OPTIMIZING VIDEO TUTORIALS FOR SOFTWARE TRAINING THROUGH CUEING

Vasiliki Ragazou[1] and Ilias Karasavvidis[2]
[1]*PhD Student, Department of Early Childhood Education, Ilias Karasavvidis University of Thessaly, Volos, Greece*
[2]*Assistant Professor, Department of Early Childhood Education, University of Thessaly, Volos, Greece*

ABSTRACT

Video tutorials substantially support demonstration-based training where the main goal is to enhance procedural knowledge by observing various understandable examples of performing a task. Although video tutorials are broadly popular nowadays, little attention is given to the design features of an instructional tutorial. The aim of this study is to investigate the use of cueing on video tutorials for software training. Task performance, mental effort, and self-efficacy were included as dependent variables to explain possible effects mechanisms. The experiment included 118 undergraduate students with ICT experience from a Computer Science department in Greece. All subjects viewed three video tutorials on video editing software followed by practice. The participants achieved significant learning gains, reaching moderate to high levels of success on task performance. No cueing effect was found. The discussion proposes several alternatives for improving the effectiveness of video tutorials.

KEYWORDS

Video Tutorials, Software Training, Cueing, Task Performance, Mental Effort, Self-Efficacy

1. INTRODUCTION

Over the past thirty years, the new advances of technology have introduced the term "digital media literacy" that refers to the individual's ability to identify the significance of media, understand, create, and share multimedia content (Buckingham, 2005). For instance, creating a poster on Photoshop, editing a video on YouTube, designing a multimedia app are examples of actions that are enabled by a subset of software which called media software or cultural software (Manovich, 2013). Therefore, many users are seeking tutorials to gain more information and consequently acquire more experience in media software.

Video tutorials are a popular learning tool that presents how-to information about software tasks (van der Meij and van der Meij, 2013). They are portrayed through a screen capture with synchronized narration. Today, popular video-sharing websites, such as YouTube and Vimeo, host thousands of informal video tutorials for performing numerous complex software-related tasks such as video editing. A question that arises is what type of software applications can be characterized as complex? According to HCI studies (Leutner, 2000), complex software applications involve a lot of related entities to accomplish complex workflows. As the number of entities rises, the degree of complexity would grow and therefore users should put more mental effort to know and understand all of them.

Since the popularity of video tutorials has been exponentially increasing, there have been many approaches for designing instructional videos. The Cognitive Theory of Multimedia Learning (CTML; Mayer, 2001) and the Cognitive Load Theory (CLT; Sweller, 2005) (1) take into consideration the limitations of human working memory capacity while processing information simultaneously, and (2) interpret how the features of the working memory influence cognitive processes. The CLT and CTML have proposed a set of guidelines for effective dynamic representations (i.e., videos). For example, learners benefit more from words and pictures than only words (multimedia principle) or learners learn better when words are presented as speech rather than on-screen text (modality principle). Several multimedia studies have explored the contribution of multimedia principles in learning with low prior knowledge users (Kalyuga, 2014). Also, Mayer (2001) argues that multimedia design principles may be more beneficial for learners with low prior knowledge than for high prior knowledge learners. Therefore, research on the effectiveness of these principles for high prior knowledge learners has received little attention. This study contributes to literature by exploring cueing with domain experts -Informatics students who had attended several courses on media but novices in the specific sub-field -video editing software.

2. THEORITICAL BACKGROUND

2.1 Cueing

The cueing (or signaling) principle (Mayer, 2001) posits that people learn better when non-content information (e.g., cues) guide user attention to the critical points of the material or emphasize the organization of the material. Cueing is operationalized in many ways, i.e., colour, shapes, zoom, luminance. The question that arises is how cueing improves task performance and, therefore, facilitates learning. A recent meta-analysis of 29 experimental studies (Alpizar et al., 2020) on cueing indicated the following. Firstly, cues may be beneficial for learners in terms of guiding the user's attention to the critical points of a multimedia presentation. Secondly, the use of cueing allows learners to organize and integrate relevant information with prior knowledge. Third, cueing can reduce the visual-search time, thereby releasing working memory resources.

Some researchers have reported that cueing can lead to improved task performance (Amadieu et al., 2011; De Koning et al. 2010) while others have found no effects on learning (Kriz and Hegarty, 2007). Previous research on cueing has some limitations. First, the studies have used self-paced animation or videos with static images and not on videos with a constant flow. Second, the video tutorials used in these studies targeted software with simple interfaces (i.e., word editing, web-based forms) rather than more complex ones (e.g., image or video editing). To the best of our knowledge, there was only one cueing study that has been conducted in the field of software training. Jamet and Fernandez (2016) integrated cueing in self-paced interactive multimedia tutorials that demonstrated how to fill out a web-based form. Cueing was empirically regulated and was implemented through green arrows pointing to elements of the interface. The participants in both conditions (cueing vs no cueing) had the opportunity to tackle each procedure in a step-by-step manner with the step names serving as labels. The results indicated that students in the cueing condition selected the relevant information more quickly compared to students in the no cueing condition. While this finding is clearly in line with MLT, cueing did not influence task performance.

2.2 Mediators of Learning

Another issue that invites further exploration is how individual characteristics such as prior knowledge, mental effort, and self-efficacy affect learning through multimedia. Not all users have the same expertise; some of them are novices while others are experts. Multimedia research considering users' expertise discrepancies has revealed that prior knowledge or prior experience is a crucial variable that influences various cognitive and affective measures. The expertise reversal effect postulates that effective strategies for novices can be redundant or even detrimental for knowledgeable users (Kalyuga, 2014). Most empirical studies have shown that users with low expertise focus on salient elements of information, while users with high expertise can ignore the irrelevant information and focus on the essential elements of the material (Jarodzka et al., 2010).

Multimedia learning materials usually have an inherent level of difficulty, and learners often have no idea of how to select the relevant information in a limited time frame. In this context, the total cognitive load that learners experience can easily surpass the limited capacity of cognitive resources. According to CLT, cueing can avoid cognitive load; however, individuals thoroughly diverge in their processing capacity (Arslan- Ari et al., 2020). Experts have a high level of experience regarding a specific task which reduces the cognitive load associated with the task. Contrarywise, novices lack experience or knowledge and thus face higher cognitive load. In multimedia research, different methods have been used to measure cognitive load with mixed results. Mental effort reflects the amount of cognitive processing a person is engaged. This conceptualization of mental effort by Paas (1992) has been widely accepted in the field of learning and instruction because it has good reliability and validity.

Self-efficacy is an important motivational factor that influences performance (Eccles and Wigfield, 2002). This construct refers to learners' belief that they feel confident to succeed in each task (Bandura, 1997). More specifically, it comprises a user's evaluation of what he or she can do in future task performance. In the last few years, self-efficacy beliefs have been targeted by several software training studies (see van der Meij, 2018). Previous studies have examined an ensemble of design features related to the Demonstration Based Training approach (Brar and van der Meij, 2017) and reported positive effects on self-efficacy. Nevertheless, to this date, no study has thoroughly investigated the unique contribution of cueing on self-efficacy.

2.3 Rationale of the Study and Research Questions

The previous literature review implies that, as a design principle for video tutorials, cueing could potentially improve task performance. This technique appears to be advantageous for learning though it has been explored in combination with other design features. Thus, its possible unique contribution to learning from videotutorials has not been verified. The present study aims to fill this gap by exploring the educational effectiveness of videotutorials that was designed with cueing. Also, it measures task performance, mental effort, and self-efficacy considering one demographics population with high ICT experience in the context of complex media software.

More specifically, the following research questions were investigated:

RQ1: Does the use of cueing on videotutorials for software training enhance task performance? Regarding previous multimedia research, it was hypothesized that cueing would lead to high scores on task performance (Amadieu et al., 2011).

RQ2: How does the use of cueing on videotutorials influence the resulting mental effort and self-efficacy? According to the Expectancy Theory (Eccles and Wigfield, 2002), self-efficacy is a crucial factor in developing a positive attitude towards task performance (Bandura, 1997). Hence, we hypothesized that cueing would boost students' self-efficacy on performing tasks. For mental effort, we hypothesized that cueing would decrease users' mental effort during training.

3. METHOD

3.1 Participants and Design

Participants in this study were 118 (90 male, 28 females) volunteer undergraduate students (mean age:21 years) at a Computer Science in mainland Greece. The students were in their fourth year of Computer Science study and had high expertise in ICT knowledge and software skills. None of the participants reported any familiarization with the video editing software application used in this study.

The research was implemented with the use of an experimental 2x2 mixed factorial repeated measures design. The research plan included two factors of two levels each: (a) cueing (plain, enriched) and (b) practice (practice after the video tutorial, stepwise viewing-based practice). Due to space limitations, we limit ourselves to the examination of one of the factors, cueing. The students were randomly assigned to four groups. The participants in each group watched three different, short video tutorials on video editing.

3.2 Materials

3.2.1 Videotutorials

Three videotutorials were used. The video tutorials were made in vitro and covered aspects of video editing using Video Sequence Editor (VSE) which is bundled with Blender 3D. The first video tutorial presented the VSE interface in Blender with an introduction to basic operations (selecting a clip, changing the position of a clip in time and space (channel). The second videotutorial presented how to apply a transformation effect to achieve a complex action (e.g., zoom, rotation). Finally, the third videotutorial presented an even more complex topic like the simultaneous projection of two pictures in a frame. As the native language of all participants was Greek, all videotutorials were in Greek.

3.2.2 Operationalization

Cueing was operationalized through shapes and high brightness frames that emerged in key points, in the enriched video tutorials for software. Figure 1 shows an example of cues used in the video tutorials of the present study.

Figure 1. Examples of cueing used in video tutorials

3.3 Measures

3.3.1 Task Performance

Three tasks were used for the purposes of the study. Every task included five questions: two declarative knowledge questions, two procedural knowledge questions, and one transfer knowledge question. The declarative knowledge test comprises of two closed-type questions (e.g., multiple-choice items with three response options, True/False). This measure assessed the amount of information the participants remembered from the videotutorial (Examples: Which of the following colours denotes a transformation effect clip? a) Cyan b) Green c) Purple). The procedural knowledge test consisted of two items that asked students to complete tasks related to those presented on the videotutorial, i.e., adding a transformation effect, adjusting scale for an object (Examples: The top screenshot features two strips from images in the VSE. Add the corresponding transform strips and rearrange them to create the stack featured in the screenshot below). The transfer knowledge test asked students to apply the knowledge gained from the last two video tutorials on a given Blender file to complete the task. Binary coding was used to score all the tasks (1: correct, 0: wrong). A sample transfer question was “The screenshot to the left depicts a composite picture. Use the image strips on VSE to create this picture effect”. The declarative items were administered in paper, while the procedural and transfer knowledge items were administered electronically via the LMS platform. For the statistical analysis, the task performance scores were converted to ratios. The reliability analysis indicated high scores for all three tasks (task 1: $\alpha = 0.80$; task 2: $\alpha = 0.81$; task 3: $\alpha = 0.81$).

3.3.2 ICT Experience

A subjective self-report measure of previous ICT experience was used to assess the participants’ previous knowledge of multimedia software and the use of the Internet and Computers on a 6-point scale, ranging from very little (1) to very much (6). A sample ICT item was “Please rate your degree of familiarity with Word Processing Applications (e.g., MS-Word, Open Office Writer), Image Editing Software Applications (e.g. Adobe Photoshop, GIMP)”. Cronbach’s alpha value was approximately 0.7.

3.3.3 Mental Effort

A subjective self-report of mental effort scale was used to assess the measure of cognitive resources that participants invested during the instruction. This item was adapted from Paas (1992) and translated in Greek. The scale asked learners to assess the mental effort they invested while studying the instructional material on a 7-point scale ranging from extremely low (1) to extremely high (7). The overall Cronbach's alpha value across the three tasks was high (0.88).

3.3.4 Self-Efficacy

The participants were asked to rate their knowledge on how well they could perform the actions on a scale from 0 to 100% (Bandura, 2006). There were three questions on Video #1, five questions on Video #2 and six questions on Video #3. (Examples: Image strip selection; Moving image strip to horizontal axis x frames; Moving image strip to vertical y-axis channel". Reliability was perfect for all three tasks 0.99, 0.96, and 0.98, respectively.

3.4 Procedure

The experimental session lasted about 2 hours. The participants were randomly assigned to four conditions. In the beginning, the students were briefed about the study. Next, they logged in the course's LMS, and, depending on their condition, they accessed a specific learning path. After introductory information was given, the students completed the demographic data and previous ICT knowledge questionnaire. Then the participants watched the first videotutorial. Next, they filled out (a) an assessment of the mental effort and (b) an assessment of their self-efficacy. The following step involved the administration of the task performance measure. The same step-sequence was followed for the second and the third videotutorial. It is worth noting here that the students watched each video tutorial once only. All students were instructed to work independently and to call for help only when they faced technical problems.

4. RESULTS

A mixed factorial repeated measures ANOVA was carried out with the cueing as the between-subjects factor and the time after the video tutorial as a within-subjects factor. An alpha value of 0.05 was used throughout the analysis. The Bonferroni correction was applied whenever multiple tests were conducted, thereby reducing the probability level as needed. Finally, because the assumption of sphericity was violated in some cases (i.e., Mauchly's test of sphericity was statistically significant), the corresponding Greenhouse-Geisser F value and degrees of freedom were used.

4.1 Task Performance

Table 1 shows the descriptive statistics for the mean success rates for the tasks in the two conditions. As the inspection of the mean scores shows, the average performance of the participants across the conditions was relatively high, ranging between 70 to 80%. Consequently, the tasks were not particularly challenging for the participants. The above issue should come as no surprise considering that they were studying applied Computer Science; this should also suggest that the students were by no means novices in ICT in general.

A two-way mixed ANOVA failed to show a significant effect of cueing on task performance, $F(1,114) = 0.574$, $p = .450$. As far as the within-subjects factor is concerned (i.e. time), the repeated measures ANOVA did not indicate any significant time by cueing interaction ($F(2,228)=0.137$, $p= .872$). Therefore, performance is not dependent upon cueing. This finding is not in line with our initial hypothesis that cueing would yield higher learning gains compared to the respective reference condition, e.g., plain videotutorials.

Table 1. Mean scores and standard deviations on task performance, mental effort, and self-efficacy rates

Condition	Task performance M (SD)	Mental effort M (SD)	Self-efficacy M (SD)
Plain (n=60)	72.56 (33.58)	3.99 (0.89)	77.82 (19.80)
Cueing (n=58)	76.67 (30.76)	3.91 (1.00)	79.47 (20.70)

4.2 Mental Effort

Interestingly enough, there was no significant effect of cueing on mental effort, $F(1,114)=0.311$, $p= .578$. Subsequent examination of differences of practice with form indicated no significant differences between the two conditions. The average perceived difficulty was 2.92 for the first video, 3.80 for the second video and 5.12 for the last one. This finding agrees with the general trend of learning scores reported in the previous section, lending support to the idea that the difficulty of the videos (and hence the tasks that followed them) increased. The pairwise comparisons of the means indicated that the mean perceived difficulty of the second video was significantly higher than the first and that the mean perceived difficulty of the last video was significantly higher than that of the second.

4.3 Self-Efficacy

The two-way mixed ANOVA failed to show a significant effect of cueing on self-efficacy, $F(1,114)=0.232$, $p= .631$. However, there was a time simple main effect, $F(1.341, 152.867)=20.758$, $p= .000$, $\eta^2=.154$. In the case of cueing, the findings indicate an increase in self-efficacy after watching each software screencast for both factor levels, plain and cueing.

5. DISCUSSION

The study reported in this paper systematically investigated whether the use of cueing in video-based software training affects task performance, mental effort, and self-efficacy.

The results showed that the participants in the cueing condition performed slightly better (M = 76.67, SD = 33.58) compared to the participants in the plain (i.e., no cueing) condition (M = 72.56, SD = 30.76). However, this difference was not systematic. One plausible explanation, which is supported by multimedia research, is that cueing favours low prior knowledge users in the stages of the selection, organization, and integration of new information with existing knowledge (van Gog, 2014). This finding also resonates in multimedia research meta-analyses (Alpizar et al., 2020; Richter et al., 2016). Compared to low experienced learners, high prior knowledgeable learners have already constructed mental models in long-term memory (Kalyuga, 2014). Hence, it might be concluded that the presence of cueing hindered high experienced users from understanding the most important information. For this reason, future research should consider the amount of cueing for high experienced users when learning a new software application.

A second possible explanation lies in the modality of cueing used. The present study has used only one type of modalities, such as arrows, geometric shapes, and high-brightness frames. The monotonous appearance of these signals may have been attenuated during software training. According to Xie's et al. (2019) meta-analysis, combining two types of modality simultaneously (visual and verbal) can help learners integrate words and images to focus more time on the essential element of learning material. Thus, future studies should investigate a dual modality of cueing in videotutorials to enhance task performance.

Regarding mental effort, the findings indicated that cueing had no influence on mental effort. This finding is in line with many empirical studies (Lowe and Boucheix, 2011). One possible explanation is that users with experience in the subject have already created a mental representation in their long-term memory. Any external information received through a teaching tool, such as dynamic representations (e.g., videotutorials), may conflict with pre-existing knowledge, and this may result in the appearance of a cognitive burden. Therefore, experienced users may need to watch the video several times to cover up their misunderstandings.

Students' self-references to the cognitive effort reinforce the above claim, stating that they used high cognitive resources. According to Kriz and Hegarty (2007), the iterative learning process benefits users with a high level of expertise to resolve the conflict that arises between new knowledge and the existing mental schemas.

Regarding self-efficacy, no cueing effect was detected. One plausible explanation lies in the participants' academic background. Yokoyama's (2019) review has shown that academic self-efficacy plays an essential role in academic task performance. For example, if a student's self-efficacy is enhanced, the student may be able to achieve higher educational scores. Several studies have assumed that self-efficacy is the most significant factor for students to achieve high scores on task execution (Honicke and Broadbent, 2016). In this study, cueing did not affect self-efficacy and hence task performance, creating a domino effect.

Taking all into consideration, the presence of cueing did not improve learning from video tutorials on software training. Empirical studies in multimedia learning have revealed positive outcomes of cueing when learning from static materials. In the case of dynamic representations, cueing may not work for video tutorials. Due to the transient nature of the video, the effect of cueing might fade. For this reason, future studies need to investigate the amount of cueing and the modality of cueing during software training. Also, future research will need to replicate the current findings with other complex software applications and different user demographics. To date, most studies have used relatively simple applications rather than complex ones.

Additionally, while former studies have examined cueing, the present study is the first one to experimentally examine it in the case of complex software training with participants who were complete novices in the software tool used but domain experts. Thus, we have attempted to systematically extend former research by investigating the effect of cueing in novel contexts, with complex software applications, and different user expertise levels. While this is, obviously, an essential step in a new direction, more systematic research is required.

5.1 Limitations

A limitation of the study is gender bias in the sample used. Since the research was conducted in a Computer Science department, the sample was dominated by males. In the future, it would be advisable to replicate the findings with a similar user population that is more balanced in terms of gender.

A second limitation is that we used a specific measure for mental effort. Even though it is a reliable and valid scale, it might not provide an overall accurate representation of the students' total cognitive load. Future studies should adopt new cognitive load strategies, i.e., electroencephalography (Antonenko et al., 2010) to provide more sufficient data for more in-depth learning.

6. CONCLUSION

All in all, the findings of the present study indicate that cueing does not improve task performance in the case of complex software as far as experts in the domain but novices in the specific sub-field are concerned. Since there is scarce empirical evidence on the role of software screencasts on learning complex software applications, it can be argued that the picture that emerges warrants further systematic exploration. Future studies need to investigate how specific design guidelines in various combinations affect complex software training. Finally, in the case of software training, the relative expertise of learners needs to be taken into consideration as high ICT knowledge users might respond differently to cueing and practice.

ACKNOWLEDGEMENT

The authors would like to thank the students of Computer Science of Central Greece for their participation in the study.

REFERENCES

Alpizar, D. et al, 2020. A meta-analysis of signaling principle in multimedia learning environments. *Educational Technology Research and Development*, pp. 1–25.

Amadieu, F. et al, 2011. The attention-guiding effect and cognitive load in the comprehension of animations. *Computers in Human Behavior*, 27(1), pp. 36-40.

Antonenko, P. et al, 2010. Using electroencephalography to measure cognitive load. Educational Psychology *Review*, 22(4), pp. 425-438.

Arslan-Ari, I. et al, 2020. How Much Cueing Is Needed in Instructional Animations? The Role of Prior Knowledge. *Journal of Science Education and Technology*, 29(5), pp. 666-676.

Bandura, A., 1997. *Self-efficacy: The exercise of control*. New York: Freeman and Company.

Bandura, A., 2006. *Guide for constructing self-efficacy scales*. Self-efficacy beliefs of adolescents, 5(1), pp. 307-337.

Brar, J. and van der Meij, H., 2017. Complex software training: Harnessing and optimizing video instruction. *Computers in human behavior*, 70, pp. 475-485.

Buckingham, D., 2005, Media Literacy of Children and Young People Literature Review: A Review of the Research *Literature on Behalf of OFCOM*, OFCOM, London.

De Koning, B. et al, 2010. Attention guidance in learning from a complex animation: Seeing is understanding?. *Learning and instruction*, 20(2), pp. 111-122.

Eccles, J. S. and Wigfield, A., 2002. Motivation beliefs, values, and goals. *Annual Review of Psychology*, 53(1), pp. 109–132.

Honicke, T. and Broadbent, J., 2016. The influence of academic self-efficacy on academic performance: a systematic review. *Educational Research Review*. 17, pp. 63–84.

Jamet, E. and Fernandez, J., 2016. Enhancing interactive tutorial effectiveness through visual cueing. *Educational Technology Research and Development*, 64(4), pp. 631-641.

Jarodzka, H. et al, 2010. In the eyes of the beholder: how experts and novices interpret dynamic stimuli. *Learning and Instruction*, 20(2), pp. 146–154.

Kalyuga, S., 2014. Prior knowledge principle in multimedia learning. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning*, New York: Cambridge University Press, pp. 576–597.

Kriz, S. and Hegarty, M., 2007. Top-down and bottom-up influences on learning from animations. *International Journal of Human Computer Studies*, 65(11), pp. 911–930.

Leutner, D., 2000. Double-fading support—a training approach to complex software systems. *Journal of computer assisted learning*, 16(4), pp. 347-357.

Lowe, R. and Boucheix, J. M., 2011. Cueing complex animations: Does direction of attention foster learning processes?. *Learning and Instruction*, 21(5), pp. 650-663.

Manovich, L., 2013. *Software takes command* (Vol. 5). A&C Black.

Mayer, R. E., 2001. *Multimedia learning*. New York: Cambridge University Press.

Paas, F., 1992. Training strategies for attaining transfer of problem solving skill in statistics: a cognitive load approach. *Journal of educational psychology*, 84(4), pp. 429–434.

Paas, F. et al, 2003. Cognitive load measurement as a means to advance cognitive load theory. *Educational Psychologist*, 38(1), 63–71. https://doi.org/10.1207/S15326985EP3801_8.

Richter, J. et al, 2016. Signaling text-picture relations in multimedia learning: A comprehensive meta-analysis. *Educational Research Review*, 17, pp. 19-36.

Sweller, J., 2005. Implications of cognitive load theory for multimedia learning. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning*. New York: Cambridge University Press, pp. 19–30.

van Der Meij, H., 2018. Cognitive and motivational effects of practice with videos for software training. *Technical communication*, 65(3), pp. 265-279.

van der Meij, H. and van der Meij, J., 2013. Eight guidelines for the design of instructional videos for software training. *Technical communication*, 60(3), pp. 205-228.

Van Gog, T., 2014. 11 The Signaling (or Cueing) Principle in Multimedia Learning. *The Cambridge handbook of multimedia learning*, 263.

Yokoyama, S., 2019. Academic self-efficacy and academic performance in online learning: A mini review. *Frontiers in psychology*, 9, 2794.

Xie, H. et al, 2019. Coordinating visual and auditory cueing in multimedia learning. *Journal of Educational Psychology*, 111(2), pp. 235–255.