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How Much Cueing Is Needed in Instructional Animations? The Role of Prior Knowledge

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Abstract

This study explored the effects of prior knowledge and cueing on the learning (retention, transfer, and matching) and mental effort of learners who studied an instructional animation with accompanying narration about photosynthesis. A 4 × 2 between-subjects factorial design with four levels of cueing (no cueing, label cueing, picture cueing, and label and picture cueing) and two levels of prior knowledge (low vs. high) was used. A total of 216 undergraduate students from various majors in a large Southwestern university volunteered to participate in this study. The results revealed no significant effect of cueing on learning or mental effort. However, high prior knowledge learners outperformed low prior knowledge learners on a retention test and reported investing more mental effort than low prior knowledge learners. Although it was not significant, high prior knowledge learners had higher transfer and matching scores when no cues were provided.

Keywords Animation · Mental effort · Cueing · Multimedia learning · Prior knowledge

Introduction

Recent technological developments have increased the use of dynamic visualizations, such as animations, in multimedia learning environments. Instructional designers often use animation in multimedia learning environments to depict instructional content that involves movement, change, and object trajectory within a single visual (De Koning et al. 2010); designers also use animations to help learners visualize abstract concepts (Betrancourt 2005) and to increase learner interactivity and engagement (Rieber 1991). Animations have been found to be particularly effective in portraying time-lapse, slow-motion, and invisible knowledge (e.g., formation of lightning) in dynamic systems (Berney and Betrancourt 2016). Although animations offer a variety of options for presenting multimedia learning content, instructional designers must consider the limitations of the human cognitive system in order to use them effectively. This realization has prompted educational researchers to pay a considerable amount of attention to learning from animations in the last decade (Lowe and Schnotz 2014). In a recent meta-analysis, Berney and Betrancourt (2016) reported a small effect size for the beneficial effects of animations over static pictures. However, surprisingly, most of the studies included in their study found no significant differences between animations and static pictures.

In fact, several studies have shown that animations might not help or might have a detrimental effect on learners' performance (e.g., Castro-Alonso et al. 2014; Castro-Alonso et al. 2018; Mayer et al. 2005; Tversky et al. 2002). A potential explanation for the lack of benefit from animations is that animations place high demands on the learner's cognitive capacity due to the transitory nature of the presented information, especially when this information includes multiple changes presented simultaneously (Ayres and Paas 2007; Tversky et al. 2002). Berney and Betrancourt (2016) stressed that the effect of animation differs by the presence and modality of accompanying verbal information. They reported a moderate animation effect when the animation has an accompanying narration.

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According to Cognitive Load Theory (CLT) and CTML, the human mind has limited capacity of processing the information in the working memory at the same time (Mayer 2001; Sweller 2005; Sweller et al. 1998). Therefore, only presenting the information with multiple modalities is not enough to ensure the superior performance when we consider the limitations of the human cognitive system (Ginns 2005; Sweller et al. 1998). CLT proposes three types of cognitive load: (a) intrinsic load, (b) germane load, and (c) extraneous load. German load is a load directly related to schema construction and automation (Sweller et al. 1998). Intrinsic load is defined as a cognitive load caused by the natural complexity of the information which has to be understood and material which has to be learned (Sweller 2010). On the other hand, extraneous load is caused by the cognitive processes which are not necessary for learning (Kalyuga 2011) and directly related to the instructional design.

According to Mayer's (2009) CTML, for meaningful learning to occur from animation with narration, learners must select relevant words from the narration, relate the words to their visual referents in the animation, organize the words and visuals into a mental model, and then integrate verbal and visual representations with prior knowledge. However, learners might have difficulty selecting the essential information from the animation because animation consists of elements that have different perceptual attributes (e.g., size, orientation) that are simultaneously in motion (De Koning et al. 2009). Due to the limited capacity of working memory, it is essential that learners select the most relevant words and images in order to understand the presented information. However, the transient nature of animation and the limitations of working memory make the task of selecting and combing a dynamically changing series of relevant words and images unlikely (Jamet et al. 2008). Consequently, essential time-sensitive information required for constructing an accurate representation of the information is often missed (De Koning and Jarodzka 2017). Also, holding verbal information while searching for relevant visual information can cause extraneous cognitive load and hinder learning (Ayres and Paas 2007). Therefore, using techniques to direct the learners' attention to essential information in an animation is crucial (Lowe and Schnotz 2014). Cueing is one technique for guiding learner attention to instructionally relevant information. Researchers have examined the effectiveness of several types of instructional cues such as directional arrows (e.g., Liu and Leveridge 2017); variations in color and luminance (e.g., De Koning et al. 2010; Ozcelik et al. 2010; Xie et al. 2019)—including colored lines (e.g., Boucheix and Lowe 2010) and circles (Jarodzka et al. 2013); and gesturing of animated agents (e.g., Castro-Alonso et al. 2018; Schroeder and Traxler 2017; Johnson et al. 2015). These cues can be applied to text (e.g., label), visuals (e.g., diagram), and both to depict the correspondence between text and visuals (van Gog 2014; Wang et al. 2020). For instance, labels with a pointer (e.g., line) linked to the corresponding element in a diagram is one form of cueing (Scheiter and Eitel 2015).

Cueing, sometimes referred to as signaling, is defined as non-content elements added to instruction in order to (1) guide learners' attention to the essential elements of a presentation (Mautone and Mayer 2001) and (2) to support the process of integrating pictorial and verbal information through highlighting the text-picture correspondences (Richter et al. 2016) when learning from multimedia materials. The attention-guiding effects of cueing should decrease visual-search time—thereby reducing extraneous cognitive processing—and free-up WM resources that can be used for meaningful learning (De Koning et al. 2009). In addition, highlighting (e.g., color coding) related information in text and pictorial representations explicitly help learners integrate information into a coherent mental representation which results in meaningful learning (Richter et al. 2016). Although the attention-guiding effects of cueing have been explored in recent research (e.g., Ozcelik et al. 2010; Jamet 2014), few studies have provided empirical support for the use of cueing with instructional animation (e.g., Boucheix et al. 2013; De Koning et al. 2009; De Koning et al. 2010; De Koning et al. 2011; Yung and Pass 2015). Also, the research findings are mixed regarding the educational effectiveness of cues in general (De Koning and Jarodzka 2017). A recent meta-analysis conducted by Alpizar et al. (2020) produced statistically significant effect sizes (1) for various types of signaling, e.g., color contrast ($d = .31$), text ($d = .36$), and combination ($d = .41$); and (2) for differing levels of signaling, high ($d = .50$) and low ($d = .29$). In another review of research on the effects of signaling, Schneider et al. (2018) reported that text signaling was more beneficial than graphic signaling for retention performance and that coloring in text and graphic affected transfer performance positively. These findings indicate that the research on signaling effects yet reports conflicting results in terms of when and how to use these signals (Alpizar et al. 2020). Furthermore, the treatment durations of the animations in the extant research studies are short. For example, Xie et al. (2019) used 130-s animation while De Koning et al. (2007, 2010) used a 286-s animation in their research studies. Therefore, further research is needed to understand the effects of various types and levels of signaling in longer instructional animations.

Besides cueing, individual differences should be considered in instructional design (Betrancourt 2005; Kalyuga 2014; Liu 2018; Lusk et al. 2009; Mayer 2001). Lowe and Schnotz (2014) stressed that understanding a complex animation might be especially difficult for learners who lack domain-specific knowledge. Compared with those with more prior knowledge, learners with less prior knowledge must invest more WM resources to comprehend new instruction, often resulting in WM overload (Kalyuga 2009). Contrarywise, learners with more prior knowledge in a specific domain (Kalyuga 2009) can learn new information by retrieving related information from long-term memory (LTM) without overtaxing their WM resources. Therefore, design principles effective for low prior knowledge learners may not help, and may even hinder, high prior knowledge learners (Kalyuga 2014).

Research studies investigating the differences between expert and novice learners have clearly demonstrated the influence of prior knowledge in distinguishing these two groups on various measures of learning and performance (Kalyuga 2008). The expertise reversal effect of instructional design predicts that high prior knowledge learners will experience a redundancy effect during new instruction (Kalyuga 2009; Kalyuga et al. 2003). More specifically, effective strategies for low prior knowledge learners—presenting information in multiple modalities, offering detailed explanations, or providing executive guidance—are often redundant, and therefore counterproductive, for high prior knowledge learners who already possess this knowledge in the LTM (Kalyuga 2009). Previous studies have shown that high prior knowledge learners can disregard irrelevant information in animation and focus on the essential information (Canham and Hegarty 2010; Jarodzka et al. 2010). On the other hand, learners with low prior knowledge focus on perceptually salient elements instead of conceptually relevant elements in the animation (Lowe 2003). Thus, according to the expertise reversal effect, while cueing is a potential strategy to guide the learners' attention to the relevant information for low prior knowledge learners, it might not be effective or may even be detrimental for high prior knowledge learners (Kalyuga 2014).

Most empirical research on multimedia design principles has been conducted with low prior knowledge learners (Kalyuga 2014). For example, research conducted by Mayer and his colleagues suggests that multimedia design principles may be more effective for low prior knowledge learners than for high prior knowledge learners (Mayer 2001). Therefore, research on the effectiveness of these principles for high prior knowledge learners has received comparatively little attention. Although the expertise reversal effect has been investigated in the context of the redundancy (Kalyuga et al. 1998) and segmenting principles (Spanjers et al. 2011), only a few studies (e.g., Johnson et al. 2015; Kriz and Hegarty 2007; Khacharem 2017; Richter et al. 2018) have considered prior knowledge in the context of cueing in static diagrams. Thus, more research is needed examining the interaction between prior knowledge and cueing (Richter et al. 2016), especially while learning from animations (De Koning and Jarodzka 2017; Xie et al. 2019). This study will fill this gap in the literature by examining the effects of cueing and prior knowledge effects in the context of animation with narration.

Another aspect of cueing that needs investigation is the amount of cues in a multimedia presentation. Mayer (2009) stressed that too much cueing might be detrimental for meaningful learning. Thus, the appropriate amount of cueing for low and high prior knowledge learners needs to be investigated (Richter et al. 2018). To fill the gaps listed above, this study examined the effects of cueing (i.e., no cueing, label cueing, picture cueing, and label and picture cueing) and prior knowledge (i.e., low, high) on the learning (retention, transfer, and matching tests) and mental effort of university students studying a self-paced animation with narration. This study will improve our understanding of the cueing principle concerning how best to use cues to guide the attention of low and high prior knowledge learners studying a complex animation. Also, this study will contribute to the literature by exploring the combined effects of labels and picture cueing in instructional animations to support the integration of pictorial and textual information.

The following research questions were investigated:

- What are the effects of cueing on the learning and mental effort of participants studying a computer-based animation with narration?
- What are the effects of prior knowledge on the learning and mental effort of participants studying a computer-based animation with narration?
- Does cueing interact with prior knowledge to affect the learning, mental effort, and study time of participants studying a computer-based animation with narration?

Methodology

Participants and Design

Participants in this study were 216 volunteer undergraduate college students at a large Southwestern university in the USA. However, only 200 participants ($M = 20$ years, $SD = 2.18$; 105 females, 95 males) were included in the data analysis because technical issues prevented the collection of posttest scores for 16 participants. The majority of participants were White (71.5%), followed by Hispanic (15.5%), African-American (9.5%), Asian (3%), and Native American (.5%).

A 4×2 factorial design, with cueing strategy and prior knowledge as between-subjects factors, was conducted to answer the research questions. Participants scoring below or equal to the median on the pretest ($Mdn = 10$) were designated as low prior knowledge learners ($n = 103$, $M = 7.91$, $SD = 3.09$), while those scoring above the median were designated as high prior knowledge learners ($n = 97$, $M = 18.04$, $SD = 3.35$). An independent t test confirmed that the prior knowledge scores between the two groups were significantly different, $t(198) = -22.17$, $p < .0001$. Participants were randomly assigned to the no cueing ($n = 52$), label cueing ($n = 50$), picture cueing ($n = 51$), and label and picture cueing ($n = 47$) conditions.

Materials

For each participant, the computer-based materials consisted of a participant questionnaire, a narrated animation, a mental effort scale, and three learning measures—retention, transfer, and matching tests. All materials were reviewed by three experts and revisions were made based on their feedback.

The participant questionnaire solicited (a) demographic information (i.e., age, gender, ethnicity, major, academic classification, and GPA), (b) experience with natural-science coursework (i.e., number of college-level biology and chemistry courses taken), and (c) knowledge of photosynthesis, which was the pretest for this study. The pretest contained seven multiple-choice items related to photosynthesis. Items were written according to the objectives of the instructional material. Participants were awarded five points for each correct response. Prior knowledge scores ranged from 0 to 35.

Four versions of a narrated animation on the photosynthesis process were developed to correspond with the four cueing treatments in this study. All four versions of the animation consisted of a brief introduction and four instructional segments: (a) introduction to photosynthesis, (b) light dependent reaction, (b) light independent reaction, and (d) summary of the photosynthesis. To ensure content validity, the animation content was adapted from a college-level plant biology textbook. After each animation segment, two buttons appeared, providing the option to replay the current segment or to continue to the next segment. However, neither reviewing segments (prior to the current segment) nor skipping segments was permitted.

Differences between the four versions of the animation pertained to the amount and type of cues in the animation (see Table 1). Different types of cueing (e.g., highlighting the text, color contrasting the visuals) has been investigated in the literature; however, cueing literature is still unclear which cues (label or picture) are more useful (Alpizar et al. 2020). Therefore, in this study, label and picture cueing were used as well as the both picture and label cueing. Figure 1 shows sample screen shots from the label cueing, picture cueing, and label and picture cueing animations investigated in this study. In all cueing versions, terminological labels or elements which are essential to understand the content of the animation became red when the term was declared in the narration.

Mental Effort Scale

A subjective self-report of mental effort scale was used to assess the amount of cognitive resources that participants invested during the instruction (Paas 1992). The participants were asked to rate the mental effort they invested while studying the instructional material on a 9-point scale ranging from extremely low (1) to extremely high (9). Although subjective rating may appear questionable, they have been used in most of the studies to assess the mental effort associated with learning instructional materials (De Koning et al. 2007; Kalyuga et al. 1999; De Koning et al. 2010). The reliability and validity of this scale have been proved by numerous research studies (Kalyuga and Sweller 2005; Paas et al. 2003).

Learning Measures

Three learning measures were used to assess the participants' learning outcomes. Questions in these tests were written aligned with the learning objectives of the instructional material.

Retention Test The retention test consisted of 10 multiple-choice items (with four response options) and five constructed-response items. This measure was designed to assess the amount of information the participants remembered from the narrated animation. Samples from the constructed response items include "What are the functions of stomata in photosynthesis?" and "How does photosystem I differ from photosystem II?" For each correct answer, 10 points were given. Percentages were used to present the retention scores. To reduce scoring bias, two raters independently scored a random selection of 30 participants' responses to the retention test. The inter-class correlation coefficients of .97 showed high agreement between the raters.

Table 1 Description of four version of animations

Conditions	Description
No cueing	No cues
Label cueing	Terminological labels became red when they were mentioned in the narration.
Picture cueing	Corresponding elements became red when they were mentioned in the narration.
Label and picture cueing	Both terminological labels and corresponding elements became red when they were mentioned.

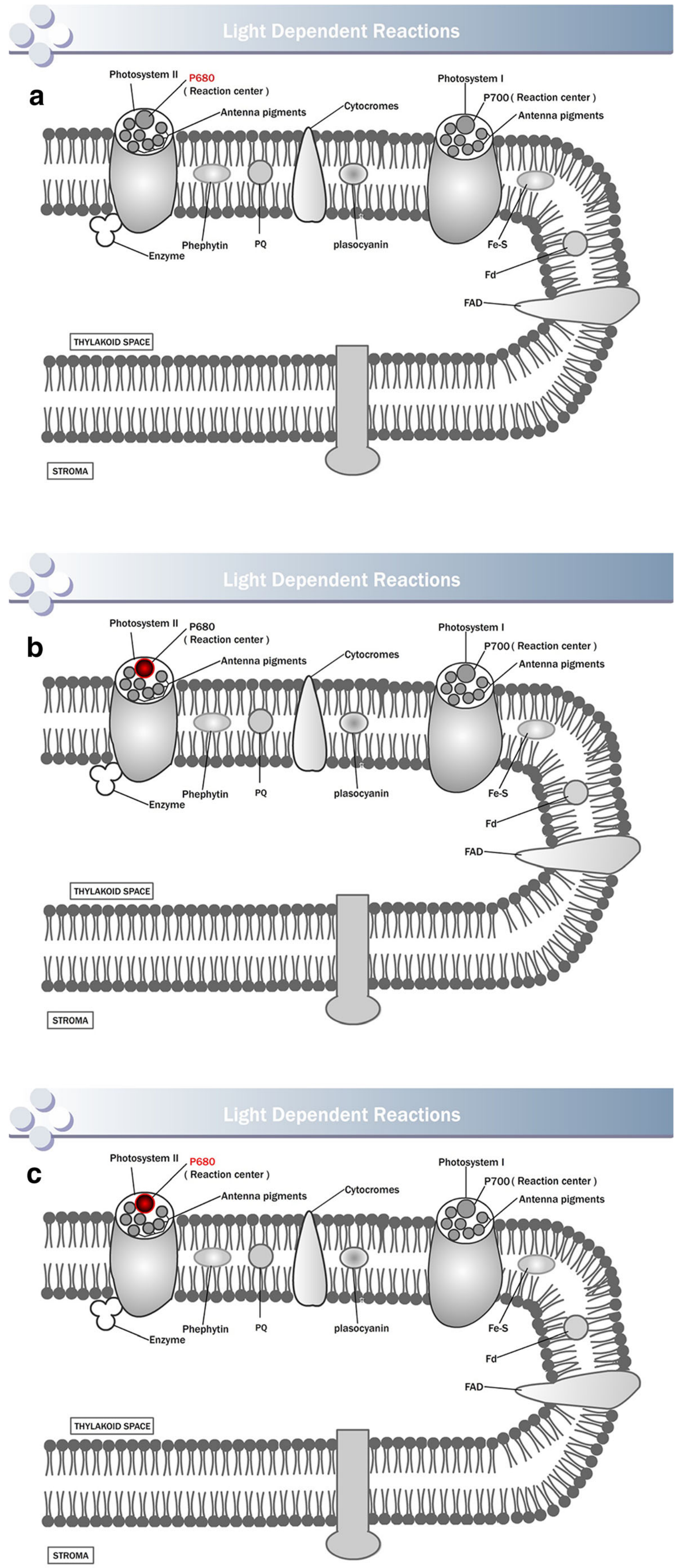

Fig. 1 Sample screen shots of label cueing condition (**a**), picture cueing condition (**b**), and label and picture cueing condition (**c**)

Transfer Test The transfer test included six open-ended questions designed to measure the extent to which participants could apply information from the animation to solve a novel problem. A sample transfer test question was "If carbon dioxide is reduced from a plant's environment, what would you expect to happen?" For each correct answer, 10 points were given. Percentages were used to present the transfer scores. As with the retention test, two raters independently scored a random selection of 30 participants' responses to the transfer test. The raters were blind to the participants' groups to eliminate the rater bias. The inter-class correlation coefficient of .89 showed good agreement between the raters.

Matching Test The matching test instructed participants to match the provided names of the 26 molecules/elements to a non-labeled version of two diagrams showing a summary of the photosynthesis process and light-dependent reaction. To score the matching test, one point was given for each correctly matched item. Percentage scores were calculated to represent the matching scores.

Procedure

This experimental study consisted of two phases. In phase I, which occurred 1 week prior to the intervention, the pretest was administered to the participants to assess their knowledge of photosynthesis. In phase II, each participant was assigned to attend an experimental session (15–24 participants per session) in a computer laboratory with 24 computers with headphones to complete the learning and assessment portions of the study. The participants were randomly assigned to one of the treatment conditions. After introductory information was given, the participants individually studied the instructional materials and completed the mental effort scale, the retention test, the transfer test, and matching test. The participants were given unlimited time to study the instructional material and complete the tests.

Results

Three main statistical analyses were performed to answer the research questions in this study. MANOVA was used to examine the effects of cueing and prior knowledge on learning (retention, transfer, and matching); follow-up ANOVAs were conducted to explore any significant multivariate effects. Separate two-way ANOVAs were used to explore the effects of prior knowledge and cueing on mental effort. All the test scores were calculated and presented in percentages.

Learning: Retention, Transfer, and Matching

The MANOVA yielded a significant multivariate main effect for prior knowledge (Wilks's $\Lambda = .93$, $F(3,190) = 4.82$, $p = .003$, $\eta^2 = .07$) and for the prior knowledge by cueing interaction (Wilks's $\Lambda = .89$, $F(9, 462.56) = 2.46$, $p = .01$, $\eta^2 = .04$). The main effect for cueing was not significant (Wilks's $\Lambda = .94$, $F(9, 462.56) = 1.35$, $p = .21$). Power to detect the prior knowledge and interaction effect was .900 and .853, respectively. As a follow-up, univariate effects were examined in conjunction with a Bonferroni adjustment to control for type I error. The effect of prior knowledge on retention was significant, $F(1,192) = 13.53$, $p < .001$, $\eta^2 = .066$, showing that 6.6% of the variance in retention scores can be explained by prior knowledge. High prior knowledge learners ($M = 42.49$, $SD = 18.27$) had a significantly higher score on the retention test than low prior knowledge learners ($M = 33.88$, $SD = 15.20$). The effects of prior knowledge on transfer ($F(1,192) = 3.85$, $p = .05$) and matching ($F(1,192) = 3.26$, $p = .07$) were not significant.

Although the MANOVA revealed a significant prior knowledge by cueing interaction effect, follow-up ANOVAs (with a Bonferroni adjusted alpha level of .0167) failed to show significant interaction effects for retention, $F(3,192) = .59$, $p = .62$, transfer, $F(3,192) = 1.65$, $p = .18$, or matching, $F(3,192) = 3.24$, $p = .02$. An examination of the mean scores (see Table 2) revealed that the achievement of low and high prior knowledge learners was disproportionally affected by the cueing strategy they received. Low prior knowledge learners in the label-cueing condition scored higher on the retention, transfer, and matching tests than low prior knowledge learners in the other cueing conditions. A similar pattern is evident among high prior knowledge learners' on the retention test. On the transfer and matching tests, high prior knowledge students who studied in the no cueing condition had the highest scores on the transfer and the matching tests.

Mental Effort and Study Time

Two-way ANOVA revealed that prior knowledge had a significant effect on mental effort, $F(1,192) = 6.30$, $p = .01$, $\eta^2 = .03$, power = .59. High prior knowledge students ($M =$ 5.58, $SD = 1.73$) indicated significantly more mental effort during their study than low prior knowledge students ($M =$ 4.98, $SD = 1.85$). However, there was no cueing effect ($F(3,192) = 2.37$, $p = .07$) nor an interaction effect ($F(3,192) = 1.37$, $p = .25$). Furthermore, two-way ANOVA indicated that there was no significant prior knowledge ($F(1,192) = 1.80$, $p = .18$), cueing ($F(3,192) = .53$, $p = .67$), or interaction effect ($F(3,192) = .21$, $p = .88$) on study time.

Discussion

This study examined the effects of cueing and prior knowledge on the learning (retention, transfer, and matching), and mental effort of learners studying a self-paced animation with

Table 2 Means and standard deviations for retention, transfer, and matching scores by group

			Retention		Transfer		Matching	
Prior knowledge	Cueing strategy	*N*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Low prior knowledge	No cueing	31	35.03	15.51	27.15	17.86	40.07	27.36
	Label cueing	22	36.14	16.51	34.92	17.04	50.35	28.31
	Picture cueing	24	31.42	16.23	29.93	13.64	27.72	15.51
	Label and picture cueing	26	32.88	13.06	30.96	15.62	40.83	24.23
	Total	103	33.88	15.21	30.42	16.22	39.58	25.33
High prior knowledge	No cueing	21	45.71	19.85	39.21	12.69	54.58	33.59
	Label cueing	28	48.04	17.39	34.40	16.15	46.84	25.08
	Picture cueing	27	35.15	18.84	35.80	16.08	49.43	26.83
	Label and picture cueing	21	41.33	14.29	31.35	16.49	35.17	26.57
	Total	97	42.49	18.24	35.**17**	15.51	46.04	26.96

narration. Results indicated that high prior knowledge learners had higher retention score than low prior knowledge learners. Consistent with this result, Kriz and Hegarty (2007) found that high prior knowledge learners remembered more steps, and developed more accurate mental models, of a system than did low prior knowledge learners. Since high prior knowledge learners had more knowledge about the content of the animation than low-prior knowledge learners, it was expected that they would retain more knowledge about the content of the animation. However, the finding of no significant difference between low and high prior knowledge learners on the transfer and matching tests suggests that *amount* of prior knowledge may not be the most important factor in higher-order learning processes, which require the successful integration of new information into existing schema in LTM. As stated by Kriz and Hegarty (2007), "the result of this integration process depends not only on how the new information is presented, but also on the quantity, specificity, and accuracy of the existing knowledge" (p. 913). Furthermore, in this study, the narrated animation may have impaired students' abilities to use their existing schema, as evidenced by the fact that high prior knowledge learners invested significantly more mental effort in studying the material than low prior knowledge learners. High mental effort may have hindered meaningful learning by increasing cognitive load in WM. Since constructing knowledge from an animation requires an iterative process and high prior knowledge learners are more likely to detect the conflict between the external information and existing schema (Kriz and Hegarty 2007), more learning iterations might have helped them to solve the conflict. Kriz and Hegarty (2007) found that most of the high prior knowledge learners had corrected their mental models and answered more transfer questions after studying the animation a second time, while there was no difference in the understanding of the low prior knowledge learners.

An alternative explanation for the lack of a significant prior knowledge effect in meaningful learning may lie with the participants' characteristics. In the present study, participants came from a variety of different majors including science, social sciences, and engineering. Even though prior knowledge was measured at the beginning and participants were divided into groups based on the mean scores of prior knowledge, this may not reflect the best fit for low prior knowledge and high prior knowledge groups. Even though high prior knowledge participants had existing knowledge about photosynthesis, the content may not have been interesting enough for the participants. Moreover, since the instructional material contained a lot of technical terms, even high prior knowledge learners may not be familiar with those terms. Thus, having participants from the biology department or considering interest to the content or biology as a covariate may give significant results.

According to the CTML, it was expected that providing cues in the animation would direct learners' attention to the essential elements, reduce their visual search, and free up WM resources for meaningful learning. However, contrary to our prediction, no significant cueing effects on learning and mental effort were found. There are several possible explanations for this non-significant result. First, the motivation of the learners might have impacted the effects of cueing (Schneider et al. 2018). Results of a recent meta-analysis conducted by Schneider et al. (2018) supported the notion that "motivational and affective factors are influenced by signaling and play an important role in learning" (p.20). Also, Lin's (2011) study examining the cueing effect in animation found intrinsic motivation as the predictor of learning. In this study, participants came from different academic majors. Therefore, they may not have been interested and motivated towards learning about photosynthesis. Thus, being less motivated to learn about photosynthesis might be one of the factors that affected participants' active engagement with the instructional material and, as a result, hindered their learning performance in this study. For this reason, participants' motivation towards instructional material should be considered as a covariate in the future experimental studies to set boundary conditions for cueing effect. Second, the characteristics of the instructional materials used in the present study might have affected the results. The instructional material used in this study took almost 10 min which is quite long compared with the previous studies. Current eye-tracking studies (Boucheix et al. 2013; De Koning et al. 2010; Ozcelik et al. 2010; Scheiter and Eitel 2015) revealed that although visual cues direct learners' attention to the relevant elements in the initial presentation, this effect disappears after several exposures. Therefore, cues may not have taken the participants' attention during the whole instruction in the current study. De Koning et al. (2009) stressed that facilitating attention to the relevant information does not always guarantee learner engagement with the instructional material. Since the cueing information in the animation is presented briefly in nature, it might be missed (Schneider et al. 2018). Third, using only visual cues was not helpful to integrate the relevant information in the narration with their visual referents in the animation. The high number of the previous studies (i.e., Crooks et al. 2012; Lowe and Boucheix 2011) examining the effect of single type cueing use a single modality cues (i.e., either visual or auditory) and did not find a significant cueing effect. Xi et al. (2019) stressed that "guiding attention with single-modality cues does not necessarily guarantee better integration of the relevant words and pictures when presenting complex multimedia" (p.238). In this study, color change might have help the learners' process the visual information in the animation but nor the integration of both verbal and visual information. Xie et al. (2019) proposed the coordinated dual-modality cues—providing both visual and auditory cues at the same time—to achieve the integration of words and graphics. They found that when coordinated dual-modality cues (both visual and auditory cues) were provided in a diagram with narration, the students performed better on learning outcomes, spent more time on the relevant part of the diagram. Therefore, future studies should use coordinated dual-modality cues in a complex animation with narration to promote the learners in the audio-visual integration.

The speed of the animation may have caused the non-significant results. Participants of this study learned through an instructional animation whose presentation speed was moderate. Fischer et al. (2008) studied the effects of presentation speed of animation on student learning and found that modified speeds in animation may enhance understanding. Furthermore, it was argued that cues are needed in high speed animations to assist the identification of relevant information (Kriz and Hegarty 2007) because learners need to find the relevant information and determine the elements and their relations in a short period of time. On the other hand, in a slow speed animation, there are few elements per unit of time. Thus, learners have enough time to find the relevant information without the need of using cues (De Koning et al. 2011). Future research should be conducted by manipulating the presentation speed of the animation.

Regarding mental effort, no cueing effect was found on the mental effort of the participants. This finding is in line with a number of previous empirical studies conducted by De Koning et al. (2011), Lin and Atkinson (2011), and Lowe and Boucheix (2011).

The lack of an interaction effect between prior knowledge and cueing strategy in this study was not consistent with prior research conducted by Johnson et al. (2015) and Khacharem (2017). Although there was no significant interaction effect, an examination of the mean scores reveals that cueing differentially affects low and high prior knowledge learners. Low prior knowledge learners studying the narrated animation in the label cueing condition did better on the retention, transfer, and matching tests than the low prior knowledge learners in the other cueing conditions. Although we found this for low prior knowledge learners only, this finding partially supports the result of a recent meta-analysis by Schneider et al. (2018) that text signaling was more beneficial for retention performance than visual signaling. On the other hand, high prior knowledge learners studying the narrated animation without cues did better on the transfer and matching tests and invested more mental effort than the high prior knowledge learners in other cueing conditions. However, high prior knowledge learners in the label cueing condition performed better on the retention test than high prior knowledge learners in the other cueing conditions. These results are partially aligned with the expertise reversal effect (Kalyuga 2014). Hence, it might be concluded that cueing enhanced learning for low prior knowledge learners but hindered learning for high prior knowledge learners when learning from a narrated animation. This finding is echoed more recently by Alpizar et al.' meta-analysis (2020) investigating the signaling principle in multimedia learning environments. Moreover, an appropriate amount of cueing seems to be better than too much cueing for better learning for low prior knowledge learners.

Implications and Conclusion

Several theoretical and practical implications for using instructional animations can be drawn from this study. This study mainly focused on the effects of cueing in a narrated animation on learning and mental effort. The investigation of the amount of cues used by low and high prior knowledge students was unique to this study. Therefore, this study contributed to the literature by showing that high prior knowledge learners retain more information from an instructional animation than low prior knowledge learners. Even though no other significant prior knowledge effects were found, the test scores support the notion that minimal visual cues, label cues, in a narrated animation help low prior knowledge learners attend to the relevant information at the right time and increase their learning, whereas high prior knowledge learners do not need visual cues. Furthermore, this study showed that besides prior knowledge, other moderating variables, such as learners' motivation, should be considered by the instructional designers and educators while designing an animation.

Many research studies (e.g., Lowe and Boucheix 2011; De Koning et al. 2010) have found significant cueing effects with short animations. However, this study extends the current literature on the effect of cueing in long animations by suggesting an important boundary condition for the cueing effect in dynamic visualizations. This boundary condition should guide instructional designers when designing animations and inform researchers as they continue to investigate the boundary conditions of the cueing effect in instructional animations.

Although positive effects of visual cueing on different learning outcomes when learning from static pictures were reported in previous research studies, the same cueing strategies may not work for animations. Thus, when static pictures are animated, the effects of cues might disappear. Several studies (e.g., Moreno 2007; Lin 2011; Ozcelik et al. 2010) highlighted the importance of cueing in selecting the relevant information and learning from animations. However, research studies examining cueing in animation are limited and those which examined cueing provided mixed results. For this reason, future research should consider the format and length of visualization while conducting research to examine the effects of visual cueing.

Although this study makes beneficial contributions, the results should be interpreted by considering the certain limitations. First, the participants in this study may not reflect the best fit for low and high prior knowledge groups, since they were coming from different majors and were categorized based on mean scores from prior knowledge tests. Therefore, these results should be interpreted with the understanding that our prior knowledge categories may not reflect those of created by subject-matter experts. Second, the instructional animation includes many terminological terms, so the participants' motivation and attention might have been lost. Third, the dependent measures were limited to a mental effort scale and achievement tests. It is unclear whether the cues in the animation achieved their role, directing attention to relevant information. Lastly, a subjective self-rating mental effort scale, developed by Pass (1992), was used to assess the mental effort. Although it is a reliable and valid scale, it might not provide the learners' actual cognitive load. Therefore, future research should be collect eye movement and electroencephalography (EEG) data to address this limitation (Antonenko et al. 2010). Also, experiments with eye movement data should be useful to determine how learners with different prior knowledge behave while studying the multimedia learning environments with cued animations. Lastly, we only considered prior knowledge as an individual difference factor in this study since the focus of this study was on examining the interaction between prior knowledge and cueing. Future research might consider adding such individual difference variables as working memory capacity, motivation, or self-efficacy.

Author Contributions All authors contributed to the study conception and design. Material preparation and data collection were performed by Ismahan Arslan-Ari and Fatih Ari. Data analysis and the first draft of the manuscript were written by Ismahan Arslan-Ari and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee (Texas Tech University Protection of Human Subjects Committee, 503187) and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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