Reducing cognitive load during video lectures in physiology with eye movements modeling and pauses: a randomized controlled study

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Abstract

Lectures constitute a basic component of physiology instruction in scientific and healthcare curricula. Technological progress has allowed a switch from face to face to video lectures, yet there is no evidence of video efficacy in physiology. Because videos increase the cognitive load during a learning task, identifying tools that decrease students' cognitive load during video lectures is critical. Segmenting videos with pauses and inducing joint attention with eye movement modeling examples (EMME) could reduce the cognitive load and improve second-year medical students' learning in physiology video lectures. Second-year medical students were randomized into four groups [EMME + pauses (EMME + P), EMME without pause`s (EMME-NoP), pauses only (NoEMME + P), and no EMME and no pause (NoEMME-NoP)], took pretest quizzes, watched a renal physiology video lecture, and answered a cognitive load questionnaire and posttest quizzes on the Moodle learning management system. Student prior knowledge was assessed by a pretest, and learning gains were assessed by the difference between posttest and pretest scores. One hundred ninety-five students completed the experiment. Pauses improved learning gains ($P < 0.01$) but not EMME ($P = 0.11$). Student prior knowledge has several interactions with other variables: low-prior knowledge students obtained better learning gains ($P < 0.001$) and high-prior knowledge students had lower learning gains with EMME ($P < 0.05$). Our study shows the potential role of tools designed to reduce students' cognitive load during a renal physiology video lecture and the critical need for empirical validation of pedagogical solutions that are adapted to the specificities of physiology lectures.

education; eye movement modeling examples; learning; physiology; segmentation effect

INTRODUCTION

Physiology is a key scientific discipline for many scientific and healthcare professions. In universities, it is taught to students in different departments and in medical schools in particular. For several years, many studies have attempted to improve physiology instruction by using new technologies like videos and animations in virtual laboratories (1). Universities encourage the use of video and podcasts (2), in massive online open courses (MOOCs) or blended courses (3), expecting improvements in organizational/financial issues and in students' learning (4). Meta-analysis of randomized controlled trials showed a general positive effect of videos versus static presentations (5), yet detailed analysis showed that videos were mainly efficient to learn something to do and less efficient to acquire declarative knowledge, like concepts and facts (5). A more recent meta-analysis confirmed a general effect of animations over static graphics. The meta-analysis revealed that animation was significantly more effective than static graphics for learning factual and conceptual knowledge on one hand and for the cognitive activities of remembering, understanding, and applying on the other hand (6). Yet there is currently no solid evidence of video efficacy in physiology lectures, with only observational studies (7) or studies addressing student preferences (8–10). Given the specificities of physiology lectures [i.e., building integrative mechanisms, combining knowledge and experiment, using graphs and mathematics modeling, and causal reasoning (11)], it is not possible to extrapolate from results obtained in other domains to physiology lectures.

In this context of lack of evidence-based education in physiology lectures and because of the striking development of video lectures in medical education these past years, it is critical to identify the determining factors of learning with video lectures in physiology. Indeed, animations and videos can be very demanding for students when supports do not take into account human cognitive architecture and its constraints (12–15). Cognitive load theory (16) and Mayer's cognitive theory of multimedia learning (17) have provided insight on how students learn with multimedia. Based on the cognitive architecture, especially on the limited capacity of working memory, cognitive load theory distinguishes intrinsic cognitive load, related to learning task complexity, and extrinsic cognitive load, related to irrelevant information in learning support. It has been demonstrated that videos generate a transient information effect (15). This effect drastically increases intrinsic

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cognitive load because learners must simultaneously encode the information currently displayed on the screen, understand it, and integrate it with the information that was previously displayed (15, 18). This effect is generally better controlled in face-to-face teaching, because the teacher can slow down, adapt, and rephrase words, using students' reactions and observing whether they understand step by step. Also, students can ask the teacher to slow down, explain, or rephrase the statements, in order to spend more time on understanding the current information before processing the next piece of information; the interaction between students and teachers is higher in face-to-face teaching (19, 20). In addition, decorative, unnecessary animations are a source of increasing extrinsic cognitive load and can impair learning (21) and memorization in physiology lectures (13). Conversely, segmentation of video lectures by adding pauses increases learning (22). The segmentation effect counteracts the transient information effect on the cognitive load. It was replicated across multiple learning topics, as shown by meta-analysis (14, 23). Specifically, the meta-analysis showed that segmentation effects increase retention and transfer performance (14). Moreover, during video lectures there is a risk of increased loss of student attention. Hence, guidance on relevant elements becomes important. In the case of a loss of attention, the visual search for relevant information along with the reception of auditory information can increase cognitive load. Attention plays a critical role in learning: students whose eye movements are not synchronized with the whole classroom learn less (24). The increase of inadequate attentional tasks during video lecture depletes working memory resources remaining for association tasks required for physiology learning. Conversely, cognitive load during video lectures has been reduced by interventions helping students to focus their attention, e.g., by signaling essential information or personalization of the oral comments (22, 25). The signaling effect allows a decrease in students' cognitive load (12, 26, 27). In particular, videos with eye movement modeling examples (EMME in the literature) consist of recording the teacher's eye movements and materializing them on video to provide visual guidance as the teacher gives oral instructions. Thus, joint attention is the phenomenon allowing individuals (teachers and students) to focus on the same visual element at the same time. Eye movement modeling is a support for joint attention between students and teacher (28–30). In particular, eye movement modeling helped learners with poor prior knowledge to better focus on relevant elements (31) and thus to improve learning (29, 30, 32). However, learning improvements were not found in a study by Chisari et al. (28). According to the authors, this negative result could be explained by the short duration of the lectures (<4 min), which could be insufficient to induce significant learning changes. Given its effect on cognitive load during video lectures, EMME could improve student learning during video physiology lectures, but maybe not for short lectures.

Therefore, the aim of the present study is to test segmentation effect and EMME effect on the learning in video physiology lectures of university students. In addition, we want to investigate whether students' prior knowledge has an effect on the segmentation effect and EMME on video physiology lectures.

MATERIALS AND METHODS

Population and Curriculum

The participants were second-year students in Montpellier-Nîmes School of Medicine and Maieutics, Montpellier University. The curriculum was vertically integrated and organized in several modules. All students were engaged in a renal and urology module (42 h of lectures), associating courses in anatomy, histology, physiology, biochemistry, and nephrology and urology, over 3 mo. The renal physiology consisted of 5-h classes of commented PowerPoint presentations by a single physiology teacher (F. Gouzi). Students were informed by the teacher that a short video on renal physiology and quizzes dealing with glomerular filtration, modeling, evaluation, and regulatory mechanism would complete the physiology course and constitute a full part of the final assessment. A total of 392 students were registered on Moodle [the learning management system (LMS) used in Montpellier-Nîmes University], had access to the online resources of the module, and were proposed to participate in the experiment. Inclusion criteria were the following: second-year medicine or maieutics students who had to validate the renal and urology module.

Study Design Randomization and Blinding

The experiment tested students learning in four different conditions, following a 2 × 2 factorial plan. The first variable was the presence/absence of eye movement modeling examples, and the second variable was the presence/absence of pauses. A centralized randomization of the students into the four groups [eye movement modeling examples + pauses (EMME + P), eye movement modeling examples without pauses (EMME-NoP), pauses only (NoEMME + P), and no eye movement modeling examples and no pause (NoEMME-NoP)] was performed before the experimentation by an investigator (L. Aalioui) using a randomization list, and groups of students were constituted on Moodle. The groups were identified by a letter (A, B, C, or D) and the videos had similar titles to ensure that participants were blind to the experimental conditions. After information from the physiology teacher (F. Gouzi) regarding the experiment organization, students had 1 wk to participate in the experiment. Participants had to perform a pretest, with only one attempt possible. Access to the video lecture was possible only after completion of the pretest and started automatically after the student's last click at the end of the pretest. No control of videos was possible. At the end of the video lecture students had to answer the Leppink cognitive load questionnaire (33), and finally only after running the questionnaire did students have access to the posttest. To ensure a full video viewing and to limit potential information seeking, re-viewing, and other behaviors that could impact our study, the completion of the experiment was defined as the following: experiment performed without disconnection, the pretest and/or the posttest performed in >2 min, and time spent between the end of the pretest and the beginning of the questionnaire between 20 min and 1 h. The experiment completion and time course of test execution were recorded by the learning management system.

Videos and Eye Movement Modeling Recording

Four versions of the same video lecture were created in an MP4 format. Each video presented 25 slides (1 topic overview, 1 lesson plan slide, 22 lesson slides, and 1 end slide) and the Leppink cognitive load questionnaire (33) and then performed the posttest.

In two versions of the video, eye movement modeling was integrated. In two other versions of the video, no eye movement modeling was added (Supplemental Fig. S1; see https://doi.org/10.6084/m9.figshare.19322288.v1). The raw video lecture duration was 20 min 59 s, and thus was >15 min. According to Chen et al. (34), a lecture duration of 15 min is enough to exhaust the working memory resources and deteriorate learning. The eye movement model of the physiology teacher (F. Gouzi) was recorded with a high degree of accuracy (0.5°) with the eye tracking system EyeLink 1000 + (SR Research Ltd, Mississauga, ON, Canada) for data analyses (Supplemental Fig. S2B; see https://doi.org/10.6084/m9.figshare.19361225.v1). The teacher was 1 m from the camera; a Dell brand screen with 1,054 × 758 pixel resolution (see Supplemental Fig. S2A) was installed 45 cm behind the camera. The target was placed on the teacher's forehead to allow optimal tracking of eye movements. After calibration of the system, the teacher's eye movements were recorded at a frequency of 500 Hz. The EyeLink Data Viewer software (SR Research Ltd, Mississauga, ON, Canada) was used for data analyses. After the recording, the teacher's eye movements were added to the video lecture with a black fixation point with 25% transparency. The video resolution was 960 × 720 pixels, and the operating system was Microsoft Windows 10.

Integration of Pauses

Integration of pauses was done with Adobe Premiere Pro software. Inserting pauses extended the original video duration by 25%. The total duration of pauses was 325 s, corresponding to 62 pauses of 5.15 s, distributed identically in the eye movement version and in the version without eye movements. These 62 pauses were inserted when the teacher's voice was already naturally paused. The pauses were executed automatically, and we did not allow any control of pauses. Allowing the students to control pauses can have a deleterious effect on learning (35). Finally, these two videos with pauses lasted 26 min and 30 s versus 20 min and 59 s for the two videos without pauses.

Pretest and Posttest Quizzes

The pretest and posttest were created by the physiology teacher who performed the renal physiology lectures (F. Gouzi) related to the video lecture on glomerular filtration (Supplemental Information S1; see https://doi.org/10.6084/m9.figshare.19322291.v1). The pretest and posttest were similarly composed of eight multiple choice questions, with five possible answers for each question. Four questions were related to general knowledge, two questions required reasoning, and two questions involved visual elements presented in the video (equations and diagrams). Each question was accompanied by five items that students had to check off or not. Each correct item was worth 0.20 point. Therefore, a question with the correct five items was worth 1 point. The results were converted into a score out of 10. No feedback was provided to the student after the pretest. The two questionnaires allowed calculation of the learning gains: posttest score minus pretest score.

Cognitive Load Questionnaire

Cognitive load was subjectively assessed with the 10-item inventory scale developed and validated by Leppink. It allows the characterization of the different types of cognitive load [intrinsic (*items 1–3*), extrinsic (*items 4–6*), and overall cognitive load (*items 7–10*)] (33). An 11-point Likert scale was used to rate how much students agreed with each statement. Higher scores indicate a high cognitive load during learning tasks. This survey was validated among medical students, and each of the items has been tested as well as each of the loads. Although lower for extrinsic cognitive load, the intrinsic and global cognitive load showed good reliability rates (36).

Ethics

The experiment was completed in accordance with European legislation and was approved by the Institutional Review Board (IRB) committee of the Montpellier University Hospital (IRB-MTP_2021_12_202100994). A letter was sent to notify the participants, and, in the absence of specific opposition, consent was considered to be obtained.

Statistical Analysis

Data was extracted from the Moodle LMS into an Excel form. Learning gains were calculated with score tests (posttest minus pretest) for each student. Data normality was verified by Shapiro–Wilk test. Values presented in the tables correspond to means ± SD, if normally distributed. Student characteristics and prior knowledge (i.e., pretest result) as well as duration of each step of the experiment in each group were compared by one-way ANOVA. The effects of the two experimental conditions (eye modeling movement example and pause) were analyzed in a 2 × 2 factorial plan with ANOVAs, and the effects of each qualitative variable and interactions were tested. A secondary analysis was performed to take into account the potential effect of students' prior knowledge. Low-prior knowledge and high-prior knowledge groups of students were defined according to pretest scores (the sample was split in two at the median score). Data were thus reanalyzed in a 2 × 2 × 2 factorial plan. The significance level validated during ANOVAs is 0.05 ($P < 0.05$). Analysis used R software version 4.0.4.

RESULTS

Characteristics of the Students

This study took place between February 2 and April 26 of 2021. Given the lockdown and the closing of universities in France, all the classes and lectures were performed online. The renal and urology physiology courses were displayed online on February 15, and 389 students (257 female, 132 male; 132 Nîmes, 257 Montpellier; 314 Medicine, 75 Maieutics) were randomized and had access to the quiz, video lecture, and questionnaire from February 22 to February 28, 2021 (Fig. 1). However, 109 students never performed the experiment, and 85 students did not complete the full experiment because of

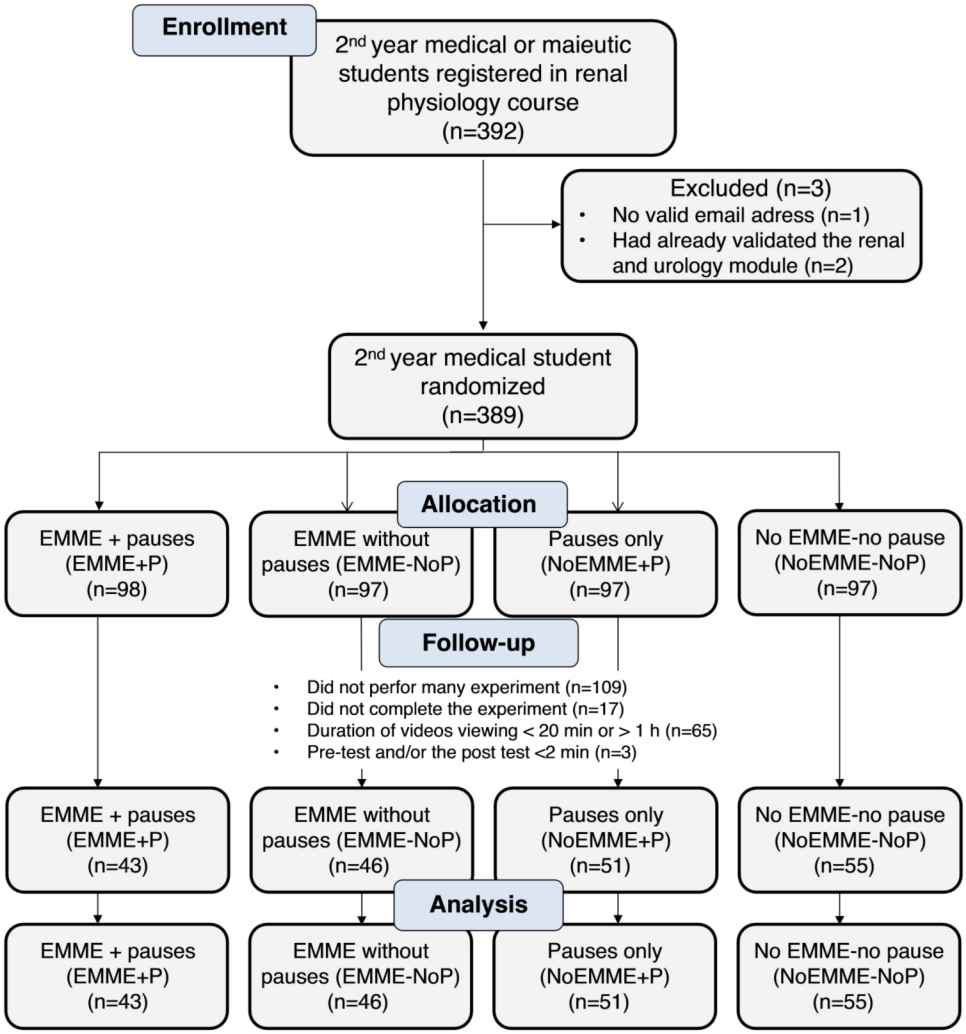

Figure 1. Chart flow diagram of the study. Students were randomized into 4 groups: *group A*: eye movement modeling examples with pauses (EMME + P); *group B*: eye movement modeling examples without pauses (EMME-NoP); *group C*: no eye movement modeling examples with pauses (NoEMME + P); and *group D*: no eye movement modeling examples and no pauses (NoEMME-NoP).

evidence of disconnection during the experiment (n = 17), because the video viewing duration was <20 min or >1 h (n = 65), or because the pretest and/or the posttest were <2 min (n = 3). Eventually, 195 students (50% of the full student population) were included in the final analysis and distributed among the study groups as follows: *group A*, EMME + P: n = 43 (22%); *group B*, EMME-NoP: n = 46 (24%); *group C*, NoEMME + P: n = 51 (26%); and *group D*, NoEMME-NoP: n = 55 (28%). In line with the students' randomization, there was no significant difference among groups in the pretest score (EMME + P: 4.58 ± 1.63, EMME-NoP: 4.78 ± 1.31, NoEMME + P: 4.11 ± 1.09, NoEMME-NoP: 4.64 ± 1.39; P = 0.081). The students performed the experiments in ~55 min. The difference between pretest and posttest was statistically significant (4.52 ± 1.37 vs. 6.39 ± 1.39; $P < 0.001$). In addition, the duration (in minutes) between the end of the video lecture and the end of the experiment (Leppink questionnaire + posttest) was not different between groups (EMME + P: 8.53 ± 5.6, EMME-NoP: 9.10 ± 5.28, NoEMME + P: 8.20 ± 4.64, and NoEMME-NoP: 8.18 ± 5.13; P = 0.798).

Pauses and Eye Movement Modeling Examples

ANOVA showed significant effect of pauses on learning gain (variable effect: P = 0.002; Table 1), meaning that adding pauses improved students' learning. However, we did not find any EMME effect on learning gain (variable effect: P = 0.11), meaning that, in contrast to our hypothesis, EMME did not allow better learning. We did not find an interaction effect between the pauses variable and the EMME variable (variable effect: P = 0.97). EMME coupled with pauses did not provide learning gain.

Integration of Prior Knowledge

Based on students' pretest performances, we split the group in two at the median (4.38/10). The low-prior knowledge group corresponded to students achieving a ≤4.38 score on the pretest; the high-prior knowledge group corresponded to

Table 1. *Pauses and eye movement model effect on learning gains*

	Pauses	No Pause
With EMM	2.02 ± 1.46	1.41 ± 1.47
Without EMM	2.34 ± 1.33	1.71 ± 1.23

Data are means ± SD (n = 195). EMM, eye movement model. Two-way ANOVA differences: with pauses, P = 0.002; EMM vs. without EMM, P = 0.11; EMM with pause vs. EMM without pause, P = 0.97.

students achieving a >4.38 score on the pretest (Table 2). Thus, we considered prior knowledge as a third independent variable (low prior knowledge vs. high prior knowledge). As in the previous 2 × 2 analysis, we obtained a main effect of pauses on learning gain with this 2 × 2 × 2 analysis (variable effect: $P < 0.001$). Pauses in videos improved learning. We also found a prior knowledge main effect on learning gain (variable effect: $P < 0.001$). The low-prior knowledge group obtained a better learning gain than the high-prior knowledge group. No main effect of eye movement model was found (variable effect: $P = 0.087$), but we obtained an interaction effect between EMME and prior knowledge (interaction effect: $P = 0.035$). EMME decreased learning gain only for the high-prior knowledge group. No interaction effect was obtained between the pauses variable and the eye movement model variable (interaction effect: $P = 0.75$). The EMME variable coupled with the pauses variable did not improve learning. No interaction effect was obtained between the pauses variable and the prior knowledge variable (interaction effect: $P = 0.50$). Insertion of pauses did not produce a difference in learning gain for low- versus high-prior knowledge students, and thus pauses benefited all students. No interaction effect was obtained between the pauses variable, the eye movement model variable, and the prior knowledge variable (interaction effect: $P = 0.93$).

Subjective Cognitive Load

ANOVA explored the effect of independent variables on subjective cognitive load, assessed with Likert scale rates attributed by students corresponding to extrinsic cognitive load, then intrinsic cognitive load, and finally global cognitive load. We found no significant effect of variables on the students' cognitive load. *P* values of the pauses effect for intrinsic, extrinsic, and global cognitive load were 0.068, 0.34, and 0.69, respectively. *P* values of the EMME effect for intrinsic, extrinsic, and global cognitive load were 0.78, 0.83, and 0.95, respectively. *P* values of the effect of students' prior knowledge on intrinsic, extrinsic, and global cognitive load were 0.26, 0.13, and 0.17, respectively. Regarding each item of the cognitive load questionnaire, there was a statistically significant effect of pauses for *item 1*, "The topic covered in the video was very complex" (variable effect: $P = 0.048$), meaning that students reported that the topic was more complex if there was no pause in the videos. In addition, we found a prior knowledge effect on *item 2*, "The video covered formulas that I perceived as very complex" (variable effect: $P = 0.028$), and on *item 6*, "The instructions were full of unclear language" (variable effect: $P = 0.049$) Thus, students with low prior knowledge found formulas more complex and instructions less clear than students with high prior knowledge.

Table 2. *Effect of student prior knowledge on learning gains*

	With EMM		Without EMM	
	Pauses	No pause	Pauses	No pause
Low PK	2.76 ± 1.49	2.19 ± 1.60	2.58 ± 1.26	2.03 ± 0.96
High PK	1.17 ± 0.85	0.86 ± 1.09	1.82 ± 1.36	1.46 ± 1.37

Data are means ± SD ($n = 195$). Low- and high-prior knowledge (PK) groups were defined according to the median pretest score (4.38/10). Two-way ANOVA differences: with pauses, $P < 0.001$; eye movement model (EMM) effect, $P = 0.087$; PK effect, $P < 0.001$; pauses + EMM interaction, $P = 0.75$; PK + EMM interaction, $P < 0.75$; pauses + PK interaction, $P = 0.50$; pauses + PK + EMM interaction, $P = 0.93$.

DISCUSSION

Main Findings

Our study showed, with second-year medical and maieutics students, that integrating pauses in a 20 min 59 s physiology lecture video (resulting in a 26 min 30 s video) improved learning gain. The insertion of pauses to reduce cognitive load of students during the learning task has been efficient on student learning and contrasted with the lack of learning effect of eye movement modeling examples on video physiology lecture. These effects were modulated by the student's prior knowledge.

Theoretical Background: Cognitive Load Theory Is Applicable to Video Lectures in Physiology

Our study hypotheses were based on the cognitive load theory (16), a concept based on the human cognitive architecture. It states that humans' cognitive capacity to process information from their environment is limited. This theory allowed us to understand how students learn with multimedia (17). During learning, human beings select and process only a small part of the information present in their environment. Thus, the more extrinsic (irrelevant) information is presented, the more difficult it is to learn, as previously demonstrated in physiology lectures (13). One of the teacher's roles is to select relevant information and to help students select relevant information, help them understand, and then let them assimilate the information before presenting other information. Yet factors of the cognitive load theory that have been evidenced in multimedia learning should logically play a role in physiology lectures. In particular, physiology lectures contents shared a high rate of interactivity [each element has a link with several others such as mathematical formulas, anatomical aspects, chemistry notions (11)], and students could have difficulty in focusing on one element after the other. According to Mayer's cognitive theory of multimedia learning (17), students need time to focus their attention on relevant elements, keep them in their working memory, and then integrate them with previous knowledge in their long-term memory. In addition, processing a piece of information before processing the next one requires time, and the transient information effect in videos increases the cognitive load and impairs learning. Thus, pauses allow the learner to keep sufficient cognitive resources (27) to process the information (14, 26). Likewise for the selection of information, attentional guidance avoided an increase in the use of resources (12, 26). In the case of unguided learning, learners may have spent too many resources finding information and had fewer resources to process the information. They became cognitively overloaded when processing and assimilating information into long-term memory. In the field of physiology education, our study was one of the first to ground its rationale and design on the cognitive load theory and to reveal relevant pedagogical design principles to improve physiology video courses.

Effect of Segmentation on Learning and Cognitive Load

This experimental study showed objective learning effects in the field of physiology education. In particular, we tested the effect of eye movement modeling examples and pauses in physiology lectures. Our study showed that adding 5 s to a teacher's natural pauses during a video lecture improves learning in physiology. Pauses implemented in the video may improve learning as long as the instructional video is long (>15 min) (23). In line with previous studies testing the segmentation effect in video lectures (14, 26), the positive effect of pauses could have been the consequence of a reduction of the students' cognitive load. Our measurement of cognitive load showed a tendency for an effect of pauses on intrinsic cognitive load (variable effect: P = 0.068), yet the lack of a statistically significant result on the subjective cognitive load questionnaire may be due to the small number of students. In fact, the statistical power of the Leppink survey in our study may be low because of the number of students in the study, in particular since the P value of the intrinsic cognitive load of students who watched the video with pauses was close to statistical significance. Nevertheless, *item 1* of the questionnaire revealed that students rated the video lecture without pauses more complex than the video lecture with pauses (variable effect: P = 0.048). Given that the renal physiology lecture (mechanisms and modeling of glomerular filtration) was based on dynamic knowledge, pauses may have reduced their cognitive load and allowed them to encode the new information and learn, regardless of their previous knowledge (Table 3).

Effect of EMME on Learning and Cognitive Load

Conversely, EMME did not improve students' learning. Furthermore, with high-prior knowledge students, there was a lower learning gain in students who watched the video with EMME compared with students who watched the video without EMME. One hypothesis is that, in contrast to low-prior knowledge students, high-prior knowledge students already knew where to look when teachers spoke. Thus, a redundancy effect of the oral and EMME information could have occurred (37). Indeed, a redundancy effect occurs when information is presented in different forms at the same time. In our study, EMME and the teacher's speech provided similar guidance information that allowed the students to focus on the same information. As previously shown, this redundancy effect increased the extrinsic cognitive load and reduced the resources for the overall cognitive load required to learn (34). The lack of EMME effect on students' learning could also be explained by the specificities of the renal physiology lecture. Indeed, our renal physiology course did not contain morphological information but rather schematics, graphs, and equations, orally explained by the teacher. Indeed, EMME has shown a positive effect on university students' learning in video lectures when spatial orientation was required (i.e., neuron functions in relation with the structure of the synaptic space and localizations of the

Table 3. *Pauses, eye movement modeling examples, and prior knowledge on Leppink's cognitive load questionnaire*

	Pauses		EMM		PK	
	No pause	With pauses	No EMME	With EMME	High	Low
*Item 1** "The topic covered in the video was very complex."	4.82 ± 2.22	4.27 ± 2.20	4.56 ± 2.40	4.55 ± 2.01	4.47 ± 2.16	4.63 ± 2.29
Item 2† "The video covered formulas that I perceived as very complex."	5.42 ± 2.47	5.14 ± 2.40	5.32 ± 2.43	5.24 ± 2.44	4.93 ± 2.21	5.61 ± 2.59
Item 3 "The video covered concepts and definitions that I perceived as very complex."	4.28 ± 2.04	3.77 ± 1.96	4.14 ± 2.02	3.90 ± 2.01	4.12 ± 2.11	3.95 ± 1.93
Item 4 "The explanations during the video were very unclear."	3.30 ± 1.92	3.16 ± 2.19	3.13 ± 1.89	3.35 ± 2.22	3.28 ± 2.12	3.19 ± 1.99
Item 5 "The explanations were, in terms of learning, very ineffective."	3.28 ± 2.39	2.97 ± 2.07	3.16 ± 2.37	3.09 ± 2.09	2.87 ± 1.96	3.37 ± 2.46
Item 6† "The explanations were full of unclear language."	2.70 ± 1.81	2.66 ± 1.84	2.68 ± 1.78	2.69 ± 1.87	2.44 ± 1.45	2.91 ± 2.09
Item 7 "The video really enhanced my understanding of the topic covered."	7.08 ± 2.22	7.22 ± 2.30	7.19 ± 2.26	7.10 ± 2.26	7.32 ± 1.95	6.99 ± 2.51
Item 8 "The video really enhanced my knowledge and understanding of renal physiology."	7.16 ± 2.13	7.20 ± 2.25	7.12 ± 2.21	7.25 ± 2.16	7.45 ± 1.68	6.93 ± 2.55
Item 9 "The video really enhanced my understanding of the formulas and diagrams covered."	7.16 ± 2.42	7.03 ± 2.30	7.08 ± 2.33	7.12 ± 2.39	7.27 ± 2.06	6.94 ± 2.60
Item 10 "The video really enhanced my understanding of concepts and definitions."	7.14 ± 2.14	7.27 ± 2.27	7.12 ± 2.19	7.29 ± 2.22	7.38 ± 1.91	7.03 ± 2.43

Data are means ± SD (n = 195). Likert scale is 1 to 11, with 1 meaning "not at all the case" and 11 meaning "completely the case." Two-way ANOVA: pauses, pauses effect; EMME, eye movement model effect; prior knowledge, prior knowledge effect. *Significant difference with pause interaction by 2-way ANOVA ($P < 0.05$). †Significant difference with prior knowledge (PK) interaction by 2-way ANOVA ($P < 0.05$).

postsynaptic membrane/neurotransmitters) (30). Conversely, van Marlen et al. (29) have shown that EMME did not improve problem-solving in geometry lectures (requiring concepts and modeling), as we found in our renal physiology lecture. Thus, because EMME appeared less efficient in video lectures presenting diagrams, mathematical formulas, and written texts, no learning benefit of EMME could have been expected in our renal physiology lecture. This hypothesis should be assessed by comparing the EMME learning effect in a "structure-function relationships" lecture and a "mechanism/regulations and modeling" lecture. In addition, pointing and tracing gestures enhanced students' learning in physiology in a structure-function relationship course (38, 39).

Relevance of the Study for Physiology Lectures in Medical Education

In France and worldwide, there is currently a large development of video lectures in medical education. The France Université Numérique (FUN) platform hosts more than 140 massive online open courses (MOOCs) and is followed by >500,000 registrants (40). Stimulated by the university lockdowns during the Covid-19 pandemic (41), the number of video lectures has dramatically increased worldwide (40, 42), as well as in France. Under the authority of the "Université numérique en santé et sport" (UNESS) (43), physiology instruction is thought to be digitalized and integrated in the e-learning platform "Système Informatisé Distribué d'Évaluation en Santé" (44) to teach, train, and assess medical students (45, 46). However, if the video lectures have appeared popular among students (47), it is interesting to note that learning with videos has not been associated with a drop in traditional face-to-face lectures (48). During face-to-face lectures, physiology teachers can manage time and adapt the content to the students' prior knowledge in classrooms. Indeed, managing the time course by introducing pauses has previously improved students' learning in physiology (49). Therefore, our study's first merit is to point out what is lost in learning during the switch from face-to-face to video lecture. Recently, issues regarding the effectiveness of MOOCs have been raised, such as failures of learners to complete a course. Explanations have been found in inadequate instructional designs of the videos that ignore human cognition (34). In this context of the change of teaching practices and a large use of video lectures, physiology teachers should be taught the cognitive load principles and the validated strategies that have improved students' learning. In addition, our study shows that tools aiming to manage the student's cognitive load (i.e., EMME) while designing a video lecture (22) may not be universally effective. In the context of the physiology lecture, our study is the first to point out that the type of the instructional material may condition the effectiveness of a teacher-managed solution.

Limitations and Strengths

Despite the strict randomization and the students' blinding, we acknowledge a few limitations. First, our experiment took place online on the Moodle learning management system and not in the laboratory. The continuity of the experiment could not be strictly controlled, as was also the case in many online studies. Thus, it is still possible that students sought feedback from their peers before or during the attempt. However, only one experiment attempt was possible, and students' pauses or disconnections during the experiment were recognized. In addition, during the period of the experiment, libraries, universities, and other student meeting places were closed because of the Covid-19 lockdown in France (50). Moreover, we did not observe synchronized results indicating that the experiments were performed in groups. Conversely, our online experiment was a strength of the study, because it used the French learning management system and was based on one actual course of the renal and urology module. Moreover, 50% of the class completed the experiment, meaning that our observations can be extrapolated to the entire class.

Conclusions

Our randomized controlled study showed in real-life settings the beneficial role of pauses during video lectures in physiology, through a decrease of the student's cognitive load. However, adding eye movement modeling examples in a physiology course did not increase student learning and even decreased learning gain for high-prior knowledge students. Finally, this study highlights the value of tools to prevent a cognitive overload during a video lecture. In addition, our study shows the critical need to validate pedagogical solutions that are adapted to the specificities of physiology lectures. Further research should be designed to replicate the experiment on video lectures in different pedagogical disciplines and with different materials.

DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the authors.

AUTHOR CONTRIBUTIONS

L.A. and A.T. conceived and designed research; L.A. and F.G. performed experiments; L.A., F.G., and A.T. analyzed data; L.A., F.G., and A.T. interpreted results of experiments; L.A. prepared figures; L.A. drafted manuscript; L.A., F.G., and A.T. edited and revised manuscript; L.A., F.G., and A.T. approved final version of manuscript.

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