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Developing a New Method for Investigating Learning Behavior in Learning with Interactive Videos using Log Files

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ABSTRACT

Learning videos are a promising opportunity to enable remote learning and enjoy a worldwide increasing popularity. However, due to the remote setting it is difficult to examine students' learning behavior. Previous research examined learners' video interaction by focusing on frequencies of user interaction (i.e. clicks). However, we assume that investigating meaningful behavior sequences instead of click frequencies can lead to a better understanding of learning behavior. The main goal of this study was to develop a new method to gain deeper insights into learners' behavior based on their digital footprints (i.e. log files) when they learned with an enhanced video-based environment. Yet, measuring a latent variable such as learning behavior is particularly tricky and time consuming. Thus, we developed an application (Logible) based on our method to automatically analyze 92 log files from one of our prior studies. We contrasted four experimental conditions differing in learning task and learning setting. Results revealed that the learning task (i.e. using annotations or hyperlinks) had a significant influence on learning behavior. Yet, no significant influence caused by the learning setting (i.e. learning individually or collaboratively) was found. Furthermore, we investigated if and how learning strategies from successful and less successful learners differ. Results showed that successful learners more thoroughly planed where to to place annotations or hyperlinks. We conclude that applying Logible led to original findings and therefore we encourage fellow researchers in the field of CSCL to consider working with Logible whenever focusing on broader behavior instead of raw clickstream data.

1. Introduction

1.1. Background video learning

Recently distance learning methods became more relevant due to the worldwide spread of the coronavirus (COVID-19) and the associated restrictions in public life, including the closing of schools and universities (UNESCO, 2020). Educational videos are according to Tiernan (2015) a good opportunity to tackle the challenges of distance education, since they can be provided asynchronously and remotely and are therefore able to support learning and conceptual understanding. Educational videos as part of teaching in educational institutions are, however, no new phenomenon but rather look back on a long tradition (Poquet et al., 2018). Through the use of *basic video control tools*, such as play, pause and rewind, learners can actively interact with the learning material. Thereby learners are in control of the learning material and are able to learn at their own pace, which minimizes the risk of cognitive overload (Cattaneo et al., 2015) and fosters knowledge acquisition (Zahn et al., 2004). While engaging with the learning material learners evolve successful strategic learning interactions (Schwan & Riempp, 2004). In addition to basic video control tools, newly designed *enhanced video-based environments* allow individual or collaborative learners to engage even more with the learning material by annotating, commenting, discussing and editing interactive videos (Franzoni et al., 2013; Yousef et al., 2015). Previous research provided evidence suggesting that note-taking in video learning is superior to working with basic control tools regarding learning success (Delen et al., 2014). Further evidence by Zahn et al. (2010) and Zahn et al. (2012) suggests that designing a hypervideo structure is successful to learn complex history topics. Through active participation in constructing information, learners can actively transform existing video representations into their own enriched information structures (Schwartz & Hartman, 2007; Yousef et al., 2015). Therefore, learners actively generate meaning (Wittrock, 1992) by designing their own learning content (e.g. Kafai & Resnick, 1996; Papert, 1994). Moreover, enhanced video-based environments are able to foster collaborative learning as they allow learners to jointly engage with content ideas and scientific practices (Sinha et al., 2015)

ORCID(s):

1.2. Investigating learning behavior

Since learning videos became a core component of many pedagogical approaches and with recent advances in video streaming technologies, the field of *learning analytics* grew more relevant (Mirriahi & Vigentini, 2017). Learners' digital footprints (log files) can be mined and analyzed to investigate and measure learning behavior and to better understand how they learned and engaged with educational videos (Mirriahi & Vigentini, 2017). Such log files contain chronological arrays of learners' interactions and are usually displayed in tabular representation. In their pure form log files are rather difficult to interpret and impede to gain quick and intuitive insights into learners' behavior. From such tabular representation, however, learners' clickstream logs can be extracted. For instance, a clickstream log can be displayed as the following string of interactions: play/pause/rewind, indicating that a learner first started to watch the video (logged interaction: play), then paused it (logged interaction: pause) and finally rewound it (logged interaction: rewind). The main focus in previous research has been on investigating interaction frequencies at the granular clickstream level, i.e. by summarizing frequencies of single interactions, such as play, pause or rewind (Wang et al., 2013; Shi et al., 2015). However, Sinha et al. (2014) warned that focusing only on frequencies of single interactions impedes tracing results back to the actual learning behavior, due to the loss of hidden information from behavior patterns. Sinha et al. (2014) therefore applied a different approach and encoded meaningful sequences from clickstream logs by grouping single interactions (i.e. clicks). As a result, they gained deeper insights into students' learning behavior in Massive Open Online Courses (MOOCs). Additionally and according to Sinha et al. (2014), encoding meaningful sequences instead of raw clicks on a granular level can help to reduce the noise in the data. However, such approaches using sequences to investigate learning behavior in video learning are still rare and require a huge effort to detect and elaborate meaningful sequences from raw clickstream logs. Hence, only a few studies examined learners' interaction behavior with behavior sequence analysis so far (Mubarak et al., 2020).

1.3. Behavior sequence analysis

Logged interaction data provided by the enhanced video-based environment can be considered and treated as sequential data since their true character reveals itself unfolded in time. Similarly to recipes, movies, and music, which can be regarded as ordered chains of objects whose identity is a product of both its order and its content (List, 2014). When behavior of any kind is subject of interest, e.g. by investigating the discussion of couples, the fighting of monkeys or the playing of children (Bakeman & Gottman, 1997) the sequentially of the data should be taken into consideration. According to Bakeman & Gottman (1997), it is often recommended to record observation data in a way that preserves sequential information. Thereby researcher make use of and illuminate the sequential nature of the observed data. Behavior sequence analysis as a methodological approach provides the right theoretical framework to analyze sequential behavioral data (Ritschard & Studer, 2018) and is helpful to comprehend an overall picture of the data. Thereby, common or atypical trajectories can be identified and trajectory patterns among groups can be compared. Sequence analysis was originally introduced in computer science in the 1960s. Few years later it became popular in molecular biology for studying DNA and RNA sequences (Ritschard & Studer, 2018). In the 1980s the sociologist Andrew Abbott transferred sequence analysis into the field of the social sciences since a wide variety of work in social science concerns sequences of events or phenomena (Abbott, 1995). The study of event sequences has also a long research history in psychology, economics, archaeology (Abbott, 1995) as well as voice recognition (Schlich, 2004) and historical linguistics (List, 2014).

An illustrative example of the importance of analyzing behavior sequentially is given by Ivanouw (2007), in which the relevance of sequential data is explained through a fictitious Tolman-like learning experiment. Thereby two rats have to choose between two doors - left or right - in order to obtain food that might be behind one of those doors. Ivanouw (2007) assumes that both rats do 21 continuous trails and the choices of the first rat are L R R L R L R R R L R R R L R L R L R R R and the choices of the second rat are L R L L R L R R R R R R L L L R R R R R R. The question arises if the two rats behave similarly or not? Both rats chose 7 times the left door (33.3%) and 14 times the right door (66.6%). Looking only at the frequencies of their choices one might be tempted to conclude that both rats would have behaved the same way. Although, when having a closer look, patterns can be discovered, e.g. the first rat always chose the right door after the left door, which is not the case for the second rat. The second rat chose the left door multiple times in a row. (Ivanouw, 2007). A further example of how sequential behavior can be examined is given by Berchtold & Sackett (2002), who analyzed the behavior of 15 nursery raised infant pigtailed macaque monkeys (Macaca nemestrina) during playroom socialization sessions. Thereby the researchers observed and coded four different behaviors: passive, explore, fear/disturbance and play. Their goal was to find a model clearly identifying differences in patterns of successive behaviors between monkeys. However, Berchtold & Sackett (2002) did not consider the time spent on each behavior, therefore each observation could have had a different duration. First, the researchers created a *contingency table* for each individual monkey. Contingency tables are considered as a basic tool for the presentation of transitional data represented as an array of the relation between two or more categorical variables. Such tables contain as many columns and rows as there are dependent variables. For instance, the four focal behaviors in this study can be represented in a 4 x 4 matrix, where the numbers in each cell represent the sequential occurrences of each pair of events. Based on these observed absolute values, transition probabilities can be calculated. According to Berchtold & Sackett (2002), this is done by dividing each number of the contingency table by the corresponding row sum. As a result, each row cell represents the given probability of an intersection and each row sums up to 1.00. In psychological literature on behavior interaction, however, contingency tables are rather rare. Usually, stochastic frameworks such as transition probability matrices or Markovian models are commonly used (Abbott, 1995). The latter was developed by the Russian mathematician A. A. Markov (1856-1922) for analyzing sequences with well-defined dependencies. According to Ivanouw (2007), however, many statistical methods require independence between the data, i.e. the observed events. Nevertheless, real live behavior is seldom independent since it is usually influenced by numerous cause effects and should therefore be analyzed sequentially. Markovian models are used to systematize and simplify such complex links. There are different orders of Markov models. A first-order Markov model for example assumes that every event is influenced only by the immediately preceding event (Ivanouw, 2007). In other words, this means that at a given point in time the next event would be influenced only by the present event, but it does not matter what determined the present event. Moreover, the second-order model assumes that a given event is influenced by the two preceding events. Markov models are usually represented as visualizations with knots and edges, whereas knots represent the events and edges the transition probabilities. The thickness of the edges indicates the level of the transitional probabilities (high transitional probabilities are represented as thick edges, low transitional probabilities are represented as thin edges). No edge between two knots indicates no linkage and therefore zero transition probability between those two events. Markov Chain Visualization captures the natural complexity of behavioral data. Such visualization can be either analyzed descriptively as well as by applying a variety of quantitative measurements from algorithms (e.g. Optimal Matching), to simple or linear algebra (Abbott & Tsay, 2000) or qualitative measurements, such as visual analytics (Rack et al., 2019; Kerren & Schreiber, 2012). According to Rack et al. (2019), visual analytics supports researchers using an exploratory framework to analyze hierarchical or sequential data.

2. Research Question

According to Sinha et al. (2014), we assume that log files hide an immense potential if the hidden information can be easily comprehended and that we can gain a deeper understanding of learning behavior from these log files by analyzing meaningful sequences instead of raw clickstream logs. Thus, the main goal of this study was to develop a new method to gain deeper insights into learners' behavior based on log files automatically collected while they learned with an enhanced video-based environment. However, measuring a latent variable such as learning behavior is particularly tricky and time-consuming. Furthermore, the authors of this study were not aware of any available tool that could have been applied for that purpose. As a result, a special focus lied on the development of a time-saving and adjustable application that enables researchers to automatically detect meaningful behavior sequences solely based on log files. We developed our method close to empirical data resulting from a data set of students who learned a complex science topic with an interactive video (see section below for study details) either individually or in groups of two (i.e. learning setting conditions) and either used hyperlinks or annotations for self-written summaries (i.e. learning task conditions). The present study was guided by the following two exploratory research questions:

RQ1: Can differences in learning behavior be made visible by developing a new method using log files?
RQ2: Can learning strategies from successful and less successful learners be discovered?

We hypothesized that (H1a) the learning behavior of individual and collaborative learners differ and these differences can be visualized by the newly developed method. Furthermore, we hypothesized that (H1b) the learning behavior of learners between the annotation and hyperlink conditions differ and these differences can also be visualized by the method. Hence, the learning setting and the learning task served as independent variables and learning behavior as the dependent variable.

In the following sections, we first give a description of the data set before we describe our newly developed method for detecting meaningful behavior sequences in detail. Then, we introduce our executive application (Logible) before we present findings for answering the research questions followed by a discussion and conclusion.

3. Material and methods

3.1. Description of the data set

In order to develop the method, we used a subsample from a data set consisting of 209 Swiss university students (75% female, M = 24.30 years, SD = 6.70). The participants were asked to learn a complex science topic (i.e. synaptic plasticity) at their own pace using an enhanced video-based environment provided by the learning application *FrameTrail*[1]. All participants received the same video and the same additional predefined learning material (in form of informative texts). The participants were randomly assigned to the experimental conditions of a 3 x 2 study plan. Participants could either add annotations in form of self-written summaries (annotation condition) or add hyperlinks containing the predefined additional learning material (hyperlink condition) directly at appropriate places into the video and change the display time on the video timeline. A third group (i.e. considerate-watching condition) functioned as the control condition and received the same video as well as the additional information but was not able to add annotations or hyperlinks. Moreover, participants learned either individually or in a group of two (dyad) using one shared desktop computer. In order to answer the research questions of this contribution the participants of the control condition were excluded. Therefore, only a subsample of the data from participants learning in the two *enhanced* conditions (annotation and hyperlink) were used to develop the method, since we were interested in investigating learning behavior in enhanced video-based environments and built behavior sequences on these conditions. Due to technical issues, few log files went missing or were damaged. Thus, the data set for the present study contained 92 log files from 134 participants (75.4% female, M = 24.18 years, SD = 6.78) provided by FrameTrail. To find differences in the learning setting and learning task on learning behavior we contrasted the four experimental conditions (see Table 1). Note that only one data set for each collaborative group was available.

Table 1
Sampling and study design RQ1 (number of participants).

		Learning setting Individual	Collaborative	Total
Learning task	Annotation	25 (25)	20 (40)	45 (65)
	Hyperlink	25 (25)	22 (44)	47 (69)
	Total	50 (50)	42 (84)	92 (134)

Before and after each video learning intervention the participants were asked to test their knowledge on synaptic plasticity by answering a short 5 question questionnaire. Concerning RQ2, four data sets for each experimental condition were selected and differentiated between the success of their knowledge gain. We classified learners as successful when they achieved at least a two points better result in the posttest compared to the pretest. Accordingly, we classified less successful learners when they achieved a less than two point better result in their posttest. Note that learners in the collaborative conditions (learning dyads) answered pretest and posttest separately. Therefore, mean scores from both learners were calculated. As a result, 16 data sets were thereby selected by differentiating between 8 successful and 8 less successful learners (see Table 2).

Table 2
Sampling and study design RQ2 (Δ = difference between pretest and posttest).

	Annotation Individual	Collaborative	Hyperlink Individual	Collaborative
Successful	IA39 ($\Delta = 4$)	CA19 ($\Delta = 2.5$)	IH62 ($\Delta = 4$)	CH35 ($\Delta = 3.5$)
	IA70 ($\Delta = 4$)	CA44 ($\Delta = 4$)	IH63 ($\Delta = 4$)	CH66 ($\Delta = 4.5$)
Less Successful	IA06 ($\Delta = -1$)	CA22 ($\Delta = 0$)	IH17 ($\Delta = -1$)	CH40 ($\Delta = -0.5$)
	IA08 ($\Delta = 1$)	CA57 ($\Delta = 1$)	IH44 ($\Delta = 0$)	CH61 ($\Delta = 0.5$)

[1] see `https://frametrail.org`

3.2. Introducing a new method for detecting behavior sequences

In the following section, we introduce the step-by-step process of developing our method for sequence detection, which was inspired by Sinha et al. (2014). While participants learned with FrameTrail, the system automatically logged the following seven user interactions (in the following referred as actions): *VideoPlay, VideoPause, VideoJumpBackward, VideoJumpForward, AnnotationAdd, AnnotationChangeTime, AnnotationChangeText*. Note that *AnnotationAdd* and *AnnotationChangeTime* were logged either when an annotation or a hyperlink was added into the video or changed in its display time. The action *AnnotationChangeText*, however, only referred to the annotation condition, as only participants in the annotation condition were able to write and change text elements. Like Berchtold & Sackett (2002) we did not consider the time spent on each behavior, therefore each observation could have had a different duration. In the first step, deduced from the initially provided log files, all actions were arranged horizontally as action-strings (by using Microsoft Excel). In the second step, the action-strings from a randomly selected subsample (n = 6) of the data set (N = 92) were analyzed more deeply by two experts. The most frequently occurred action-strings performed by learners in conjunction with each other were manually and exploratively grouped. Using these detected groups of actions many semantically meaningful behavior sequences could be identified. The idea behind this step was rather to reduce the noise in the data by grouping actions into meaningful sequences than to investigate arrays of actions or atypical trajectories from them as stated in the previous chapter. The chronological order of actions in these groups, however, could differ but still manifest in the same behavior sequence. This is illustrated by the following examples of three slightly different action-strings:

1. ... / VideoPlay / VideoPause / VideoJumpBackward / AnnotationAdd / ...
2. ... / VideoPlay / VideoPause / VideoJumpBackward / AnnotationAdd / ...
3. .../ VideoJumpBackward / VideoPlay / VideoPause / AnnotationAdd / ...

The three action-strings are similar in the way that (1) they consist of about the same amount of actions, (2) all contain the same kind of actions and (3) *AnnotationAdd* is set as the last action of the sequence. To intersubjectively validate the exploratory detected sequences we compared and revised them in many iterations. In the third step, the exploratory initial process merged into a rule-based procedure that served as a guideline to identify possible behavior sequences in fuzzy action-strings. Every behavior sequence was given an identification number and a meaningful label as well as an informative description. Furthermore, the minimum and maximum amount of allowed actions as well as the mandatory and forbidden actions were defined. Additionally, the permitted frequency of action appearance and mandatory first and last action of the sequence were defined as well. Table 3 illustrates a concrete example for behavior sequence *1.1. Search position and add annotation*.

Table 3
Concrete example for the rule-based procedure.

Behavior sequences label	1.1 Search position and add annotation
Behavior sequences description	This sequence represents an intentional search for a location in the video to add an annotation or hyperlink
Min./Max. amount of actions	3 to 5
Mandatory actions	VideoJumpBackward or VideoJumpforward, AnnotationAdd
Actions allowed only once	AnnotationAdd
Forbidden actions	AnnotationChangeText, AnnotationChangeTime
Mandatory first action	VideoPlay, VideoPause, VideoJumpBackward, VideoJumpForward
Mandatory last action	AnnotationAdd

This rule-based procedure was especially important considering the following automatically computer-supported sequences detection (see below). In a fourth step, this rule-based procedure was applied on new randomly included action-strings from the data set and thereby iteratively improved the method. This process finally resulted in 17 delimitable behavior sequences (see Figure 1).

Having closer look at the 17 behavior sequences in Figure 1, it unravels that there are several overlaps between the sequences. For instance, the behavior sequence *1.4 Search position and create annotation and adjust time* includes - by its definition - also the behavior sequence *1.3. Search position and create annotation* (see Figure 1). In other words, the behavior sequences can be considered consecutive.

Behavior Pattern	Behavior Sequences		Prioritization
	Annotation	Hyperlink	
1. Search and add	1.1 Search position and add annotation	1.1 Search position and add annotation	3
	1.2 Search position and add annotation and adjust time	1.2 Search position and add annotation and adjust time	2
	1.3 Search position and create annotation		2
	1.4 Search position and create annotation and adjust time		1
2. Search and modify	2.1 Search to adjust annotation time	2.1 Search to adjust annotation time	5
	2.2 Search to change/complement annotation text		5
	2.3 Search to change/complement annotation and adjust time		4
3. Find and add	3.1 Find position and add new annotation	3.1 Find position and add new annotation	8
	3.2 Find position and add annotation and adjust time	3.2 Find position and add annotation and adjust time	7
	3.3 Find position and create new annotation		7
	3.4 Find position and create annotation and adjust time		6
4. Find and modify	4.1 Find position and adjust annotation time	4.1 Find position and adjust annotation time	10
	4.2 Find position and add further video information		10
	4.3. Find position and add further video information and adjust time		9
5. Search and navigate	5.1 Rewatch	5.1 Rewatch	12
	5.2 Jump Forward	5.2 Jump Forward	12
	5.3 Skipping	5.3 Skipping	11

Figure 1: Overview of behavior patterns and behavior sequences with prioritization.

In a fifth step, by implementing a priority system we defined which behavior sequence should be selected whenever there was more than one possibility. Therefore, we considered the factors *priority*, *length (of sequence)* and *homogeneity* - and assigned them different weighting. The priority factor had the highest weighting as it considers different levels of interactivity between the sequences to fulfill the learning task. For instance, the behavior sequence *5.1 Rewatch* had a very low priority, as it solely contains *VideoPlay* and *VideoPause* and *VideoJumpBackward*, indicating a learners' intention to watch a certain part of the learning video again. The behavior sequence *1.4 Search position and create annotation and adjust time*, on the contrary, had the overall highest priority since it not only contains *VideoPlay* or *VideoPause*, and *VideoJumpBackward* but also contains *AnnotationAdd*, *AnnotationChangeTime* and *AnnotationChangeText*. This behavior sequence indicates that a learner actively navigates the video - similarly to the rewatch sequence - but additionally adds an annotation, then writes a summary and finally changes the display time of the annotation in the video timeline. Hence, this sequence involves a higher interactivity level than the rewatch sequence and thus should get selected by an automated system rather than the *5.1 Rewatch* sequence. Moreover, in order to reduce the noise in the action-strings caused by not assigned single actions, longer sequences were preferred over shorter sequences (= length). For sequences with similar priority and length scores, we applied the heterogeneity factor, to prefer sequences with a higher number of different actions. Note that in the process of transferring our newly developed method to a usable tool (see section below) we calculated normalized scores for each of the factors and assigned an overall rating for the given list of behavior sequences, which also took into account the respective weight of each factor (priority: 2.2, length: 1, heterogeneity: 0.4).

In a final step, the 17 behavior sequences were further subsumed into five superordinate behavior patterns (see left column in Figure 1). Each behavior pattern functions as a latent variable difficult to measure directly from data. We contrasted the five behavior patterns between their intentional level (search vs. find) and their level of content creation (add vs. modify). More precisely, the behavior patterns *1. Search and add*, *2. Search and modify* and *5. Search and navigate* contained at least one search element, i.e. either action *VideoJumpForward* or *VideoJumpBackward*, indicating that learners actively searched the video (by jumping forward or backward) for information. In contrast, the behavior patterns *3. Find and add* and *4. Find and modify* evolved "on-the-way", indicating that learners found a place in the video for further interactions. Moreover, the behavior patterns *1. Search and add* and *3. Find and add* comprised the action *AddAnnotation*, indicating that learners searched or found an appropriate place in the video to add an annotation or hyperlink. Contrary to the behavior patterns *2. Search and modify* and *4. Find and modify*, where learners searched or found a place in the video that helped them to modify already existing annotations or hyperlinks (by changing the display time of the annotation/hyperlink or by revising the self-written text). Behavior patterns play an important role in further comparisons and analyses since they show a higher ability to contrast whereas behavior sequences differ only marginally from each other due to their consecutive character. Furthermore, learners in the hyperlink condition received only predefined additional learning material they could not contribute self-written summaries and as a result the action *AnnotationChangeText* could not occur. Thus, learners in the hyperlink condition could only perform nine out of the 17 behavior sequences (see Figure 1). By identifying meaningful behavior sequences and behavior patterns we expect to reduce the noise in the data and to analyze their order in the manner of behavior sequence analysis.

3.3. Transferring the method into Logible

As mentioned earlier detecting behavior sequences out of raw clickstream data is rather difficult and time-consuming. Therefore, we developed an application called Logible (making **log** files legi**ble**) to automatically detect and visualize meaningful behavior sequences from the entire data set based on our methodological approach. The log files in their tabular format (usually Microsoft Excel) can easily be added into Logible by dragging and dropping them on the home screen. Logible quickly analyzes the data and detects all presumed possible behavior sequences according to the rule-based sequence detection and visualizes them color-coded above each individual action-string (see bottom line in Figure 2). According to the rule-based prioritization, Logible selects and marks the most valuable behavior sequence with a bold black frame. This visualized representation provides a first impression of students' learning behavior. We further implemented a function that calculates the number of actions assigned to the behavior sequences, which highlights the sensitivity of Logible.

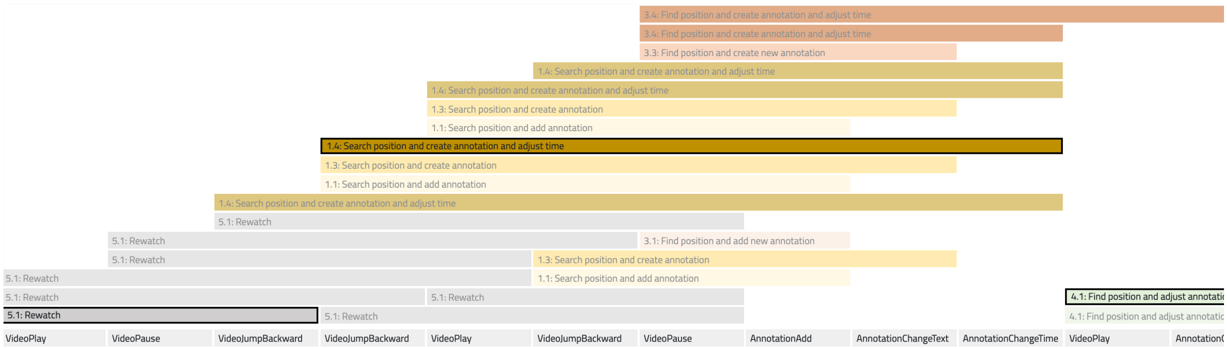
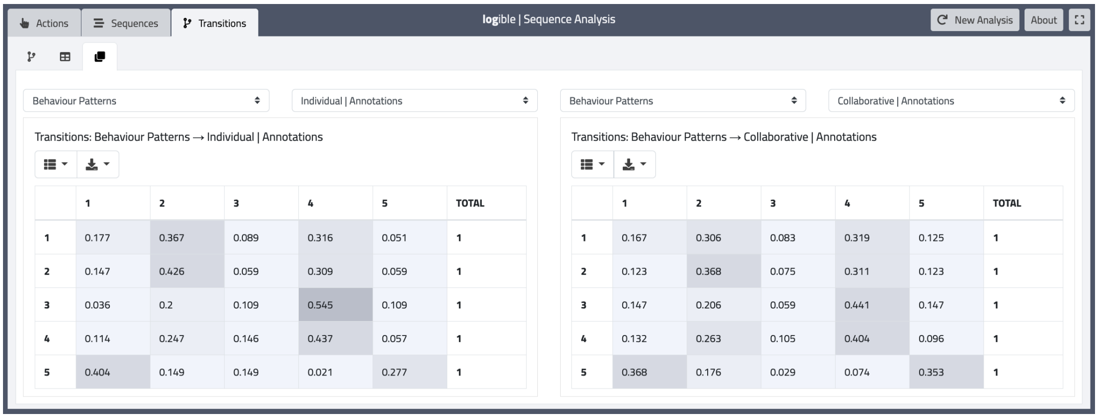


Figure 2: Visualized sequence detection in Logible.

In order to directly investigate and compare learning behavior and learning strategies, we equipped Logible with three additional functionalities: (1) *Frequency of Occurrence*, (2) *Transition Probability Matrices* and (3) *Markov Chain Visualizations*. The idea behind these functions was to directly compare relevant subsamples in Logible without using any other software. Thereby the Graphic User Interface (GUI) is divided vertically and shows on either side two adjustable tables (see Figure 3). Above each table, there are two drop-down menus (i.e. a format selector and a sample selector) for configuring each table separately. The format selector offers three possible output levels. On the most granular level *actions* can be compared. Furthermore, and on a higher level the 17 meaningful *behavior sequences* or the five *behavior patterns* can be chosen for comparison. With the second drop-down menu the sample one wants to analyze in-depth can be selected. The sample selector offers many different options to choose from. One specific single data set or aggregated data sets of one of the four experimental groups or the whole data set can be chosen for further comparison. Contrasting two experimental groups using the *Frequency of Occurrence* of the five behavior patterns enabled first insights into students learning behavior. Thereby, possible differences in absolute and relative frequencies of occurrence could be discovered.

Additionally and with RQ2 in mind, we equipped Logible with *Transition Probability Matrices* (see Figure 3). After configuring the two tables accordingly, Logible displays two separate transition probability matrices. Each cell in these matrices indicates the probability of a transition from one learning behavior to the next (according to Berchtold & Sackett, 2002). Note that we did not build contingency tables with absolute values, since we were interested in the transition probabilities. We further added a grayscale heat map to these tables to make the data interpretation quicker and more human-friendly. Cells represented in darker grayscale correspond to a higher transition probability. Furthermore, these data, i.e. *Frequency of Occurrence* and *Transition Probability Matrices* can be easily exported from Logible in various formats to apply further statistical analyses.

Next, we equipped Logible with yet another representation to contrast learning behavior visually. After configuring the two tables according to your interests, Logible presents two color-coded first-order *Markov Chain Visualizations* according to the selected format and sample (for example see Figure 5 and Figure 6). Each color-coded knot represents one of the five behavior patterns. The edges indicate the transition probabilities transferring from one behavior pattern to another. The thickness of the edges corresponds with the probability (i.e. small edges represent a low transitional probability whereas bigger edges represent a higher transitional probability).



	1	2	3	4	5	TOTAL
1	0.177	0.367	0.089	0.316	0.051	1
2	0.147	0.426	0.059	0.309	0.059	1
3	0.036	0.2	0.109	0.545	0.109	1
4	0.114	0.247	0.146	0.437	0.057	1
5	0.404	0.149	0.149	0.021	0.277	1

	1	2	3	4	5	TOTAL
1	0.167	0.306	0.083	0.319	0.125	1
2	0.123	0.368	0.075	0.311	0.123	1
3	0.147	0.206	0.059	0.441	0.147	1
4	0.132	0.263	0.105	0.404	0.096	1
5	0.368	0.176	0.029	0.074	0.353	1

Figure 3: GUI of Logible for comparing two experimental groups.

4. Measures

In order to answer RQ1, whether differences in learning behavior can be made visible using our newly developed method executed by Logible, the five behavior patterns (see Figure 1) were used for further comparison and analyses. Therefore, we first looked at the descriptive results of the entire data set (N = 92) to examine differences in the frequencies of occurrence of the behavior patterns. Furthermore, a multivariate analysis of variance (MANOVA) with learning task (annotations vs. hyperlinks) and learning setting (individual vs. collaborative) as between-subject factors and the relative values of the five behavior patterns (see Table 4) as dependent variables was applied and calculated with SPSS. Moreover, and according to RQ2, we wanted to investigate if and how learning strategies from successful and less successful learners can be discovered. Therefore, we focused on the sequentiality of the behavior patterns of learners, which can be investigated directly in Logible through Transition Probability Matrices and Markov Chain Visualizations. These two representation formats contain the same information, however, we further report results based on the Markov Chain Visualization (see Table 5 and Table 6) since we consider this format as more suitable for fulfilling our purpose, which was to descriptively explore and investigate learning strategies. We contrasted the values of the edges (i.e. the probability that one behavior pattern follows another) from successful learners and less successful learners in the same learning task condition and focused on differences >15% (symbolized by the Greek letter $Delta = \Delta$). We have set the threshold at this percentage since first due to space limitations not all differences can be reported and second smaller differences (<15%) may occur randomly due to the sample size. Furthermore, different percentages (i.e. 5%, 10%, 15% and 20%) were tested and a threshold of 15% yield a sufficient amount of differences, which could be used for discovering different learning strategies.

5. Results

Logible revealed that the 92 log files contained a total of 11'239 single actions. Thereof, Logible could successfully assign 10'106 actions (i.e. 89.92%) to one of the 17 behavior sequences, which in turn highlights the high sensitivity of the application. Moreover, a total of 2'346 behavior patterns were found in the data, indicating the capability to significantly reduce the noise in the action-strings by assigning only the presumed possible behavior sequences for each experimental condition. Logible therefore passed the manipulation check. Results revealed that the absolute number of the occurrences of behavior patterns varied among the four experimental conditions. The lowest amount of behavior patterns was found in the collaborative annotation condition (CA = 414), followed by the individual annotation condition (IA = 500) and the collaborative hyperlink condition (CH = 693). The individual hyperlink condition performed the most behavior patterns (IH = 739). Note that for the purpose of this study we focused on relative values for further comparison. Therefore, we descriptively investigated the frequency of occurrence of the five behavior patterns over the whole data set (N = 92). The data revealed that behavior pattern *4. Find and modify* occurred most frequently (26.34%) and almost twice as often as *3. Find and add* (13.94%). The behavior patterns *1. Search and add* (19.44%), *2. Search and modify* (20.72%) and *5. Search and navigate* (19.57%) occurred with almost equal frequencies.

Taking a closer look on the four experimental conditions, we saw that the relative frequencies formed distinctive patterns (see Figure 4). Learners in the annotation conditions (see solid lines) for instance generally modified previously added annotations more often (see peaks for *2. Search and modify* and *4. Find and modify*) then they added new annotations (see *1. Search and add* and *3. Find and add*). Learners in the hyperlink conditions (see dotted line), however, performed more often the behavior pattern *5. Search and navigate* compared to the learners using annotation.

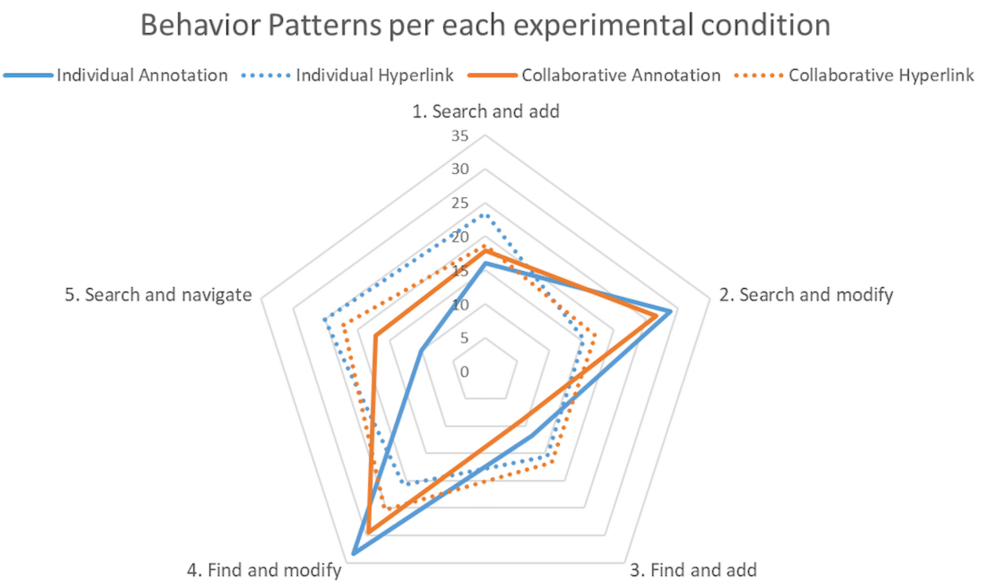


Figure 4: Relative frequencies per condition.

Table 4
Means and standard deviation (in brackets) per condition and behavior pattern.

		1. Search and add	2. Search and modify	3. Find and add	4. Find and modify	5. Search and navigate
Annotation	Individual	19.94 (14.22)	25.28 (18.34)	13.68 (15.28)	31.28 (19.00)	9.82 (8.45)
	Collaborative	21.19 (17.43)	22.24 (15.59)	11.80 (12.44)	25.82 (15.29)	18.96 (16.90)
	Total	20.50 (15.55)	23.93 (17.05)	12.84 (13.97)	28.85 (17.47)	13.88 (13.54)
Hyperlink	Individual	24.83 (11.21)	15.30 (8.30)	17.72 (12.03)	19.74 (10.29)	22.40 (12.26)
	Collaborative	21.26 (13.61)	16.32 (13.55)	19.34 (11.33)	23.09 (12.86)	20.00 (14.20)
	Total	23.16 (12.39)	15.78 (10.96)	18.48 (11.61)	21.31 (11.56)	21.27 (13.12)

Results from the MANOVA (for descriptive results see Table 4) revealed a significant main effect for learning task ($F(4, 85) = 4.650$, $p = .002$; Pillai's Trace = .180), as expected (H1b), indicating a difference in the frequencies of behavior patterns between learners in the annotation condition and learners in the hyperlink condition. More precisely, significant effects for the behavior patterns *2. Search and modify* ($p = .010$) and *4. Find and modify* ($p = .023$) were found, both indicating that these patterns occurred more often in the annotation condition (*2. Search and modify*: M = 23.93, SD = 17.05; *4. Find and modify*: M = 28.85, SD = 17.47) than in the hyperlink condition (*2. Search and modify*: M = 15.78, SD = 10.96; *4. Find and modify*: M = 21.31, SD = 11.56). In contrast, significant effects for *3.*

Find and add (p = .035) and *5. Search and navigate* (p = 0.15) indicated that these behavior patterns occurred more often in the hyperlink condition (*3. Find and add*: M = 18.48, SD = 11.61; *5. Search and navigate*: M = 21.27, SD = 13.12) than in the annotation condition (*3. Find and add*: M = 12.84, SD = 13.97; *5. Search and navigate*: M = 13.88, SD = 13.54). However, no significance was found for *1. Search and add* (p >.05). Furthermore, and contrary to our expectations (H1a), no significant main effect for learning setting (p > .05), nor any interaction effect between learning setting and learning task (p > .05) was found.

Since the MANOVA revealed no significant influence from learning setting on learning behavior, the data from the individual and collaborative learners in the same task condition were aggregated for investigating learning strategies from successful learners (SL) and less successful learners (LSL). Figure 5 shows two Markov Chain Visualizations (MCV) from SL (left) and LSL (right) both using annotations. Both visualizations contain four data sets (see Table 2).

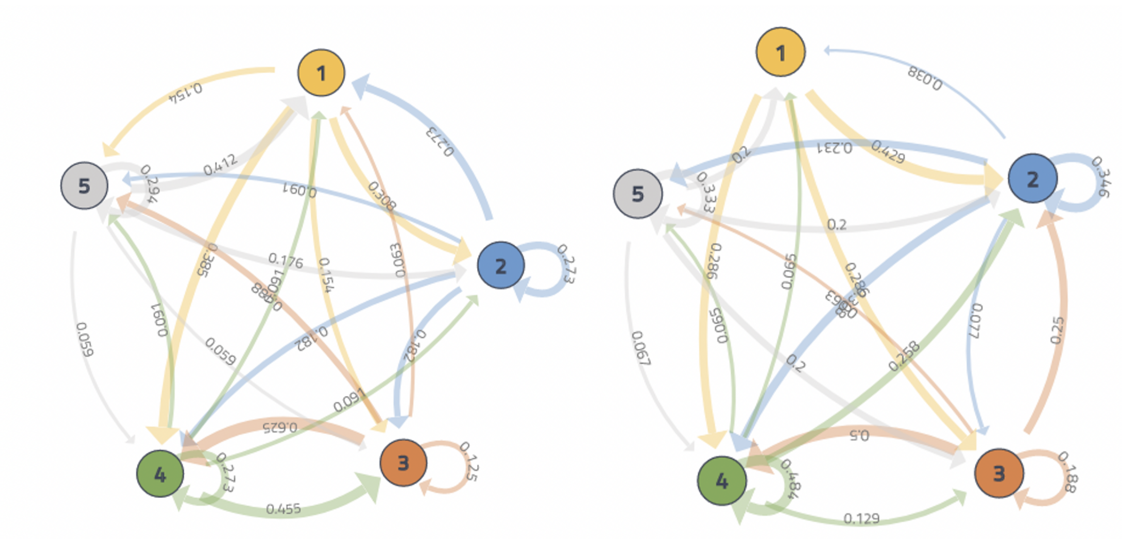


Figure 5: MCV from SL (left) and LSL (right) using Annotation.

Results revealed that SL in the annotation conditions had higher chances that behavior pattern *1. Search and add* followed after either the behavior pattern *2. Search and modify* (SL = 27.3%; LSL = 3.8%; Δ = 23.5%) and *5. Search and navigate* (SL = 41.2%; LSL = 20%; Δ = 21.2%). Furthermore, SL had a higher chance that behavior pattern *3. Find and add* followed after *4. Find and modify* (SL = 45.5%; LSL = 12.9%; Δ = 32.6%) and that the behavior pattern *5. Search and navigate* followed after *1. Search and add* (SL = 15.4%; LSL = 0%; Δ = 15.4%). On the contrary, LSL had higher chances that behavior pattern *2. Search and modify* followed after either *3. Find and add* (LSL = 25%; SL = 0%; Δ = 25%) or *4. Find and modify* (LSL = 25.8%; SL = 9.1%; Δ = 16.7%). Moreover, LSL more often performed behavior pattern *4. Find and modify* in a row (LSL = 48.4%; SL = 27.3%; Δ = 21.1%).

Concerning different transition probabilities for learners in the hyperlink condition (see Figure 6), results revealed that SL more often performed behavior pattern *1. Search and add* in a row (SL = 26.7%; LSL = 4.3%; Δ = 22.4%) as well as after behavior pattern *5. Search and navigate* (SL = 52.6%; LSL = 37.5%;Δ = 15.1%). Furthermore, SL had higher chances that behavior pattern *2. Search and modify* followed after either itself (SL = 26.3%; LSL = 6.3%; Δ = 20%) or after behavior pattern *3. Find and add* (SL = 23.5%; LSL = 5.3%; Δ = 18.2%). SL also had a higher chance that behavior pattern *4. Find and modify* followed by itself (SL = 30.8%; LSL = 15%;Δ = 15.8%). On the other hand, LSL using hyperlinks had higher chances that behavior pattern *5. Search and navigate* followed after either behavior pattern *1. Search and add* (LSL = 39.1%; SL = 20%; Δ = 19.1%) or *2. Search and modify* (LSL = 31.3%; SL = 10.5%; Δ = 20.8%). Moreover, LSL had a higher chance that behavior pattern *4. Find and modify* followed after behavior pattern *3. Find and add* (LSL = 31.6%; SL = 11.8%; Δ = 19.8%).

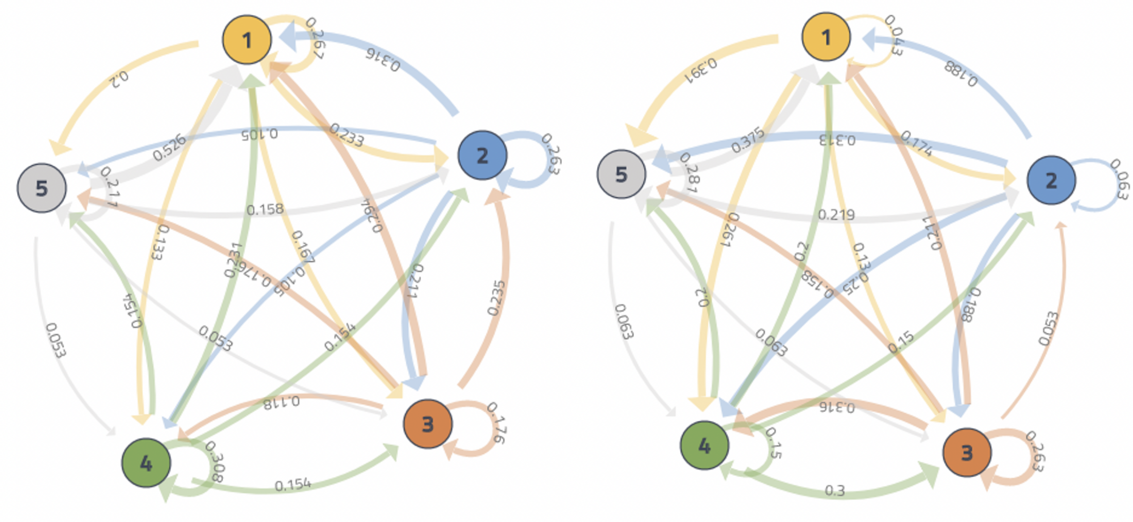


Figure 6: MCV from SL (left) and LSL (right) using Hyperlinks.

6. Discussion

The goal of this study was to develop a new method to gain deeper insights into learners' behavior based on their digital footprints (i.e. log files) when they learned with an enhanced video-based environment. Successfully, we were able to get new interesting findings by applying our new method executed by our newly developed application (Logible), which detects and visualizes meaningful behavior sequences out of fuzzy action-strings automatically and in a time-saving manner. Therefore, we conclude that differences in learning behavior can be made visible (RQ1). Results from the MANOVA confirmed hypothesis 1b assuming that learning behavior differs significantly depending on the learning task. More precisely, our data revealed that learners using annotations significantly more often modified previously added annotations than learners using hyperlinks. This can be explained by the fact that modifying annotations - in contrast to modifying hyperlinks - not only involves the modification of the display time on the video timeline but also modifications of the self-written texts. In the course of the learning time participants learned new information, which led them to change or complement their previously written texts. On the contrary, learners in the hyperlink condition significantly more often added new information by finding an appropriate position in the video (i.e. *3. Find and add*) than learners in the annotation condition. This can be explained by the fact that although both learning task conditions received the same predefined learning material, learners in the hyperlink condition simply had to add them to the video whereas learners using annotation additionally had to write summaries in their own words. Thus, the hurdle to add new information might be smaller for learners in the hyperlink condition than for learners in the annotation condition. Furthermore, our data revealed that learners in the hyperlink condition navigated more frequently in the video than learners in the annotation condition. One possible explanation for this result can be found in the consecutive character of the behavior sequences within the same behavior pattern (see Figure 1). The annotation condition had ten possible behavior sequences that contain searching a position in the video whereas the hyperlink condition had only six. Whenever learners first navigated in the video and then either added or modified an annotation the initial navigation part of the action-string resulted in a higher prioritized behavior sequence. Since we could not find any evidence confirming Hypothesis 1a, which assumed a difference in learning behavior between the learning settings (individual vs. collaborative), we therefore conclude that experimental groups belonging to different learning settings showed more similar learning behavior than experimental groups with different learning tasks (annotation vs. hyperlinks).

Furthermore, by applying our method we were able to examine learning strategies from successful and less successful learner (RQ2). The most profound difference found by investigating transitional probabilities using Markov Chain Visualizations from successful and less successful learners was that in both learning task conditions successful learners in contrast to their less successful counterparts performed with a higher chance behavior pattern *5. Search and navigate* followed by behavior pattern *1. Search and add*. In other words, successful learners were more likely to first actively search a part in the video to watch it and then jumped either back or forth in the video timeline to a specific part of the video to add an annotation or a hyperlink. We interpret this finding as evidence that successful learners thoroughly planned where to place an annotation or a hyperlink and thereby intensively engaged with the learning material. This is in line with findings from Zahn et al. (2010) and Zahn et al. (2012) since successful learners in our study designed a thoroughly planned hypervideo structure and therefore successfully learned a complex science topic. In addition, this result confirms that through active participation in constructing information, learners actively transformed existing video representations into their own enriched information structures (according to Schwartz & Hartman, 2007; Yousef et al., 2015), and therefore actively generated meaning (according to Wittrock, 1992) and designed their own learning content (according to Kafai & Resnick, 1996; Papert, 1994).

7. Conclusion, limitations and future work

We were able to add new original findings to the corpus of the rare existing research on the effects of behavior sequences for a more in-depth understanding of learning behavior in the setting of remote video learning. With Logible we created a tool that enables researchers to better understand learning processes even from afar by analyzing logged interaction data. Which is of particular interest since teachers around the world have not been able to observe students learning behavior as usual, due the coronavirus and the associated closing of schools and universities (UNESCO, 2020). We conclude that applying our newly developed method executed by Logible generated deeper insights into students' learning behavior by detecting and investigating meaningful behavior sequences and behavior patterns instead of raw user interactions on a granular clickstream level. Furthermore, Logible is designed to be a highly sensitive, customizable and time-saving application. Therefore, we encourage researchers in the field of CSCL to consider working with Logible whenever focusing on broader behavior instead of raw clickstream data.

Our methodological approach, however, was limited by the fact that we did not consider the time interval between each action. Therefore, we could not make any statement on the time spent on each behavior pattern. However, we took this into account by calculating and reporting relative values. Our methodological approach was characterized by intensive data exploration which eventually led to a rule-based sequence detection. In addition, future research could also focus on applying Artificial Intelligence (AI), since AI is particularly superior in pattern recognition and therefore could find patterns, which might differ from the ones humans detected. In literature research we further identified different approaches to compare sequential data and investigate learning strategies. However, we deliberately chose to stick with our initially exploratory approach and therefore used Markov Chain Visualizations to analyze different learning strategies. We consider this approach sufficient for answering the research question. Especially focusing and reporting differences in knowledge gain greater 15% yield to interesting new insights. Nevertheless, we consider algorithms such as Optimal Matching (OM) (for more see e.g. Abbott, 1995; Brzinsky-Fay & Kohler, 2010) as a suitable procedure for comparing behavior patterns as well, since it allows operations such as *substitution* (i.e. changing one element into another element), *insertion* (i.e. insert an element at a specific position), as well as *deletion* (i.e. delete an element at a specific position). Thereby the distance between two sequences can be calculated by the number of operations it takes to transform one sequence into another one. Using this procedure, typical learning behavior can be discovered and used for further comparison (Brzinsky-Fay & Kohler, 2010). Furthermore, we contemplate content analysis according to Mayring (2010) as a further promising approach to investigate learning strategies in-depth. Therefore, we suggest representing behavior patterns or even behavior sequences in their observed order and then transfer them into a written format. As an advantage this would preserve the real order of behavior patterns which otherwise, as in our approach calculating probabilities, would get lost. Next, the text can be evaluated in terms of content analysis. Finally, we see a further development of our method as promising, whereas behavior patterns could be treated as input data (similar to *actions* in this contribution). Through an exploratory pattern recognition process and following rule-based procedure semantically meaningful combinations of behavior patterns could lead to underlying behavior strategies. Logible, as a new and useful application that already provides interesting insights into learning behavior, is a promising solution to further explore learning behavior. Hence, we would also like to further improve Logible e.g. by implementing statistical functions such as analysis of variance, regressions, and correlations for direct comparison of data without using any other software.

A. Logible

Logible as a free demo including six example data sets is available under: https://sequence-analysis.frametrail.org/

B. Declaration

This contribution shall be understood and treated as a master thesis of the School of Applied Psychology at the University of Applied Sciences and Arts Northwestern Switzerland (submitted on January 14, 2021). It serves as a first draft and not yet as a manuscript to be submitted in the Journal *Computers & Education*. Parts of this contribution have already been submitted as a full paper in the ISLS Conference 2021. Acceptance letter will from the ISLS Conference arrive on February 20, 2021.

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