Cognitive Load Theory and Time Considerations: Using the Time-Based Resource Sharing Model

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Introduction

Ever since the discovery of human cognitive resource limitation (e.g., Broadbent, 1958), managing these limited resources has become a central issue in many fields. In education, it has been demonstrated that trying to solve a problem that overwhelms the student's available cognitive resources impairs learning (Sweller, 1988). Thus, managing cognitive load during instruction has become a matter of central importance. It is generally assumed that during explicit learning, students have to maintain information in working memory and manipulate it (Cowan, 2014). When the information to be held exceeds working memory capacity, cognitive overload is experienced. Therefore, studying working memory requirement during learning appears critical if learning efficiency is to be improved.

Cognitive Load Theory is an influential framework dividing cognitive resource allocation during explicit learning into three different loads: extraneous, intrinsic and germane (e.g., Sweller, Van Merrienboer & Paas, 1998). In this framework, cognitive overload arises from an excessive requirement of cognitive resources, described mainly as working memory capacity (Sweller, Van Merrienboer & Paas, 1998; see Sweller, Ayres &Kalyuga, 2011 for a review). Cognitive Load Theory uses working memory models to identify empirical effects reducing cognitive load during learning. One typical finding, the *modality effect,* occurs when learning is more efficient when a text referring to a map, graph, diagram or tabular information, is presented orally than visually (Leahy & Sweller, 2016). This effect appears when information to be processed is related (e.g., Tindall-Ford et al., 1997). Furthermore, it does not benefit expert learners (Kalyuga, Ayres, Chandler &Sweller, 2003). While investigating the modality effect (see Ginns, 2005 for a review), several studies found an impact of the pace of information presentation. Indeed, if the learner controls the pace of information presentation, then presenting information both visually and orally does not improve learning (e.g., Schmidt-

Weigand, Kohnert & Glowalla, 2010; see De Jong, 2010 for a review, Moreno & Valdez, 2005, experiment 2, Ginns, 2005; Sweller, Ayres & Kalyuga, 2011; Leahy & Sweller, 2011). This pace of presentation effect is also found in studies on the transience of information, the information presented being no longer available after its presentation (Sweller, Ayres & Kalyuga, 2011 for a review). Even if caution needs to be taken when considering these disappearing effects, these experiments altogether suggest an effect of pace of presentation on learning. Furthermore, in a second experiment, Schmidt-Weigand et al. showed that for the same experimental material, reducing pace of presentation had a positive effect on learning outcome.

The commonly used working memory models (e.g., Baddeley, 1986; Baddeley & Hitch, 1974; Ericsson & Kintsch, 1995) do not allow this pace of presentation effect to be described. Previous studies suggested that a working memory model taking time into account would be necessary in cognitive load theory (Spanjers, van Gog & van Merrienboer, 2010; van Gog, Paas, Marcus, Ayres & Sweller, 2009). 1 To do so, they evoked the Time based Resource Sharing model (Barrouillet, Bernardin & Camos, 2004)

The Time Based Resource Sharing model

The Time Based Resource Sharing (TBRS from now) model is a recent working memory model describing information maintenance and refreshing as a function of time (e.g., Barrouillet, Bernardin& Camos, 2004; Barrouillet & Camos, 2015). Following this model, elements in working memory are activated representations and their activation level decreases due to time decay. It assumes that attention is the single cognitive resource and can only be directed to one task at any given time. To counter time decay of information activation, attentional focus has to be applied on each *chunk* to refresh it, i.e., to raise its activation level (Vergauwe, Dewaele, Langerock & Barrouillet, 2012; Cowan, 1995 for a similar idea). If *chunk* activation decays too much for the information to be retrieved, it is forgotten (Barrouillet& Camos 2014). Thus, the TBRS model proposes to consider working memory as an attentional module maintaining information through attentional refreshing.

Since attentional focus can only be used for one controlled process at a time, it follows that multitasking is the result of frequent switching between tasks (Salvucci & Taatgen, 2010; Barrouillet& Camos, 2015 for a review). When attentional focus is used to process a concurrent task, it cannot be used to refresh information held in working memory. On the contrary, when it is used to refresh memory traces, it cannot be used to perform a concurrent task. It follows that holding items active in working memory while, for example, performing a judgment task will necessitate rapidly switching between memory trace refreshment and information processing. Each of these two tasks requires attentional focus for a given duration. From this conclusion, the authors infer that cognitive load can be modeled as the ratio between the time used to refresh memory traces and the time used to process the concurrent task. The longer the time available to refresh memory traces, and/or, the shorter the time needed to perform a concurrent task, the better the working memory performance will be. On the contrary, if the time available to refresh memory traces is shortened, or the time needed to perform a concurrent task lengthened, working memory performance will decrease. These predictions (see Figure 1) are opposite of those commonly used in Cognitive Load Theory research, based on working memory capacity conceptions. A lighter load might lead to better working memory performance with more distracter elements (but with sufficient time to process them), while fewer distracters might be associated with a heavier working memory load (with a short time to process them) and thus a lesser performance. Furthermore, if the time ratio remains constant, the number of concurrent distracters should have no effect on working memory performance (see Barrouillet& Camos, 2015 for a review).

To test these hypotheses, Barrouillet, Bernardin and Camos (2004) used a complex span task. As with a classic span task, participants were presented series of items (e.g., letters or numbers) and at the end of the sequence had to recall them in the correct order. Contrary to a classic span task, after the presentation of each item, participants had to perform a series of distracting tasks. By manipulating the time needed to perform the distracting task and the total time available, the authors could manipulate the time ratio (i.e., the cognitive load).

[Insert here the Figure 1]

Fig 1 predictions allowed by the TBRS model. In this model, working memory performance is determined by the ratio between the time needed to process a distracting task and the remaining time allowing the refreshing of memory traces. Each item (here letters G and T) are presented serially and followed by series of interfering tasks (represented with empty squares). The width of a square represents the time needed for this process, kept constant in this example. Space between two successive squares represents the remaining time available to refresh memory traces. Thus, the first two examples should induce the same performance, although a different number of distracters is used. On the contrary, example 1 should impose a lesser load on working memory than example 3 although it has a higher number of distracters.

Example 2 should impose a higher load on working memory than example 4 even though it has a lesser number of distracters.

These counterintuitive hypotheses might help to explain some empirical results obtained in the field of Cognitive Load Theory research. In particular, the differences arising from the pace of presentation observed in learning outcomes using the modality effect might be explained using this model. For a fixed amount of information, learning outcome might be superior if presentation pace is slower, the time dedicated to process this information rising while the presentation pace decreases. The TBRS model has never been used in a learning context with meaningful material that can be chunked and related to long term memory, for which one can develop expertise.

The present study

In the present study, we aimed to assess the validity of the TBRS model as a new working memory model in the field of Cognitive Load Theory research. Indeed, TBRS has so far never been used with meaningful material. On the contrary, Cognitive Load Theory research is particularly interested in the manipulation, and then learning of meaningful material. A working memory model which takes time into account could be of particular interest for Cognitive Load Theory, explaining the effect of information presentation pace and providing a theoretical framework for research on the transient information effect.

We defined meaningful material as items that can be held and manipulated together in working memory, based on the content of long term memory, a definition close to that of element interactivity (see Sweller, Ayres & Kalyuga, 2011 for a review, see also Chanquoy, Tricot & Sweller, 2007 for a model of load imposed by element interactivity). Contrary to meaningless items, meaningful ones can be gathered in *chunks* of various sizes based on the learner’s expertise with the domain (e.g., Ericsson & Kintsch, 1995). Following Van Gog and her colleagues (2009) we will consider expertise as a continuum of knowledge, learners having more knowledge than others (i.e., able to perform better on domain relevant tasks) being more expert. Since expertise allows higher performance, two groups were formed based on the results of a pre-test to determine expertise differences. One group gathered participants with higher performance and the other gathered participants with lesser performance.

In these experiments, we used a complex span task while replacing meaningless items (used in most of the Barrouillet & Camos, 2015 experiments) by terms of mental arithmetic calculations. For example, three letters B, X and H do not mean anything. When processing these three letters, the participants have to maintain B, X and H. When processing 3 + 4 = ?, the participants have to maintain 7, i.e. just one digit instead of two digits and one calculation. Common Cognitive Load Theory experimental results reveal that factors that facilitate learning of novices may impair learning of experts (named the “expertise reversal effect”, Kalyuga et al., 2003; Kalyuga, 2007). Moreover, expertise is known as reducing element interactivity (Chen, Kalyuga & Sweller, 2015; 2016). It also has other effects on arithmetic, thus, when processing 3 + 4 = ?, expertise has a strong effect, i.e. the participants who do not know that the result is 7 have to maintain 3 + 4. Expertise is here seen as allowing the use of different strategies, for example, recalling arithmetic facts rather than computing the solution (e.g., Groen & Parkman, 1972; Zbrodoff & Logan, 2005 for a review). Expertise would thus not only reduce cognitive load but also allow the use of different strategies (Chi, 2006; Anderson, 2010) which could affect the prediction of a working memory model. The aim of the present experiments was therefore to test different hypotheses allowed by the Time Based Resource Sharing model with meaningful items, by taking expertise differences into account. Indeed, as expertise allows automation and thus better performance on a task at a lesser cognitive cost, manipulation of the time ratio (i.e., of the cognitive cost) should principally affect less expert participants. For that reason, participants selected for these studies were children who did not rely completely on automated processes to compute mental calculation.

Experiment 1

Following the TBRS model assumptions, the time allowed to refresh working memory representations affects working memory performance. The longer the time allowed for refreshing, the better the working memory performance will be. If we consider complex span tasks, with a fixed trial duration, when the time needed to perform a distracting task increases, the time allowed to refresh memory traces will decrease. As a result, the working memory performance will decrease. However, expertise might affect this general assumption in many ways. Experts' representations held in working memory are larger and deeper (see Chi, 2006; Chi, Feltovitch & Glaser, 1988 for reviews) and chunks held in working memory last longer for experts than for novices (e.g., Ericson & Kintsch, 1995). Furthermore, since experts have automated many commonly used processes, they have automated routines for their expertise field (Schneider, 1985). Such effects could influence working memory span when considering meaningful items, but the TBRS model was never used with meaningful items to test this potential limit.

To address this limitation, we used terms of a mental calculation as items to be held and processed in working memory, since manipulation of mental calculation mainly relies on working memory resources (Adams & Hitch, 1997). Replacement of these items should allow chunking for expert participants but not for less expert participants. For expert participants, mental calculation is more automated than for novices. Thus, we reproduced a previous TBRS experiment (e.g., Portrat, Camos & Barrouillet, 2009, Experiment 1) by replacing items to be maintained in working memory with terms of a mental calculation. Following TBRS assumptions, performance on mental calculation should depend on the time ratio allowed to perform the distracting task. In other words, when the time ratio is smaller, performance on mental calculation should be better.

Two hypotheses were made. First, the time ratio affecting the working memory performance should have an effect on mental calculation performance. Second, as expertise allows the reduction of the reliance on working memory resources while performing cognitive arithmetic, the time ratio effect should principally affect novices. To investigate these hypotheses, participants had to perform the complex span task in both conditions of the interfering task. They were then split into two groups based on their performances during a pre-test on mental calculation.

Method

Participants. Sixty nine 7thgrade students (31 girls and 38 boys, mean age = 12.28 years, *SD* = 0.357) participated in this experiment. The parents of the children gave written informed consent and the children volunteered to participate in this study. The experiment took place at school, in a computer equipped classroom. Participants performed this experiment in group sessions.

Material and procedure. The procedure used in this experiment was similar to that used by Portrat, Camos and Barrouillet (2009), except for the series length and the items to be remembered. In this task, participants had to memorize terms of a mental calculation and perform this calculation in the order of presentation without consideration for the order of operation. They performed two complex span tasks, following the two conditions of the distracting task.

The terms of a mental calculation were composed as the distracting task in Barrouillet, Bernardin and Camos (2004, experiment 2). First, a "root term" comprising only a single digit number was presented (for example, the number "7"). Then, the terms were composed of an operand and a single digit number (for example, the term “+ 2”). Calculations were to be performed in presentation order and none of the intermediary results could be a negative or decimal number. The final result was a single digit positive number. For example, the series “7”, “-5”, “x3” was decomposed as “7” and “-5” (equals 2) and (“2”) “x3” (equals 6). The terms were randomly generated and then verified to conform to the criterion above.

After the presentation of each term, a series of eight distracting spatial judgment tasks was presented. Participants had to decide whether a square presented onscreen was located on the top or the bottom half of the screen, with two levels of difficulty (see Figure 2). The squares were black, with sides of 18mm, and were presented on a white screen. Each square was presented for 667ms and followed by a white screen for 333ms. The total length of a trial was 1s. In a *distant condition* (easy condition), the locations of the squares were 68mm apart from each other, whereas in a *close condition* (difficult condition), the locations were only 5mm apart, resulting in a partial overlap (13mm). Locations were randomly generated with half on the upper part of the screen and the other half on the lower part. This random selection served to control for a potential SNARC effect[1] (Dehaenne, Bossini & Giraux, 1993).

[Insert here the figure 2]

Fig. 2 the two conditions of the spatial judgment distracting task. On the left, the close square condition was the most demanding. On the right, the distant condition was the easiest, the squares being far apart from each other. The dotted line was added for more clarity.

[1] The SNARC effect (Spatial Numerical Association of Response Code) shows an association between numbers and spatial position. Small numbers are associated with left or top part of the screen and larger number with right or lower part of the screen. It was originally found with manual responses, responses with left hand being faster than right hand for small numbers and conversely, but further extended to cross modal responses and to all associations of space and numbers.

A series of the complex span task started with a screen that presented the number of terms and the condition of the distracting task for 1500ms (for example: 3 terms / distant squares). Then a ready signal (*) was presented for 750ms and followed by a white screen for 500ms. After this, the root term was presented for 1500ms, followed by a post-term delay of 500ms and then by eight spatial judgment tasks (see figure 3). After the distracting tasks, a second term was presented for 1500ms and followed by a 500ms post-term delay. At the end of the series, the word “result” was presented and participants had to enter the result of the mental calculation. Stimuli were presented using E-Prime 2.0 software (Psychology Software Tools, Pittsburg, USA)

[Insert here Figure 3]

Fig. 3 the time ratio of the two conditions and the time course of a trial. Part A upper panel displays the difficult condition and lower panel the easy one. The easier condition is assumed to require attentional focus for a shorter duration (the squares are shorter). Part B the trial started with a presentation screen, followed by a ready signal. Then a root term (digit without operand) was followed by eight spatial judgment tasks before the second term. After the second term, a series of spatial judgment task was presented and then the next term and its following spatial judgment tasks. At the end of the trial, the world “result” was presented until participants provided an answer.

The series started with three terms and this number increased up to a maximum of eight terms. Three calculations were presented for each series length and the experimental condition stopped if a participant failed on the three repetitions of a given series length. After a pause of a minimum of 30s, the second condition started.

The experiment began with three mental calculations to familiarize the participants with the exercise. Then, they performed a pre-test during which they had to perform as many mental calculations as possible in one minute. These calculations were three terms calculations, all terms being presented on screen simultaneously (for example, participants saw "3 + 9 - 4" and had to answer 8 by pressing the corresponding keypad touch). They were then trained on the distracting task. Participants who failed to achieve a criterion of 80% success in this training were discarded from the data (n = 13), as in Portrat, Camos and Barrouillet (2009), to prevent participants neglecting the distracting task. After these training sessions, participants performed both conditions of the task, in a balanced order.

Dependent variables and statistical analyses. Based on performance on the pre-test, two groups were created. A group called "Calc+" was composed of the 20 participants who had achieved the best results on the pre-test and group called "Calc-" gathered the 20 participants with the lowest performances. Performance was calculated as the number of correct calculations completed by the participants of each group. To test the hypothesis that difficulty would lead to a lower number of correct calculations performed, at least for the group with fewer automated mental calculations, a 2 group x 2 difficulty repeated measure ANOVA was performed. The average time needed to perform the distracting task was also measured for each series length (TR in milliseconds). To test the hypothesis that the close condition of the distracting task required attentional focus for a longer duration, the reaction times were compared using a Student t-test.

Results

The data are summarized in Table 1. The repeated measures ANOVA with group as a between subject factor showed no significant effect of the difficulty level ($F(1,38) = 1.82$, $p = .186$) but a significant difference between the groups ($F(1,38) = 22.68$, $p < .001$). The interaction between group and difficulty was not significant ($F(1,38) = 1.04$, $p = .315$). Following Howell (2007) commenting Wilcox (1987), pair comparisons using repeated Student t-tests were performed even for non significant factors. Pair comparisons allow for comparisons of two groups without taking variance of the other groups into account. This allows testing the effect of a variable on a group without considering the effect of this variable on another, independent, group. The "Calc+" group calculated as many correct calculations in the "distant" condition as in the "close" condition (*M* = 9.750, *SD* = 4.35 and *M* = 9.950, *SD* = 4.39 respectively, *t*(19) = -0.149, *p* = .883, *d* = 0.046). On the contrary, "Calc-" participants performed more correct calculations in the "distant" condition than in the "close" condition (*M* = 5.85, *SD* = 4.27 and *M* = 3.65, *SD* = 2.23 respectively, *t*(19) = 2.505, *p* = .022, *d* = 0.68). Thus, time ratio manipulation affected participants from the "Calc-" group but not those from the "Calc+" group. For participants with less automated mental calculation, time ratio manipulation allowed higher performance while the number of distracters had remained constant.

In the "Calc-" group, participants took longer to perform the concurrent task in the "close" condition than in the "distant" condition (*M* = 383.09, *SD* = 106.58 and *M* = 354.58, *SD* = 91.97 respectively, *t*(19) = -2.97, *p*= .008, *d*= 0.287). The same result appeared for the "Calc+" group (*M* = 381.53, *SD* = 64.63 and *M* = 361.02, *SD* = 35.40 for "distant" and "close" conditions respectively, *t*(19) = -1.86, *p*= .079, *d*= 0.41) though the difference was only marginally significant. Both groups performed the distracting task at the same speed (*t*(38) = -0.29, *p*= .771, *d*= 0.10 and *t*(38) = 0.06, *p*= .956, *d*= 0.018 for the "distant" and "close" conditions respectively.

	Number of correct calculations		**RT (s) on distracting task**	
	Easy condition	**Difficult condition**	**Easy condition**	**Difficult condition**
Calc-	5,85 (4,27)	3,65 (4,23)	354,58 (91,97)	383,09 (106,58)
Calc+	9,75 (4,35)	9,95 (4,39)	361,02 (35,40)	381,53 (34,63)

Table 1.Means (and Standard deviation) of the number of correct calculations for the easy (distant) and the difficult (close) conditions and of the reaction times in milliseconds on the distracting task.

To control for learning effects, the number of correct calculations performed by participants was compared following the first condition completed. Starting with one condition or the other had no effect on the number of correct calculations in either the "distant" condition ($t(38) = 1.21$, $p = .235$, or in the "close" condition ($t(38) = -0.84$, $p = .405$). Participants of both groups performed more correct spatial judgment in the distant condition (M = 81.20, SD = 11.62 and M = 83.74, SD = 12.75 for the "calc-" and "calc+" group respectively) than in the close condition (M = 55.58, SD = 12.56, $t(19) = 11.66$, $p < .001$ and M = 64.35, SD = 12.36, $t(19) = 8.16$, $p < .001$ for the "calc-" and "calc+" group respectively).

Discussion

In this experiment, we tested the hypothesis that manipulation of the time ratio would affect performance of mental calculation. We manipulated the time needed to perform a distracting task and left the inter-stimuli interval constant, thus a longer concurrent task reduced the remaining time. Following our hypothesis, performances on mental calculation were affected by the ratio between the time needed to perform the concurrent task and the time allowed for this, at least for the less proficient students in mental calculation. When the time needed to perform the distracting task was longer, the time allowed for maintaining and manipulating information decreased, resulting in an impaired mental calculation performance. Due to the lesser automation of novices, mental calculation had a higher associated cognitive cost and thus took more time to perform. As a result, it was not performed during the remaining time after concurrent task completion. On the contrary, the most proficient students in mental calculation were probably able to perform mental calculation during the available time. This would have resulted in a low working memory load at any time during the experiment. Consequently, this would explain the absence of differences between the experimental conditions, the different distracting tasks having the same effect on their mental calculation performance.

These results suggest a new interpretation of intrinsic and extraneous cognitive loads in the framework proposed by Cognitive Load Theory. Extraneous load might be viewed also as a proportion of time needed to manipulate information not relevant for the task at hand, rather than only the absolute number of information units to manipulate *per se*. Accordingly, intrinsic load could be viewed as time left to maintain and manipulate relevant information for learning rather than the number of elements of information only. Time ratio could therefore be used to describe both extraneous and intrinsic cognitive load. When the concurrent task requires attentional focus for a longer duration, the extraneous load increases. In the same way, if the time remaining to maintain and manipulate the relevant information decreases, then the intrinsic load increases accordingly. Thus, the cognitive load ratio defined by the TBRS model could be used in the Cognitive Load Theory framework to describe both intrinsic and extraneous load. These loads are not only determined by the number of elements to be processed, but also by the time available and needed to process them. Participants having more automated mental calculation would be less affected by time ratio manipulation, because they needed less remaining time to manipulate the mental calculation terms. Expertise, seen as an automation of information manipulation, has reduced the sensitivity to extraneous load (Kalyuga et al., 2003; Kalyuga, 2007). However, this new interpretation of expertise differs from the one used in Cognitive Load Theory. While Cognitive Load Theory suggests that irrelevant information might impair learning by becoming redundant in instructional procedures, the TBRS model considers effects of expertise on working memory processing. Here, expertise can be viewed as reducing the distracting task effect while this task impairs novices' performance.

Both groups performed the concurrent task with the same performance, thus mental calculation performance differences were not linked to different strategies used to carry out the mental calculation task and the spatial judgment task at the same time. The fact that the "close" condition of the spatial judgment task took longer to perform, indicates that attentional focus was captured for a longer duration, resulting in decreased working memory performance and thus in less error-free mental calculation, at least for participants with less automated mental calculation. For this group, result patterns are consistent with previous TBRS experiments (Portrat, Camos &Barrouillet, 2009), suggesting that less proficient participants had not "*chunked*" the terms by performing the calculation. Taken together, these results suggest that the Time Based Resource Sharing model might be used for Cognitive Load Theory research, providing that expertise of learners is controlled. If more time is available to maintain and manipulate information, this information will be processed more efficiently.

However, another interpretation of these results could be proposed. It is possible that the time ratio manipulation could have had an effect on the difficulty of the concurrent task. The time ratio manipulation used two different distances for the squares. One might argue that this could have resulted in two different levels of interference. This would lead to the idea that at least some of the differences observed are due to an interference effect, variations in the concurrent task affecting participants according to their expertise. Participants of the more expert group could have had greater ability because they had superior working memory capacity to develop their superior expertise (Bull, Espy & Wiebe, 2008; Raghubar, Barnes & Hecht, 2010 for review). Higher working memory capacity individuals are assumed to be better at inhibiting interference than those with lower working memory capacity (Gulbinaite et al., 2014). Thus, manipulation of the concurrent task could have resulted in a manipulation of induced interference. This manipulation would have had a detrimental effect on "novice" participants (i.e., participants with lower working memory capacity). On the other hand, it would not have affected participants from the "expert" group, who are better at inhibiting interference. Notwithstanding, other TBRS results ruling out this hypothesis (Barrouillet & Camos, 2015), we reproduced this experiment using the same concurrent task in both conditions to neutralize possible interference effect.

Experiment 2

The first experiment showed that typical predictions of the TBRS model were also observed with material that can be chunked, but only with participants who were less proficient with the principal task. However, reproducing a previous TBRS experiment (Portrat, Camos &Barrouillet, 2009), we used two different kinds of stimuli (close and distant conditions) to impose different processing times on our participants. This manipulation induced different time ratios between the time needed to perform the concurrent task and the remaining time allowed to refresh representations held in working memory.

However, since participants with different working memory capacity might rely on different strategies to maintain working memory representations active, the use of two different distracting tasks might have had a differential effect on our two groups of participants. At least some of the differences observed might be explained by variations in the load imposed by the interfering task for novices, who are more likely to be affected by interference. Consequently, the same experiment was reproduced while using another prediction of the TBRS hypothesis. Following the TBRS model, only time ratio would affect working memory capacity. This ratio is affected by the time needed to perform the task if total time available is kept constant. On the other hand, if the time needed to perform the task is kept constant, then varying the total time available will affect the time ratio in the same way.

We thus reproduced Experiment 1 using only the “close” condition but varying total time available between each distracting task. This resulted in a “fast” condition and a “slow” condition. Our hypothesis was that the “slow” condition, providing more time to refresh items held in working memory, would induce a lower Cognitive Load and would result in higher mental calculation performance, at least for “novice” participants. This hypothesis was not in line with predictions allowed by previous conceptions of working memory, for which the main determinant of working memory performance is the number of elements held in working memory (see Oberauer, Farrell, Jarrold & Lewandowsky, 2016 for review). We proposed that the same number of distracting elements might have a differential effect on working memory performance even for less proficient students, while the commonly used model assumes that a given number of distractors will always have the same effect on working memory.

Method

Participants. Fifty seven 8^{th}grade students (mean age = 13.46, *SD* = 0.57, 24 girls and 33 boys) of the same school as in Experiment 1 participated in this experiment. The parents of the children gave written informed consent and the children volunteered to participate in this study. The experiment took place at the school, in an equipped classroom. Participants performed this experiment in group sessions.

Material and procedure. The material and procedure used in this experiment were similar to those of Experiment 1, except for the distracting task. The squares used were the same as in Experiment 1 but the locations were those of the *close condition*. In a *fast condition*, participants were given 1s between each square presentation, as in Experiment 1. In a *slow condition*, the squares were presented for 667ms and followed by a white screen for 1333ms, resulting in a square presented every two seconds.

Dependent variable and statistical analyses. Based on performances on the pre-test, two groups were created, using the same thresholds as those used in Experiment 1. Participants were gathered in the group “Calc+” (*n*=33) if they had more than 12 correct answers on the pre-test and in the group called “Calc-” (*n*=11) if they had fewer than 8 correct answers on the same pre-test. The number of calculations correctly performed for each condition, *fast* and *slow*, was recorded. To test the hypothesis that the *slow condition* would result in better performances than the *fast condition* at least for the “calc-” group, a repeated measure ANOVA with the group as a between subject factor was performed on the number of correct calculations. Further pair comparisons were conducted using repeated student t-tests. As in experiment 1, the reaction time (in milliseconds) to perform the spatial judgment task was recorded and compared between experimental condition using t-tests.

Results

The results are summarized in Table 2. The repeated measure ANOVA with group as a between factor showed significant differences following the difficulty ($F(1,44) = 8.82$, $p = .005$) and following the group ($F(1,44) = 3.09$, $p = .086$) though this was only a marginally significant difference. The interaction between the two factors was not significant ($F(1,44) = 2.09$, $p = .156$). Further pair comparisons were conducted using repeated t-tests. Participants of the "Calc-" group performed more correct calculations in the "slow" condition than during the "fast" one ($M = 11.64$, $SD = 3.80$ and $M = 7.82$, $SD = 5.88$, $t(10) = 2.971$, $p = .014$, $d = 0.789$). On the contrary, the number of correct calculations accomplished by the participants of the "Calc+" group did not vary according to the condition ($M = 11.33$, $SD = 4.61$ and $M = 12.76$, $SD = 4.81$ for the "fast" and "slow" conditions respectively, $t(32) = 1.53$, $p = .136$, $d = 0.302$). As during the first experiment, time ratio manipulation affected participants having less automated mental calculation only. These participants performed better in the slowest condition though there were the same number of distracters in both conditions.

Participants from the "Calc+" group performed the concurrent task faster in the "fast" condition than in the "slow" condition ($M =389.82$, $SD = 39.85$ and $M = 468.30$, $SD = 58.26$ respectively, $t(32) = 10.82$, $p < .001$, $d = 1.600$). The same pattern appeared for the "Calc-" group ($M = 393.27$, $SD = 83.49$ and $M = 479.82$, $SD = 50.53$, $t(10) = 4.98$, $p = .001$, $d = 1.292$). Participants of both groups performed the concurrent task at the same speed for both "fast" and "slow" conditions ($t(11.56) = 0.13$, $p = .897$, $d = 0.068$ and $t(42) = 0.58$, $p = .562$, $d = 0.204$). Participants of the "calc-" group performed equally correctly in both conditions of the spatial judgment task (M = 72.14, SD = 15.38 and M = 72.56, SD = 16.93 for slow and fast condition respectively, $t(11) = 0.13$, $p = .900$). Participants of the "calc+" group also performed equally well the spatial judgment task in both conditions (M = 82.46, SD = 9.48 and M = 80.27, SD = 12.64 for slow and fast condition respectively, $t(33) = 1.62$, $p = .115$).

The presentation order had no effect on the number of correct calculations performed either during the "fast condition" ($t(42) = -0.374$, $p = .710$) or during the "slow condition" ($t(42) = 1.143$, $p = .260$).

	Number of correct calculations		**RT (s) on distracting task**	
	Slow condition	**Fast condition**	**Distracter Slow condition**	**Distracter fast condition**
Calc-	11,64 (3,80)	7,82 (5,88)	479,82 (50,53)	393,27 (83,49)
Calc+	12,76 (4,81)	11,33 (4,61)	468,30 (58,26)	389,82 (39,85)

Table 2. Means (and Standard deviations) of the number of correct calculations for the slow and fast conditions and of the reaction times (in milliseconds)on the distracting task

Discussion

In this experiment, we tested the hypothesis that manipulation of time ratio had an effect on working memory performance while ruling out interference based explanation. We reproduced the first experiment by using the exact same stimuli for the concurrent task and varying the inter-stimuli interval. Variations of the time remaining to refresh and manipulate information presented, resulted in variations in the number of correct calculations, at least for the least proficient students in mental calculation. Participants from the "expert" group showed no differences due to the time ratio, suggesting they were able to perform mental calculations during the time left by the "fast" condition. However, "Calc-" participants, having less automated mental calculation, performed better when the time ratio was lower.

Participants of both groups required the same time to perform the concurrent task, and this time was longer in the "slow" condition than in the "fast" condition. Despite this difference, the time ratio remained higher in the "fast" condition. A similar result appeared in previous experiments on the TBRS model and the authors concluded that their participants adapted their strategy to cope with a "speed-accuracy trade-off" (Barrouillet, Bernardin, Portrat, Vergauwe & Camos, 2007).

Following a TBRS based hypothesis, time ratio affected working memory performance for the "Calc-" group while the concurrent task and the number of distracters were the same in the two conditions. This result rules out the hypothesis of an interference effect, which would have affected participants differently based on their working memory capacity. It is also inconsistent with predictions allowed by models based on spatial storage metaphors, which assume that the number of elements passing through working memory is the first determinant of working memory performance. Here, providing "novices" with more time to maintain and manipulate information held in working memory resulted in better performance.

The results of this experiment are consistent with those of the first experiment and extend them. Thus the proportion of time dedicated to process irrelevant information and relevant information affects extraneous and intrinsic cognitive loads. They are not only determined by the number of elements to be processed but also by the time available and needed to process them.

General discussion

New working memory models are required to derive a more complete understanding of learning processes and the TBRS model appears to be a promising alternative. In two experiments, we assessed its validity when considering the manipulation of meaningful information and participants of different expertise levels in mental calculation. The first experiment showed that for a given duration, the time needed to process distracting elements had an effect on arithmetic performance. The second experiment extended this result, showing that the same number of distracting elements might induce different cognitive load levels, depending on the pace of presentation. Thus, the TBRS model has the potential to provide the assistance that is considered necessary in Cognitive Load Theory research by taking time into account (Paas et al., 2003; Van Gog et al., 2009; Spanjers, van Gog & van Merrienboer, 2010).

Our experiments emphasized the necessity of considering the level of expertise. Indeed, expertise affects the sensitivity to cognitive load induced by varying the time allowed to perform tasks (Experiment 1) and affects working memory performance (Experiment 2). This is consistent with previous Cognitive Load Theory research on the expertise effect (Kalyuga, Ayres, Chandler & Sweller, 2003; Kalyuga, 2007) as well as with previous works on working memory and expertise (e.g., Ericsson & Kintsch, 1995; Ericsson, 2006; Chi, 2006). In experiments on Cognitive Load Theory, expertise has been known to reverse most empirical effects on instructional procedures (Kalyuga et al., 2003; Kalyuga, 2007; Sweller, Ayres & Kalyuga, 2011; see also Sweller, 2010 for a review on expertise and interactivity). However, the present experiments showed that the TBRS model allows for prediction on manipulation of meaningful elements providing that prior knowledge level is considered.

These results were obtained with very low interactivity material, since participants had to process the terms of calculation in the presentation order. Thus, there were no links between first and last terms presented, limiting the interactivity of the material. However, expertise still had an effect, suggesting that it did not only reduce the element interactivity. This might have affected the particular form of chunking used in these experiments. At least for more expert participants, able to perform operations as they were presented, there might be virtually no limit to the number of terms one can add. This form of chunking is both quite close but also different to the commonly accepted definition of the chunk, as gathering several elements into a single meaningful element. The chunking form used here consisted in adding new elements to the “chunk” at each step, a feature that was not included in a classic definition of chunking. This conception allowed the use of meaningful items that could be manipulated together in relation to the content of long-term memory, in this instance the terms of a calculation. Participants did not learn mental calculation during these experiments; their main focus was to investigate the Time Based Resources Sharing model while using meaningful items. This allowed the role of time as a determinant of cognitive load to be emphasized. To date, most of the experiments investigating working memory have used fixed durations (for example, of one minute) and varied the number of elements (for example, from five and ten). A higher number of elements was associated with a lower working memory performance, i.e., it was considered as having a detrimental effect on learning. The TBRS model allows a reconsideration of such results, with the assumption that five elements in one minute will be processed as efficiently as ten elements in two minutes.

While some authors argued for counting the number of elements and their links in order to define a cognitive load estimation (Chanquoy, Tricot & Sweller, 2007), the TBRS model enables a different reading of these relations. Extrinsic load could be viewed as a product of a number of distracting elements and of the time needed to process units of distracting information, rather than their sole number. As shown in experiment 1, the same number of distracting elements might impose different extrinsic load depending on the time needed to process them. Our results suggest that the time ratio affects task performance and classic studies on the TBRS model suggest that time ratio rather than interference affects working memory performance (Barrouillet & Camos, 2015 for a review).

Intrinsic load, on the other hand, would rely on the remaining time available to refresh memory traces and manipulate information in working memory. The longer this time is, the easier it will be to maintain and manipulate a large quantity of information. Sweller (2011) stated that “intrinsic load refers to the intrinsic complexity of the information being processed” (p. 57) and that it is possible “to determine levels of intrinsic cognitive load by determining element interactivity” (p. 58), i.e., the number of elements to be processed simultaneously and their links. This resulted in a fixed amount of intrinsic load, at least for a given expertise level. Experiment 2 introduced time as a factor to be taken into consideration. This implies that for a given learner and a given learning task, the intrinsic load will not be the same following the time available to process information. If a learner needs two seconds to process intrinsic load, performance (and by extension, learning outcome) will not be the same if one or three seconds are available.

Expertise would allow faster refreshing and manipulation of information in working memory, reducing the influence of the time needed for the manipulation of distracting elements. Thus, expertise would decrease the sensitivity to time ratio manipulation. In the Cognitive Load Theory framework, expertise is viewed as decreasing interactivity between elements (Chen, Kalyuga & Sweller, 2015; 2016). By reducing such interactivity, expertise reduces the efficacy of Cognitive Load Theory empirical effects. Most importantly, expertise reduces both intrinsic and extrinsic cognitive loads. Our results, in a low interactivity situation, extend this conception, considering expertise as allowing faster processing of information held in working memory and thus reducing sensitivity to time ratio manipulations.

The TBRS model describes dynamic variations in working memory, and thereby allows time to be taken into account while studying working memory requirement. However, the same number of distracting tasks might result in different cognitive load levels, depending on the time they require attention for. The exact same task with the same distracters might also impose different cognitive load levels depending on the remaining time available to process intrinsic load elements. This allowed the explanation of variations of learning outcomes in the Schmidt-Weigand et al. (2010) study, the same learning material presented at different paces providing different results. Further studies should investigate the TBRS model in learning situations to extend the result of these experiments to the broad field of cognitive load theory research. In particular, it could help to provide a physiological measurement of cognitive load. It supports the idea that time should a greater role when considering the determinant of cognitive load, affecting the number of elements and their links.

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