Title
A Non-Verbal Pre-Training Based on Eye Movements to Foster Comprehension of Static and Dynamic Learning Environments

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 36(36)

ISSN
1069-7977

Authors
Skuballa, Irene T.
Renkl, Alexander

Publication Date
2014

Peer reviewed

A Non-Verbal Pre-Training Based on Eye Movements to Foster Comprehension of Static and Dynamic Learning Environments

Irene T. Skuballa (irene.skuballa@uni-tuebingen.de)
Applied Cognitive Psychology and Media Psychology, Schleichstr. 4,
D-72076 Tübingen, Germany

Alexander Renkl (alexander.renkl@psychologie.uni-freiburg.de)
Department of Educational and Developmental Psychology, Engelbergerstr. 41,
D-79085 Freiburg, Germany

Abstract

Eye movement recording is not only a research tool but can also be used as a learning tool. Previous research on eye movement modeling and analogical thinking has demonstrated that stimulating eye movements can foster learning and problem solving. Such training interventions can support learners and problem solvers without revealing the solution, but just by guiding their gaze. The present two studies investigated whether a preceding stimulation of eye movements would affect the comprehension of following learning materials. Study I revealed a positive effect of a non-verbal eye movement pre-training on learning outcomes. Study II corroborated this finding and, additionally, revealed no effect of presentation format (static versus dynamic) on comprehension. With respect to eye movements performed during the learning phase, pre-training led to more homogenous fixation strings. Moreover, the homogeneity could also be attributed to a dynamic representation (Study II). In sum, a non-verbal pre-training of eye movements before exposure to the learning content fosters comprehension in static and in dynamic representations.

Keywords: eye movement modeling; pre-training; eye tracking; knowledge acquisition; static versus dynamic.

Eye Movement Modeling: Seeing From an Expert's Angle

Experts and novices not only differ on performance as a result of their actions, but also on processes that lead to their outcomes. New methods on the field of eye movement research enable access to experts' eye movements during decision making or problem solving. The meta-analysis by Gegenfurtner, Lehtinen, and Säljö (2011) clearly revealed systematic eye movement differences between experts and novices. Based on these results, it has been suggested that expertise can be acquired faster by training novices in visual attention allocation: "a replay of the eye movements of experts, superimposed on the screen showing the visualization, can be used to model the eye movements of novices" (Gegenfurtner et al., 2011, p. 542).

Such eye movement modeling examples (EMME) can be considered as worked-out examples (Jarodzka et al., 2012). In EMMEs the replay of an expert's eye movements gives an example on where to look when performing a task. EMMEs consist of the visualization of a model's eye movements on a visual stimulus—providing the basis for information processes—and verbal explanations of the model. However, a verbalization of the processes is not necessary to make eye modeling successful. In an experiment on problem solving, Grant and Spivey (2003) identified characteristic eye movements of successful problem solvers (i.e., many saccades crossing task-relevant areas). In a second stage—testing the reversed effect—the looking behavior of successful solvers was used to develop cues for participants who were unfamiliar to the problem. These cues (short flashes) were meant to attract attention and thus trigger the 'right' eye movements. The cues were implemented in the learning materials and presented to uninformed participants. Participants who were exposed to these cues outperformed participants who learned with noncritical cues. Inspired by these results, Thomas and Lleras (2007) made an attempt to facilitate successful problem solving by making their participants "move their eyes in a pattern that embodied the problem's solution" (p. 664). Comparing several conditions, the authors not only replicated the results by Grant and Spivey (2003), but also came to the conclusion that there is a relationship between eye movements and spatial cognition: the closer the similarity between the real eye movements and cues, the better the solution rate.

Recently, the approach of training eye movements was adopted in the context of acquiring skills in medical diagnosis (Jarodzka et al., 2010). The acquisition of such skills in medicine requires efficient search, detection, and interpretation of task-relevant features. The authors tested two versions of modeling examples: one version showed the expert's eye movements as a circle; a second version showed expert's eye movements as a clear spotlight whereas the rest was blurred. A first study demonstrated that the participants in the spotlight condition outperformed the circle condition and the control condition (without cue) in diagnosing seizures (Jarodzka et al., 2010).

In a follow-up study, the participants' eye movements were analyzed (Jarodzka et al., 2012). Again, participants in the spotlight condition performed best on making medical diagnoses. The superiority of the spotlight condition was also reflected in the eye movement data: modeling eye movements by spotlights guided attention more and helped them identify relevant information at an earlier stage as well as fixate task-relevant information for a longer time. These results were extended to teaching interpretation of computer tomography scans (Seppänen & Gegenfurtner, 2012).

Participants who watched a video replaying an expert's eye movements and interpretations of such a scan improved in diagnosing.

The results from research on EMME are promising. Despite different realizations of the model's eye movements in the to-be-inspected visual stimulus, all aforementioned studies implemented the model's eye movement directly in the material. Results from a study on analogical problem solving, however, show that cues and learning material can be separated and presented chronologically (Pedone, Hummel, & Holyoak, 2001). Before solving a problem, participants were confronted with different diagrams demonstrating convergent (similar to solution) and divergent (dissimilar to solution) arrows. Four experiments demonstrated that convergent diagrams which are similar and analogue to the solution supported problem solving best. Especially dynamic (i.e. animated) analogues encouraged participants to encode the information in the initial diagram as motion and, thus, fostered spontaneous retrieval, noticing, and, above all, relational encoding. The authors conclude that "dynamic displays result in encodings that are more closely connected to the perceptual system than can be readily achieved by purely verbal materials" (Pedone et al., 2001, p. 220). However, it is not clear whether the arrows in the diagrams fostered problem solving because of the similarity to the solution or because of the eye movements that were triggered by the arrows.

Study I: Pre-Training and Static Representation

In Study I we raised the question as to whether learning can be fostered even when eye movement modeling and the visual complex learning material are presented separately. More specifically, participants had to undergo a non-verbal and content-free pre-training where they had to follow a circle moving on a white screen not revealing any contents. The circle moved analogue to the processes that were presented afterwards in a static display (Figure 1). We assumed that participants who were first exposed to the eye movement pre-training and then to the learning material should benefit from such pre-training.

We compared two groups: a group with analogue eye movement training (pre-training group) and a group without such pre-training (no-training group). We addressed the following hypotheses: We expected the pre-training group to outperform the no-training group on learning outcomes (H1). This superiority should be also reflected on the subscales assessing different knowledge types of technical systems (Kalyuga & Hanham, 2011), i.e., knowledge about structures, processes, and functions (H2). In a second step, we analyzed the eye movement data to see how the pre-training would impact the eye movement behavior when processing the learning environment. We expected the pre-training group to perform more saccades in the direction promoted by the pre-training (H3). In addition, the fixation strings within the pre-training group were expected to be more similar compared with the no-pre-training group (H4).

Method

Sample and design

Participants were 44 university students (33 freshmen; 9 male; age M = 22.12, SD = 3.14) who were randomly assigned to an experimental group with eye movement pre-training prior to the learning phase (pre-training group) or a control group without any training (no-training group). Participants were tested in individual sessions of approximately 60 minutes.

Materials

Learning material The learning environment consisted of a static picture illustrating a solar power plant which converts solar radiation into electricity (Figure 1). After a short introduction, the cycles of the system and their interdependencies were explained by a narration presented via headphones. Each cycle can be considered as a specific subsystem with its own structures and a certain flow direction of liquids in the pipes of the system. The components of the system served specific functions.

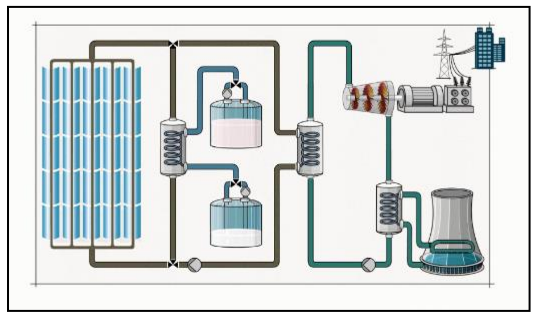

Figure 1: Learning environment (solar power plant).

Pre-training The eye movement pre-training in the experimental condition consisted of an animated single black circle (0.3 cm in diameter) moving analogue to the pipes of the technical device which was presented in the learning phase afterwards. Direction and order of the circle's movements were also congruent to the narration which accompanied the learning material. During pre-training, the background of the screen was white and no details of the actual learning environment were presented to the learner (Figure 2).

Prior knowledge To assess prior knowledge, we developed a test consisting of questions on the domain-specific content of the learning material (solar power plant). A maximum score of 36 could be achieved. The very low scores on prior knowledge indicate that the participants were novice in this area (Table 1). We also asked for the last grade in physics (1 = very good, 6 = fail).

Learning outcomes To assess learning outcomes, we developed a test based on the functions-processes-structures framework (Kalyuga & Hanham, 2011). Structures are the components a technical device consists of, processes are the operations within a device, functions refer to the purpose a device and its sub-components were designed for. Hence, our test comprised three subscales: Knowledge of structures

(15 items, ICC = .978), knowledge of processes (15 items, ICC = .921), and knowledge of functions (10 items, ICC = .920).

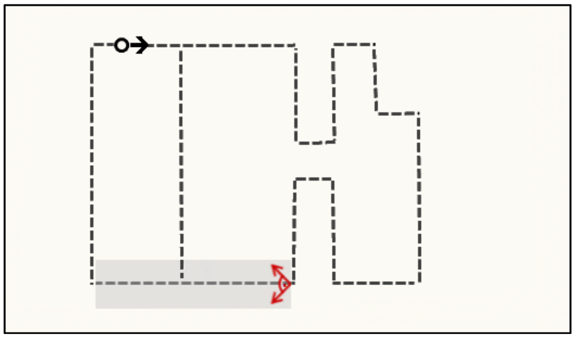

Figure 2: Schematic representation of the eye movement pre-training with dashed lines representing the movement of the black circle and an arrow indicating the direction of the movement. Dashed lines and arrow were not visible to the learner during the pre-training. Illustration of analysis of saccades in the lower part: Within a semantic AOI (grey area) all saccades in the predefined direction, from right to left in example, represented by vectors within a 90° angle were counted to analyze congruent saccades.

Apparatus

Gaze data were recorded by a SensoMotoric Instruments Remote Eye-tracking Device and iView X 2.7 (120Hz, angular error < .5). The stimulus was presented via ExperimentCenter 3.0 (22" monitor, display resolution of 1680x1050, set 60 to 80 cm in front of the participant). A fixation was defined as an event that lasted for at least 80 milliseconds with a maximum dispersion value of 100 pixels. In sum, we defined nine semantic areas of interest (AOIs) containing learning relevant information.

We analyzed the number of saccades accomplished congruent to the pre-training to capture smooth pursuit. For this purpose, vectors between each two fixations were recorded and aggregated. With respect to the directions in the pre-training, we counted only saccades with the correct direction, that means, saccades characterized by the same direction that was induced by the pre-training and the movement of the fluids in the pipes. Figure 2 illustrates one exemplary semantic AOI within which all saccades within a 90° angle were summed up.

The Levenshtein distance is the minimum of insertions, deletions, and substitutions of operations to transform one string into another string (Levenshtein, 1966). Each participant produced a string defined by the chronological order of AOIs he or she looked at. First, we calculated the pairwise distances within groups between each participant and its other group members in a matrix. We calculated the mean of all distances from one participant to each of his/her group members. A low Levenshtein distance means that few operations are necessary to transfer one string into another string, and thus, both strings are rather similar. High Levenshtein distances represent dissimilar strings.

Procedure

First, participants answered a questionnaire on demographics and worked on a test assessing prior knowledge. Participants were then randomly assigned to either a condition with pre-training or a condition without pre-training. The pre-training group was instructed to follow a black circle on a content-free screen prior to the learning environment; the control group skipped this part and immediately began with the learning environment. Finally, learning outcomes were assessed by a posttest.

Results

Table 1 displays the means and standard deviations for all variables reported. Before testing our hypotheses, we checked if prior knowledge was a potential covariate. Last grade in physics, r = -.643, p < .001, and the pretest performance, r = .304, p = .045, were positively correlated to the learning outcomes. Prior knowledge and grade were not correlated, r = -.248, p = .105. In addition, groups did not differ on pretest, $t(42)$ = -0.414, p = .681, d = -0.12, nor on grade in physics, $t(42)$ = -0.780, p = .440, d = -0.21. We, therefore, included both variables as covariates to test our hypotheses on learning outcomes (analysis of covariance).

Table 1: Means (and standard deviations) of dependent measures per condition for Study I.

	No-training *M* (*SD*)	Pre-training *M* (*SD*)
Pretest	1.68 (0.95)	1.82 (1.22)
Grade in physics	2.23 (1.15)	2.48 (0.96)
Learning outcomes	19.99 (5.81)	23.85 (5.81)
- Structures	10.82 (2.51)	11.43 (2.51)
- Processes	5.94 (2.87)	8.20 (2.87)
- Functions	3.24 (1.56)	4.22 (1.56)
Saccades	95.90 (40.58)	104.36 (41.23)
Levenshtein score	159.20 (25.60)	149.45 (18.33)

Testing the hypothesis whether the pre-training would result in better performance (**H1**), we found a positive effect of pre-training on the learning outcomes, $F(1, 40) = 4.788$, $p = .035$, $\eta_p^2 = .107$, indicating that the pre-training group outperformed the no-training group. Next, we analyzed whether this finding holds for the subscales (**H2**). There was no effect of pre-training on knowledge about structures, $F(1, 40) = 0.648$, $p = .426$, $\eta_p^2 = .016$. There was, however, a significant effect of pre-training on knowledge about processes, $F(1, 40) = 6.747$, $p = .013$, $\eta_p^2 = .144$, as well as about functions, $F(1, 40) = 4.326$, $p = .044$, $\eta_p^2 = .098$, with the pre-training group outperforming the no-training group. Next, we analyzed the eye movements performed during the presentation of the learning environment. A t-test revealed a non-significant effect of pre-training on the saccades performed within the areas of interest (**H3**), $t(41) = -0.678$, $p = .502$, $d = -0.21$. We used the Levenshtein distance to test our last hypothesis, whether the pre-training group would lead to more homogeneous eye movements (**H4**). Although the distance was lower in the pre-training group, indicating more homogenous strings, there was a non-significant effect of pre-training, $t(41) = 1.442$, $p = .157$, $d = 0.45$.

Discussion

In study I we raised the question whether a non-verbal, eye movement-based pre-training could foster comprehension of a static learning environment. Consistent with our expectations the pre-training group outperformed the no-training group. This superiority could be especially ascribed to knowledge about functions (moderate effect size) and processes (large effect size). Contrary to our expectations, the eye movement based pre-training did not result in more congruent saccades on the learning content. Moreover, the pre-training did not significantly affect homogeneity of strings. In sum, an eye-movement pre-training positively affected knowledge acquisition from a static learning environment and thus can be considered a successful instructional design intervention.

Study II: Combining Pre-Training and Presentation Format

Following up these promising findings we raised the question how the pre-training would affect comprehension of a dynamic learning environment. Study II investigated whether the pre-training might become obsolete when the learning content was dynamic and, by its nature, contained movements which guided the learner's visual attention. Alternatively, combining pre-training and a dynamic representation could also result in an additive effect. We extended the design of Study I by varying the presentation format (static versus dynamic). According to the finding in Study I, we expected a main effect of pre-training (H1a).

Based on results from a meta-analysis on animations according to which dynamic representations can have beneficial effects on learning (Höffler & Leutner, 2007), we expected a main effect of presentation format on learning outcomes (H1b): A dynamic representation should foster learning. The same pattern, namely main effect of pre-training and main effect of dynamic format, should apply to the subscales of the learning outcomes—assessed by structures, processes, and functions (H2a-H2b). With respect to saccades on relevant areas in the learning environment, we expected a main effect of pre-training (H3a) and a main effect of presentation format for the benefit of a dynamic representation (H3b). Similar to expectations in Study I, we expected the pre-training groups to show more homogeneous eye movements (H4a). We also expected a main effect of presentation format (H4b). Moreover, we also checked the interaction effect between training and presentation format asking whether combining pre-training with a dynamic representation could have further effects on learning outcomes and eye movements (H1-4c). So far, we had no expectations in how far a training*presentation interaction would have an effect on our dependent variables of interest.

Method

Sample and Design

Participants were 99 University students (59 freshmen; 28 male; age: $M = 21.63$, $SD = 3.11$) randomly assigned to four groups according to a 2x2 independent factorial design. We varied whether participants received a pre-training (pre-training versus no pre-training) and the format of the presented learning environment (static versus dynamic). Overall, there were four groups: pre-training and static; pre-training and dynamic; no pre-training and static; no pre-training and dynamic. Participants were tested in individual sessions of approximately 60 minutes.

Materials

To test the additional effect of a dynamic presentation format we created a learning environment in which the pipes of the solar plant were animated and showed the direction of the flow. The path of flow was presented as an ongoing and repeating loop of energy. All other contents were identical in every detail to the static presentation. All other materials used in Study II, such as pre-training, tests for prior knowledge, and learning outcomes, were identical to the ones used in Study I. The test on learning outcomes comprised again three subscales: structures of the system (15 items, ICC = .955), processes (15 items, ICC = .891), and functions of specific components (10 items, ICC = .868).

Procedure

The procedure of Study II was identical to Study I, except for the two additional conditions with dynamic learning environment. After filling in a questionnaire on demographics and the prior knowledge test, participants were randomly assigned to the four conditions and instructed to follow the learning environment. Finally, participants worked on the posttest.

Results

Table 2 displays the means and standard deviations for all dependent variables of interest. There was a positive relationship between pretest performance and the learning outcomes, $r = .399$, $p < .001$, but a non-significant relationship between the grade in physics and learning outcomes, $r = .118$, $p = .254$. There was no significant difference between the pre-training and the no-pre-training condition on the pretest, $F(1, 95) = 1.571$, $p = .213$, $\eta_p^2 = .016$, no difference between the different presentation formats on the pretest, $F(1, 95) = .377$, $p = .541$, $\eta_p^2 = .004$, and also no interaction between training and presentation format on the pretest, $F(1, 95) = .417$, $p = .529$, $\eta_p^2 = .004$. A factorial analysis of variance including pretest as covariate was applied to test the hypotheses regarding effects on learning outcomes.

Testing the hypotheses that provision of pre-training and a dynamic presentation format would positively affect learning outcomes, we found a significant main effect of training (**H1a**), $F(1, 94) = 5.085$, $p = .026$, $\eta_p^2 = .051$, indicating that pre-training fostered learning. However, there was a non-significant effect of presentation format on

	No Training		Pre-Training	
	Static	Dynamic	Static	Dynamic
Pretest	1.52 (1.53)	1.54 (1.53)	2.35 (3.45)	1.80 (1.66)
Grade in physics	1.17 (0.39)	1.36 (0.49)	1.43 (0.51)	1.44 (0.51)
Learning outcomes	17.46 (6.92)	18.74 (6.92)	21.75 (6.97)	20.78 (6.91)
- Structures	9.40 (2.65)	9.84 (2.65)	10.59 (2.66)	10.43 (2.64)
- Processes	5.36 (3.41)	6.10 (3.41)	7.62 (3.44)	7.15 (3.41)
- Functions	2.70 (1.88)	2.80 (1.88)	3.55 (1.89)	3.20 (1.88)
Saccades	64.35 (22.33)	78.14 (26.49)	86.57 (31.23)	69.12 (34.20)
Levenshtein score	227.56 (32.06)	211.82 (25.21)	210.26 (25.82)	205.32 (13.66)

Table 2. Means (and standard deviations) of dependent measures per condition for Study II.

learning outcomes (**H1b**), $F(1, 94) = 0.013$, $p = .909$, $\eta_p^2 < .001$. Moreover, the interaction between training group and presentation format was non-significant (**H1c**), $F(1, 94) = 0.647$, $p = .423$, $\eta_p^2 = .007$.

In a second step, we inspected the subscales of the learning outcomes (**H2a-H2c**). The main effects of training, $F(1, 94) = 2.759$, $p = .100$, $\eta_p^2 = .029$, and presentation format, $F(1, 94) = 0.075$, $p = .785$, $\eta_p^2 = .001$, as well as the interaction effect, $F(1, 94) = 0.311$, $p = .579$, $\eta_p^2 = .003$, on structures, were not significant. Concerning the processes of the learning material, we found a significant effect of training, $F(1, 94) = 5.698$, $p = .019$, $\eta_p^2 = .057$, showing that presentation format, $F(1, 94) = .111$, $p = .739$, $\eta_p^2 = .001$. Last, there was no significant interaction effect, $F(1, 94) = 0.341$, $p = .561$, $\eta_p^2 = .004$.

Addressing our next hypothesis whether participants would accomplish more saccades in the direction of the pre-training, we found neither a main effect of training (**H3a**), $F(1, 95) = 1.280$, $p = .261$, $\eta_p^2 = .013$, nor a main effect of presentation format (**H3b**), $F(1, 95) = 0.098$, $p = .755$, $\eta_p^2 = .001$. There was, however, a significant interaction (training*presentation format) on the saccades within semantic AOIs (**H3c**), $F(1, 95) = 7.175$, $p = .009$, $\eta_p^2 = .070$. Pre-training fostered congruent saccades in a static representation, but not in a dynamic presentation (Figure 3). In contrast, without pre-training, participants performed more congruent saccades when a dynamic representation was demonstrated, but not when a static representation was demonstrated.

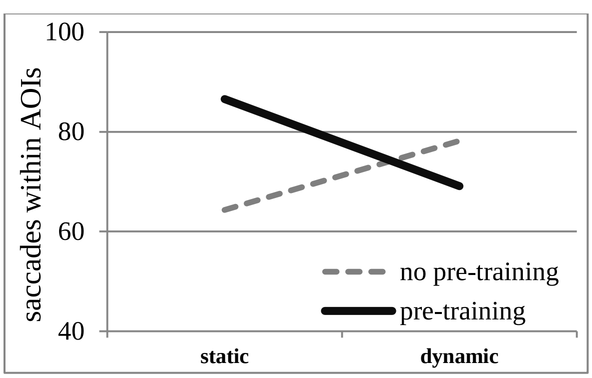

Figure 3: Interaction between presentation format (static versus dynamic) and training (pre-training versus no pre-training) on saccades within semantic AOIs.

Finally, we analysed the Levenshtein distance for all strings within each condition to examine the homogeneity of fixations. There was a significant main effect of training (**H4a**), $F(1, 95) = 5.614$, $p = .020$, $\eta_p^2 = .056$, indicating that eye movements within the pre-training group were more homogeneous. In addition, there was a significant main effect of presentation format according to which participants who watched the dynamic representation had more homogeneous eye movements (**H4b**), $F(1, 95) = 4.239$, $p = .042$, $\eta_p^2 = .043$. There was no significant interaction effect (training*presentation format, **H4c**), $F(1, 95) = 1.155$, $p = .285$, $\eta_p^2 = .012$.

Discussion

In Study II we tested a 2x2 design manipulating training (pre-training versus no-training) and presentation format (static versus dynamic) to corroborate findings from Study I and to investigate whether the effects of eye movement pre-training holds true when the representation is presented in a dynamic manner. The findings confirmed a positive effect of pre-training on learning outcomes which could be primarily ascribed to processes. There was no effect of presentation format and also no interaction effect between training and presentation format on learning outcomes. There were no main effects on saccades, but an interaction indicating that participants with pre-training performed the most congruent saccades when learning from a static learning environment. We also found a main effect of pre-training on homogeneity of eye movements. In addition, there was a main effect of presentation format according to which a dynamic representation resulted in more homogeneous eye movement behaviour.

General Discussion

On the basis of current research on eye movement modeling and analogical thinking, the present studies investigated the effect of eye movement pre-training on learning outcomes and eye movements performed during the learning process. In Study I, we expected that pre-training would lead to better learning outcomes, more saccades in the direction proposed by the pre-training, and more homogeneity. In Study II, we expected an additional effect of a dynamic presentation format. In both studies we found a stable effect of pre-training on learning outcomes which could be primarily ascribed to comprehension of processes presented in the learning materials. Contrary to our expectations, a dynamic presentation format had no additional effect on learning outcomes. There is evidence that dynamic diagrams on technical systems do not promote learning with respect to retention and transfer when compared to static diagrams (Mayer, Hegarty, Mayer, & Campbell, 2005). It is concluded that learners require instructional assistance when learning with animated representations. In this case, other approaches are in need to boost learning with dynamic representations in particular.

With regard to the homogeneity of eye movements we found mixed findings. Study II, however, indicates that pre-training and a dynamic representation can result in more similar eye movements. The results on saccades are inconclusive so far. Study I and Study II revealed a non-significant main effect of training. There was, however, an interaction effect. Alternatively, the poor link between saccades and learning outcomes could be explained by memory processes. Traces of the pre-training could have been memorized and recalled from long-term-memory during the learning processes without being performed. The eye movement pre-training could have triggered processes that could not be captured by eye tracking methods.

Finally some methodological concerns should be mentioned. Overall, the subscales measuring knowledge of structures, processes, and functions were related, all ps < .01. However, from a conceptual perspective of the framework, the knowledge types of technical systems are interdependent: processes are derived from structures and functions build on processes. In addition, some studies show that retention and transfer knowledge can also be correlated (Mayer et al., 2005). The question remains whether future research can develop a more sensitive assessment tool to reflect different knowledge levels of technical systems.

One disadvantage of expert models is that different experts do not always react in the same way to the same stimulus, and their behavior is based on differences in their learning history and professional background (Jarodzka et al., 2010b). Thus, a follow-up study should address more moderating variables (such as learning history, sex, and profession) and develop an eye movement pre-training based on real eye movements from an expert who corresponds very closely to the characteristics of the sample.

In summary, there seems to be more to learning (memorizing and understanding) than just meets the bare eye. Current theories on eye movements heavily refer to research on reading comprehension (e.g. immediacy assumption and eye-mind assumption by Just & Carpenter, 1980) which do not necessarily apply to comprehension of complex graphics and pictures. From our point of view, it is important to develop specific theoretical approaches for eye movements in learning from graphics to understand the underlying processes. The present studies make a significant contribution to this field in demonstrating that eye movements can be circumspectly used to foster learning from pictures. In sum, a non-verbal pre-training can successfully foster comprehension of processes in a static as well as a dynamic learning content. Moreover, learners have similar fixation strings following such a pre-training. The meaning of saccades on learning processes could not be clarified in this context and requires further investigations.

References

Gegenfurtner, A., Lehtinen, E., & Säljö, R. (2011). Expertise Differences in the Comprehension of Visualizations: a Meta-Analysis of Eye-Tracking Research in Professional Domains. *Educational Psychology Review*, *23*, 523–552.

Grant, E. R., & Spivey, M. J. (2003). Eye Movements and Problem Solving: Guiding Attention Guides Thought. *Psychological Science*, *14*, 462–466.

Höffler, T. N., & Leutner, D. (2007). Instructional animation versus static pictures: A meta-analysis. *Learning and Instruction*, *17*, 722-738.

Jarodzka, H., Balslev, T., Holmqvist, K., Nyström, M., Scheiter, K., Gerjets, P., & Eika, B. (2010). Learning Perceptual Aspects of Diagnosis in Medicine via Eye Movement Modeling Examples on Patient Video Cases. In S. Ohlson & R. Catrambone (Eds.), *Proceedings of the 32nd Annual Conference of the Cognitive Science Society* (pp. 1703–1708). Austin, TX: Cognitive Science Society.

Jarodzka, H., Balslev, T., Holmqvist, K., Nyström, M., Scheiter, K., Gerjets, P., & Eika, B. (2012). Conveying clinical reasoning based on visual observation via eye-movement modelling examples. *Instructional Science*, *40*, 813–827.

Just, M. A., & Carpenter, P. A. (1980). A theory of reading: From eye fixations to comprehension. *Psychological Review*, *87*, 329–354.

Kalyuga, S., & Hanham, J. (2011). Instructing in generalized knowledge structures to develop flexible problem solving skills. *Computers in Human Behavior*, *27*, 63–68.

Levenshtein, V. I. (1966). Binary codes capable of correcting deletions, insertions, and reversals. *Soviet Physics-Doklady*, *10*(8).

Mayer, R. E., Hegarty, M., Mayer, S., & Campbell, J. (2005). When Static Media Promote Active Learning: Annotated Illustrations Versus Narrated Animations in Multimedia Instruction. *Journal of Experimental Psychology: Applied*, *11*, 256-265.

Pedone, R., Hummel, J. E., & Holyoak, K. J. (2001). The use of diagrams in analogical problem solving. *Memory & Cognition*, *29*, 214–221.

Seppänen, M., & Gegenfurtner, A. (2012). Seeing through a teacher’s eyes improves students’ imaging interpretation. *Medical Education*, *1*, 1113–1114.

Thomas, L. E., & Lleras, A. (2007). Moving eyes and moving thought: On the spatial compatibility between eye movements and cognition. *Psychonomic Bulletin & Review*, *14*, 663–668.