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Investigating the Effect of Adding Nudges to Increase Engagement in Active Video Watching

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Abstract. In order for videos to be a powerful medium for learning, it is crucial that learners engage in constructive learning. Historic interactions of previous learners can provide a rich resource to enhance interaction and promote engagement fostering constructive learning. This paper proposes such a novel approach of adding nudges to AVW-Space, a platform for video-based learning. We present the enhancements implemented in AVW-Space in the form of interactive visualizations and personalized prompts. A study focusing on presentation skills was conducted in a large first-year engineering course, in which AVW-Space provided an online resource for the students to use as they wish. The students were randomly divided into the control and experimental groups, which had access to the original and enhanced version of AVW-Space respectively. Our findings show that nudging is effective in fostering constructive learning: there was a significant difference in the percentage of constructive students in the two groups. The experimental group students wrote more comments, found AVW-Space easier to use, reported less frustration when commenting, and had higher confidence in their performance on commenting.

Keywords: Video-based Learning, Intelligent support; Personalized nudges, Experimental study, Soft skill learning, Engagement

1 Introduction

Videos have become the predominant delivery method in both formal and informal online learning. However, research shows that watching videos can be a passive activity and result in limited learning [4,5,15,22,30]. A number of problems have been identified with Video-Based Learning (VBL), including limited interactivity with videos, the lack of human interaction, personalization, assessment and feedback [4]. New research strands related to VBL have appeared. There is established work on developing guidelines for producing effective videos (e.g. [10, 21]). Significant work has been done on increasing engagement with videos, by adding annotation tools, quizzes, examples and interactive exercises [8,9,14-16,28,30]. Data-driven approaches using interaction traces from VBL have been proposed to improve techniques for video navigation, such as visualizations of collective navigation traces, dynamic timeline scrubbing and enhanced in-video searches [3,4,13,17]. There are also approaches using students' ratings, annotations and forum contributions to support social navigation and collaborative learning [2,4,25,29]. While efforts on augmenting the interaction to enhance VBL exist, there is no research that explicitly considers personalization, i.e. tailoring the interaction to the engagement profile of the learner.

Our approach is to encourage engagement during VBL via interactive notetaking, tapping into learners' familiarity with commenting on videos in social networking sites. In previous work [7,18,19], we developed AVW-Space, a VBL platform, which supports reflection during interactive note taking, and also supports social learning through rating of comments. We categorized participants in previous studies into inactive, passive and constructive learners, based on the ICAP framework [5]. Our previous studies [7,18,19] show that only constructive learners, who wrote comments on videos and rated comments written by their peers, improved their conceptual knowledge.

To promote engagement with videos that leads to better learning, while at the same time preserving the learners' freedom to interact with videos in a way they prefer, we proposed the use of nudges [7,19]. Nudges were introduced in decision support [27] as a form of interventions which influence people's behavior to make choices that lead to better lives (paternalism), but in a non-compulsory manner (libertarian). Behavior change is complex and so are the corresponding interventions. Choice architecture, which defines the ways to select and present choices that can lead to better behavior, is the core when designing nudges [20,27]. To the best of our knowledge, our research is the first attempt to evaluate a choice architecture for personalized nudges in VBL.

In this paper, we describe how we implemented two types of nudges we previously proposed [19]: signposting through interactive visualizations and personalized prompts. The closest to our approach is the work by Shin et al. [26] who proposed in-video prompts as a way to assess students' comprehension and information about their learning experience. Such prompts are given to all students, at the pre-defined times during videos [26]. Our personalized prompts differ because they are adaptive: prompts given to a particular student depend on the student's interactions with the current video.

This paper also presents the study we conducted in a large first-year engineering course, in which students were required to give presentations but received no formal training on presentation skills. AVW-Space provided an online resource for the students to use as they wish. The students were randomly divided into the control and experimental groups, which had access to the original and enhanced version of AVW-Space respectively. The goal of our study was to investigate the effect of the nudges on students' engagement, learning and subjective impressions of the platform.

2 Previous Work on AVW-Space

AVW-Space is a controlled video-watching environment designed for self-study, which supports interactive notetaking and rating of comments written by peers, tapping into students' familiarity with social networking sites. We developed AVW-Space with transferable skills in mind, but the platform is general purpose and can be used for other types of skills. The environment supports engagement by providing micro-scaffolds to facilitate the commenting on videos and the reviewing of comments made by others. In order to create a learning space, the teacher needs to select a set of publicly available YouTube videos for students to watch, and specify micro-scaffolds.

Learning starts with students watching and commenting on the videos individually. In our studies [7,18,19] we used eight short videos, four of which were tutorials on how to give presentations, while the remaining four videos were example presentations. The student can enter a comment at any time during the video, and needs to select an aspect, which indicates the intention of the comment (Figure 1). For the tutorials, aspects aimed at stimulating reflection included: "I *didn't realize I wasn't doing it*", "I am rather good at this", and "I did/saw this in the past". There was one additional aspect, "*I like this point"*, to encourage the learner to externalize relevant learning points. For the example videos, the aspects corresponded to presentation skills covered in the tutorials, which included "Delivery", "Speech", "Structure", and "Visual aids".

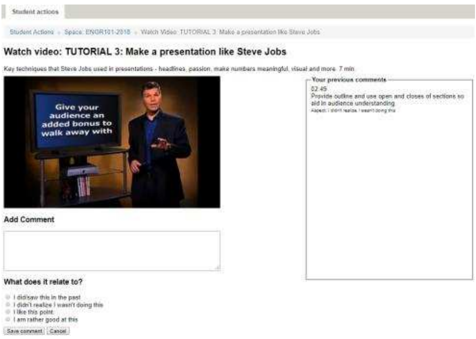

Fig. 1. The commenting interface

In the second phase, the teacher selects the comments that will be open to the whole class, so that students can review and rate each other's anonymized comments. As this second phase is not relevant for the research presented in this paper, we refer the interested reader to [7,19] for further details.

We operationalized the ICAP framework [5] in the context of AVW-Space as follows [7,19]. **Passive Learners** are those who watched videos, but had minimal other interactions with them. On the other hand, **Constructive Learners** show higher levels of engagement by commenting on videos. Comments contain remarks on important events in videos, and contain statements showing reflection and self-explanation. As AVW-Space does not currently support collaboration between students, we do not consider the Interactive mode of ICAP. In addition to passive and constructive learners, we have also added another mode to characterize students who do not engage in learning at all, i.e. do not watch videos; we refer to them as **Inactive Learners** (IL).

The findings from our previous studies showed that only constructive students improved their knowledge when interacting with AVW-Space [7,18,19]. We presented a set of requirements for fostering constructive behavior in [19]. In this paper, we focus on adding intelligent nudging to the platform.

3 Adding Nudging to AVW-Space

As a first step towards more intelligent support for active video watching, we implemented nudging in the form of signposting through interactive visualisations and personalized prompts to AVW-Space.

3.1 Interactive Visualizations

Interactive visualisations (shown below the video in Figure 2) are used to support social learning. The top visualization is the **comment timeline**; it provides signposts in terms of comments written by previous learners. Each comment is represented as a coloured dot, representing the time when the comment was made. The colour of the dot depends on the aspect used, with the legend shown on the side. We selected the best comments from previous studies to use in the comment timeline [24]. The comment timeline also allows the learner to inspect comments written by previous learners. When the mouse is positioned over a particular dot, the student can see the comment (as in Figure 2). Dots are slightly transparent, so that comments made in temporal proximity to each other can be differentiated. Clicking on a dot begins playing the video from that point.

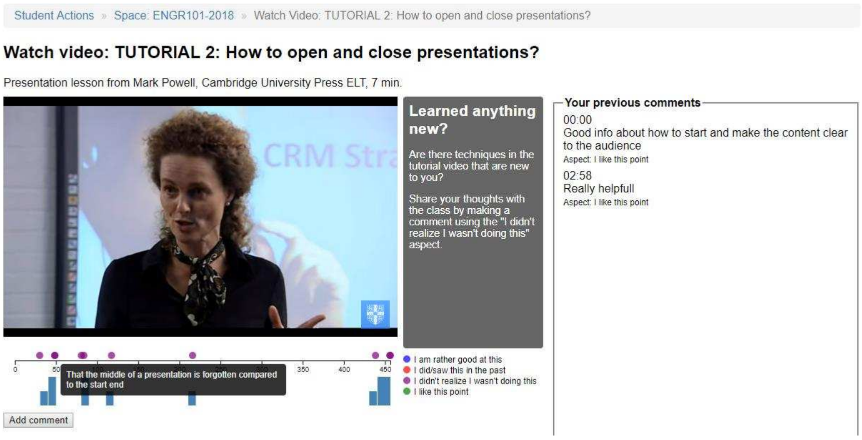

Fig. 2. Interactive visualizations and a prompt. The interactive visualizations are modified to show only comments written with the "I didn't realize I wasn't doing this" aspect.

The bottom visualization is the **comment histogram,** representing the number of comments written for various segments of the video. This visualization allows the student to quickly identify important parts of a video, where other students have made many comments. The two visualizations meet two identified needs: (1) providing social reference points so that students can observe others' comments, and (2) indicating important parts of a video and what kind of content can be expected in those parts, differentiated by aspect colours.

3.2 Personalized Prompts

Personalized prompts are designed to encourage students to write comments. An example of a personalized prompt is shown in Figure 2, to the right of the video. AVW-Space maintains a profile for each student, and uses it to select prompts adaptively.

Prompts are provided when the student is in a high-attention interval, which is a part of a video during which previous students wrote many comments. To identify high attention intervals for the videos, we used interaction traces collected previously, and identified parts of videos with high user interest and relevant comments [7]. We designed four types of prompts:

1. **No comment reminder** is a prompt encouraging the student to make a comment. This prompt is offered when the student has watched at least 30% of the video without making any comments, and is currently in a high-attention interval.
2. **No comment reference point** prompt reminds the student to make a comment, and offers an example as stimulus. The prompt is only shown if the No comment reminder prompt has not resulted in a comment. Such prompts are provided when the student has watched at least 70% of the video without comments, the student is in a high-attention interval, and this type of prompt has not been issued on the current video. The comments used as stimuli have been manually selected for each video from comments gathered in previous studies.
3. **Aspect under-utilized**: a prompt to make a comment using a particular aspect that the student has used least often (Figure 2). This type of prompt is provided when the student has made at least one comment on the current video, has watched at least 30% of it and is currently in a high-attention interval. When the prompt is issued, the visualizations change to only show comments made using the under-utilized aspect referred to in the prompt. For each aspect, the text of the nudge changes. For example, for the *'I am rather good at this'* aspect, the title of the nudge is "Are you good at this", and the description is "Are there any techniques in the tutorial that you feel you have already mastered?"
4. **Diverse Aspects**: this prompt provides positive reinforcement, displayed when the student has used all relevant aspects on the current video. The title of the prompt is "Well done!" with the explanatory message "Great job using all aspects to comment on the video!"

4 Experimental Design

The study was conducted in a first-year course mandatory for all engineering students at the University of [blinded]. The students worked on a group project and gave a presentation, during which each student presented for one minute. Due to an already full curriculum, students received no formal training on giving presentations. Instead, they were invited to use AVW-Space for online training. The students who watched at least one video in AVW-Space received 1% of the final course grade. Ethical approval was obtained from the University of [blinded].

The goal of our study was to evaluate the impact of intelligent nudging. The students were randomly allocated to the control or experimental group. The control group interacted with the original version of AVW-Space (Figure 1), while the experimental group interacted with the enhanced version (Figure 2). We defined three **research questions:**

RQ1. Are nudges effective in fostering constructive behavior? We expect to see a higher proportion of students from the experimental group engaging in constructive behavior in comparison to the control group (Hypothesis H1).

RQ2. What features of AVW-Space influence learning? Can we infer causal relationships between the use of AVW-Space's features and learning? Our previous studies showed that only constructive students improved their knowledge after interacting with AVW-Space. We anticipate that intelligent nudging will have a positive effect on the number of comments written, which will in turn have a positive effect on learning (H2).

RQ3. Do students in control/experimental group have different opinions about the usefulness of AVW-Space and cognitive load? We expect that the students in the experimental group would find the environment more useful and report smaller cognitive load (H3).

Materials. The videos used in the study were the same ones as those described in Section 3. We designed two surveys, similar to those used in the previous studies [7,18,19]. Survey 1 collected participant's profile (demographic information, background experiences, Motivated Strategies for Learning Questionnaire (MSLQ) [23]). The survey also contained three questions on the participants' knowledge of presentations (we refer to those questions as conceptual knowledge questions). The student was asked to list as many concepts related to (1) Structure, (2) Delivery and Speech, and (3) Visual Aids. For each of those three questions, students had one minute to write responses. Survey 2 included the same conceptual knowledge questions; NASA-TLX instrument [11] to check participants' perception of cognitive load; Technology Acceptance Model (TAM) [6] to check participants' perceived usefulness of AVW-Space. Additionally, Survey 2 contained questions on usability related to commenting on videos and rating of comments. The experimental group also received questions related to interactive visualizations and personalized nudges.

Procedure. The students were invited to participate in the study on 3 May 2018. After completing Survey 1, the participants were instructed to log on to AVW-Space, watch the four tutorial videos first and then to proceed to critique the example videos. The rating of comments was enabled on May 16. Invitations to complete Survey 2 were emailed on May 24, and the survey was closed on 3 June 2018.

5 Results

Table 1 presents the number of participants from the two groups who completed various parts of the study. Out of 1039 students enrolled in the course, 449 completed Survey 1. Of those, 347 have used AVW-Space, while the remaining 102 participants were inactive learners. We received 263 responses for Survey 2, but that number included some inactive students. After removing those responses, we had 119 students from the control and 102 responses from the experimental group who completed both surveys and interacted with AVW-Space.

Table 1. Number of participants who completed various parts of the study.

Group	Survey 1	Inactive	AVW-Space	Survey 2 (all)	Survey 2 (excl. IL)
Control	234	54	180	138	119
Experim.	215	48	167	125	102

Table 2 presents the demographic data for the 347 students who interacted with AVW-Space. As typical for engineering courses, there were more males than females.

The majority of participants (79.83%) were native English speakers. Most participants (95.39%) were aged between 18 and 23. The questions related to training on giving presentations, experience in giving presentations, using YouTube and using YouTube for learning were based on the Likert scale from 1 (Low) to 5 (High). There were no significant differences between the two groups on these features, as well as on MSLQ scales, with the exclusion of Task Value (U = 15,066.5, p = .043).

Table 2. Demographic data for the participants who completed Survey 1. Apart from the first three rows, the remaining rows present the mean and standard deviation in parentheses.

	Control (180)	Experimental (167)
Gender	124 males, 55 females, 1 other	118 males, 49 females
Aged 18-23	175	156
Native English speakers	135	142
Training	1.64 (.76)	1.66 (.82)
Experience	2.17 (.81)	2.19 (.79)
YouTube	4.22 (1.08)	4.22 (1.03)
YouTube for learning	3.36 (1.14)	3.28 (1.12)
Task Value	5.47 (.85)	5.22 (.79)

5.1 Do nudges foster constructive behavior?

We divided the students (post-hoc) into Constructive and Passive, using the median number of comments written by the class (median = 1).We expected to see a higher number of constructive students in the experimental group. The numbers of constructive and passive students in the two groups are given in Table 3 (for all students who completed Survey 1). A chi-square test of homogeneity between group and behavior type (i.e. Constructive or Passive) revealed a significant difference (Chi-square = 4.463, p = .035), with the effect size of (Phi) of .142. Therefore, hypothesis H1 is confirmed.

Table 3. Numbers of constructive and passive students in the two groups

	Passive (187)	Constructive (160)
Control (180)	107 (59.44%)	73 (40.56%)
Experimental (167)	80 (47.90%)	87 (52.10%)

It is also interesting to compare constructive and passive students in the experimental group (Table 4). Both subsets received nudges – why did only some participants respond to nudges? The only significant difference between passive/constructive students in the experimental group on the variables from Survey 1 is on Training (U = 2,906.5, p = .042). During interaction with AVW-Space, in addition to a significant difference on the number of comments written, these two subgroups differed significantly on the number of videos watched (t = 4.61, p < .001) and prompts received (t = 2.33, p = .022). Please note that some students watched the same video multiple times, so the average number of videos watched can be higher than 8.

Table 4. Differences between passive and constructive students from the experimental group.

	Training	Videos	Prompts
Passive (80)	1.53 (.71)	5.60 (3.50)	8.21 (5.329)
Constructive (87)	1.78 (.88)	8.41 (4.37)	12.44 (8.21)

5.2 What features of AVW-Space improve students' knowledge?

There were no significant differences between the two groups on either the number of sessions with AVW-Space (control: mean = 2.58, sd = 2.05; experimental: mean = 2.53, sd = 2.56), or the number of videos watched (control: mean = 7.03, sd = 4.34; experimental: mean = 7.03, sd = 4.22). The only significant difference (U = 17,608, p = .004) was on the number of comments written (control: mean = 4.31, sd = 7.76; experimental: mean = 6.34, sd = 9.60). We used the Mann-Whitney test as the number of comments is not normally distributed. Figure 3 shows the number of comments per video for the two groups. The distributions of comments are significantly different for the two groups (U = 51.5, p = .038).

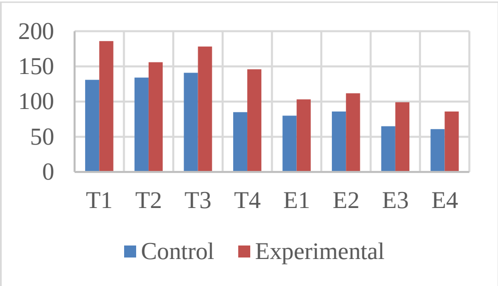

Fig. 3. Number of comments per video

In Surveys 1 and 2, the participants had one minute to list all concepts they knew related to the structure, visual aids, and delivery and speech. The students' replies were marked automatically, using the ontology of presentation skills we developed in previous work [1,7,24]. Table 5 presents the resulting conceptual knowledge scores from Surveys 1 and 2 (CK1 and CK2 respectively) for constructive/passive students in the two groups. A two-way ANCOVA found no significant interaction between group and category (i.e. Constructive vs Passive), but there was a significant main effect of Category, $F(1, 216) = 3.872$, $p = .05$, partial $\eta^2 = .018$. As in previous studies, constructive students improved their knowledge of presentation skills significantly.

Table 5. Conceptual knowledge scores for the two groups.

Group		CK1	CK2
Control (119)	Constructive (59)	13.56 (5.65)	15.76 (5.66)
	Passive (60)	12.25 (4.16)	12.88 (5.95)
	All (119)	12.28 (5.51)	14.31 (5.96)
Experimental (102)	Constructive (65)	14.00 (5.66)	14.98 (6.36)
	Passive (37)	13.35 (5.29)	13.89 (6.00)
	All	13.12 (5.50)	14.59 (6.22)
All (221)	Constructive (124)	13.79 (5.63)	15.35 (6.03)
	Passive (102)	12.67 (4.63)	13.27 (5.95)

We used IBM SPSS Amos to infer the causal relationships between CK1, CK2 and variables showing how students used AVW-Space, such as the number videos watched, the number of comments made, the number of prompts received (for the experimental group) and the number of ratings made. All these variables are observed and measured without errors. We were unable to find any well-fitting path models for the control group, except the simplest one, which shows the correlation between CK1 and CK2 (.60, $p < .001$).

Figure 4 illustrates the best fitting model for the experimental group. The chi-square test (2.55) for this model (df = 2) shows that the model's predictions are not statistically significantly different from the data ($p = .279$). The Comparative Fit Index (CFI) was .988, and the Root Mean Square Error of Approximation (RMSEA) was .052. Therefore the model is acceptable: CFI is greater than .9 and RMSEA is less than .06 [12]. The model indicates that the higher CK1 score directly causes a higher CK2 score (coefficient = .44, $p < .001$). Therefore, the effect of the number of comments on CK2 is adjusted for and above and beyond this influence (.2, $p = .024$). The number of nudges affects the number of comments (.41, $p < .001$). Therefore, hypothesis H2 is confirmed.

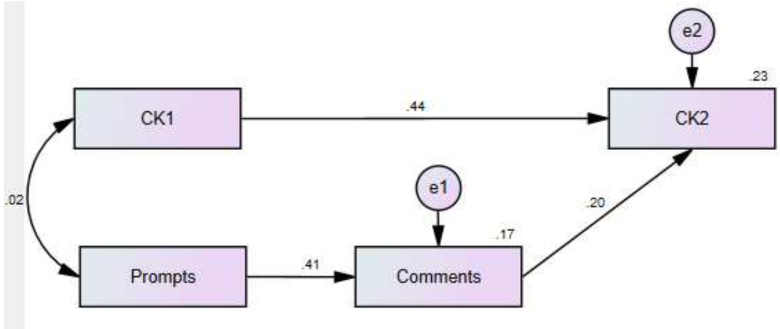

Fig. 4. Path diagram for the experimental group.

5.3 Do students in the two conditions differ in their opinions about the usefulness of AVW-Space and cognitive load?

The participants replied to the TAM questionnaire [6] using the Likert scale from 1 (highest) to 7 (lowest). We analyzed the replies using the two factor ANOVA (group and category), and found no significant interaction of the two factors. For question 8 (My interaction with AVW-Space would be clear and understandable), there was a main effect of category, $F(1,211) = 7.19$, $p = .008$, partial $\eta^2 = .033$. The average score of the 92 passive students was 3.67 (1.73), while the average score of the 123 constructive students was better, 3.05 (1.43). There was also a significant main effect of group for question 9 (I would find AVW-Space easy to use), $F = 4.86$, $p = .029$, partial $\eta^2 = .023$. The average score of the 115 control group students was 3.30 (sd=1.68), while the average score of the 100 students from the experimental group was better, 2.78 (sd=1.20).

Table 6 reports the scores on the TLX-NASA questions related to writing comments. Constructive students reported significantly lower frustration ($F(1,220) = 8.62$, $p = .004$, partial $\eta^2 = .038$), and significantly higher performance on commenting ($F(1,220) = 7.99$, $p = .005$, partial $\eta^2 = .035$). These analyses provide evidence supporting hypothesis H3.

Table 6. TLX-NASA scores on commenting. Effort and Demand: Likert scale 1 (very easy) to 20 (very hard); Frustration and Performance: 1 (not at all) to 20 (very much)

	Demand	Effort	Frustration	Performance
Passive (98)	8.96 (4.64)	8.10 (4.44)	8.76 (6.02)	10.61 (5.27)
Constructive (124)	8.13 (4.33)	7.38 (4.42)	6.54 (5.21)	12.40 (4.13)

The experimental group received two additional questions in Survey 2, the first of which asked for feedback on the usefulness of interactive visualizations. We received 100 responses, 85 of whom were positive, such as "See which parts of the video other people find useful" and "To compare yourself with the rest of the class." One student wrote "*I didn't understand them till id finished most of the videos*."

The other question was related to the usefulness of personalized prompts. We received 91 responses, 62 were positive, and 21 negative. Eight participants have not noticed nudges. Two examples of positive opinions were: "Help me to be engaged*", "*To give me a little push in the right direction of what to comment on". Some participant did not find the prompts useful: "It created subtle pressure to make comments which wasn't really useful at all" and "They were always the same so not hugely useful."

6 Conclusions

We proposed the use of nudges (signposting through interactive visualizations and personalized prompts) to encourage constructive behavior during VBL. We found that nudging was effective in fostering constructive behavior and resulted in the students in the experimental condition making more comments, found AVW-Space easier to use, reported less frustration when commenting, and had higher confidence in their performance on commenting. No differences between passive/constructive students in the experimental group suggests that nudging seems to work all types of students.

The work presented here is part of a larger research stream on adding intelligent features to augment interaction with videos for informal learning. In our future work we plan to implement more types of nudges, following the formal framework defined in [7,19]. This will take into account not just the engagement with videos but individual profiles (e.g. MSLQ scores or previous experience). Future work also includes extending the support for the rating phase.

Our research opens a new avenue in developing intelligent learning environments which adapt established interventions for behavior change in the form of nudges. This can be applied in a range of domains to foster informal learning where one can learn from their experience and that of others.

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