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INVITED ARTICLE

Integrating cognitive load theory with other theories, within and beyond educational psychology

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Abstract

Background and Aims: The long-standing aim of cognitive load theory (CLT) has been to generate instructional design principles that show teachers how to instruct students effectively, based on knowledge of the intricacies of human cognitive architecture. Historically, the focus of CLT has been on identifying cognitive processes related to learning and instruction. However, the theory has become more multidisciplinary over time, drawing on theoretical perspectives both within, and beyond, educational psychology.

Results: This Editorial presents a brief historical overview of key developments in CLT and seven key themes that are pertinent to research on CLT. These themes are as follows: Level of Expertise, Cognitive Load Measurement, Embodied Cognition, Self-Regulated Learning, Emotion Induction, Replenishment of Working Memory, and Two Subprocessors of Working Memory. Summaries of the nine empirical contributions to the special issue are presented and discussed in relation to how they provide insight into one or more of these themes.

Conclusions: Understanding the variables that impact student learning and instruction has always represented the core aim of CLT. The growing multidisciplinary features of CLT should provide researchers and practitioners with more holistic perspectives of the factors that predict student learning and, in turn, guide instructional design.

KEYWORDS
cognitive load theory, educational psychology, human cognitive architecture, instructional design guidelines, working memory and long-term memory

INTRODUCTION

A long-standing aim of scholarship in educational psychology is to influence education, including policy and teaching practice (Berliner, 1992). Over the last several years, empirical findings from research, using cognitive load theory (CLT), have been formally acknowledged by departments of government responsible for educational policy and curriculum design, in countries such as Australia (New South Wales Department of Education, 2017; Victorian Department of Education, 2020) and in England (Perry et al., 2021; Twiselton et al., 2019). The growing recognition of CLT as an effective theory of instruction for teachers and students has been underpinned by 40 years of research designed to advance what is known about how students learn (i.e., the science of learning) and how instructional methods should be designed to promote learning effectively (i.e., the science of instruction) (see Mayer, 2019).

Current scholarship in CLT is generally more multidisciplinary than it has been in the past. By this, we mean that instructional phenomena investigated through the lens of CLT are more likely to incorporate additional theoretical frameworks from within and beyond educational psychology, such as embodied cognition (e.g., Castro-Alonso et al., 2015), self-regulated learning (e.g., Nückles et al., 2020), collaborative learning (see Kirschner et al., 2018) and emotion induction (e.g., Park et al., 2015). The integration of CLT alongside other prominent views, within and beyond educational psychology, is important for providing a more holistic perspective of psychological factors that influence learning and instruction. The nine empirical articles contributing to the current special issue show several positive outcomes of these integrations.

In the following section, we provide a brief historical overview of CLT, highlighting seven themes that have emerged in the development of the theory and its current expansions. By emphasizing these themes, we can track how the articles in this special issue fit within the context of historical developments in CLT. Also, an overview of the development of CLT provides information that could benefit readers relatively unfamiliar with this cognitive theory. Readers more knowledgeable of CLT should also benefit from this brief overview, as we provide some insights into the origins of key developments in CLT that are not widely known in published literature.

BRIEF ACCOUNT OF COGNITIVE LOAD THEORY DEVELOPMENT AND SEVEN RELEVANT THEMES

The origins of CLT can be traced back to research studies on problem-solving conducted by John Sweller and colleagues in the early 1980s. The catalyst for the development of the theory was findings suggesting that learners could solve problems but surprisingly fail to deduce the solution rules that could be used to answer similar classes of problems in future (Sweller et al., 1982). At the time, these findings were puzzling. Sweller and colleagues recognized that the inherent limitations of working memory, which had been known since the 1950s (see Miller, 1956), were a key piece of the puzzle. Solving novel problems, as it turns out, prohibits learning. According to CLT, this is because limited working memory resources needed to solve a problem, tend to be exhausted before they can be allocated to learning about the problem. This was one of the first, and arguably the most enduring, intellectual contributions provided by CLT to our understanding of learning and instruction. Indeed, much of the focus of CLT over the last 40 years has been on developing and testing instructional designs that take account of the limitations of working memory.

Another significant early contribution of CLT to theories of classroom instruction concerned the role of long-term memory. Drawing on de Groot's (1965) observations of expert and novice differences in chess, it was recognized that problem-solving skilled relied heavily on domain-specific knowledge structures, stored to varying degrees of automation, in long-term memory (Sweller & Cooper, 1985). Moreover, that accessing these knowledge structures greatly reduced the cognitive burden on working memory. Insightfully, Sweller and Cooper (1985) reasoned that if skilled performance is based on prior knowledge in long-term memory, then when there is an absence of prior knowledge, worked examples, could be used as effective substitute. Worked examples involve presenting novice learners with fully worked-out solutions made by experts (e.g., teachers), so that novices can study and then emulate them. Access to solution steps allows learners to concentrate their finite working memory resources to learning about the deep structural features of the problems presented to them. Importantly, this knowledge can be applied to solve similar classes of problems in future. Notably, the worked example effect has turned out to be the most widely studied effect in CLT research (e.g., Chen et al., 2015; van Gog & Rummel, 2010; Zhang et al., 2023). Moreover, theoretical refinements to CLT now position worked examples as an illustration of the borrowing and reorganizing principle. This principle holds that human beings often acquire knowledge through borrowing information from others, usually experts, and then reorganizing this information in long-term memory (Sweller et al., 2011).

Prior to the emergence of CLT, the notion that instructional recommendations for classroom teachers in schools could be derived from knowledge about working memory and long-term memory was not widely acknowledged. Indeed, it is only in the last decade or so that educational psychology textbooks have gone beyond describing information processing models, but also include information that describes how knowledge of working memory and long-term memory apply to teaching and learning. Not surprisingly, these descriptions are usually through the lens of CLT.

Historically, much of the empirical research within CLT has utilized randomized controlled experiments (see Sweller et al., 2019). Interestingly, failed experiments have been a driver of key theoretical advances in CLT. To illustrate, the split-attention effect (see Ayres & Sweller, 2022) was identified through certain experiments in which worked examples produced suboptimal learning outcomes (Tarmizi & Sweller, 1988). Also, the concept of element interactivity came about in part to explain why under certain conditions (i.e., low element interactivity) that cognitive load effects often failed to materialize (Sweller & Chandler, 1994). For the last example, the expertise reversal effect was discovered when expert learners' outcomes were impaired when they studied the same worked examples that benefited novices (Kalyuga et al., 1998). CLT researchers have shown that expertise is an influential factor in all the investigated effects, so Level of Expertise is a relevant theme of CLT addressed by some articles in the current special issue (see Table 1 for relevant articles).

In the 1990s, as CLT findings were starting to replicate across countries, it was noted that a way of measuring cognitive load was necessary, with the aim of complementing the data that were accumulating on learning performance. The self-perceived mental effort scale by Paas (1992) has been helpful in this aim, gaining its place as the most popular instrument to measure cognitive load. However, measuring cognitive load has been a thorny issue in CLT (see de Jong, 2010), and instruments are being continually being developed and adjusted. As such, Cognitive load measurement was considered another relevant theme to be included in this special issue (see Table 1).

In the 2000s, there was a major theoretical update to CLT with the incorporation of concepts from human evolutionary biology, which appears to have occurred in part due to coincidence. Through being asked to review David Geary's theory of Evolutionary Educational Psychology (Geary, 2002, 2005),

TABLE 1 Nine contributions of this special issue to seven themes in cognitive load theory development.

CLT theme	Contribution
Level of expertise	Endres et al. (2023), Jiang et al. (2023), Schrader and Kalyuga (2023)
Cognitive load measurement	Albers et al. (2023), Altmeyer et al. (2023), Biwer et al. (2023), Chen et al. (2023), de Koning et al. (2023), Endres et al. (2023), Jiang et al. (2023), Schrader and Kalyuga (2023), Zhang et al. (2023)
Embodied cognition	de Koning et al. (2023), Zhang et al. (2023)
Self-regulated learning	Biwer et al. (2023), Zhang et al. (2023)
Emotion induction	Schrader and Kalyuga (2023)
Replenishment of working memory	Biwer et al. (2023)
Two subprocessors of working memory	Albers et al. (2023)

Sweller (2007) identified that Geary's distinction between biologically primary knowledge and biologically secondary knowledge was highly pertinent to CLT, as the cognitive theory only applied to secondary knowledge. Another major change involved the identification of analogies between human cognition and biological evolution, which occurred through Sweller's intra-family discussions, and provided a larger framework to place CLT and get further insight into the coordinated mechanisms of working memory and long-term memory (see Sweller & Sweller, 2006).

Since the 2010s, there has been a gradual integration of CLT with other prominent views within educational psychology. Furthermore, the integration of CLT with other key theoretical frameworks and methodologies has sometimes extended beyond the field of educational psychology. For example, perspectives on grounded or embodied cognition (see Wilson, 2002; see also Paas & Sweller, 2012) have been applied to CLT studies on object manipulations (e.g., Castro-Alonso et al., 2015), gesturing (e.g., Post et al., 2013) and tracing (e.g., Ginns et al., 2016). There are two contributions to this special issue (see Table 1) that involve the integration of Embodied cognition and CLT.

Also, in the last 10 years, CLT has branched into studies of group-level phenomena, such as collaborative learning (see Kirschner et al., 2018; see also Paas & Sweller, 2012). Moreover, there has been a notable integration of theories and concepts that have historically been utilized within the realm of motivation research. Concepts from social cognitive theory (Bandura, 2001), such as modelling, self-efficacy and self-regulation, have been incorporated into CLT research (e.g., de Bruin et al., 2020; Feldon et al., 2018; van Gog & Rummel, 2010). Thus, Self-regulated learning is the fourth CLT theme considered in this special issue. Please see Table 1 for relevant contributions involving self-regulated learning and CLT.

Although research in CLT has traditionally focused on cognitive processes, some researchers have successfully integrated CLT and emotion elicitation. It has been shown that levels of certain emotions can expand or contract cognitive capacities (see Plass & Kalyuga, 2019; see also Plass & Hovey, 2022). The integration of Emotion induction into CLT research is the fifth theme of the special issue (see Table 1).

Recently, CLT researchers have been interested in two ways of circumventing the limits of working memory. The first way involves resting time. It is the idea that the limitations of working memory are not fixed but vary with rest, because resting time allows working memory resources to be replenished. This idea has been gradually incorporated into CLT (e.g., Chen et al., 2018, 2021), and it is a current source of ongoing investigations. For example, the instructional strategy of spacing learning activities in time, rather than blocking the activities without interrupting breaks, can be explained by this new incorporation into CLT (see the spacing effect in Chen et al., 2021). Following this trend, the Replenishment of working memory is another theme to consider in this issue (see Table 1).

The second way in which CLT researchers have been interested in circumventing the limits of working memory involves activating two subprocessors of working memory. This idea is a revisit of the known notion that the capacity of working memory can be expanded by activating the visuospatial and the auditory subprocessors, rather than only the visuospatial subcomponent (see the modality principle in Castro-Alonso & Sweller, 2022). Also, research is being conducted related to the separate activation of the visuospatial subprocessor and another component that manages human embodied actions (e.g., gestures; see Sepp et al., 2019). Hence, the Two subprocessors of working memory is the last theme we considered in this account of CLT development and that we incorporated into the current special issue (see Table 1). The seven themes, and the nine empirical studies of this special issue contributing to these topics, are presented in Table 1.

CONTRIBUTIONS OF THIS SPECIAL ISSUE TO RELEVANT THEMES IN COGNITIVE LOAD THEORY DEVELOPMENT

Level of expertise

One of the most influential variables in CLT research is the participants' level of expertise, which usually shows a contrasting pattern: novice students benefit from the same instructional design that hinders more knowledgeable students. This contrast is commonly known as the expertise reversal effect (see Kalyuga et al., 2003). In one of the seminal studies of this effect in CLT, Kalyuga et al. (1998) reported three experiments with participants learning about electrical circuits. It was observed that more experienced learners could achieve their best performance by only studying illustrations of the circuits, whereas novices needed the illustrations and additional written information. In other words, the same written information that benefited novices was counterproductive for experts.

In the current special issue, Level of Expertise is considered in three contributions, specifically, the studies by Jiang et al. (2023), Endres et al. (2023), and Schrader and Kalyuga (2023). The contribution by Jiang et al. (2023) reports an investigation about the effect of learners' expertise on content and language-integrated learning. Integrated learning has been documented as an effective learning strategy for acquiring, for example, both math and language skills. However, it has been rarely discussed considering learners' expertise. This contribution addresses this gap by recruiting two groups of students with different levels of expertise in English skills. Participants are randomly assigned to either the integrated learning condition (learning both math and English) or the separated learning condition (learning either math or English). The results of subjective cognitive load ratings and test performance reveal an expertise reversal effect: Integrated learning is more beneficial for knowledgeable learners, whereas separate learning is more beneficial for learners with a lower level of expertise.

The contributing article by Endres et al. (2023) posits that there are circumstances in which higher learner expertise results in higher self-estimations of intrinsic cognitive load. This perspective differs from the more common assumption in CLT that, as prior knowledge increases, perceptions of intrinsic load decreases. Endres and colleagues suggest that when dealing with complex, multi-layered problems, learners with higher expertise may draw additional sources of information beyond what has been explicitly provided to them, and thus invest more cognitive load. Data from two studies, one in forestry and one in math, provide empirical data to support the notion that there are some circumstances in which higher expertise may result in higher subjective estimations of cognitive load. As learners with higher expertise consider additional information, they can comprehend the complexity of a problem scenario more readily. This can be contrasted with learners with lower expertise, who may be oblivious to critical additional information, and thus might be overconfident about their performance (cf. Dunlosky & Rawson, 2012). As such, lower-knowledge students may attribute less intrinsic load to the task than the actual load needed to solve it correctly.

The contribution by Schrader and Kalyuga (2023) reports, among other factors, the effects of cognitive load and learning-centred emotions in two groups of students with different levels of expertise in writing Japanese letters. The study describes an expertise reversal effect between novices and advanced learners regarding the emotions of enjoyment and frustration. Due to the notable effects of emotion reported in this contribution, the article is described in more detail under Emotion Induction (see the theme, below).

Cognitive load measurement

Being able to develop an instrument to measure cognitive load in the predicted directions by CLT has been difficult. For example, previous special issues (e.g., Castro-Alonso & de Koning, 2020; Kirschner et al., 2011) have described these measurements as problematic and have recommended relying on more than one measuring instrument. Commonly, the instruments have been classified into two groups (see Castro-Alonso & de Koning, 2020): subjective instruments, such as self-ratings of cognitive load that are marked on paper, or objective instruments, such as pupil responses to levels of cognitive load.

Subjective instruments tend to be preferred, as they are simpler to implement. For example, the single-item subjective scale developed by Paas (1992) has been the most frequently used scale in CLT research. The current special issue is no exception, as five out of the nine empirical contributions use the scale by Paas (1992) or a similar instrument. Over the last decade, there have been efforts to develop and test multi-item subjective scales (e.g., Krieglstein et al., 2023), and the other four contributions here use either the multi-item subjective instrument developed by Leppink et al. (2013) or that by Klepsch et al. (2017).

Although there is updated evidence that subjective ratings are reliable instruments to measure cognitive load (see Krieglstein et al., 2022), there are also several studies showing that subjective measures did not produce the predicted results. This is also manifested in the present special issue. As such, the scale by Paas (1992) produces expected outcomes in two contributions, namely, Albers et al. (2023) and Chen et al. (2023), but it is less sensitive in the contributions by Biwer et al. (2023), de Koning et al. (2023), and Zhang et al. (2023). The multi-item scales show more consistent results, all in the predicted directions by CLT. This is observed in the two contributions (Jiang et al., 2023; Schrader & Kalyuga, 2023) employing the scale by Leppink et al. (2013), and the two contributions (Altmeyer et al., 2023; Endres et al., 2023) using the scale by Klepsch et al. (2017).

The need for complementary data has led CLT researchers to look for objective cognitive load instruments, particularly those that are easy to implement in a learning setting. Two contributions from this special issue (Altmeyer et al., 2023; Chen et al., 2023) provide interesting examples of effective and relatively simple objective instruments. The contribution by Altmeyer et al. (2023) reports school-aged children (7 to 12 years old) using, as an objective instrument, a digital pen equipped with multiple motion and pressure sensors. The participants complete drawing tasks of varying complexity, while also providing self-reports of cognitive load (Klepsch et al., 2017). The data provided by digital pen technology show that velocity measures of drawing can be related to drawing performance and task difficulty and that these measures are reflected in the cognitive load assessed employing a subjective scale.

The contribution by Chen et al. (2023) provides evidence regarding objective eye measures for different types of loads. In fact, four types of load (cognitive, perceptual, communicative and physical) are measured by pupillometric and blink rate measures, in adult participants completing different computer tasks. Results show that participants' pupil size increases when either cognitive or communicative loads are changed from low to high. Also, participants' blink rate increases when cognitive load is increased. Notably, it is also observed that subjective self-ratings (Paas, 1992) can discriminate between low and high loads in all four load tasks. Hence, this contribution supports the two objective measures of pupil size and blink rate, and a subjective scale, as valid methods to measure changes in cognitive load.

Embodied cognition

As described by Paas and Sweller (2012), embodied cognition can be linked to CLT when embodied actions, such as object manipulation and gestures, are used to optimize instruction (e.g., Castro-Alonso et al., 2015; Ginns et al., 2016; Post et al., 2013). Several examples have shown that making participants either watch the execution or execute themselves embodied actions, can help them learn better, and usually, this higher performance can be related to a reduction in cognitive load (see Castro-Alonso et al., 2019). However, there are influential variables that need to be considered when watching or executing embodied actions, to deliver the best learning performance. Two empirical contributions from this special issue (de Koning et al., 2023; Zhang et al., 2023) consider the theme of Embodied Cognition and these influential variables.

The study de Koning et al. (2023) considers the influential variable of viewing perspective, when watching an embodied action (manipulative-procedural task) through video. Extending previous findings (e.g., Fiorella et al., 2017), the results of de Koning et al. (2023) reveal that learning how to tie knots through video can be more effective when the instructional depiction is watched in the perspective known as over-the-shoulder (first-person), compared to the perspective face-to-face (third-person). These results on performance are not reflected in the cognitive load self-ratings, as there are no significant differences between the two perspective conditions. In conclusion, for learning a manipulative task, it may be more effective to watch an over-the-shoulder instructional video, as this is the perspective that will be seen when attempting the task in reality.

The contribution by Zhang et al. (2023) considers the variable of self-regulated management of cognitive load as an influential variable when executing an embodied action (finger pointing) to learn through a multimedia module. This study is another example of gesturing activity with the fingers as an effective embodied action to execute when learning. The study is framed as students' self-regulation of cognitive load, so it is described in more detail in the following theme.

Self-regulated learning

Recently, there has been a concerted effort to build explicit links between CLT and self-regulated learning (e.g., Seufert, 2020), which has resulted in novel approaches, such as the effort monitoring and regulation framework (see de Bruin et al., 2020) or the self-management of cognitive load (see Castro-Alonso et al., 2021). Historically, cognitive load management has focused largely on the role of the instructor, so the management of this load by the learner (self-management of cognitive load) is a more recent addition to CLT (see Castro-Alonso et al., 2021). But self-regulated learning involves more than just self-managing the cognitive load levels when learning. For example, self-regulation of breaks during learning episodes is also considered in this special issue. Here, there are two contributions that consider the CLT theme Self-Regulated Learning. The contribution by Zhang et al. (2023) provides an example of self-regulated management of cognitive load, whereas the study by Biwer et al. (2023) is an example of self-regulated breaks during learning.

The contribution by Zhang et al. (2023) reports executing finger pointing as a self-management strategy for dealing with materials presented in split-attention formats in online settings (see split-attention in Ayres & Sweller, 2022). The performance results of the study by Zhang and colleagues suggest that finger pointing may be superior to mouse pointing, supporting that embodied signals may be more effective than non-embodied signals (e.g., de Koning & Tabbers, 2013). This contribution also advocates the execution of pointing with fingers, as a helpful strategy for managing mutually referring sources that have been spatially separated in an online environment (see Ayres & Sweller, 2022). Finger pointing can be incorporated within the repertoire of self-regulation strategies that students utilize for their learning. Thus, the study by Zhang et al. (2023) provides links between CLT, embodied cognition and self-regulated learning.

The contribution by Biwer et al. (2023) reports differences between students' self-regulated breaks and the breaks imposed by an online system. In this investigation with university students, Biwer and colleagues observe the importance of breaks or resting time for an effective online learning experience. As this resting time is key to allow working memory resources to be replenished, the study by Biwer et al. (2023) is addressed in more detail under Replenishment of Working Memory (see the theme, below).

Emotion induction

Plass and Kalyuga (2019) described four ways in which emotion could be considered in CLT research. One way is when emotions add unnecessary (extraneous) cognitive load to learning, so this is linked to the redundancy effect of CLT (see Kalyuga & Sweller, 2022) or the related seductive details effect (e.g., Park et al., 2011). This perspective would recommend avoiding emotion induction, so emotion does not interfere with learning. Another way described by Plass and Kalyuga (2019) is to regulate which emotion is elicited in the students, with the aim of increasing their motivation to learn and their academic performance. This is the way taken by the contribution in this special issue that investigates the theme Emotion Induction.

As such, the contribution by Schrader and Kalyuga (2023) investigates the interaction between learner expertise and task complexity, considering both cognitive load and learning-centred emotions in university students attempting to write Japanese letters. Subjective measures of cognitive load and learning-centred emotions were collected for three different levels of complexity. As predicted, the self-ratings show that higher cognitive load is reported by novices compared to advanced learners, and when both groups of students attempt the more complex compared to the easier complexity tasks. Regarding self-perceived emotions, the results suggest that advanced learners are more likely than novices to report higher enjoyment and less frustration with tasks moderate and high in complexity. Interestingly, the authors posit that enjoyment serves as a motivator, as well as a factor for increasing cognitive resources. This means that enjoyment should be promoted as an emotion conducive to learning. In contrast, results show that frustration serves as a demotivator, reducing working memory resources. So, frustration should not be an emotion to induce when learning. In all, the contribution by Schrader and Kalyuga (2023) addresses two CLT themes: Level of Expertise and Emotion Induction.

Replenishment of working memory

The extension of CLT provided by Chen et al. (2018) aimed to open new research about cognitive load hindering a limited working memory. The study by Chen and colleagues, which supported that learning conditions that included breaks could be better than conditions without breaks, extended CLT by indicating that the limits of working memory are not fixed but may depend on previous working memory activity. For example, working memory is more limited immediately after being active than after a resting time that allows its resources to be replenished (see also the spacing effect in Chen et al., 2021). The Replenishment of Working Memory theme was investigated by one contribution in this special issue.

The effect of resting time or breaks on cognitive load and learning was studied in the contribution by Biwer et al. (2023), which reports an investigation on university online sessions. System-imposed breaks are compared to students' self-managed breaks in dependent variables such as break time, task experience and cognitive load (mental effort). Concerning break time, it is observed that when the university students manage their breaks, these rests are fewer but longer, compared to the breaks forced by the online system. Task experience is better when students have imposed breaks, as indicated by lower self-ratings of fatigue and distraction. Self-reported cognitive load is not influenced differently under system versus self-managed breaks, which might suggest that the replenishment of working memory resources occurs similarly under both conditions. In conclusion, system-managed breaks seem to be shorter, more regular, and may lead to a better task experience, compared to self-managed breaks. The contribution by Biwer and colleagues provides further links between CLT, self-regulated learning and the replenishment of working memory.

Two subprocessors of working memory

The modality effect of CLT (e.g., Mousavi et al., 1995; see Castro-Alonso & Sweller, 2022) can be partially explained by an increased overall working memory capacity when two of the working memory subprocessors are used in parallel. Usually, the effect has been investigated in CLT by showing that students who use the visuospatial and auditory modalities (two subprocessors) have fewer chances of cognitive overload and better learning results than students who only use the visuospatial modality (one subprocessor). However, CLT researchers are also considering, as an additional subprocessor, one that handles human embodied actions, including manipulations and gestures (see Sepp et al., 2019). The contribution to this theme in this special issue deals with the most investigated visuospatial and auditory modalities, adding the consideration of redundancy for one or two subprocessors.

As such, the article in this issue by Albers et al. (2023) reports the effects of content and modal redundancies on the learning of university students. As defined by Albers and colleagues, content redundancy is the broader type, which includes all redundant information typically assessed in CLT (see Kalyuga &

Sweller, 2022), such as written information being duplicated in dynamic images, static images or narrations. Modal redundancy, narrower, only considers when these duplications occur in the same modality, such as written information and images being redundant only on the visuospatial modality. Results show an interesting contrast: content redundancy enhances learning and reduces self-perceived cognitive load, whereas modal redundancy decreases learning and increases self-perceived cognitive load. Modal redundancy may be more problematic as it overloads one modality or subprocessor in working memory. In contrast, content redundancy affects two modalities or subprocessors, so both can work in parallel, increase overall capacity, and be less affected by this redundancy.

CONCLUSION

Since the inception of cognitive load theory (CLT) in the 1980s by John Sweller and colleagues, CLT researchers have produced evidence-based guidelines to help develop instructional resources and optimize instructional approaches. Currently, CLT is as influential as ever, having been incorporated into official educational and curriculum documents, and integrated by researchers from several areas within and beyond educational psychology. In this editorial for a special issue, we provided a brief account of the development and expansions of CLT, highlighting seven themes that have emerged over time. The themes are as follows: Level of Expertise, Cognitive Load Measurement, Embodied Cognition, Self-Regulated Learning, Emotion Induction, Replenishment of Working Memory, and Two Subprocessors of Working Memory. We described each of the themes and how the nine empirical contributions of the current special issue are helping ongoing research on these themes, CLT, and other prominent views in educational psychology. With this special issue, we hope to inspire future researchers in advancing these themes and continuing expanding the limits of cognitive load theory.

AUTHOR CONTRIBUTIONS

Juan Cristobal Castro-Alonso: Conceptualization; funding acquisition; writing – original draft; writing – review and editing. **Ouhao Chen:** Conceptualization; writing – original draft; writing – review and editing. **José Hanham:** Conceptualization; project administration; writing – original draft; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

None to declare.

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