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META-ANALYSIS

A Meta-analysis of the Segmenting Effect

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Abstract
The segmenting effect states that people learn better when multimedia instructions are presented in (meaningful and coherent) learner-paced segments, rather than as continuous units. This meta-analysis contains 56 investigations including 88 pairwise comparisons and reveals a significant segmenting effect with small to medium effects for retention and transfer performance. Segmentation also reduces the overall cognitive load and increases learning time. These four effects are confirmed for a system-paced segmentation. The meta-analysis tests different explanations for the segmenting effect that concern facilitating chunking and structuring due to segmenting the multimedia instruction by the instructional designer, providing more time for processing the instruction and allowing the learners to adapt the presentation pace to their individual needs. Moderation analyses indicate that learners with high prior knowledge benefitted more from segmenting instructional material than learners with no or low prior knowledge in terms of retention performance.

Keywords Multimedia learning · Cognitive theory of multimedia learning · Segmenting effect · Interactivity · Learner control

Introduction

A multimedia instruction is a presentation that involves words and static or dynamic pictures that are intended to foster learning (Mayer 2014b). Approaching facilitative design issues, one conceivable technique is to divide the multimedia instruction into several segments. The

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segmenting effect, also known as the segmentation effect, states that people learn better when multimedia instructions are presented in (meaningful and coherent) learner-paced segments, rather than as continuous units (Mayer and Pilegard 2014). For example, consider a multimedia presentation concerning the process of lightning in several steps (e.g., Mayer 1997). Such an instruction can be presented as a continuous unit or as a version segmented into meaningful and coherent segments by the instructional designer. In the latter case, the learner may press a continue button to begin the next segment. Overall, the two key features concerning the segmenting effect consist of breaking the multimedia instruction into sequentially presented parts and allowing learners to pace the (segmented) multimedia instruction (Mayer and Pilegard 2014). The second part is often referred to as the pacing of a learning material, which is separated between *learner pacing* (i.e., learners are able to control the pace of the material) and *system pacing* (i.e., the system is set to a predefined pace).

Mayer and Chandler (2001) were two of the first researchers to investigate the segmenting effect. In their second experiment, students received a 140-s narrated animation describing the steps in lightning formation, followed by a retention and problem-solving transfer test. Learners received either a segmented version of the animation twice, in which each of the 16 segments could be started sequentially by pressing a continue button, or the animation that was shown two times as a continuous unit. In the segmented version, each segment explained one major step in the process of lightning formation by presenting one or two sentences of narration and a corresponding 8- to 10-s animation. Results revealed that learners receiving the segmented version performed better on transfer, but not on retention than learners who received the nonsegmented, system-paced animation.

The purpose of this paper is to present theoretical explanations and empirical findings of the segmenting effect and its moderators. First, the cognitive theory of multimedia learning (CTML) is introduced. Second, theoretical explanations concerning the segmenting effect and its moderating effects are presented. Third, this research area is investigated for the first time using a meta-analysis to test the segmenting effect and its moderating effects, followed by a discussion of the theoretical and practical implications, limitations, and future directions of this research.

Cognitive Theory of Multimedia Learning

The CTML (Mayer 2014a) is based on three assumptions. First, the human information-processing system contains a visual/pictorial channel and an auditory/verbal channel (dual-channel assumption). Second, each channel has a limited capacity for processing (limited capacity assumption), and third, active learning involves carrying out a coordinated set of cognitive processes during learning (active processing assumption). These three assumptions are verified in numerous experiments and are closely associated with Paivio's dual coding theory (Clark and Paivio 1991; Paivio 1986), Baddeley's model of working memory (Baddeley 1992, 1999), and Sweller's cognitive load theory (CLT) (Sweller 1988; Sweller et al. 2011).

Furthermore, three different memory stores are postulated in which words and images are processed including a sensory memory, a working memory, and a long-term memory. Selecting, organizing, and integrating are the major cognitive processes required for learning with words and images. Selecting relevant words means that the learner is paying attention to some of the spoken or written words that are presented in the multimedia instruction as they pass through the auditory sensory memory (Mayer 2014a). A mental representation of selected words or phrases is created in the learner's verbal working memory through this active process. Selecting relevant images involves paying attention to static or dynamic pictures that are presented in the multimedia instruction as they pass through the visual sensory memory (Mayer 2014a). This process is also active and leads to a mental representation of selected pictures in the learner's visual working memory.

Organizing selected words refers to making connections between pieces of verbal knowledge. The output is a coherent verbal model of the selected words or phrases in the learner's working memory. By organizing selected images, the learner makes connections between pieces of pictorial knowledge, resulting in a coherent pictorial model in the learner's working memory as output. Finally, integrating word-based and image-based representations refers to making connections between verbal and pictorial models, as well as the learner's prior knowledge from long-term memory (Mayer 2014a).

Explaining the Segmenting Effect

There are different, but not mutually exclusive, theoretical explanations which can be assumed for the segmenting effect (Spanjers et al. 2010). These explanations concern facilitating chunking and structuring due to segmenting the multimedia instruction by the instructional designer, providing more time for processing the instruction and allowing the learners to adapt the presentation pace to their individual needs.

First, the segmenting effect can be explained by facilitating chunking and structuring the multimedia instruction due to segmenting the instruction into meaningful and coherent segments by the instructional designer (Spanjers et al. 2010). Learners receiving multimedia instructions presented as continuous units may have more problems in chunking and structuring the instruction into meaningful and coherent segments than learners receiving multimedia instructions presented in structured segments. Such facilitates both the selecting and organizing processes postulated in the CTML (Mayer 2014a). Segmentation can be seen as a form of temporal cueing, which increases the salience of natural boundaries between events in a process or procedure (e.g., Spanjers et al. 2012). Finally, segmenting multimedia instructions is also in line with the segmentation theory (Zacks et al. 2007), which proposes that people perceive and conceive actions in terms of discrete events. Therefore, segmenting multimedia instructions helps learners to mentally represent events. In this context, learners' continuous engagement in the learning material can be regarded as series of educational events that are split up by segmentation. Beyond the event definition in basic memory research, such emphasizes a more procedural perspective on multimedia learning with reference to the global "storyline" underneath instructional episodes. Overall, learning performance should be improved by facilitating chunking and structuring the multimedia instruction due to segmenting the instruction into meaningful and coherent segments by the instructional designer (Spanjers et al. 2010).

Second, the segmenting effect can be explained by providing more time for processing the multimedia instruction (Spanjers et al. 2010; Tabbers and de Koeijer 2010). Learners receiving a (fast and transient) system-paced multimedia instruction as a continuous unit may not have sufficient time to mentally organize the essential words and pictures into a verbal and pictorial model and integrate these two mental representations with prior knowledge in their long-term memory. In line with evidence from the CTML (Mayer 2014a), these learners might be cognitively overloaded at certain points during the multimedia instruction and their working memory capacity for maintaining information may be exceeded (Spanjers et al. 2010).

According to Wickens et al. (2013), a cognitive overload situation emerges, if the task-related resource demands extend the reserve capacity of available resource supply. In consequence, learners' performance decreases.

Temporal and visual split-attention effects which are included in the multimedia instruction may also impair the cognitive processing of the (fast and transient) system-paced instruction (Stiller et al. 2011). The split-attention effect is an effect which arises when multiple sources of information are in a learning environment. This information should be integrated spatially and temporally. Otherwise, learners are forced to split their attention between the information in order to integrate the multiple sources of information and learning is inhibited (Chandler and Sweller 1992). For example, the captions of a graphic should be segmented and placed directly to the relevant area of the graphic instead of placing them as a whole text next to the graphic. By contrast, learners receiving a segmented learner-paced multimedia instruction may have enough time for the cognitive processing of the instruction and might not be cognitively overloaded and their working memory capacity may not be exceeded (cf. Kurby and Zacks 2008; Schnotz and Lowe 2008; Spanjers et al. 2010). These learners may also have enough time to repeat the multimedia instruction mentally and might be capable of reducing or compensating potential split-attention effects (Stiller et al. 2011). Overall, learning performance should be improved by learner-pacing multimedia instructions due to the provision of more processing time (Spanjers et al. 2010).

Third, the segmenting effect can be explained by allowing the learners to adapt the presentation pace to their individual needs (e.g., Hasler et al. 2007). Learners receiving multimedia instructions without learner-control options do not have the option to actively adapt the pace of the instructions to their individual needs, as opposed to learners receiving the instructions with learner-control options, such as pause and play buttons. In addition, these learners may perceive having more control over the task, resulting in higher learning performance (Wouters 2007). Overall, the learning performance should be improved by the segmenting effect due to the possibility of adapting the presentation pace to the individual learner's needs such as their pace of learning, their amount of available cognitive resources, or their need of a pause.

Moderating Effects

The segmenting effect may be moderated by additional variables. This section considers the possible moderating effects of the learner's prior domain knowledge since prior knowledge of the learner moderates several design effects derived from the CLT and CTML (Kalyuga et al. 2003; Kalyuga and Renkl 2010). Furthermore, it was pointed out that learner pacing of the learning material has a positive influence on learning processes (Spanjers et al. 2010). Therefore, the possibilities of the learner to interact with the multimedia instruction were investigated in detail. More precisely, the potential to repeat the multimedia instruction and the option to manipulate the sequence of the instruction were included and discussed as moderators.

First, the learner's prior domain knowledge or expertise may moderate the segmenting effect. This can be explained considering the expertise reversal effect (Kalyuga et al. 2003; Kalyuga and Renkl 2010). For example, presenting additional material (e.g., a written explanation to an animation) in multimedia instructions might be beneficial for novices but harmful to experts in terms of learning outcomes. In this case, an expertise reversal effect occurs in terms of the redundancy effect (i.e., excluding redundant information improves the learning outcome). The expertise reversal effect is not limited to the moderation of the redundancy effect but can also apply to other design effects, such as the visual split-attention effect or the worked example effect (Kalyuga 2007). Whereas the former refers to beneficial effects of spatially integrating related information in learning material, the latter states that providing learners with step-by-step solutions to a task instead of conventional problems increases instructional effectiveness. Often, the concerned design effect does not reverse entirely, but the relative effect is moderated by the specific level of learners' expertise, which relates to the demand for tailored instructional procedures (Kalyuga et al. 2003; Kalyuga and Renkl 2010).

The expertise reversal effect may also moderate the segmenting effect. Learners with low prior domain knowledge might depend on a learner-paced segmented multimedia instruction due to their lack of schemata. The segmentation may help these learners to reduce their (high) cognitive load, preventing a cognitive overload. By contrast, learners with high prior domain knowledge might not depend on a learner-paced segmented multimedia instruction. These learners may even be hampered through segmented guidance due to the lack of fit between the (low) task difficulty and their (high) prior knowledge (Schnotz and Kürschner 2007; Vygotski 1963). In addition, actively segmenting multimedia instructions on their own, rather than receiving segmented instructions, might be even more beneficial for these learners, as opposed to learners with low prior domain knowledge (Spanjers et al. 2010). Furthermore, a cognitive conflict between cognitively and externally segmented representations, specifically the learner's own schemata and the multimedia instruction, must be reconciled for learners with high domain knowledge, rather than for learners with low domain knowledge (Kalyuga 2009; Kalyuga et al. 2003; Spanjers et al. 2010). Overall, learners with low prior knowledge should benefit more from segmented multimedia instructions than learners with high prior knowledge, which was, for instance, indicated by the results of Spanjers et al. (2011). They showed that learners with low prior knowledge needed to invest less mental effort with segmented compared to continuous animated worked-out examples. Research on aptitude–treatment interaction (ATI; Tobias 1976) aims at adapting instructional treatments to individual differences, such as individual domain knowledge, working memory capacity, or level of intelligence. Arising evidence also supports differences in instructional effects (e.g., Lusk et al. 2009).

Second, the opportunity to repeat the multimedia instruction may also moderate the segmenting effect. Learners receiving a (fast and transient) multimedia instruction without the option of repeating the instruction may not have enough time to process the presented information compared to learners receiving a multimedia instruction which can be repeated, especially if they invest in metacognitive processes and want to repeat the material. The opportunity to repeat the multimedia instruction relates to the transient information effect (Singh et al. 2012; Wong et al. 2012) that occurs when content-related information disappears before it can be processed in an adequate manner. In addition, it might also lead to cognitive overload and exceed the capacity of the working memory, as opposed to an instruction, which can be repeated. Beneficial effects resulting from segmenting the multimedia instruction (e.g., due to the provision of more time for processing) should diminish due to the opportunity to repeat the instruction. Therefore, learners receiving multimedia instructions without the opportunity to repeat the instruction should benefit more from segmenting the instructions than learners receiving multimedia instructions, which can be repeated.

Third, the option to manipulate the sequence of the multimedia instruction may also moderate the segmenting effect. Similar to evidence from research on hypertext learning regarding linear vs. nonlinear information access (Lawless and Brown 1997; Scheiter and Gerjets 2007), an enhanced task engagement with the free choice of individual navigation paths would support the learning process. The resulting increased investment of cognitive resources for processing the multimedia instruction could also foster the establishment of more elaborated and stable schematic knowledge structures. Since learners with the option to manipulate the sequence already held the outlined advantage with regard to learning performance, no additional advantage would arise from segmenting the multimedia instruction. Thus, learners without the option to manipulate the sequence of the multimedia instruction should benefit more from the segmenting effect than learners with the option to manipulate the sequence. However, many variables moderate these navigational decisions and have to be considered on this account, including prior knowledge and metacognitive skills.

Hypotheses

The present meta-analysis investigates the segmenting effect, as well as three explanations concerning this effect: facilitating chunking and structuring due to segmenting the multimedia instruction by the instructional designer, providing more time for processing the instruction, and allowing the learners to adapt the presentation pace to their individual needs. The first hypothesis postulates that learners who receive multimedia instructions in learner-paced segments perform better on retention and transfer, perceive a lower overall cognitive load, and increase their learning time than learners who receive multimedia instructions in continuous units.

The second hypothesis assumes that learning performance is improved by the segmenting effect due to segmenting the instruction into meaningful and coherent segments by the instructional designer. The third hypothesis postulates that learning performance is improved by the segmenting effect due to the provision of more time for processing. The fourth hypothesis states that learning performance is improved by the segmenting effect due to the learners' possibility of adapting the presentation pace to their individual needs.

Further hypotheses were postulated in regard to variables that may moderate the segmenting effect on the learning outcome. These variables concern the learner's prior domain knowledge and the opportunity to repeat the multimedia instruction. The fifth hypothesis postulates that learners with lower prior knowledge should benefit more from the segmenting effect than learners with higher prior knowledge. The sixth hypothesis states that learners receiving multimedia instructions without the option of repeating the instructions should benefit more from the segmenting effect than learners receiving multimedia instructions, which can be repeated. Finally, the seventh hypothesis assumes that learners receiving multimedia instructions without the option of manipulating the sequence of the instructions should benefit more from the segmenting effect than learners receiving multimedia instructions with the option of manipulating the sequence.

Method

The meta-analysis is described according to comparable meta-analyses in similar fields of research (e.g., Ginns 2005, 2006; Schneider et al. 2018a). The 56 investigations and $k = 88$

pairwise comparisons (Tables 1 and 2) served as the database for the meta-analysis and were collected from a literature search concerning the segmenting effect, which considered studies conducted between 1990 and 2018. The literature was searched up to January 10, 2018, by using ERIC, SSCI, PsycINFO®, PSYNDEX, and Google Scholar, as well as the keywords "segmenting effect," "segmenting principle," "segmentation effect," "segmentation principle," and "learner pacing." In addition, the references of previously found manuscripts were examined for further studies concerning the segmenting effect. Finally, the function "articles citing this article" was used for the already included manuscripts. The literature search only considered works in English language and included published articles, doctoral dissertations, master theses, book chapters, conference papers, and technical reports.

Study Selection

Studies that tested at least one of the two key features of the segmenting effect (i.e., breaking the multimedia instruction into sequentially presented parts and allowing learners to pace the multimedia instruction) were included in the meta-analysis. Therefore, studies that only tested the effect of breaking the multimedia instruction into sequentially presented parts were included in the analysis. For example, in two studies from Wouters (2007), among others, the author compared a continuous nonsegmented animation with a segmented animation that paused for 3 s and then continued automatically. Experiments investigating the effects of allowing learners to pace the multimedia instruction into segments were also included in the meta-analysis. For example, in a study from Ding and Jiang (2011), learners received either a learner-controlled pacing animation providing stop and play buttons or a system-paced animation without pauses and without giving the learner an opportunity to control the presentation in any form. In addition, studies were included in which learners in the experimental group could choose the sequential order of the multimedia instruction, but learners in the control group could not (e.g., Mayer et al. 2003, Experiment 2a and 2b; Tabbers and de Koeijer 2010).

In addition, studies where the experimental group received different kinds of additional user-control options to manipulate the sequence of the multimedia instruction, but not the control group (e.g., Chen 2016; Hatsidimitris and Kalyuga 2013; Izmirli and Kurt 2016), were included in the analysis and analyzed separately in line with the seventh hypothesis. However, studies that tested the segmenting effect, but which were inextricably linked with other variables, such as self-assessment questions and an interactive simulation (see Evans and Gibbons 2007), were not included in the meta-analysis.

Moreover, articles possibly concerning the segmenting effect, but which did not contain a subsequent test that could either be assigned as a retention or transfer test (e.g., Spanjers et al. 2010), were not included in the meta-analysis. In this regard, retention is considered as the ability to store information and retrieve or recognize the information later. This multidimensional ability can be measured by testing if learners can repeat, list, name, recognize, or reproduce factual information (cf. Anderson et al. 2001; Bloom and Krathwohl 1956; Bloom et al. 1981). Therefore, retention questions should be answered with the information that was given in the multimedia instruction without the inference of additional information. In the current study selection, a broad definition of retention was applied and both recognition measures (such as multiple-choice tests) and recall measures (such as free and cued recall) were considered. Transfer performance is related to the multifaceted potential to acquire the meaning of the stored information and apply it to new contexts. Therefore, in transfer questions, inferences should be drawn from the presented information in the multimedia instruction (cf. Anderson et al. 2001; Bloom and Krathwohl 1956; Bloom et al. 1981; Mayer 2014b). Following Barnett and Ceci (2002), transfer can be defined according to the extent of similarity between learning and transfer context. Contrary to a far transfer, which directs toward the improvement of general cognitive skills, the selected studies employed questions targeting near transfer due to the high similarity to the learning task.

Coding of Study Features

Tables 1 and 2 contain 88 pairwise comparisons. Table 1 presents the year of the study was published; the number of participants, which is relevant for the segmenting effect; the mean age in years; the proportion of females; the assignment to system or learner pacing; the learning topic as well as the learning topic group; the modality of the multimedia instruction; and the type of interactivity tools. Table 2 includes the effect sizes of each pairwise comparison for retention, transfer, overall cognitive load, and learning time, the three investigated explanations for the segmenting effect, and three moderating variables. A minimum of two raters coded each study and clarified discrepancies among themselves. If they were not able to do so, a third rater and in some cases a fourth rater discussed the discrepancies until a solution could be provided.

The three hypotheses concerning the explanations for the segmenting effect were coded separately. The first explanation postulates that segmenting the multimedia instruction into meaningful segments by the instructional designer facilitates chunking and structuring (see above). If only the segmented experimental group received a multimedia instruction segmented by the instructional designer, the experimental effect was included for this explanation. If the study did not explicitly specify the use of meaningful or random segments for the segmentation and no information in the article casts doubt on this assumption, it was also assumed that the researchers used meaningful segments rather than random segments (e.g., by the usage of exactly equally long segments). However, if the multimedia instruction of a study seemed impossible to segment into meaningful segments, the experimental effect was not considered for the first explanation. For example, it was presumed that the instructional materials used in the studies of Schnotz (2002, Exp. 2) and Schneider and Boucheix (2006) would not be possible to segment into meaningful units. First, in the second experiment of Schnotz (2002), a simulation showed the earth as a sphere rotating in a shell of different time states. Learners could circumnavigate the earth in western or eastern direction with four different speeds. They received either a segmented version in which they could circumnavigate stepwise or a continuous version. Second, Schneider and Boucheix (2006) used an animated diagram of a pulley system. Learners received either a noncontrollable animation or a sequential dynamic version where the animation was split into five short segments. In the animation, accordingly, the five segments could be activated by clicking with the mouse in the diagram area.

The second explanation postulates that providing more time for processing the multimedia instruction led to the segmenting effect (see above). If the learning time of the nonsegmented control group was shorter than the learning time of the segmented experimental group, in regard to the particular segments of the multimedia instruction, the segmentation of the material should lead to improved learning outcomes. Therefore, learning time in seconds was coded both for the experimental and for the control group in each study. For example, a continue button or a pause button provides more time for processing the multimedia instruction.

Table 1 Overview of all features of the included studies in the meta-analysis

No.	Study	Year	Sample *N*	Mean age (in years)	Proportion of females	System pacing	Learning topic	Learning topic group	Modality	Type of interactivity tools
1	Ali and Madar	2010	65	20.0	–	CG	Transmission media	Social science	Visual	Forward and backward buttons
2	Ali and Madar	2010	69	20.0	–	CG	Transmission media	Social science	Visual	Play, pause, and replay buttons
3	Ali and Madar	2010	101	20.0	–	–	Transmission media	Other	Visual	–
4	Ali and Madar	2010	48.5	20.0	–	–	Transmission media	Other	Visual	–
5	Ali and Madar	2010	52.5	20.0	–	CG	Transmission media	Other	Visual	Play and pause buttons
6	Biard, Cojean, and Jamet	2018	68	21.9	87.0%	CG	Orthopedic technology	Social science	Mixed	Play and pause buttons
7	Biard, Cojean, and Jamet	2018	34.5	21.9	87.0%	CG	Orthopedic technology	Social science	Mixed	Play and pause buttons
8	Biard, Cojean, and Jamet	2018	33.5	21.9	87.0%	CG	Orthopedic technology	Social science	Mixed	Play and pause buttons
9	Boucheix and Guignard	2005	123	–	–	CG	Gearing system (with two wheels)	Natural science or mechanics	Visual	Play, pause, and replay buttons
10	Boucheix and Schneider	2009	29	20.6	91.1%	LP	Functionality of a pulley	Natural science or mechanics	Visual	Forward by mouse click
11	Chen	2016	60	–	–	CG	Adobe Illustrator Pen Tool	Other	Mixed	play, pause, forward, and replay buttons; menu buttons
12	Chung	2006	150	22.0	74.7%	CG	Cardiovascular system	Natural science or mechanics	Mixed	Forward, backward, and replay buttons
13	Dalton	1990	98		45.9%	CG	Structure and flight curves of comets	Natural science or mechanics	Mixed	Forward by space key
14	Ding and Jiang	2011	120	15.0	46.7%	CG	Causes of a solar eclipse	Natural science or mechanics	Mixed	Play and pause buttons
15	Doolittle, Bryant, and Chittum	2015	212	20.1	51.4%	CG	Analyzing historical references	History	Mixed	Play and pause buttons
16	Doolittle	2010	269	20.3	46.3%	CG	Analyzing historical references	History	Mixed	Forward buttons
17	Ertelt	2007	81	25.1	60.4%	CG	Software RagTime	Other	Mixed	Forward buttons
18	Ertelt	2007	83	22.4	44.7%	CG	Software RagTime	Other	Mixed	Play, pause, forward, and replay buttons
19	Falvo, Urban, and Suits	2011	96	–	–	LP	Dissolving of salt in water	Natural science or mechanics	Mixed	Pause buttons
20	Falvo, Urban, and Suits	2011	96	–	–	LP	Dissolving of salt in water	Natural science or mechanics	Mixed	Pause buttons
21	Fong, Lily, and Por	2012	165	–	–	Yes	Meiosis	Natural science or mechanics	Visual	–
22	Hasler, Kersten, and Sweller	2007	54	10.0	0.00%	Yes	Formation of a day–night shift	Natural science or mechanics	Mixed	Play, pause, and forward buttons
23	Hasler, Kersten, and Sweller	2007	36	10.0	0.00%	Yes	Formation of a day–night shift	Natural science or mechanics	Mixed	Forward buttons

Table 1 (continued)

No.	Study	Year	Sample *N*	Mean age (in years)	Proportion of females	System pacing	Learning topic	Learning topic group	Modality	Type of interactivity tools
24	Hasler, Kersten, and Sweller	2007	36	10.0	0.00%	Yes	Formation of a day–night shift	Natural science or mechanics	Mixed	Play and pause buttons
25	Hassanabadi, Robatjazi, and Savoji	2011	80	–	100.0%	CG	Formation of a lightning	Natural science or mechanics	Mixed	Forward buttons
26	Hatsidimitris and Kalyuga	2013	20	–	–	CG	Chinese symbols	Social science	Mixed	Timeline scrollbar
27	Hatsidimitris and Kalyuga	2013	23	–	–	CG	Physical waves	Natural science or mechanics	Mixed	Timeline scrollbar
28	Hatsidimitris and Kalyuga	2013	23	–	–	CG	Physical waves	Natural science or mechanics	Mixed	Timeline scrollbar
29	Huffman	2016	84	19.3	56.0%	Yes	Quantitative analyzing models	Mathematics or statistics	Mixed	–
30	Izmir and Kurt	2016	97	–	63.3%	CG	Basic concepts of computer-aided instruction	Social science	Mixed	Play, pause, forward, and replay buttons
31	Kapli	2010	33	20.5	–	LP	Energy and hydraulic grade lines in a fluid mechanics (engineering)	Natural science or mechanics	Mixed	–
32	Karim and Behrend	2014	323	–	34.0%	Yes	Excel calculations	Other	–	Play, pause, forward, and replay buttons; menu buttons
33	Khacharem, Spanjers, Zoudji, Kalyuga, and Ripoll	2013	24	26.2	0.0%	LP	Tactical combinations of a soccer play	Other	Visual	–
34	Khacharem, Spanjers, Zoudji, Kalyuga, and Ripoll	2013	24	25.8	0.0%	LP	Tactical combinations of a soccer play	Other	Visual	–
35	Koc-Januchta	2016	235	21.7	74.5%	Yes	Photosynthesis	Natural science or mechanics	Mixed	Play, pause, forward, and replay buttons
36	Kühl, Eitel, Damnik, and Körndle	2014	79	20.6	86.1%	CG	Weather phenomena	Natural science or mechanics	Mixed	Play, pause, and forward buttons
37	Lusk	2008	167	–	–	CG	Formation of a lightning	Natural science or mechanics	Mixed	Forward buttons
38	Lusk, Evans, Jeffrey, Palmer, Wikstrom, and Doolittle	2009	133	20.1	55.6%	CG	Analyzing historical references	History	Mixed	Forward buttons
39	Mariano	2008	214	–	–	CG	Functionality of a car break	Natural science or mechanics	Mixed	Forward buttons
40	Mariano	2014	214	–	–	CG	Functionality of a car break	Natural science or mechanics	Mixed	Forward buttons
41	Mayer and Chandler	2001	29	18.9	89.9%	CG	Formation of a lightning	Natural science or mechanics	Mixed	Forward buttons

Table 1 (continued)

No.	Study	Year	Sample N	Mean age (in years)	Proportion of females	System pacing	Learning topic	Learning topic group	Modality	Type of interactivity tools
42	Mayer, Dow, and Mayer	2003	37	–	–	CG	Functionality of a motor	Natural science or mechanics	Mixed	Menu buttons
43	Mayer, Dow, and Mayer	2003	41	–	–	CG	Functionality of a motor	Natural science or mechanics	Mixed	Menu buttons
44	Mayer, Howarth, Kaplan, and Hanna	2018	196	19	75.0%	LP	Graphic information system	Mathematics or statistics	Mixed	–
45	Mayer, Moreno, Boire, and Vagge	1999	48	–	–	Yes	Formation of a lightning	Natural science or mechanics	Mixed	–
46	Mayer, Moreno, Boire, and Vagge	1999	48	–	–	Yes	Functionality of a car break	Natural science or mechanics	Mixed	–
47	Milheim	1990	99	–	–	LP	Computer program for photography	Natural science or mechanics	Visual	Forward buttons
48	Moreno	2007	121	25.3	73.5%	CG	Knowledge about teacher behavior	Social science	Mixed	Forward buttons
49	Moreno	2007	114	25.0	72.7%	CG	Knowledge about teacher behavior	Social science	Mixed	Forward buttons
50	Ng, Kalyuga, and Sweller	2013	152	19.4	–	Yes	Electric circuits	natural science or mechanics	Visual	Play and pause buttons
51	Patwardhan and Murthy	2015	76	–	18.7%	Yes	Transformation of time signals	Mathematics or statistics	Visual	Play and pause buttons
52	Rusli, Ardhana, Sudana, and Kamdi	2014	164	–	–	–	Applying object-oriented modeling concepts	Other	Mixed	Play and pause buttons
53	E. Schneider and Boucheix	2006	81	–	–	LP	Functionality of a pulley	Natural science or mechanics	Visual	Forward by mouse click
54	Schnotz	2002	27	–	–	LP	Time zones	Natural science or mechanics	Visual	Speed and direction buttons
55	Schnotz	2002	27	–	–	LP	Time zones	Natural science or mechanics	Visual	Speed and direction buttons
56	Schüler, Scheiter, and Gerjets	2013	41	24.3	55.7%	CG	Mitosis	Natural science or mechanics	Auditive	Forward and backward buttons
57	Schüler, Scheiter, and Gerjets	2013	41	24.3	55.7%	CG	Mitosis	Natural science or mechanics	Visual	Forward and backward buttons
58	Schüler, Scheiter, and Gerjets	2013	41	24.3	55.7%	CG	Mitosis	Natural science or mechanics	Mixed	Forward and backward buttons
59	Schwan and Riempp	2004	36	23.0	–	CG	Nautical knots	Other	Visual	Stop, slow motion, forward, and direction change buttons
60	Singh, Marcus, and Ayres	2012	32	15.5	0.0%	Yes	Understanding laws	Social science	Auditive	–

Table 1 (continued)

No.	Study	Year	Sample *N*	Mean age (in years)	Proportion of females	System pacing	Learning topic	Learning topic group	Modality	Type of interactivity tools
61	Singh, Marcus, and Ayres	2012	31	15.5	0.0%	Yes	Understanding laws	Social science	Mixed	–
62	Singh, Marcus, and Ayres	2012	32	15.5	0.0%	Yes	Understanding laws	Social science	Auditive	–
63	Singh, Marcus, and Ayres	2012	32	15.5	0.0%	Yes	Understanding laws	Social science	Mixed	–
64	Singh, Marcus, and Ayres	2017	29	15.5	0.0%	Yes	Economics	Social science	Auditive	–
65	Song	2016	61	9.0	–	Yes	English course	Social science	Visual	–
66	Song	2016	60	9.0	–	Yes	English course	Social science	Visual	–
67	Spanjers, van Gog, Wouters, and van Merriënboer	2012	161	14.8	50.9%	Yes	Probability calculations	Mathematics or statistics	Mixed	–
68	Spanjers, van Gog, Wouters, and van Merriënboer	2011	75	16.2	53.0%	Yes	Probability calculations	Mathematics or statistics	Mixed	–
69	Stiller and Zinnbauer	2011	77	29.5	39.0%	CG	Genetic fingerprint	Natural science or mechanics	Mixed	Forward buttons
70	Stiller, Freitag, Zinnbauer, and Freitag	2009	110	23.2	76.4%	CG	Structure and functions of the eye	Natural science or mechanics	Mixed	Forward buttons
71	Stiller, Petzold, and Zinnbauer	2011	142	23.5	81.7%	CG	Structure and functions of the eye	Natural science or mechanics	Visual	Forward buttons
72	Tabbers	2002	63	20.5	91.5%	CG	Designing a training program	Social science	Mixed	Forward and replay buttons
73	Tabbers and de Koeijer	2010	52	22.5	67.3%	CG	Formation of a lightning	Natural science or mechanics	Mixed	Stop and play buttons, menu buttons
74	Tullis and Benjamin	2011	148	–	–	CG	Word lists	Other	Visual	Forward by space key
75	Tullis and Benjamin	2011	234	–	–	CG	Word lists	Other	Visual	Forward by space key
76	Tullis and Benjamin	2011	156	–	–	CG	Word lists	Other	Visual	Forward by space key
77	Tullis and Benjamin	2011	156	–	–	Yes	Word lists	Other	Visual	Forward by space key
78	Visser	2009	108	20.8	80.6%	Yes	Excel calculations	Other	Mixed	–
79	Ward	2008	87	25.5	81.2%	Yes	Division of integer numbers	Mathematics or statistics	Mixed	Forward buttons
80	Wong, Leahy, Marcus, and Sweller	2012	33	10.5	57.6%	Yes	Folding paper figures	Other	Visual	–
81	Wong, Leahy, Marcus, and Sweller	2012	33	10.5	57.6%	Yes	Folding paper figures	Other	Mixed	–
82	Wong, Leahy, Marcus, and Sweller	2012	21	11.5	–	Yes	Temperature–time graphs	Natural science or mechanics	Visual	–
83	Wong, Leahy, Marcus, and Sweller	2012	21	11.5	–	Yes	Temperature–time graphs	Natural science or mechanics	Mixed	–
84	Wouters	2007	60	15.8	51.7%	CG	Probability calculations		Mixed	–

Table 1 (continued)

No.	Study	Year	Sample *N*	Mean age (in years)	Proportion of females	System pacing	Learning topic	Learning topic group	Modality	Type of interactivity tools
								Mathematics or statistics		
85	Wouters	2007	60	15.8	51.7%	CG	Probability calculations	Mathematics or statistics	Mixed	Forward and backward buttons
86	Wouters	2007	78	16.0	42.3%	CG	Probability calculations	Mathematics or statistics	Visual	–
87	Wouters	2007	78	16.0	42.3%	CG	Probability calculations	Mathematics or statistics	Visual	Forward and backward buttons
88	Yeh and Lehman	2001	111	20.0	–	CG	English course	Other	Mixed	Play, pause, and replay buttons; menu buttons

CG, only in the control group; *LP*, learner pacing

Table 2 Overview of experimental findings concerning the segmenting effect as well as all moderators postulated in the hypotheses

No.	Study	Effect sizes (*d*)				Explanations for the segmenting effect			Further moderating variables		
		Retention	Transfer	Cognitive load	Learning time	Segmenting	Longer learning time in the EG	Pause option only in the EG	Prior knowledge	Repeat option	Option to manipulate sequence
1	Ali and Madar	0.90	–	–	–	Yes	Yes	No	No	No	Yes
2	Ali and Madar	0.14	–	–	–	No	Yes	Yes	No	EG	No
3	Ali and Madar	–	0.49	–	–	–	–	–	No	–	No
4	Ali and Madar	–	0.91	–	–	Yes	No	No	No	Yes	–
5	Ali and Madar	–	0.14	–	–	No	Yes	Yes	No	Yes	No
6	Biard, Cojean, and Jamet	0.17	–	–	–	–	–	–	No	–	No
7	Biard, Cojean, and Jamet	−0.08	–	–	–	No	–	Yes	No	No	No
8	Biard, Cojean, and Jamet	0.41	–	–	–	Yes	–	Yes	No	No	No
9	Boucheix and Guignard	0.06	−0.05	–	–	No	Yes	No	Low	No	No
10	Boucheix and Schneider	1.11	−0.06	–	−1.38	No	Yes	No	No	Yes	No
11	Chen	0.45	0.64	–	−0.26	No	–	Yes	No	EG	Yes
12	Chung	0.00	–	–	–	No	Yes	No	–	EG	No
13	Dalton	0.92	–	–	−2.05	No	Yes	No	No	No	No
14	Ding and Jiang	0.27	0.90	0.37	–	No	Yes	Yes	No	No	No
15	Doolittle, Bryant, and Chittum	0.86	0.74	–	−2.39	Yes	Yes	Yes	–	No	No
16	Doolittle	0.40	0.32	–	–	Yes	Yes	No	No	No	No
17	Ertelt	−0.36	0.38	–	–	Yes	No	No	No	Yes	No
18	Ertelt	−0.32	–	–	–	Yes	No	No	No	Yes	Yes
19	Falvo, Urban, and Suits	−0.07	–	–	–	No	Yes	Yes	Low	Yes	Yes
20	Falvo, Urban, and Suits	−0.71	–	–	–	No	Yes	Yes	Low	Yes	No
21	Fong, Lily, and Por	0.60	–	–	–	Yes	No	No	No	No	–
22	Hasler, Kersten, and Sweller	–	0.90	0.42	–	–	Yes	–	Low	Yes	No
23	Hasler, Kersten, and Sweller	–	0.82	0.44	–	Yes	Yes	No	Low	Yes	No
24	Hasler, Kersten, and Sweller	–	0.93	0.34	–	No	Yes	Yes	Low	Yes	No
25	Hassanabadi, Robatjazi, and Savoji	0.53	0.24	0.55	–	No	Yes	No	–	No	No
26	Hatsidimitris and Kalyuga	4.21	–	–	–	No	–	No	No	EG	Yes
27	Hatsidimitris and Kalyuga	0.92	–	–	–	No	–	No	No	EG	Yes
28	Hatsidimitris and Kalyuga	−0.36	–	–	–	No	–	No	No	EG	Yes
29	Huffman	–	−0.49	–	–	Yes	No	No	–	No	–
30	Izmir and Kurt	0.35	–	−0.29	–	No	No	Yes	No	EG	Yes

Table 2 (continued)

No.	Study	Effect sizes (*d*)				Explanations for the segmenting effect			Further moderating variables		
		Retention	Transfer	Cognitive load	Learning time	Segmenting	Longer learning time in the EG	Pause option only in the EG	Prior knowledge	Repeat option	Option to manipulate sequence
31	Kapli	0.00	−0.34	–	−0.43	Yes	No	No	Low	No	–
32	Karim and Behrend	−0.28	–	–	–	No	–	Yes	–	EG	Yes
33	Khacharem, Spanjers, Zoudji, Kalyuga, and Ripoll	1.50	–	–	–	Yes	Yes	No	No	Yes	–
34	Khacharem, Spanjers, Zoudji, Kalyuga, and Ripoll	0.38	–	–	–	Yes	Yes	No	High	Yes	–
35	Koc-Januchta	−0.21	–	–	–	No	No	Yes	Low	EG	Yes
36	Kühl, Eitel, Damnik, and Körndle	1.06	0.55	0.60	−2.47	No	Yes	Yes	–	No	No
37	Lusk	−0.15	−0.18	–	–	Yes	Yes	No	Low	No	No
38	Lusk, Evans, Jeffrey, Palmer, Wikstrom, and Doolittle	0.54	0.38	–	–	Yes	Yes	No	No	No	No
39	Mariano	−0.16	−0.08	–	–	No	Yes	No	No	No	No
40	Mariano	−0.16	−0.08	–	–	Yes	–	No	Low	No	No
41	Mayer and Chandler	−0.31	1.15	−0.3	–	Yes	Yes	No	No	No	No
42	Mayer, Dow, and Mayer	–	0.83	–	–	No	Yes	Yes	–	EG	Yes
43	Mayer, Dow, and Mayer	–	1.00	–	–	No	Yes	Yes	–	EG	Yes
44	Mayer, Howarth, Kaplan, and Hanna	–	0.34	0.28	−0.41	Yes	Yes	No	No	No	–
45	Mayer, Moreno, Boire, and Vagge	0.86	1.63	–	–	Yes	No	No	–	No	No
46	Mayer, Moreno, Boire, and Vagge	1.54	1.25	–	–	Yes	No	No	–	No	No
47	Milheim	−0.07	–	–	–	No	Yes	No	Low	No	No
48	Moreno	0.68	0.40	0.61	–	Yes	Yes	No	–	No	No
49	Moreno	0.75	0.62	0.90	–	Yes	Yes	No	–	No	No
50	Ng, Kalyuga, and Sweller	−0.05	–	−0.12	–	No	No	Yes	No	No	No
51	Patwardhan and Murthy	−0.42	−0.27	–	–	No	–	Yes	No	No	No
52	Rusli, Ardhana, Sudana, and Kamdi	–	0.48	–	–	No	–	Yes	–	No	No
53	E. Schneider and Boucheix	0.20	−0.08	–	–	No	Yes	No	No	Yes	No
54	Schnotz	−0.34	1.21	–	–	No	No	No	Low	Yes	No
55	Schnotz	1.00	0.24	–	–	No	No	No	High	Yes	No
56	Schüler, Scheiter, and Gerjets	0.28	−0.10	−0.08	–	No	–	Yes	Low	No	Yes

Table 2 (continued)

No.	Study	Effect sizes (d)				Explanations for the segmenting effect			Further moderating variables		
		Retention	Transfer	Cognitive load	Learning time	Segmenting	Longer learning time in the EG	Pause option only in the EG	Prior knowledge	Repeat option	Option to manipulate sequence
57	Schüler, Scheiter, and Gerjets	0.13	0.09	−0.14	–	No	–	Yes	Low	No	Yes
58	Schüler, Scheiter, and Gerjets	0.17	0.08	0.11	–	No	–	Yes	Low	No	Yes
59	Schwan and Riempp	–	–	–	1.18	No	No	Yes	No	EG	Yes
60	Singh, Marcus, and Ayres	0.57	0.16	–	–	Yes	Yes	No	High	No	–
61	Singh, Marcus, and Ayres	1.09	0.21	–	–	Yes	Yes	No	High	No	–
62	Singh, Marcus, and Ayres	0.78	0.95	–	–	Yes	Yes	No	High	No	–
63	Singh, Marcus, and Ayres	1.37	2.29	–	–	Yes	Yes	No	High	No	–
64	Singh, Marcus, and Ayres	−0.29	−0.57	–	–	Yes	Yes	No	Low	No	–
65	Song	−0.41	−0.47	0.08	–	Yes	No	No	No	No	–
66	Song	0.28	0.80	0.07	–	Yes	No	No	High	No	–
67	Spanjers, van Gog, Wouters, and van Merriënboer	–	0.33	–	–	Yes	No	No	No	No	–
68	Spanjers, van Gog, Wouters, and van Merriënboer	–	0.24	–	0.20	Yes	No	No	Low	No	–
69	Stiller and Zinnbauer (2011)	0.10	0.53	−0.33	−1.34	Yes	Yes	No	Low	No	No
70	Stiller, Freitag, Zinnbauer, and Freitag	0.14	0.19	0.35	0.18	Yes	Yes	No	Low	Yes	No
71	Stiller, Petzold and Zinnbauer	0.29	0.23	0.72	0.15	Yes	Yes	No	Low	No	No
72	Tabbers	0.42	0.24	–	−2.24	No	Yes	No	–	EG	No
73	Tabbers and de Koeijer	0.23	0.55	–	−1.24	No	Yes	Yes	No	EG	Yes
74	Tullis and Benjamin	0.35	–	–	–	No	Yes	Yes	No	No	No
75	Tullis and Benjamin	0.69	–	–	–	No	Yes	Yes	No	No	No
76	Tullis and Benjamin	0.44	–	–	–	–	–	–	No	No	No
77	Tullis and Benjamin	0.93	–	–	–	–	–	–	No	No	No
78	Visser	–	0.19	–	–	Yes	No	No	No	No	No
79	Ward	–	0.06	–	0.49	No	Yes	No	Low	Yes	No
80	Wong, Leahy, Marcus, and Sweller	0.56	–	–	–	Yes	No	No	No	No	–
81	Wong, Leahy, Marcus, and Sweller	−0.66	–	–	–	Yes	No	No	No	No	–

Table 2 (continued)

No.	Study	Effect sizes (*d*)				Explanations for the segmenting effect			Further moderating variables		
		Retention	Transfer	Cognitive load	Learning time	Segmenting	Longer learning time in the EG	Pause option only in the EG	Prior knowledge	Repeat option	Option to manipulate sequence
82	Wong, Leahy, Marcus, and Sweller	−0.97	–	–	–	Yes	No	No	No	No	–
83	Wong, Leahy, Marcus, and Sweller	1.56	–	–	–	Yes	No	No	No	No	–
84	Wouters	–	−0.23	–	0.77	Yes	Yes	Yes	Low	No	–
85	Wouters	–	−0.15	–	0.03	No	Yes	No	Low	No	Yes
86	Wouters	–	−0.09	–	0.22	Yes	Yes	Yes	Low	No	–
87	Wouters	–	0.44	–	0.28	No	Yes	No	Low	No	Yes
88	Yeh and Lehman	0.57	–	–	–	No	Yes	Yes	–	EG	Yes

EG, only in the experimental group

The third explanation assumes that the segmenting effect arises due to allowing the learners to adapt the presentation pace to their individual needs (see above). If learners in the segmented experimental group could interrupt the multimedia instruction to suit their individual needs, and the nonsegmented control group could not, the experimental effect was considered for this explanation. For example, a pause button represents the possibility to adapt the presentation pace to the learner's individual needs, while a continue button normally does not. If studies fitted in more than one explanation due to the design of the specific experiment or due to the information which was provided by the authors, the data was incorporated in the analyses of multiple explanations.

Three moderator variables were coded in Table 2. First, the learner's prior domain knowledge was considered. In the present meta-analysis, learners either possessed no prior domain knowledge, only some prior domain knowledge, or higher prior domain knowledge. No prior knowledge was assigned to studies, where the authors explicitly wrote that participants did not have any prior knowledge before the experiment. For example, Hatsidimitris and Kalyuga (2013) wrote that "All candidates who had prior knowledge in a character-based language were excluded from participating." High prior knowledge was assigned to studies, where the authors explicitly wrote that participants had a high prior knowledge before the experiment. For example, Song (2016) wrote "The scores of the English competition test which had been officially administered by the school two months earlier than this experiment were used to measure students' prior knowledge. By using a median split, the participants were assigned to a high score group ($n = 60$) […]".

Second, the learners' opportunity to repeat the multimedia instruction varied. Learners could either repeat the multimedia instructions, could not repeat the instructions, or could repeat the instructions only in the experimental condition. For example, the opportunity to repeat the multimedia instruction can refer to replay the presentation after it ended (e.g., Hasler et al. 2007) or to replay the narration accompanying a particular slide (Ward 2008).

Finally, the opportunity to manipulate the sequence of the multimedia instruction of the study was added as a moderator. Learners could either manipulate the sequence (i.e., the order in which the segments can be viewed) or could not manipulate the sequence of the multimedia instruction. For example, assume you have three segments A, B, and C. If you cannot manipulate the sequence of the multimedia instruction, then the order of the three segments is fixed (i.e., A–B–C). In contrast, if you can manipulate the sequence, then you can view the segments in six different orders (i.e., A–B–C, A–C–B, B–A–C, B–C–A, C–A–B, and C–B–A). Furthermore, Table 2 includes the effect size d for the dependent measurements of retention, transfer, overall cognitive load, and learning time. A positive value of d in Table 2 is defined as supporting the segmenting effect: higher retention or transfer scores for the segmented experimental group compared to the nonsegmented control group, lower overall cognitive load scores, and less time for the experimental group compared to the control group. Cognitive load was assessed in the studies by subjective ratings with five-, seven-, or nine-point Likert scales that referred to either mental effort or difficulty. Both measures reflect cognitive demands in instructional situations and comprise vested means of assessment in multimedia research (e.g., Kalyuga et al. 1999; Paas 1992).

Sample Characteristics

The overall sample size of all studies, which were relevant for the segmenting effect, amounted to $N = 7713$ ($N = 3662$ for the segmentation condition). For retention performance, 6120 participants divided into 68 pairwise comparisons were considered in the meta-analysis, 4786 participants divided into 57 pairwise comparisons for transfer performance, 1687 participants divided into 20 pairwise comparisons for overall cognitive load, and 1625 participants divided into 19 pairwise comparisons for learning time. The 88 pairwise comparisons that included these effect sizes were published mainly as journal articles (69), followed by 14 doctoral dissertations, four conference proceedings, and one master thesis. The mean age of the participants considered for the meta-analysis was 19.71 years, and the overall percentage of women was 56.4%. The prior domain knowledge of the majority of the participants was low rather than high. Forty-one pairwise comparisons indicated no prior domain knowledge of the participants, 25 pairwise comparisons refer to some prior domain knowledge, seven refer to high prior domain knowledge, and 15 experiments lacked information on participants' expertise. All of the experiments used a between-subject design. The sample sizes, which were relevant for the segmenting effect, varied from $N = 20$ to $N = 323$. The mean sample size was $N = 87.65$ (SD = 63.89). Pairwise comparisons are outlined in Table 2, separated by outcome measure.

The multimedia instruction was presented either visually (29 pairwise comparisons), or auditory (four pairwise comparisons) or mixed (54 pairwise comparisons). The learning topics of the multimedia instructions included mainly natural scientific topics or mechanics (39 pairwise comparisons), such as the development of lightning formation or the functioning of a car brake. Ten pairwise comparisons included mathematics or statistics such as probability calculation, three comparisons used historical science and historical inquiry, 17 comparisons were in the social sciences, such as teaching skills, while the remaining 19 comparisons used other subject areas. The average reported presentation duration of the multimedia instructions for the control group without segmentation was approximately 19 min ($M = 1137.21$ s, SD = 1437.53). Furthermore, participants received an average reported segment length of 75.49 s (SD = 109.63). Multimedia instructions could be repeated by the participants in 17 pairwise comparisons in both conditions (i.e., segmentation group and control group), in 15 pairwise comparisons only in the segmentation group, while 54 pairwise comparisons did not include the possibility of repeating the multimedia instructions in both conditions.

Analysis Methods

The implementation and statistical evaluation of the meta-analysis were based on Field and Gillett's (2010) approach. In this meta-analysis, d was defined as the difference between the means of the segmented experimental group and the nonsegmented control group, which were later divided by the pooled standard deviation and then adjusted for the small bias due to the small sample sizes (Hedges and Olkin 1985). Therefore, a positive d value supports the segmenting effect. The criterion for a small, medium, or large effect size was based on Hattie's (2009) study, which investigated over 800 meta-analyses. For educational achievements, values of $d = 0.20$, 0.40, and 0.60 were used to describe small, medium, and large effects, respectively. The effect sizes of all pairwise comparisons were computed using the means and standard deviations reported in the studies. For each outcome measure, only one mean effect size was computed per experiment. Thus, the aggregated effect sizes from all the studies were independent even if the effect sizes within the studies were dependent (Hedges et al. 2010). When standard deviations were not reported and only means were displayed, test scores (t or F values) were used to compute the average standard deviation. If only t or F values were reported and means and standard deviations were not presented, these t and F values (or the corresponding p values) and sample sizes were used to calculate the effect sizes and the standard errors, using the practical meta-analysis effect size calculator (Wilson 2001). If the experiment included more than one effect size per dependent measure, the effects were averaged. For example, if the experiment apportioned transfer performance in different subcategories (e.g., near and far transfer), the effects were averaged. Formulae reported in Rustenbach (2003) were used to convert other effect sizes into the effect size *d*. Segmenting techniques, segmenting conditions, and the media under which segmenting was operationalized varied significantly across the studies. Therefore, a random-effects model was preferred to a fixed-effect model (Hedges and Vevea 1998). This approach is based on Field and Gillet (2010), who recommended a random-effects model in social sciences. Each computed effect size was standardized by the inversed squared standard error to increase the weighting of studies with larger sample sizes (e.g., Cooper et al. 2009). Calculations were carried out using SPSS 25.0 (IBM Corp. 2017). The SPSS scripts “MetaES” and “MetaF” (Lipsey and Wilson 2001; Wilson 2010) were used to aggregate effect sizes.

The publication bias analysis was carried out using two methods. First, funnel plots were conducted and observed (cf. Sterne et al. 2005). Additionally, the rank correlation was computed (Begg and Mazumdar 1994).

Results

Outlier and Publication Bias Analyses

First of all, the calculated effect sizes were tested for outliers. Therefore, a Grubbs’ test (Grubbs 1969) was conducted for all dependent variables. Regarding retention performance, following the approach postulated by Hoaglin et al. (1983), the effect size of $d = 4.21$ from Hatsidimitris and Kalyuga (2013) was excluded from publication bias and further analyses. In terms of transfer performance, the effect size of $d = 2.29$ from Sing et al. (2012) was excluded from the meta-analysis. There were no significant outliers in regard to overall cognitive load and learning time.

Since most of the included studies were published, a publication bias analysis was conducted. Therefore, a possible publication bias distortion should be examined for all outcome measures. Regarding retention, the funnel plot indicates no publication bias (all funnel plots are displayed in the Appendix). According to Sterne et al. (2005), no effect sizes are underrepresented. An additional rank correlation was nonsignificant, $\tau(N = 67) = 0.06$, $p = 0.63$, which indicates that a publication bias was probably not present for retention performance. With respect to transfer performance, the funnel plot showed no publication bias as well. The rank correlation supports this assumption, $\tau(N = 56) = 0.02$, $p = 0.88$. Less empirical data was available concerning overall cognitive load and learning time. Therefore, an interpretation of the funnel plots is difficult. In terms of overall cognitive load, the funnel plot indicates no publication bias. Furthermore, the rank correlation supports the missing publication bias, $\tau(N = 20) = 0.03$, $p = 0.89$. Finally, learning time was investigated. The funnel plot shows heterogeneous data (ranging from $d = -2.47$ to $d = 1.18$). According to rank correlation, there was a significant publication bias regarding learning time, $\tau(N = 19) = 0.51$, $p = 0.03$. In consequence, results concerning the dependent variable learning time have to be interpreted with caution.

The Overall Segmentation Effect

An overview of the overall segmentation effect on all outcome measures is provided in Table 3.

Table 3 Aggregated effect sizes and confidence intervals for outcome measures of the overall effect and separated in terms of system-paced segmentation and learner-paced segmentation

Outcome measure	Number of comparisons *k*	Number of participants *n*	Effect size *d*	95% CI for *d*
Overall effect				
Retention	67	6100	0.32***	[0.20, 0.43]
Transfer	56	4754	0.36***	[0.24, 0.48]
Cognitive load	20	1687	0.23**	[0.06, 0.39]
Learning time	19	1625	− 0.92*	[− 1.64, − 0.20]
System-paced segmentation				
Retention	32	2578	0.42***	[0.21, 0.63]
Transfer	30	2890	0.35***	[0.16, 0.54]
Cognitive load	10	946	0.29*	[0.05, 0.53]
Learning time	9	983	− 0.87*	[− 1.65, − 0.09]
Learner-paced segmentation				
Retention	21	2351	0.19	[− 0.04, 0.45]
Transfer	16	1190	0.45***	[0.24, 0.66]
Cognitive load	8	607	0.08	[− 0.12, 0.28]
Learning time	7	577	− 0.81	[− 2.51, 0.89]

*$p < .05$; **$p < .01$; ***$p < .001$

Regarding retention performance, 45 out of 67 effect sizes were positive, meaning the segmented instructional materials appeared to impact retention performance positively. The weighted mean effect size was $d = 0.32$, $SE = 0.06$, $z = 5.36$, $p < 0.001$, indicating a significant effect for the segmentation. The homogeneity statistic was highly significant, $Q = 2093.94$, $df = 66$, $p < 0.001$, indicating one or more moderators to this mean effect. Concerning transfer performance, 34 out of 56 effect sizes were positive. Again, it can be suggested that segmented instructional materials foster learning more effectively compared to nonsegmented materials. The computed effect size was significant, $d = 0.36$, $SE = 0.06$, $z = 5.96$, $p < 0.001$. The homogeneity statistic was also significant, $Q = 537.69$, $df = 55$, $p < 0.001$. Fourteen out of 20 overall cognitive load effect sizes were positive, indicating that segmentation reduces cognitive load. The weighted mean effect size for overall cognitive load was $d = 0.23$, $SE = 0.08$, $z = 2.75$, $p = 0.01$, indicating a significant effect with a small effect size. The homogeneity statistic was significant, $Q = 133.62$, $df = 19$, $p < 0.001$. Nine out of 19 effect sizes were negative for learning time, indicating that it took more time to learn using segmented materials rather than nonsegmented materials. The computed significant effect size was high, $d = -0.92$, $SE = 0.37$, $z = -2.50$, $p = 0.01$. The homogeneity test revealed that learning time effect sizes were heterogeneous ($Q = 58.52$, $df = 18$, $p < 0.001$).

Overall, the results of the meta-analysis reveal significant effect sizes supporting the segmenting effect with regard to retention and transfer performance, as well as to overall cognitive load and learning time. Furthermore, the tests for homogeneity indicate one or more moderators for the segmenting effect. Since our definition of the segmentation effect includes segmentation of the learning material through the lecturer and segmentation of the learning material through the learner (Mayer and Pilegard 2014), additional analyses were conducted in order to separate the effects of system-paced segmentation and learner-paced segmentation.

At first, effect sizes for all dependent variables were aggregated for the system-paced segmentation effect. Regarding retention performance, 21 out of 32 effect sizes were positive, meaning the segmented instructional materials appeared to impact retention performance positively. The weighted mean effect size was $d = 0.42$, $SE = 0.11$, $z = 3.89$, $p < 0.001$, indicating a significant effect for the segmentation. The homogeneity statistic was highly significant, $Q = 327.42$, $df = 31$,

$p < 0.001$, assigning one or more moderators to this mean effect. Concerning transfer performance, 20 out of 30 effect sizes were positive. Again, it can be suggested that segmented instructional materials foster learning more effectively compared to nonsegmented materials. The computed effect size was significant, $d = 0.35$, $SE = 0.10$, $z = 3.65$, $p < 0.001$. The homogeneity statistic was also significant, $Q = 260.28$, $df = 29$, $p < 0.001$. Eight out of ten overall cognitive load effect sizes were positive, indicating that segmentation reduces CL. The weighted mean effect size for overall cognitive load was $d = 0.29$, $SE = 0.12$, $z = 2.34$, $p = 0.02$, indicating a significant effect with a small effect size. The homogeneity statistic was significant, $Q = 86.29$, $df = 9$, $p < 0.001$. Five out of nine effect sizes were positive for learning time, indicating that system-paced segmentation might influence learning time. The computed significant effect size was high, $d = -0.87$, $SE = 0.40$, $z = -2.19$, $p = 0.03$. The homogeneity test revealed that learning time effect sizes were heterogeneous ($Q = 58.63$, $df = 8$, $p < 0.001$). Overall, the results of system-paced segmentation did match the overall effects. The Q values are smaller than the Q values regarding the overall effect, indicating that implementation of segmentation (system vs. learner-paced) is an important moderator. However, the tests for homogeneity point out that there are still moderators which have to be taken into account.

Second, effect sizes for all dependent variables were aggregated for the learner-paced segmentation effect. Regarding retention performance, 13 out of 21 effect sizes were positive, meaning the segmented instructional materials appeared to impact retention performance positively. The weighted mean effect size was $d = 0.19$, $SE = 0.12$, $z = 1.64$, $p = 0.10$, indicating a nonsignificant effect for the segmentation. The homogeneity statistic was highly significant, $Q = 673.52$, $df = 20$, $p < 0.001$, indicating one or more moderators to this mean effect. Concerning transfer performance, 11 out of 16 effect sizes were positive. Again, it can be suggested that segmented instructional materials foster learning more effectively compared to nonsegmented materials. The computed effect size was significant, $d = 0.45$, $SE = 0.11$, $z = 4.21$, $p < 0.001$. The homogeneity statistic was also significant, $Q = 57.61$, $df = 15$, $p < 0.001$. Four out of eight overall cognitive load effect sizes were positive, indicating that segmentation had no effect on CL. The weighted mean effect size for overall cognitive load was $d = 0.08$, $SE = 0.10$, $z = 0.80$, $p = 0.43$, indicating a nonsignificant effect. The homogeneity statistic was significant, $Q = 25.55$, $df = 7$, $p < 0.001$. Three out of seven effect sizes were positive for learning time, indicating that learner-paced segmentation might not have an influence on learning time. The computed significant effect size was high but nonsignificant, $d = -0.81$, $SE = 0.87$, $z = -0.94$, $p = 0.35$. The homogeneity test revealed that learning time effect sizes were heterogeneous ($Q = 23.45$, $df = 6$, $p < 0.001$).

Overall, the results of learner-paced segmentation did not entirely match the overall effects. Again, the Q values are smaller than the Q values regarding the overall effect, indicating that implementation of segmentation (system vs. learner-paced) is an important moderator. The tests for homogeneity indicate that there are still moderators which have to be taken into account.

Explanations for the Segmenting Effect

Consistent with Ginns et al. (2013), separate analyses were computed for retention and transfer performance, respectively. Statistical data for moderator retention and transfer performance are outlined in Table 4. Differences between the explanation and moderator categories were tested using the 95% CIs for significance.

The second hypothesis postulated that learning performance was improved by the segmenting effect due to segmenting the instruction into meaningful and coherent segments by the instructional designer. The meta-analysis revealed that the mean weighted effect size for

Table 4 Overall effect (hypothesis 1), explanations (hypotheses 2–4), and moderating effects (hypotheses 5–7) for the segmenting effect regarding retention and transfer performance

		Retention performance			Transfer performance		
		Number of comparisons k	Effect size d	95% CI for d	Number of comparisons k	Effect size d	95% CI for d
Overall effect							
Hypothesis 1: learning is improved due to the segmenting effect							
Overall effect		67	0.32***	[0.20, 0.43]	56	0.36***	[0.24, 0.48]
Explanations							
Hypothesis 2: learning is improved due to segmenting by the designer							
Segmenting	Yes	32	0.41***	[0.24, 0.58]	30	0.35***	[0.18, 0.52]
	No	32	0.20*	[0.04, 0.36]	24	0.36***	[0.16, 0.56]
Hypothesis 3: learning is improved due to more time for processing							
More time	Yes	36	0.41***	[0.25, 0.56]	35	0.38***	[0.22, 0.53]
	No	17	0.21(*)	[− 0.01, 0.44]	13	0.42**	[0.17, 0.68]
Hypothesis 4: learning is improved effect due to the learner-pacing							
Learner pacing	Yes	21	0.19(*)	[− 0.02, 0.40]	16	0.45***	[0.23, 0.66]
	No	43	0.36***	[0.21, 0.51]	38	0.31***	[0.18, 0.45]
Moderating effects							
Hypothesis 5: learners with lower prior knowledge benefit more from the segmenting effect							
Prior knowledge	No	33	0.29***	[0.15, 0.43]	18	0.31***	[0.13, 0.48]
	Low	16	− 0.12	[− 0.34, 0.10]	21	0.17*	[0.0001, 0.34]
	High	7	0.73***	[0.43, 1.04]	5	0.51**	[0.20, 0.83]
Hypothesis 6: learners without the option of repeating the instructions should benefit more from the segmenting effect							
Option to repeat	Yes	11	0.14	[− 0.14, 0.42]	12	0.55***	[0.25, 0.85]
	No	44	0.40***	[0.26, 0.54]	38	0.29***	[0.16, 0.42]
	Only in the exp. group	11	0.19	[− 0.08, 0.46]	5	0.65***	[0.27, 1.02]
Hypothesis 7: learners without the option of manipulating the sequence of the information should benefit more from the segmenting effect							
Option to manipulate	Yes	14	0.15	[− 0.11, 0.40]	9	0.46**	[0.13, 0.79]
	No	38	0.32***	[0.17, 0.46]	33	0.45***	[0.29, 0.60]

(*) $p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$

experimental effects that included a multimedia instruction segmented by the instructional designer only for the experimental group was $d = 0.41$, $Z = 4.78$, $p < 0.001$ for retention performance and $d = 0.35$, $Z = 4.05$, $p < 0.001$ for transfer performance. The mean weighted effect size for experimental effects that did not include a multimedia instruction segmented by the instructional designer was $d = 0.20$, $Z = 2.41$, $p = 0.02$ for retention performance and $d = 0.36$, $Z = 3.55$, $p < 0.001$ for transfer performance. The effect sizes marginally differed in terms of retention performance ($Q = 3.21$, $df = 1$, $p = 0.07$) but not in terms of transfer performance ($Q = 0.01$, $df = 1$, $p = 0.92$). Overall, the Q tests did not support the second hypothesis, which assumes that learning performance is improved by the segmenting effect due to segmenting the instruction into meaningful and coherent segments by the instructional designer.

The third hypothesis postulated that learning performance was improved by the segmenting effect due to the provision of more time for processing. The meta-analysis revealed that the mean weighted effect size for experimental effects with a shorter learning time in the control group compared to the experimental group was $d = 0.41$, $Z = 5.21$, $p < 0.001$ for retention performance and $d = 0.38$, $Z = 4.68$, $p < 0.001$ for transfer performance. By contrast, the mean weighted effect size for experimental effects with no shorter learning time in the control group compared to the experimental group was $d = 0.21$, $Z = 1.83$, $p = 0.07$ for retention performance and $d = 0.42$, $Z = 3.27$, $p = 0.001$ for transfer performance. Retention ($Q = 1.88$, $df = 1$, $p = 0.17$) and transfer ($Q = 0.10$, $df = 1$, $p = 0.76$) effect sizes were not affected. Overall, the Q tests did not support the third hypothesis, which postulated that learning performance is improved by the segmenting effect due to the provision of more time for processing.

The fourth hypothesis assumed that learning performance was improved by the segmenting effect due to giving the learners the opportunity to adapt the presentation pace to their individual needs. The meta-analysis revealed that the mean weighted effect size for experimental effects where the participants only in the experimental group could pause the multimedia instruction was $d = 0.19$, $Z = 1.78$, $p = 0.07$ for retention and $d = 0.45$, $Z = 4.03$, $p < 0.001$ for transfer. By contrast, the mean weighted effect size for experimental effects where the participants were not able to pause the multimedia instruction only in the experimental group was $d = 0.36$, $Z = 4.73$, $p < 0.001$ for retention performance and $d = 0.31$, $Z = 4.53$, $p < 0.001$ for transfer. Again, retention ($Q = 1.78$, $df = 1$, $p = 0.18$) and transfer ($Q = 1.03$, $df = 1$, $p = 0.31$) effect sizes were not affected. Overall, the Q tests could not support the fourth hypothesis, which postulated that learning performance is improved by the segmenting effect due to the learners' possibility of adapting the presentation pace to their individual needs.

Moderating Effects

The fifth hypothesis stated that learners with lower prior knowledge should benefit more from the segmenting effect than learners with higher prior knowledge. Overall, prior knowledge was a moderator for retention performance ($Q = 20.49$, $df = 2$, $p < 0.001$) but not for transfer performance ($Q = 3.87$, $df = 2$, $p = 0.14$). Regarding retention, results revealed that the mean weighted effect size for experimental effects for learners with no prior domain knowledge was $d = 0.29$, $Z = 3.96$, $p < 0.001$, with at least some prior knowledge was $d = -0.12$, $Z = -1.05$, $p = 0.30$ and with high prior knowledge was $d = 0.73$, $Z = 4.67$, $p < 0.001$. Contrary to the postulated hypothesis, learners with high prior knowledge benefitted more from segmenting instructional material than learners with no or low prior knowledge. Furthermore, transfer performance was not moderated by prior knowledge.

The sixth hypothesis postulated that learners receiving multimedia instructions without the option of repeating the instructions should benefit more from the segmenting effect than learners receiving repeatable multimedia instructions. Results revealed that the opportunity to repeat instructions did not moderate retention performance ($Q = 3.76$, $df = 2$, $p = 0.15$). Nevertheless, the aggregated effect size only reached significance when learners were not able to repeat the instructions, $d = 0.40$, $Z = 5.51$, $p < 0.001$. Effect sizes were not significant when learners were able to repeat the instructions, $d = 0.14$, $Z = 0.97$, $p = 0.33$, or when learners were able to repeat the instructions only in the experimental condition, $d = 0.19$, $Z = 1.36$, $p = 0.18$. The opportunity to repeat instructions did not moderate transfer performance ($Q = 4.87$, $df = 2$, $p = 0.09$). Overall, the results of the meta-analysis did not support the sixth hypothesis.

The seventh hypothesis postulated that learners receiving multimedia instructions without the option of manipulating the sequence of the instructions should benefit more from the segmenting effect than learners receiving multimedia instructions with the option of manipulating the sequence. Results revealed that the option of manipulating the sequence did not moderate retention performance ($Q = 1.26$, $df = 1$, $p = 0.26$). Nevertheless, the aggregated effect size only reached significance when learners had no opportunity to manipulate the sequence of the instructions, $d = 0.32$, $Z = 4.21$, $p < 0.001$. The effect size was not significant when learner had the opportunity to manipulate the sequence, $d = 0.15$, $Z = 1.14$, $p = 0.25$. The option of manipulating the sequence did not moderate transfer performance ($Q = 0.004$, $df = 1$, $p = 0.95$). Again, the results of the meta-analysis did not support the seventh hypothesis.

Discussion

Overall, the results of this meta-analysis support the segmenting effect with regard to retention and transfer performance with small to medium effect sizes. Segmentation also reduces the overall cognitive load of learners and increases their learning time. These four effects are fully confirmed for a system-paced segmentation. By contrast, a learner-paced segmentation only fostered a significant increase in transfer performance. Furthermore, the meta-analysis reveals that the effect may be ascribed to different explanations. More precisely, the results suggest that none of the three postulated explanations can be ruled out. Therefore, the effect might be traced back to facilitating chunking and structuring due to segmenting the multimedia instruction by the instructional designer, providing more time for processing the instruction, and allowing the learners to adapt the presentation pace to their individual needs.

Why could none of the postulated explanations be ruled out by the present meta-analysis? Possibly, the segmenting effect is a heterogeneous effect as it contains two different key features. First, the multimedia instruction is broken into sequentially presented parts, and second, learners are allowed to pace the multimedia instruction. Therefore, different aspects seem to be responsible for the segmenting effect and cannot be clearly distinguished in the present meta-analysis due to significant effects for these explanations with partly similar effect sizes. Moreover, a learner-paced material might evoke other effects into account (e.g., Keehner et al. 2008; Khooshabeh and Hegarty 2010). These materials might only be effective when learners are able to evaluate their own information—no matter if the material is segmented or not.

Regarding retention performance, the segmenting effect seems to be mainly generated due to segmenting the instruction into meaningful and coherent segments by the instructional designer and due to the provision of more time for processing. By contrast, the effect does not appear to improve retention performance as a result of the learner adapting the presentation pace to their individual needs. Regarding transfer performance, none of the three postulated explanations for the segmenting effect can be ruled out. Therefore, the learners' opportunity to adapt the presentation pace to their individual needs seems to affect transfer performance rather than retention performance. Probably, learners might not only benefit from having the possibility to adapt the presentation pace but may also *have to* adapt the pace of the multimedia instruction *actively* to suit their individual needs. This challenge could activate cognitive processes (e.g., monitoring processes), which might also foster transfer performance. In addition, these learners may perceive more control over the task, resulting in higher transfer performance (Wouters 2007).

Furthermore, the present results reveal that the segmenting effect is at least partly moderated by the learners' prior domain knowledge. Learners with high prior domain knowledge benefit more from the segmenting effect than learners with no or low prior domain knowledge in regard to retention performance. By contrast, moderating effects for learners' prior domain knowledge were not found with regard to transfer performance.

Why do learners with high rather than with no or low prior domain knowledge benefit more from the segmenting effect, and why is this moderating effect restricted to retention performance rather than transfer performance? In the present meta-analysis, the learners' prior domain knowledge is mainly restricted to studies including participants with no prior domain knowledge or only some prior domain knowledge, with only one exception that included expert male soccer players as participants (Khacharem et al. 2013). Therefore, the variance of the learners' prior domain knowledge is very limited, which might constrain the moderating impact of this variable on the segmenting effect. In addition, learners who participated in the studies of the present meta-analysis may not have enough prior domain knowledge to enter into a cognitive conflict between their own representations and external segmented representations (i.e., the multimedia instruction). Because such a conflict might not exist due to the missing cognitive schemata of the participants, it must not be reconciled and also does not impair learning performance. The few learners with high prior domain knowledge might have already relied on acquired cognitive schemata, requiring fewer resources in the process of schema acquisition. Such pattern receives support from ATI research on effects of individual differences in available working memory capacity (e.g., Lusk et al. 2009). The unemployed cognitive resources could be devoted to the exploration of additional task-inherent opportunities like self-regulated task segmentation. In consequence, such features had developed their full potential and increased learning performance for learners with high prior domain knowledge.

The opportunity of repeating the multimedia instruction does not moderate the segmenting effect. Possibly, only providing more (overall) time for processing the multimedia instruction to allow for repeating the (whole) presentation may be insufficient to improve learning outcome. At certain points in time, learners might not have enough time to store the essential words and pictures in a verbal and pictorial model. They might perceive cognitive overload during the presentation and their working memory capacity might be exceeded at certain points in time. In contrast, a segmented learner-paced multimedia instruction provides enough time at these important points in time and thereby might prevent cognitive overload. Therefore, the beneficial effects resulting from segmenting the multimedia instruction (e.g., due to the provision of more time for processing) do not diminish due to the opportunity of repeating the multimedia instruction.

The lack of influence regarding the sequence manipulation might be explained by the learners' limited cognitive resource supply. Similar to evidence from research on hypertext learning, without proper guidance on the advantages of the increased freedom in navigation choice, learners experience a cognitive overload (DeStefano and LeFevre 2007). For this reason, they might use preexisting structures rather than building customized learning paths and, thus, neglect the enhanced opportunities that arise from the learning environment. Taking into account the previously discussed predominantly low level of prior domain knowledge, which results in already demanded cognitive resources due to schema acquisition processes, such an assumption receives further support.

Implications

On the practical side, multimedia instructions should be presented in (meaningful and coherent) learner-paced segments, rather than as continuous units, to improve learning performance and reduce the learners' overall cognitive load. First, instructional designers should facilitate chunking and structuring due to segmenting the multimedia instruction. Second, learners should have enough time to process the multimedia instruction. Third, they should be given the possibility to adapt the presentation pace to their individual needs. Furthermore, especially learners with high rather than no or low prior domain knowledge should receive segmented learner-paced multimedia instructions rather than unsegmented system-paced instructions. In line with evidence on influences of individual differences in learning settings (Lusk et al. 2009; Tobias 1976), these are more tailored to available cognitive resources. Recent software (e.g., Mura et al. 2013) delivers simple opportunities to incorporate segmenting in multimedia learning environments.

On the theoretical side, the present results are consistent with the CTML (Mayer 2014a), particularly with the segmenting effect (Mayer and Pilegard 2014). First, the results of the meta-analysis support the assumption that the segmenting effect can be explained among others by segmenting the instruction into meaningful and coherent segments by the instructional designer. Learners receiving multimedia instructions presented as continuous (unsegmented) units may have more problems in chunking and structuring the instruction into meaningful and coherent segments than learners receiving multimedia instructions presented in structured segments. These learners are supported by segmentation as a form of temporal cueing, which increases the salience of natural boundaries between events in a process or procedure (e.g., Spanjers et al. 2012). Segmenting multimedia instructions is also in line with the segmentation theory (Zacks et al. 2007), which proposes that people perceive and conceive actions in terms of discrete events. Second, the results reveal that the segmenting effect can in part be explained by providing more time for processing the multimedia instruction (Spanjers et al. 2010). Learners receiving (fast and transient) system-paced multimedia instructions as continuous units seem to not have enough time to store the essential words and pictures in a verbal and pictorial model. They may also be cognitively overloaded at certain points in time during the presentation and their working memory capacity exceeded, in contrast to learners receiving segmented learner-paced multimedia instructions (cf. Kurby and Zacks 2008; Schnotz and Lowe 2008; Spanjers et al. 2010). Third, the results support the assumption that the segmenting effect can in part be explained by the possibility of adapting the presentation pace to the learners' individual needs (e.g., Hasler et al. 2007). Learners receiving multimedia instructions without learner-control options do not have the option to actively adapt the pace of the instructions to their individual needs, unlike learners receiving the instructions with learner-control options, such as pause and play buttons. These learners might perceive more control over the task, resulting in higher transfer performance (Wouters 2007).

Limitations and Future Directions

The present results concerning the explanations for the segmenting effect and the moderator analyses may be confounded by other variables due to the nonexperimental nature of meta-analyses. For example, a pause button provides more time for processing a multimedia instruction but also includes the possibility to adapt the presentation pace to the learner's individual needs. Therefore, this meta-analysis cannot replace empirical studies concerning the segmenting effect, which unravel these confounding variables with appropriate experimental designs. More precisely, the three explanations for the segmenting effect should be investigated empirically with an experimental design including different learning outcomes (e.g., a retention and a transfer test) to shed light on differential effects on these dependent measures. Further studies should also explore whether the provision of more time for processing a multimedia instruction always improves learning performance or if the provision of an (optimal) time period as well as a proper presentation pace (cf. Stiller et al. 2011) might be better. Moreover, future experiments might also differentiate more precisely between additional time given by the system and additional time occupied by the learner due to learner pacing (cf. Tabbers and de Koeijer 2010). In this context, the results of the present meta-analysis concerning the dependent variable learning time have to be interpreted with caution due to the significant publication bias. A combination of moderators (and a combination of hypotheses), like pacing and time restriction, might have revealed additional results in order to explain the segmentation effect. However, based on the relatively low number of studies, these combinations would have led to a rather low statistical power.

The meta-analysis investigated only three moderating effects (i.e., learners' prior domain knowledge, the opportunity to repeat the multimedia instruction, and the possibility to manipulate the sequence of the instructions) rather than numerous other potential moderating effects in regard to the segmenting effect (e.g., the kind of learning material and the mode of presentation). The results of these moderator analyses are limited as a result of the somewhat low number of studies. Other moderator effects were not analyzed in the meta-analysis due to the lack of a sufficient number of studies required to perform meta-analytical analyses as well as due to the problem of confounding variables (see above).

This meta-analysis also relied on the assumption that all studies decomposed their learning materials into meaningful and coherent events by their type of segmentation. This assumption might be challenged. Readers should take this limitation into account when interpreting the results. In order to take up this limitation, future studies should examine possible differences between a segmentation of meaningful and coherent units and less coherent and meaningful units.

Furthermore, the present meta-analysis was limited by the restricted variance of the learners' prior domain knowledge. Therefore, future experiments concerning the segmenting effect should use more genuine experts to unravel the full impact of the learners' prior domain knowledge (see Oksa et al. 2010, for an example of the expertise reversal effect with genuine experts). In particular, the impact of the learner's prior domain knowledge on the segmenting effect might depend on the type of pacing (learner pacing vs. system pacing). For example, learners with low prior domain knowledge should benefit more from system pacing, whereas learners with higher prior domain knowledge should benefit more from learner pacing (see above).

Moreover, the present meta-analysis was limited by the rough categorization of learning outcomes in retention and transfer performance. Subsequent studies and meta-analyses should classify learning outcomes in a more sophisticated manner and use finer subcategorizations (e.g., near and far transfer scores), although this increases the problem of stochastically dependent variables due to these multiple measures. Finally, cognitive processes underlying the segmenting effect should be examined more comprehensively and thoroughly in future experiments. Potentially applicable methodologies to support this goal relate to the assessment of cognitive load in instructional scenarios. In particular, continuously obtained indicators have proven value in this context, such as physiological and behavioral parameters. Antonenko et al. (2010) outlined the potential of electroencephalography (EEG) in explaining differences in cognitive processing related to effects of instructional interventions. Examples from research on online reading and hyperlink selection indicate that such an approach can hold benefits for fine-grained inspections of underlying patterns of cognitive resource investment (Scharinger et al. 2015). Alternative markers that reflect cognitive processing emerge from heart rate and galvanic skin response. These also hold a demonstrated scope to address research questions in basic and applied multimedia learning research (e.g., Schneider et al., b; Wirzberger et al. 2018). Besides physiological measures, behavioral parameters are suited to provide insights into learners' task-related cognition. They originate, for instance, in attentive gaze patterns

(Cook and Wei 2017; Skuballa et al. 2012) or recorded mouse events (e.g., moving, clicking, dragging) or trajectories (Chen et al. 2016).

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