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Editorial

Latest trends to optimize computer-based learning: Guidelines from cognitive load theory

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1. Introduction

Despite evidence that educational technology research is frequently lacking a conceptual base (e.g., Hew, Lan, Tang, Jia, & Lo, 2019), there is a theory that is gradually permeating the fields of educational technology and computer-based learning: cognitive load theory (see Sweller, 2020; Sweller, van Merriënboer, & Paas, 2019). As reported in the bibliometric review of recent articles about multimedia learning by Li, Antonenko, and Wang (2019), cognitive load theory can be regarded as the leading conceptual framework to investigate the effectiveness of educational multimedia. In the same bibliometric analysis, Li et al. (2019) showed that the top journal publishing research on multimedia learning is *Computers in Human Behavior*. In the period from 1996 to 2016, this journal published 46 articles about multimedia learning. Hence, the current special issue for the journal Computers in Human Behavior, which addresses computer-based learning based on cognitive load theory, is expected to contribute to these prominent international trends.

2. Cognitive load theory and this special issue

Cognitive load theory is an instructional theory aimed at optimizing educational materials and activities by developing design guidelines based on the knowledge of the human cognitive architecture (see Sweller, 2020; Sweller et al., 2019). In the past decades, many researchers have contributed to the development of cognitive load theory and a wide range of instructional guidelines is currently available which are based on rigorous experimental research (Sweller et al., 2019). Cognitive load theory is continually updating itself with new experimental findings, such as those included in this special issue which includes six papers that focus on novel cognitive load theory approaches to optimize computer-based learning, and applied new techniques to measure cognitive load. The six empirical studies and their relationship to these topics are presented in Table 1.

3. Novel cognitive load theory approaches to optimize computer-based learning

The contributions of the papers can be categorized around three themes: refining existing cognitive load theory design guidelines (Armougum, Gaston-Bellegarde, Marle, & Piolino, 2020; Lee, Donkers, Jarodzka, Sellenraad, & van Merriënboer, 2020), novel directions in supporting computer-based learning (de Koning, Rop, & Paas, 2020a; Hefter & Berthold, 2020), and effects of research methodology on visuospatial and cognitive processing (Park, Korbach, & Brünken, 2020).

3.1. Refining existing cognitive load theory design guidelines

In cognitive load theory research, one design guideline is the *expertise reversal effect*, which refers to the finding that processing methods that are effective for novices are less effective or even ineffective when the level of expertise increases (see Kalyuga, Ayres, Chandler, & Sweller, 2003). The study by Armougum et al. (2020) extends prior work on expertise-related processing differences by investigating how the context in which the required processing occurs impacts cognitive load and performance, and studying this phenomenon in a virtual real-life situation instead of a lab-based situation. The participants were 124 adults, novice and experienced train travelers, who were presented with a task in which they had to find their way to a given destination. Performance and cognitive load were measured when the train station presented either few (normal condition) or many (disturb condition) travelers. This study provides new insights in the practical application of expertise-related differences in processing in a real-life setting.

Another design strategy that has emerged is avoiding the *transient information effect*, which occurs when information in a learning task disappears before it can be adequately processed (see Ayres & Paas, 2007). There are basically two techniques to elude this effect in many animations and videos (see Merkt, Ballmann, Felfeli, & Schwan, 2018; Spanjers, van Gog, & van Merriënboer, 2010; see also Castro-Alonso, Ayres, & Sweller, 2019). In one technique, called *segmenting* or *system-determined pauses*, the designer of the dynamic visualization cuts the

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Table 1
Overview of the six empirical studies in the special issue.

Novel cognitive load theory approaches to optimize computer-based learning:		
Study in the Special Issue	**Guideline**	**Key Reference**
Armougum et al. (2020)	Expertise reversal effect	Kalyuga et al. (2003)
de Koning, Rop, & Paas (2020a)	Split-attention effect	Ayres and Sweller (2014)
Hefter and Berthold (2020); Lee et al. (2020)	Transient information effect	Ayres and Paas (2007)
Park et al. (2020)	Redundancy effect	Kalyuga and Sweller (2014)
Applied new techniques to measure cognitive load:		
Study in the Special Issue	**Measure**	**Key Reference**
Armougum et al. (2020); Johannessen et al. (2020)	Electrodermal activity	Boucsein (2012)
Johannessen et al. (2020); Lee et al. (2020)	Pupillary response	Hess and Polt (1964)
Johannessen et al. (2020)	Cardiac response	Grassmann et al. (2017)

whole presentation in shorter and meaningful sections. The other technique, termed *pace-control* or *learner-determined pauses*, involves including features in the visualization that allow learners to control its pace (e.g., a pause/resume button) to give time for working memory resources to replenish (cf. Chen, Castro-Alonso, Paas, & Sweller, 2018). The study by Lee et al. (2020) focused on this latter technique. In this study, 70 medical university students (73% females) engaged in a computerized simulation game to practice emergency medicine and were given the option to pause the simulation or not. This study extends earlier work on the pace-control technique by investigating the effects of pausing the learning content in a non-linear task that is highly dynamic in nature.

3.2. Novel directions in supporting computer-based learning

A novel direction for the transient information effect is explored in this special issue by Hefter and Berthold (2020). While typically the cognitive load theory research is concerned with developing guidelines for the (re)design of the main learning task itself, Hefter and Berthold focused on how to design the instructions for (and thus preceding) the main learning task. This is something that is usually overlooked or simply designed based on intuition. In their study, 42 adult participants (50% females) had to self-explain video-examples and were given the self-explanation instructions either in video format (transitory) or in textual format (non-transitory). This study contributes to cognitive load theory research by applying guidelines to an earlier phase in the instructional process than the main learning task, as well as providing empirical work on the effectiveness of learning from video-examples and the transient information effect.

In the past decades, cognitive load theory research has provided guidelines for instructors to optimize the design of instructional materials (i.e., instructor-management of cognitive load). As an example, the *split-attention effect* holds that learners obtain higher learning performance when spatially separated text and pictures are presented in a physically integrated format than in a spatially separated format (see Ayres & Sweller, 2014; e.g., Pouw, Rop, de Koning, & Paas, 2019; Thees et al., 2020). Despite the value of optimized instructional materials for learning, many instructional materials are still available that are sub-optimally designed (e.g., text and picture presented in a split-attention format). Following recent studies (de Koning, Rop, & Paas, 2020b; Sithole, Chandler, Abeysekera, & Paas, 2017), de Koning, Rop, & Paas (2020a) investigated the effectiveness of a self-management of cognitive load approach wherein 92 psychology undergraduates (70% females) were taught a physical or mental integration strategy to support learning from split-attention materials presented on the computer. The effects of both self-management guidelines were compared on tests of retention, comprehension and transfer. Also, effects of spatial distance (large or small) between text and picture were investigated. This study thus contributes to the literature by exploring a novel approach to manage cognitive load in instructional materials that is focused on the learner instead of the instructional material itself.

3.3. Effects of research methodology on visuospatial and cognitive processing

In many instructional materials, learners are confronted with interesting information that is not necessary for achieving the learning goal. Learning from such instructional materials usually results in lower performance compared to studying the same materials without these unnecessary details, which is referred to as the *seductive details effect* (Lehman, Schraw, McCrudden, & Hartley, 2007) and is related to the *redundancy effect* of cognitive load theory (Kalyuga & Sweller, 2014). The study by Park et al. (2020) extends research in the seductive details effect by investigating the extent to which engaging in a think-aloud procedure inhibits or helps processing visuospatial and textual instructions with (or without) seductive details. Inhibition might be experienced because the think-aloud procedure is a secondary task that needs to be performed simultaneously with the main learning task. Engaging in a think-aloud might help processing of the presented information because it supports self-regulatory behavior during learning. This was tested with 116 psychology students (84% females) in a lab setting where participants engaged in think-aloud or not while they learned from textual and visual materials presented on a laptop, including or not seductive details. Together, the present study makes both a methodological and a theoretical contribution to the literature.

4. Applied new techniques to measure cognitive load

In this section, we describe how the empirical papers in this special issue describe new techniques to measure cognitive load, which can be applied to computer-based learning. Traditionally, the most common measures of cognitive load are subjective methods (see Anmarkrud, Andresen, & Bråten, 2019; Mutlu-Bayraktar, Cosgun, & Altan, 2019; Naismith & Cavalcanti, 2015), such as self-reported ratings of experienced cognitive load (e.g., Beege, Schneider, Nebel, Mittangk, & Rey, 2017; Colliot & Jamet, 2018; Weng, Otanga, Weng, & Cox, 2018).

Measurement of cognitive load has been an ongoing source of debate ever since cognitive load theory was first introduced (e.g., Kirschner, Ayres, & Chandler, 2011), and typically centered around the subjective nature of the measurement. Hence, researchers have also started to investigate the potential of objective methods to measure cognitive load. Examples of objective methods to measure cognitive load that can be applied in computer-based learning scenarios include pupillary response (e.g., Hess & Polt, 1964; Huh, Kim, & Jo, 2019), electrodermal activity (see Boucsein, 2012), cardiac response (e.g., Grassmann, Vlemincx, von Leupoldt, & Van den Bergh, 2017), linguistic cues (e.g., Khawaja, Chen, & Marcus, 2012), secondary-tasks (e.g., Haji et al., 2015), and electroencephalography (e.g., Örün & Akbulut, 2019).

In three studies of this special issue (Armougum et al., 2020; Johannessen et al., 2020; Lee et al., 2020), objective measures of cognitive load were collected in addition to subjective measures, which enables direct comparisons between both methods. Lee et al. (2020) investigated medical students practicing emergency medicine producers in a computerized simulation game. The subjective measure of cognitive load employed was the mental effort scale developed by Paas (1992), and the objective measure used was pupillary response (pupillometry, pupil dilation).

In the experiment by Armougum et al. (2020), novice and expert train travelers were asked to find certain destination in a virtual train station. Cognitive load was manipulated by presenting the trials in peak hours (high cognitive load) or in non-peak hours (low cognitive load) at the virtual station. The subjective measure used was the NASA-TLX (Task Load Index) developed by Hart and Staveland, 1988.

Electrodermal activity (galvanic skin response) was the choice for the objective measure of cognitive load.

Johannessen et al. (2020) conducted an exploratory study with three trauma physicians performing resuscitation in an emergency department. The subjective measure of cognitive load was the mental effort scale by Paas (1992), and three objective measures were collected with sensors in wearable devices. One measure, obtained via eye tracking glasses, included pupillary response. The two other measures, obtained via a wristband, calculated electrodermal activity and cardiac response.

5. Discussion

The current special issue includes six articles about computer-based learning. Crucially, the studies were all conducted under the umbrella of a leading framework for instructors and instructional designers, namely, cognitive load theory. As such, these articles are expected to invigorate cognitive load theory research by describing novel approaches to this theory, as well as new applications to measure cognitive load.

5.1. Implications for cognitive load theory research

Concerning novel approaches to cognitive load theory, the studies in this special issue employed different computer-based learning scenarios. Media included virtual reality, laptops, and desktop computers. Visualizations included simulation game, video, and animated multimedia. All these scenarios were appropriate to test novel approaches to optimize design guidelines based on cognitive load theory. In other words, the value of cognitive load theory permeates different forms of technology. An implication following from this versatility of cognitive load theory is that research about this theory should continue placing the human cognitive architecture before the latest technology fad.

Concerning measurement of cognitive load, the studies in this special issue showed that subjective and objective measures tend to assess different aspects of cognitive load and produce different results, as previously reported (e.g., Korbach, Brünken, & Park, 2017; Makransky, Terkildsen, & Mayer, 2019). Moreover, the three objective assessments presented here—pupillary response, electrodermal activity, and cardiac response—have also two key differences with the subjective ratings: (a) they are controlled by the autonomous system, and (b) they are calculated during learning. This contrasts the conscious and somewhat delayed measurement of subjective ratings, so employing these different approaches will likely provide complementary data. An implication is that contemporary studies about cognitive load theory should pursue including more than one measurement, including subjective and objective methods.

5.2. Implications for computer-based educational practice

The six papers in this special issue show that design guidelines are applicable to a wide range of media (e.g., laptops, virtual reality) and visualization types (simulation, video), suggesting that the results of these papers are relevant for learning in different educational settings and contexts. Additionally, the papers provide further guidance to educational practitioners by offering insight into effective use of existing and novel design guidelines. One aspect that becomes clear in the papers in this special issue is that the context in which learning takes place matters and could determine the effectiveness of certain design guidelines. This can be found in the complexity or intensity of the task (Lee et al., 2020), the number of people around learners (Armougum et al., 2020), or in the (type and number of) tasks that students are required to do, such as engaging in think-aloud while learning which is often used in educational practice (Park et al., 2020).

Another important finding presented in this special issue (Hefter & Berthold, 2020) is that design guidelines, which are typically applied to the main learning task, can also be effectively used to the pre-instructional phase, and that, in turn, influences performance on the main learning task. Another implication is that educational professionals can teach students strategies to overcome negative effects of sub-optimally designed instructional materials (de Koning, Rop, & Paas, 2020a). This means that teachers have a new type of strategies, in addition to strategies focusing on deeper understanding of the content such as self-explaining, at their disposal to support students to understand the content of a lesson.

A final practical implication relates to the measurement of cognitive load. Objective measures of cognitive load appear useful to give an indication of experienced cognitive load and can be measured with easy-to-use tools such as a wristband (Johannessen et al., 2020). This gives teachers the possibility to have online insight into the demands a task places on learners, so they can timely intervene in the students' learning without having to continuously ask the student. Using tools such as a wristband is unobtrusive and offers a possibility to monitor fluctuations in cognitive load over prolonged periods of time (e.g. a whole lesson) and identify parts of the lesson that are particularly demanding for learners.

5.3. Future research directions

Regarding cognitive load theory approaches to optimize computer-based learning, areas for future research could investigate the usefulness of design guidelines in relatively novel learning contexts such as virtual environments, or different phases of the learning process as well as to further investigate the intricacies between design guidelines and personal factors such as expertise (see also de Koning, Hoogerheide, & Boucheix, 2018). Another promising line of research concerns the teaching of strategies to learners to empower them to deal with learning materials that are not optimally designed based on cognitive load theory guidelines. It would, for example, be useful to investigate teaching of self-management strategies beyond the split-attention effect.

Concerning applied techniques to measure cognitive load, in addition to the methods presented in this special issue, a promising objective technique is electroencephalography, which can measure immediate brain activity indicating changes in cognitive load during learning (e.g., Castro-Meneses, Kruger, & Doherty, 2020; Makransky et al., 2019; Wang, Antonenko, Keil, & Dawson, 2020; Örün & Akbulut, 2019). Also, objective techniques could measure how different personal factors—including (a) gender (e.g., Castro-Alonso, Wong, Adesope, Ayres, & Paas, 2019; Heo & Toomey, 2020; Wong, Castro-Alonso, Ayres, & Paas, 2018), (b) visuospatial working memory processing (see Castro-Alonso, 2019), and (c) verbal working memory capacity (e.g., Merkt et al., 2018)—moderate changes in cognitive load.

Declaration of competing interest

The authors declare that they have no conflict of interest.

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