visual inspection and interpretation.

Supplementary information from memory recall measures shows that exploratory patterns differ do not only in navigation style but also in learning outcome. A/B testing of slightly different UI designs of the DIL website is also supported by the sequence and clustering techniques. The additional UI cues increased the number of free exploration patterns among the learners who were not assigned any search task. Changing the UI assisted the learners who were assigned search tasks to be either more efficient in performing their tasks or more exploratory in their behavior.

The findings showed the short-term influences of additional UI cues under different task conditions.

Future studies could investigate any long-term effects and could help answer the question about the role of UI in DIL websites. Practitioners would benefit from information on whether the effort and costs involved in changing the UI of a DIL website are justified with corresponding effectiveness.

Our results show that the navigational data of the 82 learners exploring an educational website were successfully visualized in a single chart. This chart revealed the exploratory aspects of the learners regarding their browsing between major sections of the website. Because the major sections were related to different topics, the visualization of the sequences shows how the learners explored the topics in terms of order and timing. Scalability of this type of visualization is relatively high because hundreds of sequences can be rendered on a single chart. The key for educators is to determine what aspect of exploration they are interested. In the present study, we focused on exploratory behaviors among different sections of the website by using codes and colors to represent the various sections. Thus, the sequences represent how visitors browse between major sections.

This study shows that the clustering technique facilitated identifying similar navigational patterns. Combined with the visualization technique, the identified clusters of patterns were visually inspected and interpreted. Meanings were then assigned to these patterns through assigning the five labels. Educators can perform this step according to their purposes. The key point here is that the visual representation of multiple groups of exploratory behavior requires only a visual inspection of several charts rather than examining all the navigational records of individual learners. The automatic clustering method also assists in reducing the effort required for identifying patterns, which can save educators a considerable amount of effort in comparing the usage patterns of individual learners. However, during the process, educators may still need to make some decisions regarding the similarity measures to be used. As shown in the current study, using the most common method, OM, can generate interpretable results. For example, if educators were interested in the beginning of navigations only, then another similarity measure called leading common subsequence, which involves counting the number of common states at the beginning of sequences,



might be a suitable choice.

Measuring learner ability to recall the content of a DIL website after visiting it does not provide a comprehensive view of their learning outcomes. We are not arguing that this is how constructivist learning should be done; rather, our proposition is that automatic clustering methods can be employed to identify various behavioral patterns that affect at least some aspects related to learning outcomes. The results of the memory recall task suggest that the clusters identified differ in certain aspects of learning outcomes (i.e., memory recall of site content). This supports this view.

The visualization technique provides an alternative view of information for educators adopting A/B testing to improve the design of their DIL websites. With a focus on exploration, visualizing navigational paths under different conditions may provide insights for educators on how to modify their UI designs.

According to Wilson (1997), constructivism is a philosophy (i.e., a way of understanding learning and the world) rather than a strategy. Considering the findings in the context of constructivist philosophy, additional cues on hyperlinks on the UI are parts of the reality “out there.” They represent information about more information in the reality (i.e., the additional materials accessible through the hyperlinks). The results suggest that additional cues encourage learners (both those with and without a search task) to explore freely on the website—or the materials in the reality. Navigation to different sections of a website is one of the signs of exploratory behavior. The results imply that additional cues may assist learners when exploring the reality. The results also clarify the use of sequence analysis with other measures. In our case, navigational behavior (which indicates how learners interact with the world “external” to their minds) and memory recall immediately following a visit (which reflects what is “internal” to their mind) are analyzed together.

The sequence analysis approach used in the current study is useful for educators who wish to enhance the learning experience (LX—e.g., by modifying the materials) and user experience (UX—e.g., by modifying the UI) of students. The findings suggest that educators could consider adding cues to the hyperlink presentations on the UI of DIL websites. The cues can summarize the content on the web pages accessible through hyperlinks. Educators

could explore creative alternatives for cues, such as encouraging slogans to engage learners to explore or letting senior or former students create and submit cues to educators. Educators could employ the sequence analysis technique presented in the current study to evaluate the influences of any changes to their DIL websites and consider conducting A/B testing by randomly dividing their classes into halves. If that strategy is not feasible, then an alternative approach is collecting navigational data before and after the inclusion of additional cues and then conducting a sequence analysis. Educators can observe differences or changes in learner behavior on DIL websites.

## CONCLUSION

Understanding learner exploration is a complex task. It is even more challenging in DIL environments where learner behaviors are not directly observable. The current study illustrates that sequence analysis techniques can be useful to educators in the context of DIL website design. Learners’ navigational behaviors, which are inherently sequential, can be visualized, analyzed, and clustered through sequence analysis techniques. To continually enhance the LX and UX, educators can remotely observe the influences of changes in the UI and learning scenarios on learners’ behaviors. Small changes in the UI (additional cues in the current study) were shown to encourage learners to explore learning materials on a DIL website; however, several limitations should be noted. First, the method reveals the navigation paths of learners but not their cognitive processing while visiting the website, which is arguably similar to observing behaviors during face-to-face interactions in classrooms in which only visible behaviors can be observed. This can be improved through follow-up usability testing to examine learners’ thoughts and understandings. Second, the current study focused only on the first-time visit to a DIL website as well as the immediate learning outcomes. The primary reason for this was to measure memory recall in a controlled setting for comparisons. The set of techniques used in this study can be applied in actual teaching environments over a longer period.

Future research can investigate learners’ behaviors longitudinally over a specific period. The current study compared only memory recall as a type of learning outcome among the various

clusters. Future studies should consider focusing on other aspects (e.g., learning attitude) of different behavioral patterns identified using this clustering method.

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