Segmentation of Dynamic Visualizations Enhances Novice Students' Learning –But Why?

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Abstract. Dynamic visualizations are not always more effective for learning than a series of static pictures. Segmentation, that is, showing dynamic visualizations in pieces with pauses in between, is proposed to improve their effectiveness. We would like to discuss two not mutually exclusive processes which might underlie the effectiveness of segmentation. Additionally, we present an experiment in which we examined the occurrence of an expertise reversal effect (i.e., the effect that techniques which are effective for novices have no or even negative effects for students with higher levels of prior knowledge) with segmentation of dynamic visualisations. In this experiment secondary education students studied either segmented or non-segmented, animated worked-out examples on probability calculation. Segmented examples were more efficient than non-segmented ones (i.e., equal test performance with lower investment of mental effort during learning) for students with lower levels of prior knowledge, but not for students with higher levels of prior knowledge.

Keywords: Dynamic visualizations; Segmentation; Cognitive Load; Learning

Dynamic visualizations are attractive for students. However, they are not always more effective than series of static pictures (e.g., Tversky, Bauer-Morrison, & Betrancourt, 2002), although for certain types of tasks they seem to be more effective, especially demonstrations of procedures involving human movement (Höffler & Leutner, 2007). One instructional measure that has been proposed as a means to improve the effectiveness of dynamic visualizations, is segmentation, that is, showing dynamic visualizations in pieces with pauses in between (e.g., Ayres & Paas, 2007; Mayer & Moreno, 2003; Schnotz & Lowe, 2008). A number of studies found that segmentation enhances learning for novices (e.g., Mayer & Chandler, 2001; Mayer, Dow & Mayer, 2003).

Theoretical Explanations for the Effectiveness of Segmentation for Novices

We propose that two possible though not mutually exclusive processes might underlie a positive effect on learning from segmentation of dynamic visualizations. Because the information presented in dynamic visualisations is often transient (i.e., information is continuously replaced) learners have to maintain presented information in working memory to link it with information that is presented later in order to learn (Wouters, Paas, & Van Merriënboer, 2008); however, they have to process new information simultaneously (Mayer & Moreno, 2003). These simultaneous maintaining and processing activities impose high cognitive load on novice learners' working memory (Ayres & Paas, 2007). A first explanation for why segmentation might foster learning is that the pauses between the segments give learners time to perform necessary cognitive activities on the information presented in the previous segment without having to attend to new incoming information (e.g., Mayer & Moreno, 2003). Thus, segmentation reduces the high cognitive load that occurs due to dynamic visualizations' transience (e.g., Ayres & Paas, 2007; Mayer & Moreno, 2003; Schnotz & Lowe, 2008). A second explanation is that segmentation breaks the presentation down into meaningful pieces (cf. Arguel & Jamet, 2009; Schnotz & Lowe, 2008), and can consequently be seen as a form of cueing, which could aid students' learning by making them aware of particular sub-steps (cf. Catrambone, 1998; see also Wouters, Paas, & Van Merrienboer, 2008). Since learners do not have to search for the boundaries of the different sub-steps anymore, if they are cued, a decrease in cognitive load is to be expected based on this second explanation as well (Schwan, Garsoffky, & Hesse, 2000; Wouters et al., 2008).

However, unlike novices, students with higher levels of prior knowledge often do not need additional instructional measures; it may even have negative effects for them (Kalyuga, 2007). When learners gain knowledge, they construct cognitive schemas. More information elements are combined in those schemas, but the schemas can be handled in working memory as a single information element (Sweller, Van Merrienboer, & Paas, 1998). For students with higher levels of prior knowledge, the amount of cognitive resources they can devote to cognitive activities with a positive effect on learning is reduced when they have to reconcile instructional guidance with guidance given by their schemas (Kalyuga, 2007). This might also apply to segmentation. Therefore, we studied the occurrence of an expertise reversal effect of segmentation in learning from animated worked-out examples.

Method

The participating 75 Dutch secondary education students were randomly assigned to the segmented or non-segmented examples condition. They first completed a test about probability calculation. After that they studied eight examples in which it was demonstrated and explained how probability calculation problems can be solved. The examples included a pedagogical agent and spoken text. In the non-segmented condition each example was shown as one continuous stream of information. In the segmented condition each example was divided into segments with pauses of 2 seconds between them, during which the screen was slightly darkened. After each example learners rated their invested mental effort as an estimate of cognitive load. Finally, students completed a near transfer test (similar problem solving structure, but different surface features than the problems in the examples) and a far transfer test (different problem solving structure and surface features than the problems in the examples).

Findings

Significant interactions between prior knowledge and condition were found with regressions analyses with pre-test scores, condition and the interaction term pre-test scores * condition as predictors, and efficiency (i.e., combination of near and far transfer scores and mental effort during learning) as outcome variables (near: $b = -0.35$, $t(71) = -2.07$, $p = .04$; far: $b = -0.34$, $t(71) = -2.00$, $p = .05$). Follow-up analyses showed that at one standard deviation below the mean, segmented examples were more efficient than non-segmented ones, that is, they attained equal performance with less investment of mental effort during learning (near: $\beta = 0.39$, $t(71) = 2.60$, $p = .01$, far: $\beta = 0.33$, $t(71) = 2.20$, $p = .03$). However, the superiority of segmented examples had disappeared at one standard deviation above the mean (near: $\beta = -0.05$, $t(71) = -0.36$, $p = .72$, far: $\beta = -0.10$, $t(71) = -0.67$, $p = .51$).

Discussion

This experiment suggested that segmentation indeed successfully reduced the high load imposed by dynamic visualizations for students with lower levels of prior knowledge. This study does not, however, tell us which explanation mentioned in the theoretical discussion is most plausible, that is, whether it are the pauses, the cueing of important sub-steps, or both, that caused this effect on cognitive load. In a next study (Spanjers, Van Gog, Wouters, & Van Merriënboer, in preparation) we will investigate the two alternative explanations directly.

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