Computers in Human Behavior 101 (2019) 30–41

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

The impact of Co-actors on cognitive load: When the mere presence of others makes learning more difficult

Irene T. Skuballa*, Kate M. Xu, Halszka Jarodzka

Welten Institute - Research Centre for Learning, Teaching and Technology, Open University of the Netherlands, the Netherlands

ABSTRACT

A large body of research has established the value of learner characteristics on cognitive load. However, little attention has been paid to the physical environment where learning takes place. The present study takes a step to address this gap by studying the impact of the presence of others during learning on cognitive load. In a between-subject design, participants (N = 115) were randomly arranged in groups of different group sizes to study computer-based multimedia materials (group size range: 1-13, continuous variable). Further, participants' working memory capacity, topic interest, and their prior knowledge were measured to reveal relevant learner characteristics. Dependent variables were learning performance, perceived task difficulty (mental load), and invested mental effort. We tested the predictions from cognitive load theory with alternative path models to identify the best model fit. Our results show that group size predicted learners' perceived task difficulty: the larger the group of co-actors in the learning situation was, the higher the perceived task difficulty. Moreover, higher topic interest led to lower perceived task difficulty, and more mental effort, although that effect became non-significant after multiple testing adjustment. Perceived task difficulty mediated the effect of group size and topic interest on mental effort.

1. Introduction

Towards the end of the term, university libraries are crowded with students preparing for their exams. Some students study in halls where they might experience the presence of other learners as soothing or motivating, even without engaging in social interactions; on the other hand, students who might find such situations distracting seek to study in absolute solitude to enhance their learning performance (Beckers, van der Voordt, & Dewulf, 2016; Harrop & Turpin, 2013; Meumann, 1925). So which situation facilitates learning? This leads to the question as to the role the physical environment plays in learning, particularly the mere presence of others, and whether it interacts with individual learner characteristics.

The social facilitation perspective assumes that the mere presence of others can suffice to facilitate or inhibit a person's performance (Cottrell, 1972; Zajonc, 1965). The cognitive load theory (CLT), on the other hand, favors the inhibitory effect of other co-learners exclusively because people are part of the physical learning environment that can provide superfluous information and overburden a learner's limited cognitive capacities (Paas & Van Merriënboer, 1994a). The CLT provides a comprehensive framework through which to understand the relevance of others in learning situations. Yet an investigation specifically addressing the effect of others' presence on learning through a variation of group size is still lacking. In our study, we operationalized the presence of others through different group sizes to examine its effect on cognitive load and learning performance within the CLT model. In a nutshell: the social facilitation perspective advocates that others exert a facilitative or inhibitory effect on learning, whereas the CLT clearly predicts an inhibitory effect. Both perspectives will be outlined below before we lay down our research question regarding the effect of others on learning.

2. The social facilitation versus the inhibition perspective

Evidence came to light over a hundred years ago that people performed better on motoric tasks when competing with another person (Triplett, 1898). Furthermore, the research on social presence suggests that learners perform differently when they believe that they are part of a community and that their actions are directed at other people (Rourke, Anderson, Garrison, & Archer, 1999). For instance, research on audience design has shown that people draft messages for themselves differently than messages for someone else, even if that person is absent (Rogers, Fay, & Maybery, 2013). It is suggested that learning improves when people experience enhanced feelings of an audience's social presence (Hoogerheide, Deijkers, Loyens, Heijltjes, & Van Gog, 2016: Hoogerheide, Renkl, Fiorella, Paas, & van Gog, 2019). Such effects occur despite the learners' knowing that they will not interact with the other person or that the audience is just imagined. Later research has demonstrated that the presence of another co-actor can detract from or improve learning processes even in a situation with neither an

* Corresponding author. Postbus 2960, 6401 DL, Heerlen, the Netherlands.
E-mail address: irene.skuballa@ou.nl (I.T. Skuballa).

https://doi.org/10.1016/j.chb.2019.06.016
Received 15 December 2018; Received in revised form 18 June 2019; Accepted 30 June 2019
Available online 03 July 2019
0747-5632/

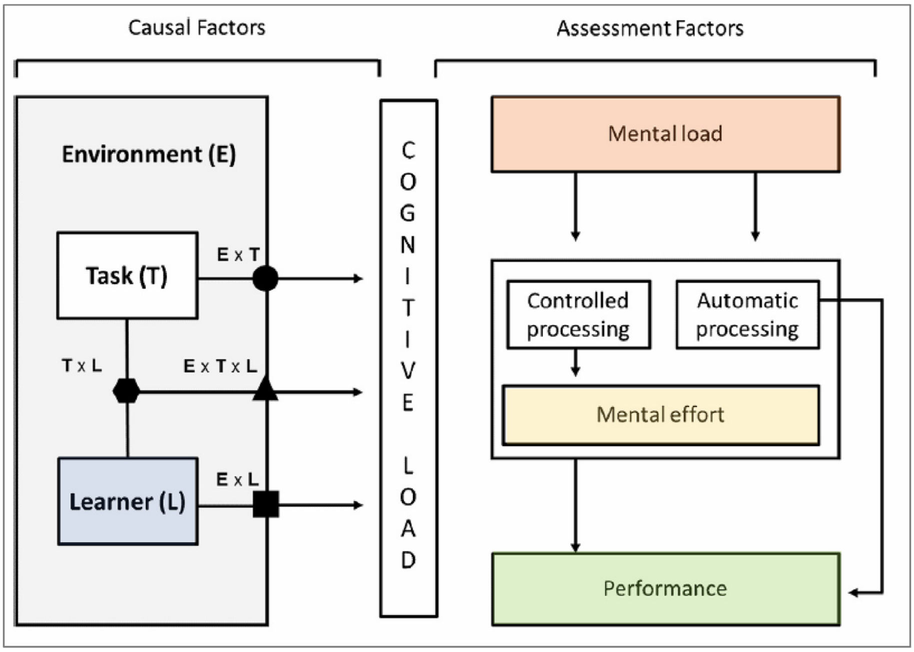


Fig. 1. Adapted and revised model of construct of cognitive load (E = physical learning environment, T = learning task, L = learner). This model assumes possible interactions between a.) the environment and task, b.) the task and learner, c.) the environment and learner, and d.) a three-way interaction between the environment, task and learner (from Choi et al. (2014), *Educational Psychology Review, 26*, p. 229).

obvious competitive facet nor a social addressee (Knepp, Krafka, Boulton, & Myers, 2014).

According to the social facilitation effect, the mere presence of others itself improves performance, even if instructed competition and group pressure have been ruled out (Allport, 1924; Guerin, 1993). In the context of education, Meumann (1925) argued that other learners are the source of many auditory and visual distractors that deflect attention from learning. Such distractors may spur learners to try harder to concentrate so as to compensate for these distractions and restore focus which might result in an even better learning performance. Several mechanisms were discussed, such as motivation, cognition, and social comparisons, for why social facilitation increases performance, and yet the underlying mechanisms remain unclear (Cottrell, 1972; Guerin, 1993; Zajonc, 1965).

However, researchers during the first half of the 20th century detected mixed effects of presence on individual performance. In some studies, performance was enhanced, and in others impaired (Aiello & Douthitt, 2001; Cottrell, Wack, Sekerak, & Rittle, 1968. Therefore, the hypothesis of a facilitative effect does not hold true consistently. For instance, people tested in individual sessions outperformed those tested in group sessions on neurocognitive tests such as visual and verbal memory (Moser, Schatz, Neidzwski, & Ott, 2011). We can assume that during learning, the mere presence of others can be distractive and lead to an attentional conflict between the ongoing task and external distracters, thus harming performance (distraction-conflict hypothesis, Baron, 1986). Supporting evidence from reviews and meta-analyses on this 'social inhibition effect' indicates that the mere passive presence of other persons, without any interaction or evaluation from that person, suffices to distract attention away from a task (Bond & Titus, 1983; Guerin, 1993). In an attempt to integrate these contradictory findings, Zajonc (1965) synthesized findings on performance into an inversed U-function. Zajonc asserted that the presence of others increases drive, which in turn enhances performance on the dominant routine responses, but it inhibits new, unlearned responses. In other words, the presence of others triggers physiological arousal that reflects positively on concentration and thus routine performance, however, when physiological arousal becomes excessive due to a task's novelty, concentration weakens, resulting in performance decay (cf. Yerkes & Dodson, 1908). We consider learning novel contents a non-dominant task and expect larger group sizes of co-actors to unfold a negative effect on performance.

3. The cognitive load perspective

The current literature provides little if any support for the facilitative effect of the mere presence of others in performance scenarios, but a plethora of findings supports the inhibitory effect as theorized by the CLT. Information processing during learning imposes load on the human cognitive system (Paas & Van Merriënboer, 1994a; 1994b; Sweller, Ayres, & Kalyuga, 2011). Cognitive load is a "multidimensional construct that represents the load that performing a particular task imposes on the cognitive system of a learner" (Paas & Van Merriënboer, 1994b, p. 353). It consists of factors affected by cognitive load (assessment factors) and factors that affect cognitive load (causal factors). According to the cognitive architecture underlying CLT, successful learning is the result of interplay between working memory and long-term memory processes (Choi, van Merriënboer, & Paas, 2014). Once new information is processed in working memory, it can be linked to information retrieved from long-term memory. Working memory, however, is limited in its capacity and duration (Paas & Van Merriënboer, 1994b; Sweller, van Merriënboer, & Paas, 2019). Its limitations become especially apparent when humans process novel information requiring them to simultaneously organize multiple information pieces. The cognitive challenges can be overcome by constructing cognitive schemas that incorporate cohesive information pieces stored and organized into chunks of knowledge in long-term memory. Successful practice and automation can lead to comprehensive schemas that can be easily retrieved from long-term memory to working memory when dealing with complex and new learning materials (Choi et al., 2014).

Causal factors determine the cause and degree of cognitive load (Paas & Van Merriënboer, 1994b). They include task and learner characteristics. And, as recently stressed by Choi and colleagues the physical learning environment (Fig. 1). The p*hysical learning environment* is understood as a range of manifold physical characteristics immanent in a teaching and learning setting. Such characteristics are defined by architectural conditions, furniture, room temperature, the presence of other people, the nature of the learning materials, or tools. They are accessible to the learner's senses and carry olfactory, visual, haptic or aural information from the surroundings. Often, the physical learning environment is unrelated to the learning process per se, but still maintains an impact on learning success or failure through changes in learners' cognitive load. This physical learning environment is a relevant but rarely investigated determinant of cognitive load and of learning performance. Its features can impact learning: due to our cognitive system's limitations, relevant task-related information competes with features from the physical learning environment that may be extraneous to learning (Choi et al., 2014). Such superfluous and learning-unrelated information competes with learning-related processes for our working memory's limited attentional resources (Chandler & Sweller, 1991; Sweller et al., 2011). Consequently, the additional information from the physical learning environment may distract from and hamper learning processes.

The second group of factors are *assessment factors.* These refer to variables that can inform or serve as measurements of cognitive load such as a learner's performance, mental load (measureable by the perceived task difficulty) and the amount of invested mental effort (Mayer & Chandler, 2001; Paas & Van Merriënboer, 1994a; Pollock, Chandler, & Sweller, 2002; Sweller et al., 2011). According to the model displayed in Fig. 1, mental load determines mental effort, which in turn, affects learning performance. The more difficult a task or material is perceived to be, the more effort that is needed and invested to process the task. In general, we would expect that more effort would result in better performance. Within the realm of CLT in learning, performance refers to acquired knowledge as a learning outcome measurable via knowledge tests such as comprehension, recall, or transfer tests (Sweller et al., 2019). Mental load is task-centered and refers to the task's characteristics such as the complexity of interacting information elements; mental effort is human-centered and refers to the amount of resources and capacities a learner needs to fulfill the task's demands (Choi et al., 2014; Paas & Van Merriënboer, 1994b; Sweller et al., 2019). Within load, Sweller et al. (2019) distinguish two categories: intrinsic and extraneous load. Intrinsic cognitive load is determined by how interactive the information elements being processed are; "extrinsic cognitive load is determined by the manner in which the learning task is presented (i.e., instructional design)" (Choi et al., 2014, p. 227). For instance, increasing the number of technical terms can result in a greater intrinsic load, increasing the number of co-actors can result in a greater load extraneous to the learning task.

While task and learner characteristics have been well investigated, causal factors for cognitive load and the physical environment within the CLT have been empirically neglected. This study aims to help bridge this gap. As the number of other co-actors and learner characteristics are key predictors in CLT, we will provide some additional information on both causal factors in the following sections.

3.1. Causal factor physical environment (E): Impact of others on learning

Features of the physical environment do not necessarily need to actively attract learners' attention; already the mere presence of posters and drawings on the wall can hamper the performance of working memory and attentional tasks (Rodrigues & Pandeirada, 2014). Similar considerations apply to the presence of other people. Other co-actors are accompanied by serious environmental stressors such as crowding and noise that can put individuals at risk when their learning efforts end in permanent failure (Evans & Stecker, 2004). There is empirical evidence that the level of cognitive stress experienced rises in conjunction with the number of coworkers in an open plan-office (Seddigh, Berntson, Danielson, & Westerlund, 2014), and that performance worsens with a rise in task-unrelated sounds (Jahncke, Hygge, Halin, Green, & Dimberg, 2011). Background noise and speech are predominant distractors in open-plan offices and are known to impair cognitive performance as measured by memory for prose and arithmetic tasks (Banbury & Berry, 1998; Seddigh, Stenfors, Berntsson, Baath, Sikström, & Westerlund, 2015). Also, adverse effects of other people are attributable to cognitive and motivational factors (Evans & Stecker, 2004; Klatte, Bergström, & Lachmann, 2013): First, the presence of other people in the learning situation competes with cognitive learning processes. Second, the exposure to inescapable and uncontrollable distractors is associated with a drop in motivation and can even result in learned helplessness which, in turn, can manifest in learning difficulties. The detrimental effect of external distractors becomes even more apparent when background distractors are present during both the learning and recall phase (Banbury & Berry, 1998; Baron, 1986). Therefore, researchers concluded that tasks requiring intense concentration are best performed in solitude without any distractions (Seddigh et al., 2014; Zajonc, 1965). These findings can be understood within the CLT framework. Information from the physical environment that is extrinsic to the task competes with learning-relevant information for the learner's limited working-memory capacities. Consequently, learners experience a heavier cognitive load.

The empirical evidence supports the inhibitory effect for novel, non-dominant tasks as predicted by CLT. Previous studies established a link between the presence of other co-actors and cognitive performance, but the impact on and of cognitive load and whether it mediates such links has been missing. Moreover, the effects on learning have not been sufficiently explored, as group size was seldom considered (Mayer, 2009; Moreno, 2006). We varied the number of others during learning and testing to explore whether the relationship between the number of distractors, varied through number of people, and learning performance is affected as predicted by the overload view.

3.2. Causal factor learner (L): Impact of learner characteristics

A given learner's individual characteristic may interact with the learning environment and impact learning outcomes. They can facilitate or harm the effects of the physical environment (Choi et al., 2014). One of the most prominent and most influential learner prerequisites for learning is their prior knowledge, which explains between 30% and 60% of the variance in learning outcomes (Dochy, 1990). It is thus one of the key determinants of learning (Simonsmeier, Flaig, Deiglmayr, Schalk, & Schneider, 2018; Tobias, 1994). Little attention has been paid to the relation between prior knowledge and the presence of others during learning on learning outcomes.

A learner's prior knowledge is linked to working-memory capacity and the efficient processing of information. Working memory is key to inhibiting disruptive and irrelevant information (Engle, 2002). Learners differ in their working-memory capacity and thus their ability to control and process information (Wiley, Sanchez, & Jaeger, 2014). Learners with a larger working-memory capacity are cognitively more flexible, and can more easily ignore irrelevant seductive details (which are interesting but irrelevant to the learning task) and disregard attention-drawing information (Garner, Brown, Sanders, & Menke, 1992), in favor of relevant information, all of which result in more efficient processing (Bleckley, Durso, Crutchfield, Engle, & Khanna, 2003; Sanchez & Wiley, 2006; Unsworth & Engle, 2007). In line with these considerations, higher scores on working-memory capacity are often associated with better performance in multimedia learning (Doolittle, Terry, & Mariano, 2009; Pazzaglia, Tosco, & Cacciamani, 2007; Schüler, Scheiter, & van Genuchten, 2011). The CLT proposes an interaction between the physical environment and individual cognitive prerequisites (Choi et al., 2014; Paas & Van Merriënboer, 1994a): We can assume that learners with higher levels of working-memory capacity are less prone to distractors originating in the physical learning environment (Conway, Cowan, & Bunting, 2001); although the exact effects of social factors within this context have not yet been explored.

Finally, interest is considered a relatively stable orientation towards specific topics. However, as situational domain-specific interest can vary across stimuli and different situations, it is a situation-dependent determinant (Schiefele & Krapp, 1996). Situational interest comprises emotion-related aspects as well as value-related aspects towards a task or situation (Krapp, 2005). Empirical findings established a positive relationship between interest and learning outcomes (Ainley, Hidi, & Berndorff, 2002; Krapp, 2005). In particular, since positive affect is hypothesized to facilitate the investment of cognitive engagement (Choi et al., 2014), it is assumed that situational interest is favorably associated with cognitive load and performance. Interest can make people choose tasks with higher difficulty levels, which also makes them more willing to invest greater cognitive effort into things they are already interested in (Milyavskaya, Galla, Inzlicht, & Duckworth, under review). Since the physical learning environment may also influence learner affect, a potential interaction between the physical environment and situational interest can be anticipated. In our study, we investigated not only the association between interest and performance, but also the interaction with the physical learning environment as suggested by the cognitive load theory (Choi et al., 2014; Paas & Van Merriënboer, 1994b).

4. Present study

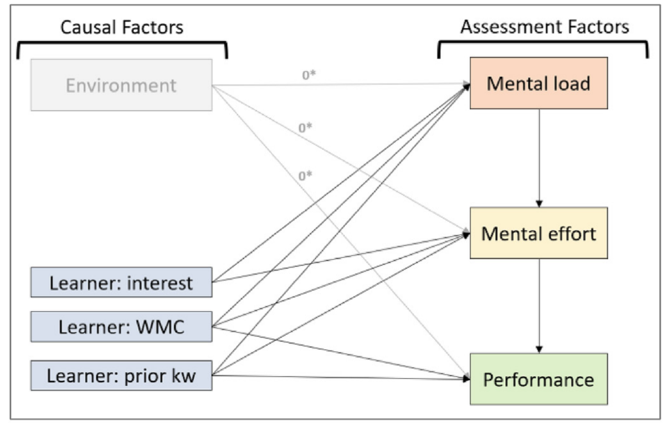
Based on the CLT (Fig. 1), we expected to observe direct effects of learner characteristics as represented by prior knowledge, working-memory capacity, and topic interest, on cognitive load as represented by mental load and mental effort, and performance. Furthermore, we also expected environment features, in this case group size, to exert a direct effect on cognitive load. Finally, we expected to observe an interplay between the environment and learner characteristics on cognitive load. To test our expectations, we transposed the CLT model (Fig. 1) into three path models by consecutively adding predictors to the previous model. We tested a.) only the direct effects of learner characteristics; Classic Model (Fig. 2a); b) the direct effects of learner characteristics and the physical environment, Main Effect Model, (Fig. 2b); and finally c.) the direct effects of both causal factors and their interplay on cognitive load, Full Model (Fig. 2c).

5. Method

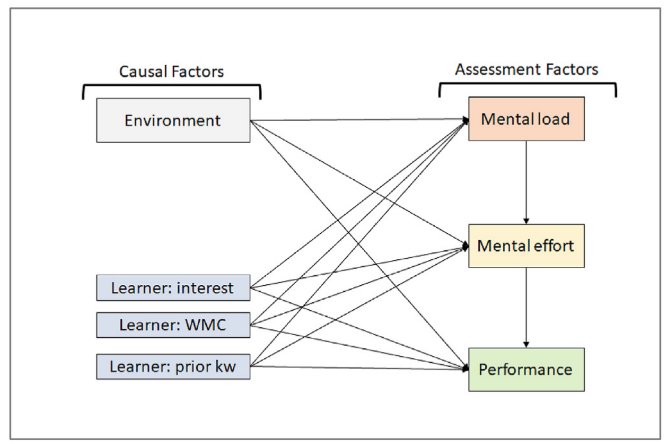
5.1. Participants and design

In total, there were 134 participants. Due to technical issues with data storage in our self-developed environment, data form 19 participants could not be stored. Finally, data was obtained from 115 international students from a European university in Sweden. Participants were approached via email, social media, posters and leaflets. The average age of the participants was 24.15 years (SD = 3.34) and proportion of female participants was 0.52. On average, participants had been studying 4.34 semesters at the time of the study (SD = 3.34, ranging from 1st to 14th semester). Over a period of two weeks, we scheduled 26 sessions for participation. The sessions comprised different group sizes ranging from 1 to 13 people. Across all groups, three participants worked alone, three groups with size of two, two groups with size of three, five groups with size of four and five, four groups with size of six and there were one group each with sizes of 7, 9, 10, 11 and 13. Each participant could only take part in one of the sessions. At the end of the experiment, the participants received a voucher for the cinema and 100 SEK in compensation.

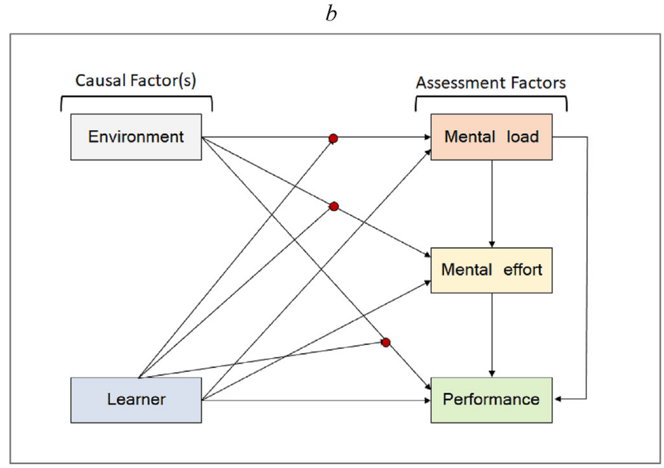
Of the 115 participants, eight had data missing on the working-memory capacity test. Since the study was conducted in English, participants had to take a brief English test. Participants with zero points on the English language proficiency test were excluded from the analyses (n = 4), leaving a final analysis sample of 103. Based on individuals included in the analysis (n = 103), three groups (three participants) worked alone, two groups (two students) with size of two, two groups (five students) with size of three, five groups with size of four (17 students), five groups with size of five (22 students), four groups with size of six (19 students) and there were one group each with sizes of 7 (five students), 9 (seven students), 10 (ten students), 11 (seven students) and 13 (six students). The distribution of group size is



a



b



c

Fig. 2. a. Path model of the Full Model with main and interaction effects. b. Path model of the Main Effect Model with two causal factors, environment and learner characteristics, and their main effects only. c. Path model of the Full Model with main and interaction effects. Paths of interaction terms between environment and each learner characteristic are represented by solid red dots. Interaction terms for each learner characteristic are not illustrated in the diagram to avoid crowding the model presentation. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

approximately normal (skewness = 0.61, kurtosis = −0.47) within the boundary of −2 and 2 which is the thresholds of non-violation of normality (Gravetter & Wallnau, 2012). Descriptive statistics are summarized in Table 1. Most variables did not correlate closely with group size, except for cognitive load as measured by task difficulty (r = .262,

Table 1
Descriptive Statistics and Inter-correlation Matrix (with r-values) for Relevant Variables.

	N = 103	M	SD	Range		Correlation						
				min	max	1	2	3	4	5	6	7
Physical learning environment												
1	group size	6.476	2.982	1	13							
Assessment factors												
2	learning performance (0-35)	6.117	5.769	0	31	-.118						
3	cognitive load: mental load (1–7)	4.029	1.510	1	7	***.262***	-.151					
4	cognitive load: mental effort (1–7)	4.864	1.428	1	7	.036	.049	***.380***				
Causal factors												
5	prior knowledge	1.951	1.471	0	7	**-.207**	***.282***	-.104	-.068			
6	Working-memory capacity (0-21)	8.398	3.735	0	17	-.057	**.188**	-.183	.127	-.003		
7	interest[a] (10–70)	35.165	12.441	10	70	.055	-.144	***.340***	-.032	***-.248***	-.152	

Note. [a] interest is reversely coded so that higher values mean lower interest; Values in bold are different from zero at $p < .05$; values in bold and italics are different from zero at $p < .01$.

$p < .01$) and prior knowledge ($r = -0.207$, $p < .05$).

5.2. Learning material

The computer-based learning environment consisted of a text-picture presentation on a screen preceded by a brief introduction of the topic on corals and an instruction to "Study the following material carefully, as you will have to answer questions about it afterwards". The learning content comprised two text blocks with 164 words and 185 words, respectively, describing the anatomy and hunting behavior of corals (Fig. 3). The texts were accompanied by two corresponding pictures depicting a coral and its parts. Relevant technical terms were bold in the text and labeled in the pictures. Key parts of the anatomy in the picture were labeled and referred to key words in the text that were highlighted in bold. There were no time restrictions on learning time ($M = 4.13$, ranging between 1.188 and 12.023 min, $SD = 1.764$). The distribution is borderline normal-distributed with a skewness of 1.548 and kurtosis of 4.033.

5.3. Causal factors of cognitive load: Learner characteristics

Prior knowledge. Two open questions were posed to estimate participants' prior knowledge of the learning content. The first question asked participants to describe what a coral is, and the second question asked participants to describe the anatomy of a polyp. Coral and polyp were key concepts thematized in the subsequent learning environment. Participants were assigned one point per each correctly-mentioned concept about corals and about a polyp's anatomy. Answers from 25% of the participants were double-coded by an independent rater yielding a high agreement, ICC = 0.936 (two-way mixed), therefore, the remaining data were coded by one rater. A low mean on prior knowledge ($M = 1.951$, $SD = 1.471$) is indicative of low previous knowledge. Prior knowledge was positively skewed, and the distribution was heavy-tailed (skewness = 1.146; kurtosis = 1.842).

Topic interest. Participants' interest in the learning topic was assessed by ten items which were subdivided into two subscales (Schiefele, 1990; Schiefele & Krapp, 1996). Six items covered feeling-related valences (Cronbach-Alpha = .884) reflecting how the participant felt during the learning process, and four items covered value-

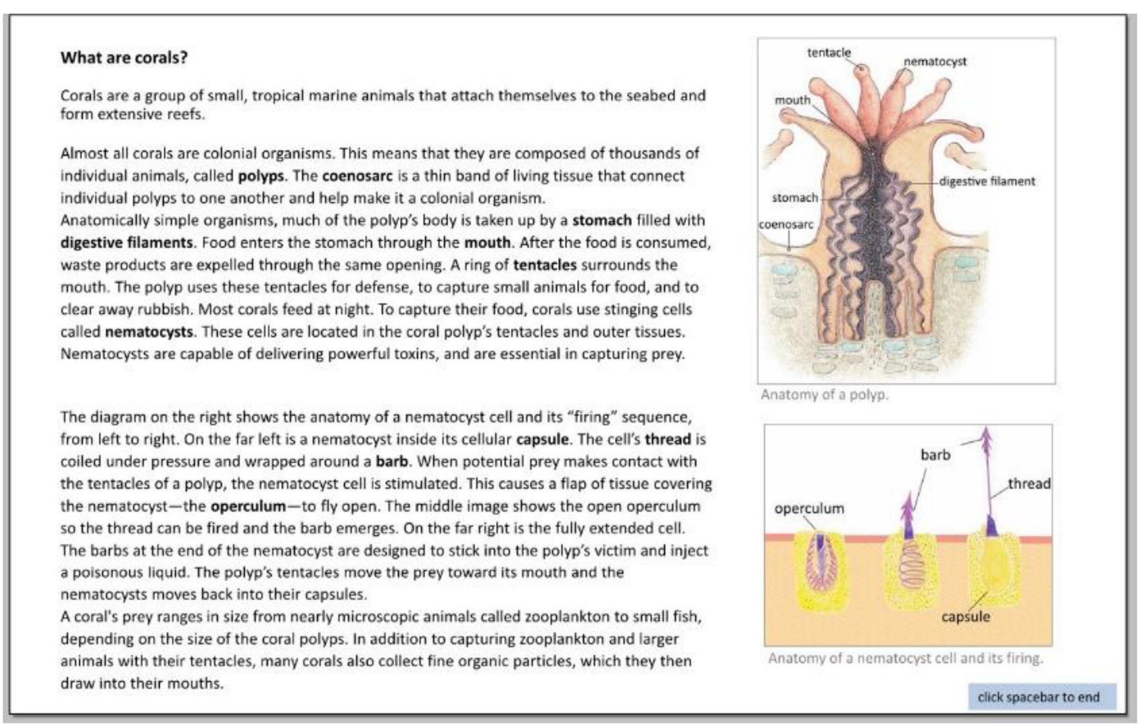


Fig. 3. Learning material (adapted from National Ocean Service).

related valences (Cronbach-Alpha = .812) reflecting the value of the learning content to the participant. Participants had to rate the items on a seven-point Likert scale from *1 = completely true* to *7 = not at all true*.

Working memory capacity. The Letter–Number Sequencing test, a subtest for the measurement of the verbal intelligence quotient (adapted from the German version of the Wechsler Adult Intelligence Scale-III; Von Aster, Neubauer, & Horn, 2009), was used to assess working memory capacity. Sequences of individual letters and numbers (e.g., T–9–A–3) were displayed on participant's screens and they were asked to place the numbers in numerical order and the letters in alphabetical order (e.g., 3–9–A–T). The test started with two elements and gradually increased the level of complexity by adding one element. Each level consisted of three sequences. The end of the test was marked by a sequence of eight elements (level seven). Participants received one point for each correctly-recalled sequence (total score 21 points).

5.4. Assessment factors of cognitive load

Cognitive load is a broader concept and defined as "a multidimensional construct representing the load that performing a particular task imposes on the learner's cognitive system of a particular" (Paas & Van Merriënboer, 1994a, p. 122). Cognitive load is conceptualized as mental load, mental effort, and performance (Paas & Van Merriënboer, 1994a; Choi et al., 2014).

Mental load and mental effort. The learning environment was followed by a self-rating item on mental load and on invested mental effort each (Kalyuga, Chandler, & Sweller, 1999; Paas, Tuovinen, Tabbers, & Van Gerven, 2003). Participants responded to the following questions: "How difficult was it for you to learn the information about corals?" and "How much mental effort (e.g., thinking, recalling) did you invest to process/understand the information about corals?", on a seven-point Likert scale ranging from 1 = *extremely easy/very low* to 7 = *extremely difficult/very high*. The items were proven reliable and provide a simple but sensitive overall measure of cognitive load comprising an intrinsic and extraneous aspect (Sweller et al., 2019).

Learning performance. Similar to previous research on multimedia learning (e.g., Mayer & Estrella, 2014), learning outcomes were assessed by one open question, intended to measure retention, asking participants to write down what corals are based on the information they have learned. We developed a coding scheme with 35 points covering all aspects described in the learning environment. We assigned one point per aspect correctly mentioned in the answer. For instance, aspects such as corals are colonial organism, they use toxin, and they hunt at night were part of the learning material and thus awarded one point each on the posttest. Answers from 20 participants were double-coded by a second independent coder. Coder agreement can be considered as excellent (ICC = 0.993), therefore, one coder only coded the rest of the materials.

5.5. Procedure

The experiment took place in a classroom equipped with computers. Each participant was seated in the testing room in front of a screen; participants could choose a seat according to the U-shaped arrangement in the classroom (Fig. 4). The experimenter welcomed the participants, and the information on the procedure and study aims were presented in writing with the consent form informing about data privacy. Participants were informed that their participation was voluntary, they could withdraw from the study at any time without any repercussions, and that all collected data was anonymized. Next, participants completed questions on demographic information concerning age, sex, study subject, and semester. This was followed by a prior knowledge test, the language proficiency test and working-memory capacity test. Participants were introduced to the learning topic about corals. After the learning phase, participants had to indicate how difficult they found the learning content to be, and how much mental effort they had invested

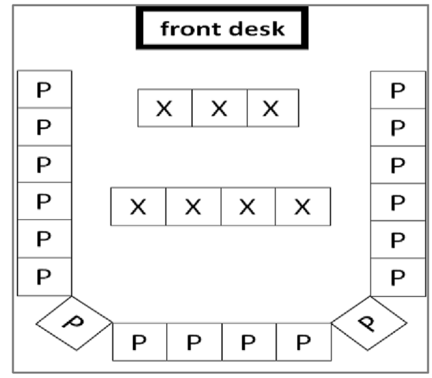


Fig. 4. Seating arrangement. Ps represent workstations for participants, Xs represent workstations blocked during data collection. Participants were happy to choose a seat.

to comprehend the learning content. Then, participants' topic interest was assessed followed by a learning outcome measurement. Finally, they were asked to note down their experience of other learners in the same room. Except for the information letter and consent form, all information and materials were presented on the screen.

5.6. Statistical analysis

We translated the research questions based on Choi et al, (2014) cognitive load model (Fig. 1) into path model representations (Fig. 2a–c). In total, three models were tested. We applied a stepwise forward procedure where we start with a model which comprises only one main effect, namely learner characteristics (Classic Model, Fig. 2a). We then add a second main effect, namely the environment (Main Effect Model, Fig. 2b), and finally the interaction terms (Full Model, Fig. 2c).

Path analysis based on structural equation models (Skrondal & Rabe-Hesketh, 2004; Tabachnick & Fidell, 2006) was used to estimate the previously described models. The goodness of fit of these models was evaluated by a range of recommended indices including the Tucker-Lewis Index (TLI; Tucker & Lewis, 1973), the Root Mean Square Error of Approximation (RMSEA; Steiger, 1990), and the Comparative fit indexes (CFI; Bentler, 1990). CFIs and TLIs exceeding 0.95 indicate an acceptable model fit, whereas the RMSEAs less than/under 0.06 indicate good fit. We also present the chi-square statistic to test the model fit difference between the Classic Model and the less restrictive Main Effect Model. A significant difference of the two models implies improved model fit in the Main Effect Model, which can be attributed to the addition of environment effects to cognitive load factors. In terms of other fit indices, a less restrictive model (Classic Model) is similarly preferred if the change in model fit indices is significantly better than that of the less restrictive model (Main Effect Model). In terms of the RMSEA, the change should be more than 0.015 (Chen, 2007). For CFI, the change should exceed 0.01 (Chen, 2007; Cheung & Rensvold, 2001). Based on the model revealing the best balance between parsimony and goodness of fit to the data, we also estimated mediation effects for the paths from environment, learner characteristic to performance via mental load and mental effort, and to mental effort via mental load.

Although participants were clustered within learning groups, random intercept multilevel modelling analysis exhibited no statistically significant group level variances in cognitive load variables on mental effort (Var = 0.01, $\chi^2(1) = 0$, $p > .05$), mental load (Var = 0.01, $\chi^2(1) = 0$, $p > .05$), or on learning performances (Var = 0.73, $\chi^2(1) = 0$, $p > .05$). Therefore, we did not adjust clustering effects for further analysis.

All analyses were carried out in Mplus 7.4 (Muthén & Muthén, 2015), with maximum likelihood estimator. For mediation effect

Table 2
Fit indices of the models tested.

	RMSEA	CFI	TLI	chi-square	*df*	*p*
Classic Model	.023	.985	0.969	12.655	12	.395
Main Effect Model	0	1	1*	4.741	9	.856
change (Classic vs. Main Model)	.023	.015	0.031	7.914	3	.048
Full Model	0	1	1	0	0	0

Note. *the estimated value given by model is 1.268 which is out of bound, therefore we fixed it to 1.

estimation, we used bootstrapping estimator (1000 draws) as it yields more robust results.

6. Results

6.1. Test of CLT models

Three models representing alternative specifications of the CLT were estimated and fit indices are summarized in Table 2. The Classic Model (Figs. 2a and 5a) represents effects of learner characteristics on cognitive load factors. In estimating this model, the parameters were constrained to zero for the paths from environment to cognitive load factors, as well as paths for interaction terms between environment and learner characteristics. Model fit indices indicated good fit to the data (RMSEA = 0.023, CFI = 0.985, TLI = 0.969; Chi-square = 12.655, *df* = 12, *p* = .395). In the less restrictive Main Effect Model (Figs. 2b and 5b), three additional parameters representing the effects of environments on mental load, mental effort, and performance were estimated. The fit indices for this model were very good (RMSEA = 0, CFI = 1, TLI = 1.268 [we fixed it as 1 as that is the boundary]; Chi-square = 4.741, *df* = 9, *p* = .856) and further improved compared to the Classic Model (RMSEA = 0.023, CFI = 0.015, TLI = 0.031, chi-square difference = 7.914, *df* = 3, *p* = .048). The Full Model (Figs. 2c and 5c was also estimated where the interaction terms were added in addition to the effects of environment and learner characteristics. As described in the analysis section, the model fit of the Full Model was perfect given that it was the saturated model. However, our results showed that none of the interaction terms was statistically significant. Given that the Main Effect model already demonstrated very good fit to the data and was superior to the Classic Model, we chose it to be the model that best describes the theory proposed by Choi et al., 2014. Estimated path coefficients based on the Main Effect model were thus interpreted accordingly.

Path coefficients from the Main Effect model (Fig. 5b, Appendix Table S1) indicated that group size was associated with higher perceived mental load (*beta* = 0.243, *p* = .006, *p*[FDR] = 0.022). Learner characteristics were also predictive of cognitive load factors: lower topic interest was associated with higher mental load (*beta* = 0.314, *p* < .001, *p*[FDR] = 0.005) but less mental effort (*beta* = - 0.187, *p* = .049); working memory capacity was borderline associated with higher mental effort (*beta* = 0.183, *p* = .037, *p*[FDR] = 0.111); prior knowledge was associated with better learning performance (*beta* = 0.268, *p* = .004, *p*[FDR] = 0.02).

To further test whether there was a non-linear effect of the group size, a quadratic term of group size variable was added to the Main Effect Model. We found no effect of non-linear effect on mental load (*beta* = 0.304, *p* = .472), mental effort (*beta* = −0.151, *p* = .727), or learning performance (*beta* = −0.119, *p* = .787). Thus, based on our dataset, the relationship is linear in nature. However, we acknowledge that although there might be a cut-off where the effect of group size becomes non-linear. This cut-off will be most probably above 13, whereas within the size of 13, adding more people does not increase the mental load associated with the task.

6.2. Test of mediation

Based on the Main Effect Model (previously shown to fit data better than the Classic Model), we estimated the indirect effects of learner characteristics and group size on performance via mental load and via mental effort, as well as the indirect effect of learner characteristics and group size on mental effort via mental load. Our results (Table 3) reveal no mediation effects on learning performance outcome. However, the effect of environment on mental effort was positively mediated by mental load (indirect effect estimate = 0.119). Mental load also positively mediated the effect of the learner characteristic *topic interest* on mental effort (indirect effect estimate = 0.154, however, note that this is a negative effect on mental effort because interest was reversely coded). These findings indicate that group size and interest can influence mental effort, initially directly through an influence on mental load, then through the effect of mental load on mental effort.

6.3. Power analysis of interaction terms

Given this study's medium sample size, its statistical power is restricted in detecting weak interaction effects between learning environment and learner characteristics. To assess the power required to detect the interaction terms specified in the Full Model, we performed statistical simulations based on post hoc power analysis. Population parameters for the simulations were based on the parameters estimated in the Full Model. Simulations of 1000 replication samples were generated for sample sizes of 100, 300, 500, 1000, 1500, 2000 and 2500 participants, respectively. Results (Table 4) showed that for learning performance outcome, for the estimated interaction effect size between group size and topic interest, analysis based on 500 participants can reach a statistical power of 0.833. For interaction between group size and working memory, a sample size of 1500 attains a power of 0.862. In terms of mental effort, for the interaction between group size and prior knowledge, a sample size of 1000 yields a power of 0.837. All other interactions did not reach a power exceeding 0.8 at or below a sample size of 2500.

7. Discussion

The present study is one of the few approaches empirically addressing the complexity of the CLT model by including various main and interaction effects. Based on considerations derived from cognitive load theory, we investigated the impact of the number of co-actors present and of learner characteristics on cognitive load. We took a forward approach by successively adding variables to statistical models and testing each model for its predictive power. As expected, learner characteristics were predictive of cognitive load as assessed through mental load, mental effort, and performance, albeit to different degrees. Also, the addition of a second causal factor, namely physical environment, revealed a meaningful added value. However, contrary to our expectations, our more advanced model entailing the interaction term between learner characteristics and physical environment did not improve the model fit significantly. In addition, we tested the mediating effect of mental load on mental effort. All causal factors were potential predictors, but only the group size of co-actors and topic interest qualified as such. In sum, our findings partially support the theoretical framework of cognitive load: In line with the assumption by Choi et al. (2014) the physical environment has an impact on cognitive load, and the effect of topic interest and group size on mental effort is mediated by mental load. However, not all effects of learner characteristics were confirmed, and we could not establish an association between mental load and learning performance as it was suggested by the CLT model. Thus, the CLT model was not fully confirmed. In the following, we will discuss the findings in more detail in the context of the CLT framework.

The more co-actors there were in the same room, the more difficult the task was perceived, and the more load that was invested in

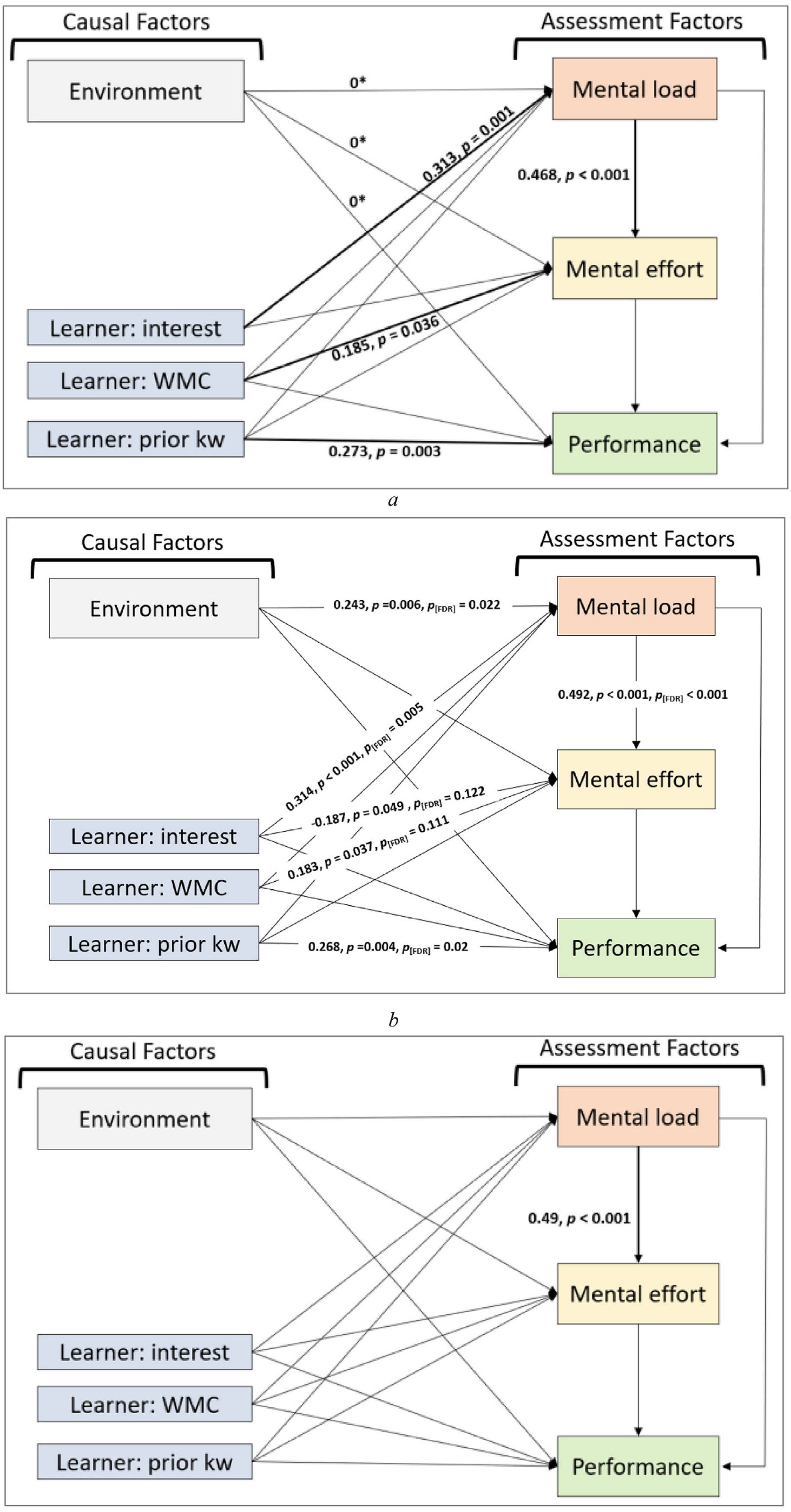


Fig. 5. a. Classic Model. Only statistically significant path coefficients presented (beta values, in standardised metric); *path from learning environments were fixed to zero. Paths of interaction terms between learner characteristics and learning environment were also fixed at 0. b. Main Effect Model. Only statistically significant path coefficients are presented (beta values, in standardised metric). Paths of interaction terms between learner characteristics and learning environment were also fixed at 0. $p_{[FDR]}$ represents p values adjusted for multiple testing. c. Full Model. Only statistically significant path coefficients are presented (beta values, in standardised metric). Paths of interaction terms were specified and estimated between environment and each learner characteristic but are not illustrated in the diagram so as to avoid overcrowding the model.

Table 3
Estimated mediation effects based on main effect model with 95% bootstrapping confidence interval.

Indirect effect	Outcome: performance				Outcome: mental effort			
	est	0.025	0.975	*p*	est	0.025	0.975	*p*
Group size								
Total Indirect	−0.027	−0.097	0.020	.374	**0.119**	0.037	0.232	.015
Group size via mental load	−0.030	−0.107	0.009	.311				
Group size via mental effort	−0.009	−0.064	0.005	.545				
Group size via mental load and mental effort	0.011	−0.004	0.045	.318				
Prior knowledge								
Total Indirect	−0.010	−0.070	0.020	.625	0.012	−0.083	0.113	.804
Prior knowledge via mental load	−0.003	−0.054	0.019	.856				
Prior knowledge via mental effort	−0.008	−0.058	0.008	.585				
Prior knowledge via mental load and mental effort	0.001	−0.006	0.024	.862				
Working memory capacity								
Total Indirect	0.027	−0.007	0.093	.251	−0.060	−0.160	0.030	.223
Working memory capacity via mental load	0.015	−0.008	0.082	.445				
Working memory capacity via mental effort	0.017	−0.008	0.074	.346				
Working memory capacity via mental load and mental effort	−0.006	−0.031	0.003	.456				
Topic interest								
Total Indirect	−0.041	−0.135	0.021	.293	**0.154**	0.055	0.289	.013
Topic interest via mental load	−0.038	−0.132	0.019	.323				
Topic interest via mental effort	−0.018	−0.090	0.007	.423				
Topic interest via mental load and mental effort	0.015	−0.008	0.061	.356				

Note. est = estimated effect. Values in bold indicate significant difference from zero at $p < .05$.

comprehending the learning content. These findings support empirical work on the detrimental effects of the presence of others on performance and can be derived from the CLT. Following the line of argumentation of the CLT, due to humans' limited working memory resources, the more co-learners are present, the more distractive stimuli compete for resources from working memory and the task is perceived as more difficult. Co-learners can be considered such external-to-the-task distractors. The more difficult learners perceive the task, the more mental effort they must invest for cognitive processing of the learning information in order to reach a certain performance level. So far, our findings are in line with the CLT. The CLT also suggests a link between mental effort and performance. One might expect that learners who invest more effort, perform better. However, our findings do not support the latter expectation. We consider two possible explanations. Firstly, the increase in mental effort could compensate for an increase in distractors and protect the learner from a decrease in performance. However, working memory capacity is limited (Sweller et al., 2011). If working memory is already occupied by distractors, learners must invest more effort to redirect attention from the distractors toward the processing of the learning task. Secondly, it is possible that an association simply does not exist. In the context of multimedia learning the efficiency of an instructional message is assessed through its effect on cognitive load. In multimedia learning, design principles based on CLT were developed to foster learning. Good instructional design based on CLT is expected to relieve working memory and thus reduce extrinsic cognitive load ascribed to "the way in which the learning task is presented" (Choi et al., 2014, p. 227). Reducing load frees working memory capacities for the task and should result in superior performance. But, the link between mental effort and performance is not straight forward and the expectation of a positive relationship between these variables is not fully supported by empirical findings (Anmarkrud, Andresen, & Bråten, 2019). The studies in the meta-analysis by Anmarkrud and colleagues mainly use two-group experimental designs to compare the effects of instructional design messages on cognitive load and performance. Effective instructional design was expected to relieve working memory, and thus reduce mental load. However, more than 50% of the studies yielded inconsistent findings: mental load and mental effort were not reduced in the conditions with good instructional design. Also, the meta-analysis found that the majority of researchers operationalized cognitive load as mental effort, mental load seemed to be of less interest. Therefore, research is needed paying attention to the direct associations between mental effort, mental load, and performance to address adjustments to the CLT model in Fig. 1 based on empirical work.

Regarding learner characteristics, except for prior knowledge, we detected neither direct nor indirect effects on performance. Contrary to the aforementioned empirical work by other researchers, we found that topic interest, working-memory capacity, and group size exhibited no direct effect on performance. Topic interest and group size affected mental effort indirectly. Although the effect became non-significant

Table 4
Estimated power for interaction effects estimates based on the full model.

outcome	interaction	population	power						
	terms	estimate	*n* = 100	*n* = 300	*n* = 500	*n* = 1000	*n* = 1500	*n* = 2000	*n* = 2500
Performance	Size*prior knowledge	−0.033	.094	.078	.108	.149	.212	.264	.323
	Size*working memory	−0.041	.139	.282	.404	.713	**.862**	**.94**	**.968**
	Size*interest	0.019	.281	.616	**.833**	**.986**	**1**	**1**	**1**
Mental effort	Size*prior knowledge	0.025	.175	.401	.552	**.837**	**.94**	**.983**	**.996**
	Size*working memory	−0.001	.055	.049	.057	.054	.06	.068	.07
	Size*interest	0	.065	.051	.061	.044	.056	.044	.05
Mental load	Size*prior knowledge	0.005	.07	.06	.063	.072	.105	.101	.126
	Size*working memory	−0.008	.102	.186	.269	.457	.626	.751	**.856**
	Size*interest	0	.067	.067	.052	.045	.035	.047	.048

Note. Values in bold indicate statistical power > 0.80.

after adjusting for the multiple testing effect, on the other hand there is still an indication that greater interest led to lower task difficulty and to lower mental effort invested. It remains unclear why the mediation effect was not achieved for prior knowledge and working-memory capacity. Both are desirable cognitive prerequisites that should lower the perception of the task's difficulty, and should thus reduce load investment. The role of interest in CLT could be linked to the “willingness” to invest mental effort. Such considerations deserve further attention in future studies.

Against our expectations, our findings failed to support an interaction between the causal factors as suggested by the theoretical framework by Choi et al. (2014). For instance, according to the CLT, working memory capacity can be understood as a protection factor. Learners with higher working memory capacity levels are expected to overcome the impact of distractors in the environment and experience the task as less difficult. However, our findings do not support the interplay. One reason could be that there is no such interaction; another could lie in a sample size too small to detect such an effect (see Table 4). Finally, another possible reason could be the learning task's duration. Several studies have shown that the length of the exposure to environmental stressors may determine its impact (Evans & Stecker, 2004). Other co-actors can be considered such stressors. For example, participants may exhibit a drop in motivation when external stressors last longer. Similar patterns would be expected for learning performance and experienced load: learning performance is expected to drop, and the load to increase the longer the exposure to other people lasts. However, the exposure time to other people is also confounded with learning time - another factor affecting learning performance. We therefore decided to apply a user-paced setup with no time restrictions. Supplemental analysis showed that learning time was not associated with group size – in other words, learners in larger groups did not learn for longer or shorter time; moreover, including this variable in the main regression analysis did not change the effect of group size on outcome variables (cognitive load measures and performance). It is possible that time-on-task, a variable where the effects of group size would be expected to unfold, can be considered rather brief. For instance, it is conceivable that all learners manage to withstand distractive influences for a short period of time, but only learners with high topic interest, prior knowledge or working memory manage to continue withstanding over the long run. Therefore, a more complex and lengthier task might unravel interaction effects between learning environment and learner characteristics.

To capture the amount of knowledge gained, we asked participants to write down what they had learned from the materials in an open question, which can be considered a measure of retention. Retention can be considered an adequate measure of learning performance; but, transfer knowledge is key to meaningful learning with multimedia because it requires higher levels of processing and elaboration (Mayer, 2009). With this in mind, as we would expect the detrimental effects of group size to become more obvious on transfer knowledge as compared to retention, it might be worthwhile for future researchers to incorporate transfer measures. Alternatively, challenges during the learning phase can be considered a desirable difficulty (Bjork & Bjork, 2011): some circumstances that make a task difficult require greater effort during learning, but are likewise known to benefit consolidation in long-term memory. Keeping the “desirable-difficulties” perspective in mind: perhaps the presence of others impairs cognitive processing during learning, but reveals beneficial effects over the long term. Taken together, future research should investigate the effects of group size on more complex test performances comparing immediate and delayed posttests (Schweppe & Rummer, 2016).

Finally, we would like to make a note on the measurement of cognitive load. Cognitive load was assessed by learner's perceived task difficulty and the mental effort invested in studying the materials. Each was assessed retrospectively with one item. Although both cognitive load measures, that means mental load and mental effort, correlated, $p < .001$, our data indicate that it is important to differentiate between these measures as they do not yield identical results and thus assess different aspects of cognitive load. Some researchers argue that measuring cognitive load via a single item is insufficient and at a distinction between different load types, more specifically intrinsic and extraneous load, should be reflected in the assessments (Klepsch, Schmitz, & Seufert, 2017; Leppink, Paas, Van der Vleuten, Van Gog, & Van Merriënboer, 2013). These concerns are linked to the assessment of cognitive load using a one-item measurement (Ayres & Paas, 2012). This study employed self-reports to capture experienced load, whereas follow-up studies could benefit from objective direct measures of load and further learner characteristics. Using more advanced scales or a dual-task methodology also has promising potential (Klepsch et al., 2017; Krell, 2017; Schoor, Bannert, & Brünken, 2012). Furthermore, Krell (2017) proposes a 12-item instrument with two subscales, one each for mental load and mental effort. However, one must acknowledge that Choi et al.'s approach is primarily based on CLT paradigm directly positing theoretical constructs based on mental load - the assessment of which remained based on the single-item instrument as used in our study. Moreover, more sophisticated methods to assess cognitive load lead to similar results and the simple one-item measure has yielded overly-consistent results in the past (Sweller et al., 2011, 2019).

We conclude that first, adding features of the physical learning environment is relevant to understanding the manifestation of load during learning. Second, group size does not interact with learner characteristics, but the main effect of each causal factor matters for cognitive load: larger group size and less topic interest are associated with more mental load; lower topic interest revealed a marginally statistically significant inhibitory effect on mental effort, while a greater working-memory capacity marginally predicts an increase in mental effort; finally, greater prior knowledge exerted a facilitating effect on learning performance. Lastly, we would like to present some limitations which should stimulate opportunities for future research.

8. Limitations and future directions

We showed that group size affects cognitive load. But, the presence of other co-actors has a both cognitive and social effect on learners. Some researchers claim that the presence of others has a facilitating effect such as increased motivation, whereas other studies have demonstrated an inhibitory effect such as stress (Huguet, Galaing, Monteil, & Dumas, 1999; Pessin, 1933; Zajonc, 1965). The presence of other learners may be perceived as a challenge or a threat (Blascovich, Mendes, Hunter, & Salomon, 1999). However, even the latter can count as distracting because students withdraw attention from their own materials to see how others in the room are doing (Schmitt, Gilovich, Goore, & Joseph, 1986). We recommend that future studies address these descriptive learner experiences to investigate the relevance of other learners' presence and to elaborate on the various social and motivational aspects on performance and load through the mere physical presence of other co-actors.

With regard to the causal factors of cognitive load, allow us to point out that we aimed to address a diverse range of cognitive learner characteristics. As we assessed few learner characteristics, future research should focus on developing more and more broad-based ones (including those not cognitive) to reveal the motivational and social effects that group size has on learning (cf. MiSTIC model, Cromley (2019)). Such adaptations will enable us to test more complex and combined interactions of several learner characteristics on learning, as proposed by Cromley (2019).

We examined the relevance of physical environment via group size because we consider it a valid representative feature of students' authentic learning settings. It should be noted, however, that this factor has many more properties that can be deliberately manipulated and tested for their impact on cognitive load. For example, high temperature, noise, and poor lighting are known to increase discomfort and harm learning (Rodrigues & Pandeirada, 2014; Siqueira, da Silva, Coutinho, & Rodrigues, 2017). A drawback of our study is the fact that we did not vary group size to its fullest extent. It remains to be tested whether the tentative effects we identified such as the impact of working-memory capacity and interest on performance become more obvious in even bigger groups. For instance, the ability to hold information in working memory might reveal greater importance when more distractors are competing with the learning information for limited cognitive capacities.

Another plausible variation to the design could address an experimental approach where varying group sizes could be defined as factors, and not as a continuous variable as was done in our study. In such a design, researchers could pre-define group sizes in conditions to compare the effects of different group sizes. For instance, they could compare the effects of a group size of five people with a group size of twenty people. A more experimental large-scale approach could allow to investigate the function of group size in more detail. It is conceivable that the group size has an asymptote so that, for example, the effect of one hundred versus two hundred co-actors becomes negligible. However, it should be considered that such a design requires a very large total sample size.

Finally, although our findings support the CLT and an inhibitory effect on load, we cannot rule out possible facilitating effects or a U-shaped function beyond the maximum number of group members in the present study for several reasons. First, our participants learned the materials once only, whereas superior performance, in the presence of others builds on the premise that the acquired knowledge should have been learned thoroughly, thereby resembling a dominant response when retrieved from memory. Secondly, we did not include any measurement of arousal in our study – a factor that can be the driving factor in explaining the interplay between dominant versus non-dominant tasks in the presence of co-actors. However, and thirdly, according to Zajonc, "the presence of others may have effects considerably more complex than that of increasing the individual's arousal level" (Zajonc, 1965, p. 274). In this vein, Zajonc assumes that the presence of others can also reduce anxiety related to performance, or increase imitation behavior. There is a paucity of systematic empirical evidence from research with human subjects on the mere presence of others with no social components, including load and arousal measures, nor has anyone demonstrated an association between cognitive load and arousal (Hoogerheide et al., 2019). In sum, our data set might not be sensitive enough to capture a facilitating effect (should one exist in the context of other co-actors' presence in learning situations), but our data do speak for an inhibition effect within the framework of CLT.

9. Conclusion

Overall, this study supports the cognitive load theory whereby the physical environment and learner characteristics are defined as important determinants for cognitive load. However, not all variables contribute to the same degree to all three cognitive load factors. The impact of group size on mental load speaks for methodological implications of group size in the context of instructional design in learning and in the context of research. Effects detected in small group settings are not automatically generalizable to bigger group settings. More specifically, studies conducted in natural settings such as classrooms which possess high ecological validity but varying group sizes should report on the subsample sizes and account for them in analyses.

Future research should expand upon the framework we used and focus on the interaction between hitherto well-established instructional design messages such as task features that promote learning and the interplay with the presence of others. Instructional designs that work in single or small groups might become ineffective in large groups. Or, put the other way round, can a beneficial instructional design compensate for the detrimental effects of a physical learning environment? We therefore encourage other researchers to expand upon this study with a larger sample and systematic variations of other variables, such as relevant features of the physical environment and learner characteristics, to complement our findings with higher order interaction analyses. More research focusing on the whole model, instead of isolated effects, could contribute to refining the CLT model.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2019.06.016.

References

Aiello, J. R., & Douthitt, E. A. (2001). Social facilitation from Triplett to electronic performance monitoring. *Group Dynamics: Theory, Research, and Practice, 5*(3), 163–180. https://doi.org/10.1037/1089-2699.5.3.163.

Ainley, M., Hidi, S., & Berndorff, D. (2002). Interest, learning, and the psychological processes that mediate their relationship. *Journal of Educational Psychology, 94*(3), 545. https://doi.org/10.1037/0022-0663.94.3.545.

Allport, F. H. (1924). The group fallacy in relation to social science. *Journal of Abnormal Psychology & Social Psychology, 19*(1), 60–73. https://doi.org/10.1037/h0065675.

Anmarkrud, Ø., Andresen, A., & Bråten, I. (2019). Cognitive load and working memory in multimedia learning: Conceptual and measurement issues. *Educational Psychologist, 54*(2), 61–83. https://doi.org/10.1080/00461520.2018.1554484.

Ayres, P., & Paas, F. (2012). Cognitive load theory: New directions and challenges. *Applied Cognitive Psychology, 26*(6), 827–832. https://doi.org/10.1002/acp.2882.

Banbury, S., & Berry, D. C. (1998). Disruption of office-related tasks by speech and office noise. *British Journal of Psychology, 89*(3), 499–517. https://doi.org/10.1111/j.2044-8295.1998.tb02699.x.

Baron, R. S. (1986). Distraction-conflict theory: Progress and problems. *Advances inExperimental Social Psychology, 19*, 1–40. https://doi.org/10.1016/S0065-2601(08)60211.

Beckers, R., van der Voordt, T., & Dewulf, G. (2016). Learning space preferences of higher education students. *Building and Environment, 104*, 243–252. https://doi.org/10.1016/j.buildenv.2016.05.013.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238–246. https://doi.org/10.1037/0033-2909.107.2.238.

Bjork, E. L., & Bjork, R. A. (2011). Making things hard on yourself, but in a good way: creating desirable difficulties to enhance learning. In M. A. Gernsbacher, R. W. Pew, L. M. Hough, & J. R. Pomerantz (Eds.). *Psychology and the Real World: Essays Illustrating Fundamental Contributions to Society* (pp. 56–64). New York: Worth.

Blascovich, J., Mendes, W. B., Hunter, S. B., & Salomon, K. (1999). Social "facilitation" as challenge and threat. *Journal of Personality and Social Psychology, 77*(1), 68–77. https://doi.org/10.1037/0022-3514.77.1.68.

Bleckley, M. K., Durso, F. T., Crutchfield, J. M., Engle, R. W., & Khanna, M. M. (2003). Individual differences in working memory capacity predict visual attention allocation. *Psychonomic Bulletin & Review, 10*(4), 884–889. https://doi.org/10.3758/bf03196548.

Bond, C. F., & Titus, L. J. (1983). Social facilitation: A meta-analysis of 241 studies. *Psychological Bulletin, 94*(2), 265–292. https://doi.org/10.1037/0033-2909.94.2.265.

Chandler, P., & Sweller, J. (1991). Cognitive load theory and the format of instruction. *Cognition and Instruction, 8*(4), 293–332. https://doi.org/10.1207/s1532690xci0804_2.

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(3), 464–504. https://doi.org/10.1080/10705510701301834.

Cheung, G. W., & Rensvold, R. B. (2001). The effects of model parsimony and sampling error on the fit of structural equation models. *Organizational Research Methods, 4*(3), 236–264. https://doi.org/10.1177/109442810143004.

Choi, H.-H., van Merriënboer, J. J. G., & Paas, F. (2014). Effects of the physical environment on cognitive load and learning: Towards a new model of cognitive load. *Educational Psychology Review, 26*(2), 225–244. https://doi.org/10.1007/s10648-014-9262-6.

Conway, A. R. A., Cowan, N., & Bunting, M. F. (2001). The cocktail party phenomenon revisited: The importance of working memory capacity. *Psychonomic Bulletin & Review, 8*(2), 331–335. https://doi.org/10.3758/bf03196169.

Cottrell, N. B. (1972). Social facilitation. In C. G. McClintock (Ed.). *Experimental social psychology* (pp. 185–236). New York: Holt, Rinehart & Winston.

Cottrell, N. B., Wack, D. L., Sekerak, G. J., & Rittle, R. H. (1968). Social facilitation of dominant responses by the presence of an audience and the mere presence of others. *Journal of Personality and Social Psychology, 9*(3), 245–250. https://doi.org/10.1037/h0025902.

Cromley, J. G. (2019). The MiSTIC Model of multimedia learning: A theoretical synthesis and meta-theory. In J. G. Cromley, S. N. Beretvas, & L. Lawrence (Eds.). *Models of multimedia comprehension: A review and synthesis of the literature in STEM* Book in progress.

Dochy, F. J. R. C. (1990). Instructional implications of recent research and empirically-based theories on the effect of prior knowledge on learning. *Learning Environments,* 339–355. https://doi.org/10.1007/978-3-642-84256-6_26.

Doolittle, P. E., Terry, K. P., & Mariano, G. J. (2009). Multimedia learning and working memory capacity. In R. Zheng (Ed.). *Cognitive effects of multimedia learning* (pp. 17–33). Hershey: Information Science Reference.

Engle, R. W. (2002). Working memory capacity as executive attention. *Current Directions in Psychological Science, 11*(1), 19–23. https://doi.org/10.1111/1467-8721.00160.

Evans, G. W., & Stecker, R. (2004). Motivational consequences of environmental stress.

Journal of Environmental Psychology, 24(2), 143–165. https://doi.org/10.1016/s0272-.
Garner, R., Brown, R., Sanders, S., & Menke, D. (1992). "Seductive details" and learning from text. In K. A. Renninger, S. Hidi, & A. Krapp (Eds.). *The role of interest in learning and development* (pp. 239–254). Hillsdale, NJ: Erlbaum.
Gravetter, F. J., & Wallnau, L. B. (2012). *Statistics for the behavioral sciences.* Belmont, CA: Wadsworth Cengage Learning.
Guerin, B. (1993). *European monographs in social psychology. Social facilitation.* New York, NY: Cambridge University Press.
Harrop, D., & Turpin, B. (2013). A study exploring learners' informal learning space behaviors, attitudes, and preferences. *New Review of Academic Librarianship, 19*(1), 58–77. https://doi.org/10.1080/13614533.2013.740961.
Hoogerheide, V., Deijkers, L., Loyens, S. M. M., Heijltjes, A., & Van Gog, T. (2016). Gaining from explaining: Learning improves from explaining to fictitious others on video, not from writing to them. *Contemporary Educational Psychology, 44–45*, 95–106. https://doi.org/10.1016/j.cedpsych.2016.02.005.
Hoogerheide, V., Renkl, A., Fiorella, L., Paas, F., & van Gog, T. (2019). Enhancing example-based learning: Teaching on video increases arousal and improves problem-solving performance. *Journal of Educational Psychology, 111*(1), 45–56. https://doi.org/10.1037/edu0000272.
Huguet, P., Galvaing, M. P., Monteil, J. M., & Dumas, F. (1999). Social presence effects in the Stroop task: Further evidence for an attentional view of social facilitation. *Journal of Personality and Social Psychology, 77*(5), 1011–1025. https://doi.org/10.1037/0022-3514.77.5.1011.
Jahncke, H., Hygge, S., Halin, N., Green, A. M., & Dimberg, K. (2011). Open-plan office noise: Cognitive performance and restoration. *Journal of Environmental Psychology, 31*(4), 373–382. https://doi.org/10.1016/j.jenvp.2011.07.002.
Kalyuga, S., Chandler, P., & Sweller, J. (1999). Managing split-attention and redundancy in multimedia instruction. *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition, 13*(4), 351–371. https://doi.org/10.1002/acp.1773.
Klatte, M., Bergström, K., & Lachmann, T. (2013). Does noise affect learning? A short review on noise effects on cognitive performance in children. *Frontiers in Psychology, 4*. https://doi.org/10.3389/fpsyg.2013.00578.
Klepsch, M., Schmitz, F., & Seufert, T. (2017). Development and validation of two instruments measuring intrinsic, extraneous, and germane cognitive load. *Frontiers in Psychology, 8*. https://doi.org/10.3389/fpsyg.2017.01997.
Knepp, M. M., Krafka, E. R., Boulton, A. N., & Myers, M. P. (2014). Group administration influences design but not written word fluency testing. *Laterality: Asymmetries of Body, Brain and Cognition, 19*(5), 615–637. https://doi.org/10.1080/1357650x.2014.892507.
Krapp, A. (2005). Basic needs and the development of interest and intrinsic motivational orientations. *Learning and Instruction, 15*(5), 381–395. https://doi.org/10.1016/j.learninstruc.2005.07.007.
Krell, M. (2017). Evaluating an instrument to measure mental load and mental effort considering different sources of validity evidence. *Cogent Education, 4*(1), https://doi.org/10.1080/2331186x.2017.1280256.
Leppink, J., Paas, F., Van der Vleuten, C. P. M., Van Gog, T., & Van Merriënboer, J. J. G. (2013). Development of an instrument for measuring different types of cognitive load. *Behavior Research Methods, 45*(4), 1058–1072. https://doi.org/10.3758/s13428-013-0334-1.
Mayer, R. E. (2009). *Multimedia learning* (2nd ed.). Cambridge: Cambridge University Press.
Mayer, R. E., & Chandler, P. (2001). When learning is just a click away: Does simple user interaction foster deeper understanding of multimedia messages? *Journal of Educational Psychology, 93*(2), 390–397. https://doi.org/10.1037/0022-0663.93.2.390.
Mayer, R. E., & Estrella, G. (2014). Benefits of emotional design in multimedia instruction. *Learning and Instruction, 33*, 12–18. https://doi.org/10.1016/j.learninstruc.2014.02.004.
Meumann, E. (1925). *Haus- und Schularbeit. Experimente an Kindern der Volksschule.* Leipzig: Julius Klinkhardt.
Milyavskaya, M., Galla, B., Inzlicht, M., & Duckworth, A. (2018). *More effort, less fatigue: How interest increases effort and reduces mental fatigue.* Manuscript submitted for publication https://psyarxiv.com/8npfx.
Moreno, R. (2006). Does the modality principle hold for different media? A test of the method-affects-learning hypothesis. *Journal of Computer Assisted Learning, 22*(3), 149–158. https://doi.org/10.1111/j.1365-2729.2006.00170.x.
Moser, R. S., Schatz, P., Neidzwski, K., & Ott, S. D. (2011). Group versus individual administration affects baseline neurocognitive test performance. *The American Journal of Sports Medicine, 39*(11), 2325–2330. https://doi.org/10.1177/0363546511417114.
Muthén, L. K., & Muthén, B. O. (2015). *Mplus user's guide.* Los Angeles: Muthen & Muthen.
National Ocean ServiceCorals. What are corals? Retrieved in Feburary 2015 from National Ocean Service, National Oceanic and atmospheric adminsitration website. https://oceanservice.noaa.gov/education/tutorial_corals/coral01_intro.html.
Paas, F., Tuovinen, J. E., Tabbers, H., & Van Gerven, P. W. M. (2003). Cognitive load measurement as a means to advance cognitive load theory. *Educational Psychologist, 38*(1), 63–71. https://doi.org/10.1207/s15326985ep3801_8.
Paas, F. G. W. C., & Van Merriënboer, J. J. G. (1994a). Instructional control of cognitive load in the training of complex cognitive tasks. *Educational Psychology Review, 6*(4), 351–371. https://doi.org/10.1007/bf02213420.
Paas, F. G. W. C., & Van Merriënboer, J. J. G. (1994b). Variability of worked examples and transfer of geometrical problem-solving skills: A cognitive-load approach. *Journal of Educational Psychology, 86*(1), 122–133. https://doi.org/10.1037/0022-0663.86.1.122.
Pazzaglia, F., Toso, C., & Cacciamani, S. (2007). The specific involvement of verbal and visuospatial working memory in hypermedia learning. *British Journal of Educational Technology, 39*(1), 110–124. https://doi.org/10.1111/j.1467-8535.2007.00741.x.
Pessin, J. (1933). The comparative effects of social and mechanical stimulation on memorizing. *American Journal of Psychology, 45*(2), 263. https://doi.org/10.2307/1414277.
Pollock, E., Chandler, P., & Sweller, J. (2002). Assimilating complex information. *Learning and Instruction, 12*(1), 61–86. https://doi.org/10.1016/s0959-4752(01)00016-0.
Rodrigues, P. F. S., & Pandeirada, J. N. S. (2014). Attention and working memory in elderly: The influence of a distracting environment. *Cognitive Processing, 16*(1), 97–109. https://doi.org/10.1007/s10339-014-0628-y.
Rogers, S. L., Fay, N., & Maybery, M. (2013). Audience design through social interaction during group discussion. *PLoS One, 8*(2), e57211. https://doi.org/10.1371/journal.pone.0057211.
Rourke, L., Anderson, T., Garrison, D. R., & Archer, W. (1999). Assessing social presence in asynchronous, text-based computer conferencing. *The Journal of Distance Education, 14*(3), 51–70.
Sanchez, C. A., & Wiley, J. (2006). An examination of the seductive details effect in terms of working memory capacity. *Memory & Cognition, 34*(2), 344–355. https://doi.org/10.3758/bf03193412.
Schiefele, U. (1990). The influence of topic interest, prior knowledge, and cognitive capabilities on text comprehension. *Learning Environments,* 323–338. https://doi.org/10.1007/978-3-642-84256-6_25.
Schiefele, U., & Krapp, A. (1996). Topic interest and free recall of expository text. *Learning and Individual Differences, 8*(2), 141–160. https://doi.org/10.1016/s1041-6080(96)90030-8.
Schmitt, B. H., Gilovich, T., Goore, N., & Joseph, L. (1986). Mere presence and social facilitation: One more time. *Journal of Experimental Social Psychology, 22*(3), 242–248. https://doi.org/10.1016/0022-1031(86)90027-2.
Schoor, C., Bannert, M., & Brünken, R. (2012). Role of dual task design when measuring cognitive load during multimedia learning. *Educational Technology Research & Development, 60*(5), 753–768. https://doi.org/10.1007/s11423-012-9251-8.
Schüler, A., Scheiter, K., & van Genuchten, E. (2011). The role of working memory in multimedia instruction: Is working memory working during learning from text and pictures? *Educational Psychology Review, 23*(3), 389–411. https://doi.org/10.1007/s10648-011-9168-5.
Schweppe, J., & Rummer, R. (2016). Integrating written text and graphics as a desirable difficulty in long-term multimedia learning. *Computers in Human Behavior, 60*, 131–137. https://doi.org/10.1016/j.chb.2016.02.035.
Seddigh, A., Berntson, E., Danielson, C. B., & Westerlund, H. (2014). Concentration requirements modify the effect of office type on indicators of health and performance. *Journal of Environmental Psychology, 38*, 167–174. https://doi.org/10.1016/j.jenvp.2014.01.009.
Seddigh, A., Stenfors, C., Berntsson, E., Bååth, R., Sikström, S., & Westerlund, H. (2015). The association between office design and performance on demanding cognitive tasks. *Journal of Environmental Psychology, 42*, 172–181. https://doi.org/10.1016/j.jenvp.2015.05.001.
Simonsmeier, B. A., Flaig, M., Deiglmayr, A., Schalk, L., & Schneider, M. (2018). *Domain-specific prior knowledge and learning: A meta-analysis.* submitted for publication.
Siqueira, J. C. F., da Silva, L. B., Coutinho, A. S., & Rodrigues, R. M. (2017). Analysis of air temperature changes on blood pressure and heart rate and performance of undergraduate students. *Work, 57*(1), 43–54. https://doi.org/10.3233/wor-172533.
Skrondal, A., & Rabe-Hesketh, S. (2004). *Generalized latent variable modeling: Multilevel, longitudinal, and structural equation models.* Boca Raton, Florida: CRC Press.
Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research, 25*(2), 173–180. https://doi.org/10.1207/s15327906mbr2502_4.
Sweller, J., Ayres, P. L., & Kalyuga, S. (2011). *Cognitive load theory.* New York: Springer.
Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review*. https://doi.org/10.1007/s10648-019-09465-5.
Tabachnick, B. G., & Fidell, L. S. (2006). *Using multivariate statistics.* Needham Heights, MA: Allyn & Bacon, Inc.
Tobias, S. (1994). Interest, prior knowledge, and learning. *Review of Educational Research, 64*(1), 37. https://doi.org/10.2307/1170745.
Triplett, N. (1898). The dynamogenic factors in pacemaking and competition. *American Journal of Psychology, 9*(4), 507. https://doi.org/10.2307/1412188.
Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika, 38*(1), 1–10. https://doi.org/10.1007/bf02291170.
Unsworth, N., & Engle, R. W. (2007). Individual differences in working memory capacity and retrieval: A cue-dependent search approach. In H. L. Roediger, & J. S. Nairne (Eds.). *The foundations of remembering. Essays in honor of Henry L. Roediger III* (pp. 241–258). New York: Psychology Press.
Von Aster, M., Neubauer, A., & Horn, R. (2009). *Wechsler Intelligenztest für Erwachsene WIE. Deutschsprachige Bearbeitung und Adaptation des WAIS-III von David Wechsler.* Frankfurt: Pearson Assessment.
Wiley, J., Sanchez, C. A., & Jaeger, A. J. (2014). *The individual differences in working memory capacity principle in multimedia learning.* The Cambridge Handbook of Multimedia Learning598–620. https://doi.org/10.1017/cbo9781139547369.029.
Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology, 18*(5), 459–482. https://doi.org/10.1002/cne.920180503.
Zajonc, R. B. (1965). Social facilitation. *Science, 149*(3681), 269–274. https://doi.org/10.1126/science.149.3681.269.