How Students Learn using MOOCs: An Eye-tracking Insight

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Abstract: We present the results of an eye-tracking study on a Massive Open Online Course (MOOC) lecture showing the relation between gaze variables and students' performance and learning strategy. 40 students watched a MOOC lecture while their eye-movements were being recorded. We present a method to define stimuli-based gaze variables that can be defined for any kind of stimulus. The advantage of using stimuli-based gaze variables is that the relation of the gaze indicators with performance measures and behavioral measures can be interpreted differently for different kinds of stimulus. MOOCs are very diverse in nature; having such a variable description enables the researchers to have a common measure for the different kind of stimulus present in different MOOCs. The long-term goal is to create student profiles based on their performance and learning strategy using stimuli-based gaze variables and to provide the students with gaze-aware feedback to improve the overall learning process.

Introduction

In the present decade, off the shelf mobile eye-trackers have become readily available. These devices provide researchers and software designers with unprecedented access to users' attention. With further developments in webcam based eye-trackers the cost of technology will also be brought to a non-significant level. This will make the eye-tracking methods available to world outside research labs as well.

Through this contribution, we address the topics of "student experiences and outcomes". We present a method to use physiological (eye-tracking) data to understand learning process in a deeper way. In this method we use stimuli-based indicators to qualify performance and learning strategy indicators. Our working hypothesis is that there exists a relation between behavioral indicators, performance, and the probability to drop out in a course. The general question we address is "how can we help students to watch videos more efficiently (e.g., with deeper attention)".

The advantage of using stimuli based indicators to derive variables is that we define generic variables to be computed for any kind of stimulus and relation between performance and behavioral indicators with such variables can be explained according to the stimulus type. Our long-term goal is to be able to create students' profiles based on their performance and learning strategy and provide them with feedback to improve the learning process.

The rest of the paper is organized as follows. The second section presents the previous research contextualizing the present research. The third section highlights the main features and the questions addressed in the present study. The fourth section presents the experiment and different variables. The fifth section presents the results. The sixth section discusses the results. Finally, in the seventh section, we conclude the paper.

Related Work

Video-based Learning

Existing research on video-based learning resembles many features of today's MOOCs lectures. Volery and Lord (2000) identified 3 success factors in online education: usable and interactive technology design, instructors' enthusiasm and interest in the tool and students' exposure to the web. Tobagi (1995) developed an online distant learning system to capture lectures real time, compress them, store them on an on-demand system and transmit the videos to internal server. The on-demand video system server eliminated distance limitations and provided time independent access to study material.

Tobagi (1995) compared different modalities of video lectures (interactive video, instructional television and television) and preconceptions of difficulty for different modalities and found that there was no significant difference in the learning outcome but there was a significant difference in the level of preconceived difficulty in television and interactive videos. Cennamo (1991) studied the effect of video based instruction on students problem solving skills and attitude' towards mathematics and instruction and concluded that there was a significant improvement after the treatment in students problem solving skills and in mathematical as well as the instructional attitude. Chio (2005) compared learning outcome and learners motivation (attention, relevance, confidence, satisfaction) in video based learning to traditional textual-instruction based learning and found no difference in learning outcome for the two conditions. However, the students wore more attentive in video based learning condition that the textual-instruction condition.

Paivio (1971, 1991) argued that information provided by both auditory and visual channels should increase recall and retention. Studies by Mayer (2003) have also shown that visual information helps to process and remember verbal information and vice versa. This argument was strengthened by cue-summation theory showing that learning performance in the combined audio and pictures was better than in the combined audio and text, if the numbers of available cues or stimuli are increased (Severin, 1967). Schwartz (2007), Bates (1985) and Doerksen (2000) listed same more benefits for video as a facilitator of educational content. The major benefits include presentation of detailed information (harder with text and image), efficient grabbing of students' attention, simulating discussions and providing concrete real life examples with visualizations.

Eye-tracking and Expertise / Task-based Performance

Previous research provides insights about the relationship between the gaze patterns and the behavioral and task-based performance indicators in diverse scenarios. Existing results show a clear relation between gaze patterns and expertise. Hasse et al. (2012), in an air traffic-monitoring task found out that the experts looked less at the scenario-specific information than novices. Eivazi et al. (2012), Tien et al. (2010) and Law et al. (2004) studied the effect of expertise on the gaze patterns in different surgical tasks and concluded that experts look less at the instruments than the novices, instead they focus more on the task specific areas. Reingold et al. (2001) showed that expert chess players pay more attention on the relative positions of the pieces, rather than the individual pieces, than novice chess players. Blignaut et al. (2008) also studied the difference between experts and novice chess players in a checkmate avoidance task and concluded that the experts have more gaze falling on the important squares than the novices. In a program debugging task Sharif et al. (2012) showed that the expert programmers scan through all the lines in the program faster than the novices. In a collaborative Tetris game, Jermann et al. (2010) showed that experts pay more attention on the stack of Tetronimoes while novices allocate more attention to the new pieces falling from the top.

Existing results also show a clear relation between gaze patterns and task based performance. In a pair-programming task, Jermann et al. (2012) showed that the good pairs have more synchronized gaze on different parts of a program than the bad pairs. In a similar task, Sharma et al. (2012) showed that the good performing pairs pay more attention to the data-flow of the program than the poor performing pairs. Moreover, Sharma et al. (2013) showed that while describing the functionality of a program the well performing teams had more gaze on the variable modification parts in the program while poor performing teams have equal distribution of gaze on different parts of the program during similar phase of the task.

Learning Strategy and Performance

In the learning context, Bidjerano and Dai (2007) and Pintrich and De Groot (1990) showed that personality and learning strategy of an individual has an impact on his/her achievement. Montague and Bos (1986) studied the effect of a cognitive strategy on the math problem solving performance and concluded that students who received the training on the strategy performed better than those who did not receive the training. Wolters (1999) studied the relation between learning strategies and the classroom performance for high school students and found a strong correlation between the strategy measures and the classroom performance. O'Malley et al. (1985) found a strong correlation between the learning strategy and the performance in learning English as a second language. This encouraged us to link the gaze not only with the performance but also with the study process and personality factors.

Present Study and Research Questions

We present the results of an eye-tracking study contextualized within a MOOC class. We choose MOOC videos as a stimulus for the eye-tracking because the effectiveness of video as a medium for delivery of educational content is already being studied and established in literature (see section "Related Work"). Through this contribution we propose to use the stimulus-based variables (introduced in the section "Experiment") to differentiate between the levels of expertise, performance and learning strategy. The benefit of using stimulus based variables is that these variables are generic enough to be computed for any kind of stimulus. Moreover, relation between performance and other behavioral constructs with such variables can be explained according to the stimulus type. The MOOC videos are very diverse as per the content of the video is considered. Using stimuli-based variables in the analysis enables the researchers to analyze diverse content of the MOOC videos in a similar manner. The present study addresses following methodological question:

1. What are the stimuli based variables that can be computed for a variety of stimulus and can be related to the performance and behavioral indicators?

Apart from the methodological question, through this contribution we address following research questions:

1. What is the relation between the expertise, performance and learning strategy in the context of the present study?
2. How are the stimuli-based variables related to the expertise and performance?
3. How are the stimuli-based variables related to the different learning strategies?

Experiment

In this section we will describe the experiment, procedure and different variables we define for the analysis presented in the current paper.

Participants and Procedure

In the experiment, the participants watched two MOOC videos from the course "Functional Programming Principles in Scala" and answer programming questions after each video. Participants' gaze was recorded, using SMI RED 250 eye-trackers, while they were watching the videos. Participants were not given controls over the video for two reasons. First, the eye-tracking stimulus for every participant was the same which intern facilitates the same kind of analysis for each of the participants. Second, the "time on task" remains the same for each participant.

40 university students from École Polytechnique Fédérale de Lausanne, Lausanne participated in the experiment. The only criterion for selecting the participant was that each participant took the Java course in the previous semester. Upon their arrival in the experiment site the participants signed a consent form, then they answered three self-report questionnaires for a 20-point study processes questionnaire (Biggs et. al., 2001), 10-point openness scale (Goldberg, 1999) and 10-point conscientiousness scale (Goldberg, 1999). Then they took a programming pretest in Java. In the last phase of the experiment, they watched two videos from the MOOC course and after each video they answered programming questions based on what they were taught in the videos. In the following subsections, we describe different variables related to the present analysis.

Participant Categorization

1. **Expertise:** We used median split on the pretest score (max=9, min=2, median=6) and we divide the participants in **"experts"** (more than median score) and **"novices"** (less than median score).
2. **Performance:** We used median split on the posttest score (max=10, min=4, median=8) and we divide the participants in **"good-performers"** (more than median score) and **"poor-performers"** (less than median score).
3. **Learning Strategy:** We used median split on the study process questionnaire score (max=42, min=16, median=31.5) and we divide the participants in **"deep-learners"** (more than median score) and **"shallow-learners"** (less than median score).

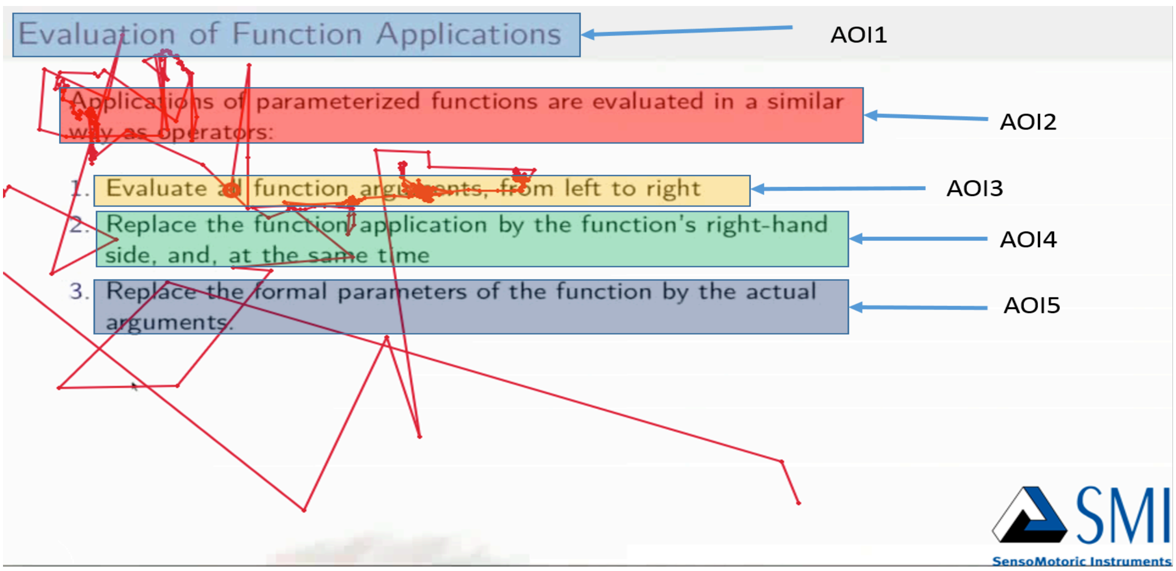


Figure 1: Example of a scan-path and Areas of Interest (AOI) definition. The rectangles show the AOIs defined for the displayed slide in the MOOC video and the red curve shows the visual path for 2.5 seconds. We compare AOI misses and AOI back-tracks across the levels of performance and learning strategy.

Process Variables

1. **Area of Interest (AOI) misses:** An area of interest (AOI) is said to be missed by a participant who does not look at that particular AOI at all during the period the AOI was present on the stimulus. In terms of learning behavior AOI misses would translate to completely ignoring some parts of the slides. We calculate the number of such AOIs per slide in the MOOC video as a scan-path variable and compare the number of misses per slide across the levels of performance and learning strategy (for details on areas of interest see Holmqvist et. al., 2001).
2. **Area of Interest (AOI) backtracks:** A back-track is defined as a saccade that goes to the AOI which is not in the usual forward reading direction. For example, in the figure 1, if a saccade that goes from AOI3 to AOI2 it will be counted as a back-track. AOI back-tracks would represent rereading behavior while learning from the MOOC video. The notion of term rereading in the present study is slightly different than what is used in existing research (for example, Mills and King (2001), Dowhower (1987) and Paris and Jacobs (1984)). The difference comes from the fact that in the present study the students don't reread the slides completely but they can refer to the previously seen content on the slide until the slide is visible. We calculate the number of back-tracks per slide in the MOOC video as a scan-path variable and compare the number of back-tracks per slide across the levels of performance and learning strategy.
3. **Attention Points:** Attention points are computed using the heat-maps (for details on heat-maps see Holmqvist et. al., 2001) of the participants. We divided the MOOC lecture in slices of 10 seconds each and computed the heat-maps for each participant. From heat-maps we compute the attention points using method described in figure 2. Attention points typically represent the different areas where the students focus their attention. The number of the attention points will depict the number of attention zones and the area of the attention points will depict the total time spent on a particular zones. We compare the number of attention points and the average area covered by attention points per 10 seconds across the levels of performance and learning strategy.

Figure 2: Steps for computing the attention points from the heat map. (a) A slide with the overlay of 10 seconds heat-map. (b) A slide (same as (a)) without the overlay of heat-map. (c) Resulting image after subtracting image without the heat-map from heat-map overlaid image. (d) Applying connected component on the image (c) gives us attention points.

Results

1. **General Statistics:** We observe no clear relation between the three variables. There is no significant relation between expertise and performance (χ^2 (df=1) = 9.72, p > .05). There is no significant relation

between expertise and learning strategy (χ^2 (df=1) = 3.12, p > .05). There is no significant relation between learning strategy and performance (χ^2 (df=1) = 4.18, p > .05).

2. **Expertise vs. Process variables:** We also did not observe any significant relation between expertise and other variables. Expertise has no relation with the number (F(1,38) = 1.00, p > .05) or the average area (F(1,38) = 1.17, p > .05) of the attention points. Moreover, expertise has no relation with misses (F(1,38) = 2.06, p > .05) or back-tracks (F(1,38) = 4.00, p > .05) of the attention points. In the following subsections, we report the relationships for the heat-map and scan-path variables with learning strategy and/or performance.
3. **Attention Points vs. Performance and Learning Strategy:** There is no difference in the number of attention points for good and bad performers (F(1,38) = 1.00, p > .05). Moreover, there is no difference in the number of attention points for deep and shallow learners (F(1,38) = 1.00, p > .05). However, the good-performers have significantly more average area for the attention points than the poor-performers (F(1,38) = 5.47, p < .05). Furthermore, the deep-learners have significantly more average area for the attention points than the shallow-learners (F(1,38) = 4.21, p < .05), figure 3 shows the difference margins. This suggests that, the good-performers spend more time reading the content than the poor-performers and the deep-learners spend more time reading the content than the shallow-learners. To confirm this we also measured the reading time for a 2-way ANOVA shows two single effects. First, the good-performers have a significantly higher reading time than the poor-performers (F(1,36) = 9.99, p < .01). Second, the deep-learners have a significantly higher reading time than the shallow-learners (F(1,36) = 4.26, p < .05), figure 4 shows the difference margins.

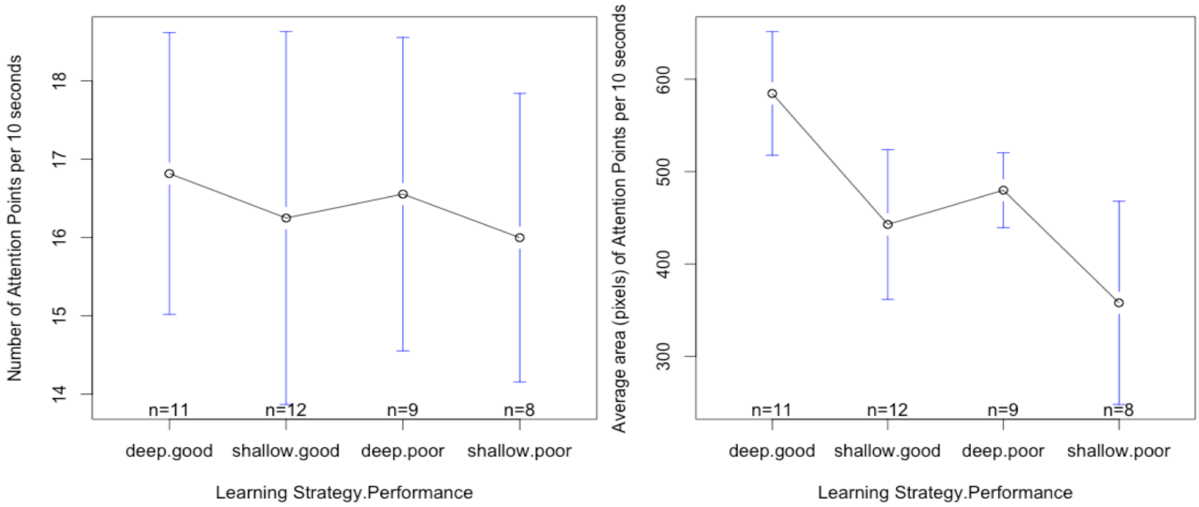


Figure 3: Difference margin for number of attention points and their average areas per 10 seconds for different levels of learning strategy and performance.

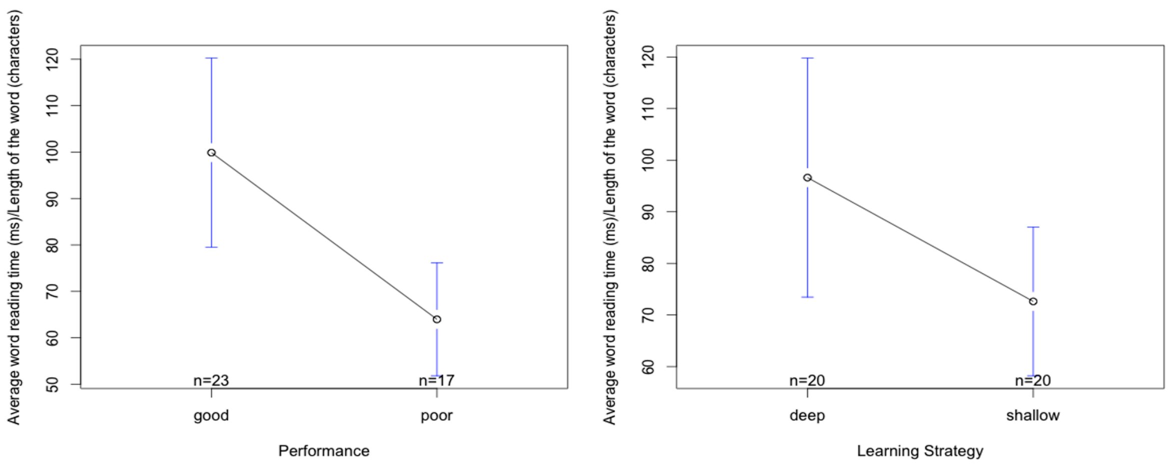
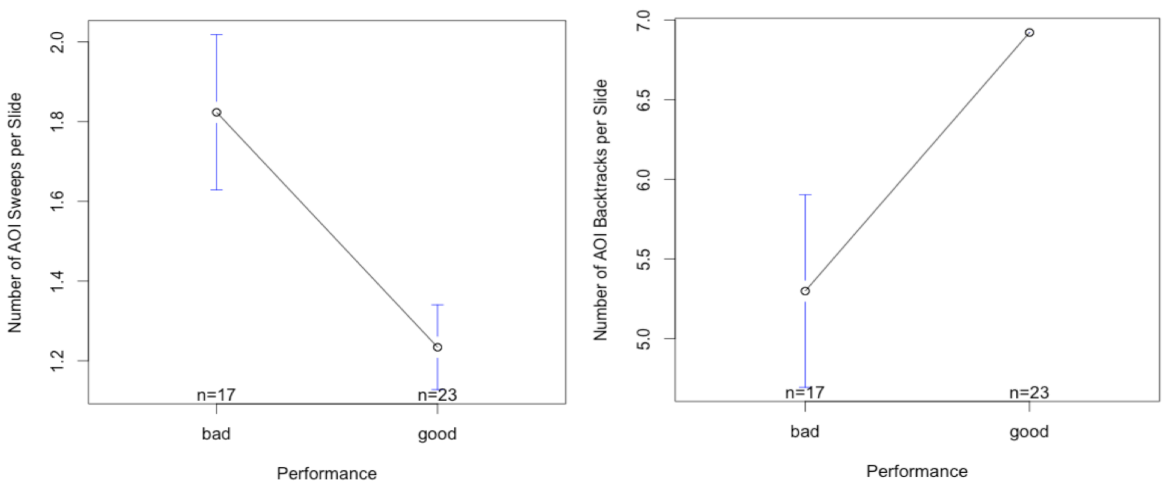


Figure 4: Difference margin for reading time levels of learning strategy and performance.

4. **AOI misses and AOI-backtracks vs. Learning Strategy:** There is no significant relation between the learning strategy and the number of area of interest (AOI) misses (F(1,38) = 0.04, p > .05) as well as the number of AOI back-tracks (F(1,38) = 0.21, p < .05).

5. **AOI misses and AOI-backtracks vs. Performance:** The poor-performers miss significantly more AOIs per slide than the good-performers (F(1,38) = 35.61, p < .01). Whereas, the good-performers back-track to significantly more AOIs per slide than the poor-performers (F(1,38) = 44.29, p < .01), figure 5 shows the difference margins. This suggests that the good-performers miss less content on the slide and reread more content than the poor-performers. We looked at the AOI misses every slide of the MOOC lecture and used a median cut on the number of AOI misses per student. We divided the AOI misses in high-misses and low-misses and compare the AOI misses across the performance levels. We observe that 65% of the poor-performers have low misses as compares to 87% of the good-performers (χ^2 (df=1) = 28.9, p < .05).



<u>**Figure 5:**</u> Difference margin for number AOI misses and AOI back-tracks per slide for different levels of performance. AOI back-tracks for good-performers have a special distribution because all the good-performers have the average back-tracks equal to the average number of AOIs per slide.

Discussion

We presented the results from an eye-tracking study. Through this contribution we emphasize on the fact that the diversity of the MOOC videos should not have an effect on the way the related data is analyzed. We present a method to define stimuli-based variables as the process variables. These variables essentially correspond to the attention measures and the fact that how much the students connect different knowledge points. Moreover, these measures also indicate how much the content on a slide do the students miss and how much they refer back to the previously seen content.

The attention points, derived from the heat-maps, are indicative of the students' attention both in the screen space and time. The area of the attention points depends on the time spent on a specific area on the screen. Higher average area of the attention points can be interpreted as more reading time during a particular period. The good performing students having a deep learning strategy have the highest average area of the attention points per 10 seconds among all the participants, despite having the same number of attention points during the same time period.

However, more reading time does not always guarantee higher performance. Byrne et. al. (1992) showed the inverse in a longitudinal reading study by proving that the best performing students were the fastest readers. On the other hand, Reinking (1988) showed that there is no relation between the comprehension and reading time. As Just et al. (1980) puts "*There is no single mode of reading. Reading varies as a function of who is reading, what they are reading, and why they are reading it.*" The uncertainty of results about the relation between the performance and the reading time led us to find the relation between the reading time, performance and learning strategy. We found that the good-performers have more reading time than poor-performers and the deep-learners have more reading time than shallow-learners. Thus, we can interpret this reading behavior, based upon the reading time differences, in terms of more attention being paid by the good performing students having a deep learning strategy than other student profiles. The attention points are important because we can use attention points to give feedback to the students about their attention span. Moreover, one could use the attention points for student profiling as well based on the performance and the learning strategy.

The area of interest (AOI) misses and back-tracks are temporal features computed from the temporal order of AOIs looked at. We found that good-performers have significantly less AOI misses than the poor-performers (F(1,38) = 35.61, p < 0.001). AOI misses are important because they can be an important factor in providing students with the feedback about their viewing behavior just by looking at what AOIs they missed.

The AOI back-tracks are indicative of the rereading behavior of the students. We found that the good performers have significantly more back-tracks than the poor-performers ($F(1,38) = 44.29$, $p < 0.001$). Moreover, the good-performers back-track to all the previously seen content, this explains the special distribution of AOI back-tracks for good-performers. Mills and King (2001) and Dowhower (1987) showed in their studies that rereading improves the comprehension. In the present study, the scenario is somewhat different than Mills and King (2001) and Dowhower (1987). In the present study, the students did not read the study material again. Instead, the students referred back to the previously seen content again in the duration the slide was visible to them. Thus the relation between rereading of the same content and the performance should be taken cautiously, clearly further experimentation is needed to reach a causal conclusion.

One interesting finding in the present study is the fact that the attention points have significant relationships with both the performance and the learning strategy. Whereas, the AOI misses and AOI back-tracks have significant relationships only with the performance. This can be interpreted in terms of the type of information we consider to compute the respective variables. For example, the attention-points' computation takes into account both the screen space and the time information and AOI back-tracks (and misses) computation requires only the temporal information. However, in the context of present study, we cannot conclude the separation between spatial and temporal information and how it affects the relation between the gaze variables and performance and learning strategy.

Conclusion

We found interesting relationships between the stimuli-based gaze variables and indicators for performance and learning strategy. The good-performers with the deep learning strategy has the largest average area for the attention points whereas the bad-performers with the shallow learning strategy has the smallest average area for the attention points. The good-performers have less AOI misses and more AOI back-tracks than the bad-performers. We also found that aggregation of different type of information (spatial and/or temporal) can affect the relation between stimuli-based gaze variables and indicators for performance and learning strategy. The results reported are only interrelationships between the variables and there is no causality claimed in the present contribution. Another important point worth mentioning here is the limitation of having stimuli-based gaze measures. The measures are independent of the content, which makes it difficult to compare the distribution of the gaze over the areas of interest, which are important for the understanding of the educational context.

The results also contribute towards our long-term goal of defining the student profiles based on their performance and learning strategy using the gaze data. The attention points can serve the purpose of a delayed feedback to the students based on their attention span. While AOI misses can be used to give feedback to students about what they missed in the lecture. Moreover, AOI back-tracks can be used to give feedback to students about their rereading behavior. Although, the results reported here are to be taken cautiously and certainly more experimentation are needed to find any causality. In a nutshell, we can conclude that the results are interesting enough to carry out further investigation in the direction of using the stimuli-based gaze variables to define student profiles and to provide them feedback to improve their overall learning process.

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