Probing the Effect of Interactivity in Online Video Lectures on the Attention Span of Students: A Learning Analytics Approach

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Abstract

Online video lectures are rapidly gaining popularity in formal and informal learning environments. Interactivity is perceived as increasing the attention span of learners and improving the quality of learning. However, interactivity may be regarded as an interruption, which distracts students. Furthermore, adding interactive elements to online video lectures requires additional investment of various resources. Therefore, it is important to investigate the impact of adding interactivity to online video lectures on the attention span of learners. This study employs a learning analytics approach, and investigates the influence of adding interactivity to online video lectures on students' attention span. We analyzed data of two Massive Open Online Courses (MOOCs) that were developed by the Open University of Israel in order to make English for academic purposes (EAP) courses freely accessible. The findings suggest that interactivity may increase the attention span of learners, as measured by the average online video lecture viewing completion percentage, before and after the addition of interactivity.

Keywords: online video lectures, interactive video, students' attention span, learning analytics, attention economy.

Introduction

Online video lectures are becoming a main constituent of online learning within formal courses and informal learning environments, such as Massive Open Online Courses (MOOCs) (Daniel, 2012; Kalman, 2014; Siemens, Gašević, & Dawson, 2015). While online video lectures have been successfully used for supporting face-to-face learning (Brecht, 2012; Whatley & Ahmad, 2007; Wieling & Hofman, 2010), they are not a silver bullet solution for solving the challenges of online learning (Guri-Rosenblit, 2009).

One of the main drawbacks of online video lectures is that their availability may lead to procrastination, which eventually would cause student dropout (Geri, 2012; Geri, Gafni, & Winer, 2014; Geri & Winer, 2015). Another challenge is the short attention span of the viewers. According to a comprehensive study of MOOC learners, which involved analysis of nearly seven million MOOC video viewing episodes, the engagement time in viewing video lectures was six minutes at most (Guo, Kim, & Rubin, 2014; Kim, Guo, Seaton, Mitros, Gajos, & Miller, 2014; Lagerstrom, Johanes, & Ponsukcharoen, 2015).

Interactivity is a crucial element for improving the quality of online learning (Guri-Rosenblit, 2009; Siemens et al., 2015). Furthermore, empirical studies demonstrated the effectiveness of interactivity in extending the attention span of learners and enhancing their achievements (Cherrett, Wills, Price, Maynard, & Dror, 2009; Dror, Schmidt, & O'connor, 2011). Conversely, interactivity may be regarded as an interruption, which distracts students' attention (Davenport & Beck, 2001). Moreover, adding interactive elements to online video lectures requires additional investment of various resources, pedagogical, as well as technological. Therefore, it is important to investigate the impact of adding interactivity to online video lectures on the attention span of learners.

The purpose of this study is to investigate the influence of adding interactivity to online video lectures on students' attention span. We employed a learning analytics approach (Long & Siemens, 2011) and analyzed data of two MOOCS of English for academic purposes (EAP) courses that were developed by the Open University of Israel. We analyzed over 100,000 episodes of online video lectures, and compared the viewing completion percentage, before and after the addition of interactivity.

Theoretical Background and the Research Questions

This interdisciplinary study is based on concepts from the domains of: cognitive fit theory (Vessey, 1991), student retention in online learning (Ferguson & Clow, 2015; Geri & Winer, 2015; Guo et al., 2014; Kim et al., 2014; Lagerstrom et al, 2015), and attention economy (Davenport & Beck, 2001), and applies them to student viewing patterns of online video lectures.

According to cognitive fit theory (Vessey, 1991), compatibility between task and information presentation format would improve task performance. In the context of viewing online video lectures, adding interactive elements is expected to increase student engagement and performance (Cherrett et al, 2009; Dror et al., 2011). However, adding interactive elements to a video may interrupt the viewing experience, and as the students stop watching the video, they may be distracted, and use the break for checking email, answering messages on social applications, or tending to other external requests for their limited attention resources (Davenport & Beck, 2001). Several factors may affect the effectiveness of interactivity. This initial study is conducted at the course level, and explores whether the knowledge level of the students may affect the way they react to addition of interactive elements to online video lectures. On the one hand, advanced students have been found to gain more benefits from learning technologies (e.g., Geri & Winer, 2015). On the other hand, weaker or beginner students may benefit from the addition of interaction, as it is expected to improve their learning experience (Cherrett et al, 2009; Dror et al., 2011).

This study examined the following research questions:

- How does adding interactivity to online video lectures affect the attention span of students?
- Are there differences in the influence of interactivity in online video lectures on learners' attention span, between students who study a higher-level course and students who study the same sort of subject matter at a lower level?

Methodology

This study adopts a learning analytics approach (Long & Siemens, 2011), which evolved from the general trend of data analytics research and practical applications (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011) particularly its use in learning environments (e.g., Geri & Winer, 2015; Hershkovitz & Nachmias, 2009; Levy & Ramim, 2012; Romero & Ventura, 2013; Romero, Ventura, & Garcia, 2008).

We investigated how adding interactivity to online video lectures affects students' attention span by analyzing usage data of two MOOCs, which were developed by the Open University of Israel (OUI) in order to make English for academic purposes courses freely available. All undergraduate Israeli students must take a series of exams in EAP until they reach an exemption level. The initial EAP level is determined by a national exam. Typically, the academic institution offers a series of courses to prepare the students for the following internal exams and charges additional tuition fees for each course.

The Israeli Council for Higher Education asked the OUI in 2015, to develop four MOOCs, two pre-basic EAP courses, a basic level course, and an advanced one. The most advanced level of EAP course was not included in the project. During the first stage of the project (from January 1, 2016 until August 6, 2016), the MOOCs were based on online video lectures and basic exercises. On the second stage of the project, which started on August 7, 2016, the online video lectures provided interactive assessment and feedback via advanced technological tools. The two phases of the project created a natural “before and after intervention” testing environment. In order to examine the effect of interactivity on the attention span of learners, as measured by their viewing completion percentage, we analyzed aggregate viewing data of the online video lectures that were the main instructional method of these MOOCs. The actual aggregate viewing data of each one of the online video lectures was obtained via Google Analytics (GA) (Clifton, 2012; Geri et al., 2014).

The two higher levels of EAP MOOCs: the basic and the advanced courses were selected for the study in order to decrease a possible influence of dropout due to students’ inability to cope with academic requirements. The sample included 59 video lectures, which comprised most of the online video lectures of both courses. Few outlier videos were excluded because their aggregate viewing patterns suggested that they included a relatively high proportion of viewers who only sampled the videos, but were not engaged in learning (Ferguson & Clow, 2015). The excluded lectures were mainly the first videos of each study unit within the two MOOCs.

Results

Table 1 illustrates a descriptive comparison of the two MOOCs before and after the addition of interactive questions to the videos (i.e., the intervention). Due to the novelty of the EAP courses, both average and median results are presented. There might have been instructors who would like to explore the videos, and their viewing patterns are different from those of learners. Furthermore, the intervention occurred before the beginning of the academic year, and the period afterwards was relatively short, hence the viewing patterns might not be representative. However, as shown in Table 1, the average and median results were similar, so the following analyses related only to the average data.

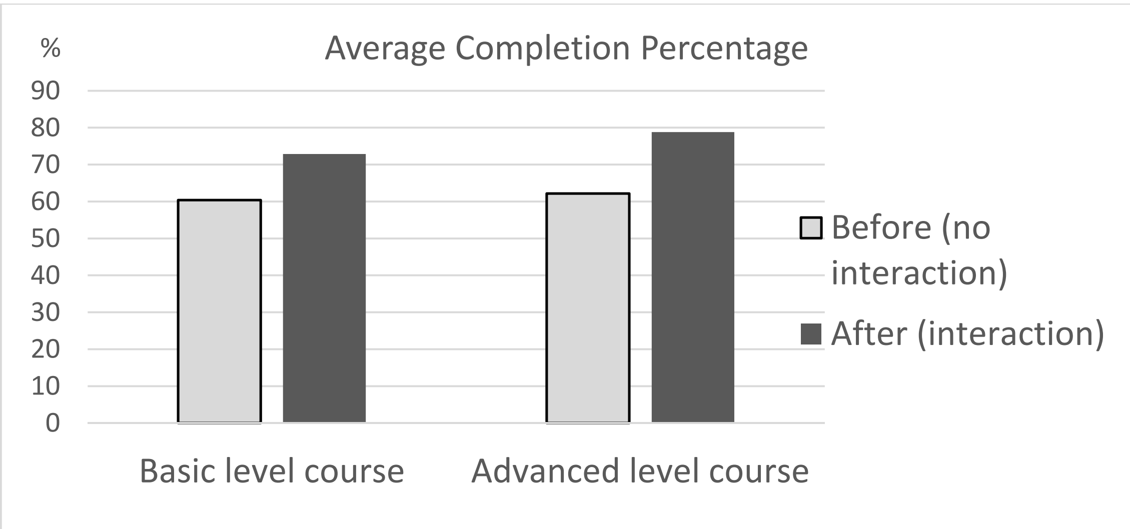

Figure 1. Average completion percentage of online video lecture viewing by course level with (after) and without interaction (before)

The same videos were used in the English for Academic Purposes basic and advanced courses before and after the intervention. Since the videos varied in their length, the relevant measurement that was used for evaluating the change was the average completion percentage.

Table 1. Descriptive comparison of video lecture viewing by course level with (after) and without interaction (before)

Course Level	Basic		Advanced	
Number of videos (n)	**28**		**31**	
Average video length (standard deviation)	13.28 minutes (4.91)		10.41 minutes (3.57)	
Interactivity	**Before (no interaction)**	**After (interaction)**	**Before (no interaction)**	**After (interaction)**
Period (duration)	Jan. 1, 2016 – Aug. 6, 2016 **(218 days)**	Aug. 7, 2016 – Sep. 26, 2016 **(51 days)**	Jan. 1, 2016 – Aug. 6, 2016 **(218 days)**	Aug. 7, 2016 – Sep. 26, 2016 **(51 days)**
Total views	37,566	8,690	47,737	14,342
Total time viewed	256,567 minutes	76,338 minutes	240,695 minutes	103,950 minutes
Average views per calendar day	172.32	170.39	218.98	281.22
Average video view duration (standard deviation)	7.79 minutes (2.34)	9.34 minutes (2.71)	6.60 minutes (2.24)	8.30 minutes (2.53)
Average completion percentage (standard deviation)	60.40% (7.25)	72.85% (8.57)	62.17% (5.96)	78.80% (5.19)
Median video view duration (standard deviation)	7.52 minutes (2.18)	9.56 minutes (2.62)	6.40 minutes (2.03)	8.45 minutes (2.64)
Median completion percentage (standard deviation)	58.68% (8.05)	75.00% (10.30)	60.68% (5.85)	80.07% (5.03)

Table 2 and Figure 1 present online video lecture viewing completion percentage by course level with and without interaction. The intervention significantly increased the average completion percentage of video lecture viewing for both courses: by 20.61% for the basic course (from 60.40% to 72.85%), and by 26.75% for the advanced course (from 62.17% to 78.80%). The paired samples two-tailed t-test results for the basic course are $t = -14.73$, 27 degrees of freedom (df), $p < .0001$, and for the advanced course $t = -13.50$, 30 df, $p < .0001$.

Regarding differences between the two courses, before the intervention, there was no significant difference between the completion percentage of the basic (60.40%) and the advanced (62.17%) courses ($t = -1.030$, $p = .21$, 57 df, equal variances assumed, Levene's test for equality of variances: $F = 2.773$, $p = .101$). After the intervention, the differences between the course increased and became significant with a medium-large effect size ($t = -3.185$, $p = .003$, 43.513

df, equal variances not assumed, Levene's test for equality of variances: $F = 7.273$, $p = .009$, Cohen's $d = -0.840$).

Table 2. Online video lecture viewing completion percentage by course level with (after) and without interaction (before)

Setting	Course level	n	Mean (%)	Standard deviation
Before (no interaction) Average	Basic	28	60.40	7.25
	Advanced	31	62.17	5.96
Before (no interaction) Median	Basic	28	58.68	8.05
	Advanced	31	60.68	5.85
After (interaction) Average	Basic	28	72.85	8.57
	Advanced	31	78.80	5.19
After (interaction) Median	Basic	28	75.00	10.30
	Advanced	31	80.07	5.03

Discussion and Conclusions

Our findings suggest that interactivity may increase the attention span of learners, as measured by the average online video lecture viewing completion percentage, before and after the addition of interactivity, for both basic and advanced English for Academic Purposes courses. Nevertheless, further study is required for substantiating the findings. The relative short time after the intervention limits the ability to draw conclusions from the results.

From a pedagogical point of view, we have shown that the interactive layer, which was added to video lectures, allowed learners to significantly extend their attention span. However, interactivity involves additional cost and adds complexity to the production process. This study demonstrated the potential of learning analytics to identify ways to improve learning processes, and to provide important insights to decision makers. The ability to track and analyze behavior of learners who are presented with new features and capabilities is paramount for improving the effectiveness of learning environments, as well as supporting productive allocation of resources.

As we move forward, we would like to improve the understanding whether interactive online video lectures might narrow the gap between weak and strong learners and allow better social inclusion.

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