How Do We Choose Among Strategies to Accomplish Cognitive Tasks? Evidence From Behavioral and Event-Related Potential Data in Arithmetic Problem Solving

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ABSTRACT—We used event-related potentials (ERPs) to determine the time course of mechanisms underlying strategy selection. Participants had to select the better strategy on multiplication problems (i.e., $51 \times 27$) to find approximate products. They could choose between rounding up and rounding down both operands to their nearest decades. Two types of problems were tested, homogeneous problems (e.g., $34 \times 61$) and heterogeneous problems (e.g., $61 \times 36$). Homogeneous problems are easier to solve because both operands are close to the lowest or the upper decades. Behavioral data revealed that participants selected the better strategy more often on homogeneous problems. ERPs showed that homogeneous problems elicited more positive cerebral activities than heterogeneous problems in the 0–200 and 800–1,000 ms windows, and more negative cerebral activities than heterogeneous problems in the 400–600 ms window. These findings have important theoretical implications for our understanding of the mechanisms underlying strategy selection.

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One of the most fundamental aspects of human cognition is strategy variability. In a wide variety of cognitive tasks, participants use several strategies and select a given strategy on a problem-by-problem basis (see Siegler, 2007, for a review). This has been observed in different populations and in different cognitive domains, shaped by education, as diverse as arithmetic (Siegler & Lemaire, 1997), memory (Touren & Hertzog, 2009), reasoning (Hartley & Anderson, 1983), decision making (Mata, Schooler, & Rieskamp, 2007), or language (Kail, Lemaire, & Lecacheur, 2012). An important issue is how participants determine which strategy is the better one or what mechanisms underlie better strategy selection on each problem. Lemaire and Reder (1999, p. 365) defined a strategy as “a procedure or a set of procedures for achieving a higher level goal or task.” The present work aimed at further our understanding of strategy selection by using event-related potentials (ERPs) to decipher the time course of processes underlying strategy selection.

Previous empirical research has found that strategy selection is influenced by problems (e.g., Zbrodoff & Logan, 2005), situations (e.g., Trbovich & LeFevre, 2003), strategies (e.g., Lemaire & Lecacheur, 2002), and participants’ characteristics (e.g., Imbo & Vandierendonck, 2007). For example, Lemaire, Arnaud, and Lecacheur (2004) found that the type of strategies, of problems and of speed/accuracy pressures influenced participants’ performance in a computational estimation task. When they had to find...
approximate products to two-digit multiplication problems like $53 \times 67$, participants were asked to select the better strategy on each problem between rounding down (RD) and rounding up (RU) on small-unit versus large-unit problems (i.e., $41 \times 56$ vs. $39 \times 54$). The RD strategy was described as rounding both operands down to the nearest decades, like when doing $50 \times 60 = 3000$ to estimate $53 \times 67$. The RU strategy was described as rounding both operands up to the nearest decades, like when doing $60 \times 70 = 4200$ to estimate $53 \times 67$. Both groups exhibited longer reaction times when they were asked to be most precise. However, older adults slowed down less than young participants when they had to use the RU strategy on problems with large units.

Several cognitive theories of strategy selection have been proposed (e.g., Siegler & Araya’s strategy choice and discovery simulation (SCADS) model, 2005; Lovett & Schunn’s “represent the task, construct a set of action strategies, choose from among those strategies according to success rate, learn new success rates” (RCCL) model, 1999; and Rieskamp & Otto’s strategy selection learning (SSL) model, 2006). Although they differ in some computational details and theoretical tenets, these models share common assumptions regarding mechanisms underlying strategy selection. First, all models assume that participants choose a strategy on each problem. Second, each strategy is associated with particular speed and accuracy performance, and these associations result from experience. Third, strategy choices involve a selection process based on relative strategy performance and/or problem features so that participants try to select the better strategy on each problem. Finally, they assume that encoding problems activates all available strategies and that the strategy that receives the highest level of activation, on the basis of strategy performance and/or problems characteristics, is selected.

One of the most important limitations of previous work concerns the time course of strategy selection processes. This limitation is important to address because uncovering the time course of strategy selection processes may reveal different processes when participants select different strategies on different types of problems. Right now, most previous work implicitly or explicitly assumes that participants use the same set of processes when selecting different strategies on different items. However, it is possible that participants use different sets of strategy selection processes on each item. For example, participants may differ in how they select strategies to encode concrete versus abstract words during episodic memory encoding. Similarly, in arithmetic, the focus of this study, participants may use different sets of strategy selection processes when they solve problems like $41 \times 52$ or $27 \times 32$. To solve these problems, a rule can be used to select the better strategy. Indeed, the better strategy is RD if the sum of unit digits is smaller than 10 (e.g., $34 \times 62$) and RU if this sum is larger than 10 (e.g., $63 \times 38$). Models assume that participants will use the same set of processes to solve $41 \times 52$ and $27 \times 32$. Participants will first add both unit digits and then compare the sum to 10. But, it is possible that participants use different sets of processes to solve different types of problems. For example, when the sum of unit digits is close to 10, participants need to do an exact calculation to decide which strategy is better. When the sum of unit digits is far from 10, like in $31 \times 52$, participants only need to do an approximate calculation to decide that the better strategy is the rounding down. Or, they can use a heuristic like “Both unit digits <5, use RD; both unit digits >5, use RU.” Thus, the original goal of this study was to determine whether strategy selection for different types of problems involves different sets of processes. Here, we used the ERP technique given its high temporal resolution that is necessary to achieve this goal.

Previous studies revealed that both electroencephalography (EEG; e.g., De Smedt, Grabner, & Studer, 2009; Grabner & De Smedt, 2011, 2012) and ERP (e.g., Dehaene, Spelke, Pinel, Stanescu, & Tsivkin, 1999; El Yagoubi, Lemaire, & Besson, 2003; Hainault, Dufau, & Lemaire, 2015; Kiefer & Dehaene, 1997; Luo, Liu, He, Tao, & Luo, 2009; Uittenhove, Poletti, Dufau, & Lemaire, 2013) can be useful not only to uncover cognitive processes underlying mathematical problem-solving performance but also to further understand cognitive and neural mechanisms underlying strategic aspects of participants’ performance. For example, El Yagoubi et al. (2003) collected ERPs during a problem verification task. Participants were presented two operands like 18 and 67 and had to determine whether their sum was smaller or larger than 100. Participants used two different strategies, an approximate-calculation strategy to solve problems for which 100 and correct sums had a large difference (e.g., $18 + 67$) and an exhaustive-verification strategy to solve problems for which 100 and correct sums had a small difference (e.g., $32 + 67$). El Yagoubi et al. found that the choice between the two strategies occurred within 250 ms poststimulus presentation.

As another example, Uittenhove et al. (2013) used ERPs to determine the time course of strategy sequential difficulty effects. In strategy sequential difficulty effects, participants take longer to execute a strategy on a given problem following execution of a harder strategy than after executing an easier strategy on the immediately preceding problem. Uittenhove et al. found larger cerebral activities while executing strategies on current problems following harder compared with easier strategies between 250 and 500 ms after current problems display. Their results suggest that strategy sequential difficulty effects act during the stimulus encoding phase rather than during execution processes.

Thus, results of previous studies showed the usefulness of ERPs to study arithmetic strategies. However, none of the previous studies focused on strategy selection processes.
This made it impossible to examine the time course of these strategy selection processes. In this study, we originally used ERPs to examine neural correlates of strategy selection processes in conditions where difficulty of selecting the better strategy was manipulated. We pursued this goal in the context of computational estimation tasks.

In computational estimation tasks, participants are given arithmetic problems like $53 \times 38$ and have to provide an approximate product for each problem. Previous work found that participants use a wide variety of strategies to find approximate products to two-digits multiplication problems and select strategies on a problem-by-problem basis, that some strategies are easier (i.e., yield faster latencies and lower error rates) than others, and that strategy selection is influenced by problem, situation, and participants’ characteristics (e.g., Hanson & Hogan, 2000; Imbo & LeFevre, 2011; LeFevre, Greenham, & Waheed, 1993; Lemaire & Lecacheur, 2004; Lemaire et al., 2004; Reys, Reys, Nohada, Ishida, & Yoshikawa, 1991; Sowder & Wheeler, 1989; Star & Rittle-Johnson, 2009; Xu, Wells, LeFevre, & Imbo, 2014). In previous work, focusing on strategy selection (e.g., Lemaire & Leclère, 2014a, 2014b; Lemaire et al., 2004), participants were asked to select the better of two rounding strategies on each problem, the RU (e.g., doing $40 \times 60$ for $37 \times 51$) or the RD (e.g., doing $30 \times 50$ for $37 \times 51$) strategies. One robust finding is that participants select the better strategy more often (and are faster) on so-called homogeneous problems (i.e., problems with unit digits of both operands either smaller or larger than 5, as in $43 \times 51$) than on so-called heterogeneous problems (i.e., problems with unit digit of one operand smaller than 5 and unit digit of the other operand larger than 5, as in $53 \times 68$). The present work used the same approach and examined differences in ERPs between homogeneous and heterogeneous problems.

In the present experiment, to find approximate products to two-digit multiplication problems, participants were instructed to select the better of two rounding strategies on each problem, the RU or the RD strategy. Participants were explained that the better strategy is the strategy that, among the available RD and RU strategies, yields the closest product from the correct product. We manipulated problem features so that the better strategy was easier to select on homogeneous problems and harder on heterogeneous problems. Behaviorally, we predicted to replicate previous findings that participants select the better strategy more often on homogeneous than on heterogeneous problems. Concerning ERP data, we tested differences in the time course of mechanisms underlying the better strategy selection. If selecting the better strategy which involves different sets of strategy selection processes, we expected qualitative differences in ERPs. More specifically, we expected a difference in the very early ERP signals between homogeneous and heterogeneous problems. This was expected because for homogeneous problems, participants do not need to add both units to quickly decide which strategy is the better. Moreover, if participants engage in activating a more complex rule (i.e., if one unit digit is smaller than 5 and the other larger than 5, and if the sum of unit digits $<10$, then choose RD; if one unit digit is smaller than 5, and the other larger than 5, and if the sum of unit digits $>10$, then choose RU) for selecting the better strategy on heterogeneous problems, extraprocessing demands of such rules were expected to yield differences in later ERP signals between homogeneous and heterogeneous problems.

## METHOD

### Participants

Twenty two participants were tested (13 women; age range 20–28 years). They were all undergraduate students from Aix-Marseille University (Marseille, France). All participants were paid 20 euros for their participation.

### Stimuli

Stimuli were 160 multiplication problems presented in standard form (i.e., $a \times b$) with the operands $a$ and $b$ being two-digit numbers. Two types of problems were created, 80 homogeneous and 80 heterogeneous. Unit digits of both operands were smaller than 5 (e.g., $43 \times 51$) in half the homogeneous problems and larger than 5 (e.g., $79 \times 26$) in the other homogeneous problems. Unit digit of one operand was smaller than 5 and that of the other operand was larger than 5 (e.g., as in $53 \times 68; 64 \times 36$) in heterogeneous problems. For each type of problems, the better strategy was RD on half the problems and RU on the other problems.

Mean correct products were statistically nondifferent for the two types of problems ($F < 1.0$). More precisely, mean correct products were 2,935 (range: 1,092–5,963) for homogeneous and 3,020 (range: 1,288–5,727) for heterogeneous problems. This was necessary for the difficulty of determining which strategy is the better strategy on each problem to be unconfounded with the difficulty of calculating correct products. Similarly, we controlled the differences in mean percentages of deviations between correct products and estimates for the two (RD and RU) strategies and for the two types of problems ($F < 1.0$). More specifically, mean percentages of deviations between correct products and estimates were 19.9% (range: 4.4%–45.1%) and 22.4% (range: 4.3%–58.7%) when using RD and RU strategies, respectively, on homogeneous problems. Corresponding mean percentages of deviation for heterogeneous problems were 20.1% (range: 9.6%–36.1%) and 21.5% (range: 9.7%–50.4%) when using RD and RU strategies, respectively.

Previous findings indicate several variables to control for when selecting problems (see Campbell, 2005, for a review). Therefore, problems were selected so as to control for the
following factors: (a) no operands had 0 (e.g., 30 × 48) or 5 as unit digits (e.g., 35 × 48); (b) the decades were between 2 and 8; (c) digits were not repeated in the same decade or unit positions across operands (e.g., 43 × 47); (d) no digits were repeated within operands (e.g., 44 × 59); (e) no reverse order of operands were used (e.g., if 52 × 76 was used, then 76 × 52 was not used); (f) no tie problems were used (e.g., 32 × 32); (g) the first operand was larger than the second in half the problems and the reverse in the other problems; and (h) no operand had its closest decade equal to 0, 10, or 100.

Procedure
Before the start of the experiment, all participants signed an informed consent form. They were then comfortably seated in a quiet room and told that they were going to do computational estimation. Computational estimation was explained as giving an approximate answer to an arithmetic problem that is as close as possible from the correct answer without actually calculating the correct answer. Participants were told that they would use one of two rounding strategies, RD or RU strategies. The RD strategy was described as rounding both operands down to the nearest decades, like when doing 50 × 80 to estimate 51 × 89. The RU strategy was described as rounding both operands up to the nearest decades, like when doing 60 × 90 to estimate 51 × 89. Instructions emphasized that participants should not use any other strategies, should do only the initial rounding up or down, and should do nothing more (i.e., adding or subtracting small amounts) after calculating the product of rounded operands.

A total of 160 problems, divided into four blocks of 40 problems each, were presented. There were 20 problems of each type in each block. Stimuli were presented on an 800 × 600 resolution screen in a 42-point Times New Roman font. Each trial began with a 500-ms blank screen, followed by a ready signal (“*”) appearing for 400 ms in the center of the screen. Then, the stimulus appeared and remained on the screen until participant’s response (see Figure 1). They were asked to round each strategy out loud to know which strategy was chosen and executed. They were also asked to refrain from moving and blinking during the presentation of the stimuli. All participants received the same random order of problems, and each participant was permitted 5–10 min between each block. Before the experiment started in earnest, participants received 20 training (similar to but different from experimental) problems to familiarize themselves with the apparatus, procedure, condition, and task.

Data Acquisition
Electrophysiological activity was recorded with an Active Two Biosemi system with 64 electrodes positioned on an elastic cap following the 10–10 international system (Fp1/2, AF7/8, AF3/4, F7/8, F5/6, F3/4, F1/2, FT7/8, FC5/6, FC3/4, FC1/2, T7/8, C5/6, C3/4, C1/2, TP7/8, CP5/6, CP3/4, CP1/2, P9/10, P7/8, P5/6, P3/4, P1/2, PO7/8, PO3/4, CMS/DRL, O1/2, FPz, AFz, Fz, FCz, Cz, CPz, Pz, POz, Oz, Iz). We used six external electrodes: two on the right and left mastoids, two below the right and left eyes, and two on the right and left temples. Electrodes below the eyes and on the temples allow us to identify eye blinks and horizontal eye movements. The signal was registered at a frequency of 256 Hz, and data were analyzed using EEGLAB software (Delorme & Makeig, 2004). Data were first re-referenced offline using the average of the left and right mastoids. Then, the signal was filtered (1 Hz high-band and 20 Hz low-band) and epochs were extracted from stimulus display to 1,500 ms post stimulus. We did not analyze beyond 1,500 ms for two reasons. First, as previous work (e.g., El Yagoubi et al., 2003; Uittenhove et al., 2013) showed, strategy selection studied here occurs during the first steps of problem solving. Second, after choosing a strategy, participants begin to verbalize their response, which may produce artifacts on the signals. Finally, the signal was baselined from 200 ms before the stimulus display to the stimulus. Epochs with movement artifacts or activity exceeding 50 μV were rejected.

RESULTS
First, we analyzed behavioral data (i.e., percentages of choice of the better strategy, mean solution latencies, and mean percentages of errors). Then, we analyzed electrophysiological data on correctly solved problems. An error was made when the provided estimates differed from the expected estimates given the strategy that was used. For example, estimates of 1,900 with the RD strategy for 42 × 57 were coded as an error; an estimate of 2,000 was coded as correct. We removed from the analyses 5.3% of problems corresponding to latencies larger than the mean plus 2 standard deviations. Data for three of the 22 participants were dropped because they did not perform the task correctly (i.e., they used the same strategy on more than 90% of the problems). For all the results, unless otherwise noted, differences are significant to at least p < .05.

Behavioral Data
One-way analyses of variance (ANOVAs) with two (problem type: homogeneous and heterogeneous) as a
within-participants factor were conducted on mean percentages of the better strategy selection, on mean solution latencies, and on mean percentages of errors (see means in Table 1). Results showed a main effect of problem type, \( F(1, 18) = 92.59, \text{MSE} = 142.8, \eta^2_p = .84, p < .001 \). Participants selected the better strategy more often on homogeneous (94.5%) than on heterogeneous problems (67.2%). Analyses of estimation latencies revealed a main effect of problem type, \( F(1, 18) = 4.33, \text{MSE} = 771,167, \eta^2_p = .19, p = .05 \). Participants were faster to estimate homogeneous (5,413ms) than to estimate heterogeneous problems (6,160ms), \( F(1, 18) = 6.59, \text{MSE} = 805,590, \eta^2_p = .27, p = .02 \). Finally, analyses of mean percentages of errors revealed that the difference between homogeneous and easier heterogeneous problems on percentages of errors was not significant (\( F < 1.0 \)).

**Electrophysiological Data**

The goal of ERP analyses was to test differences in ERPs on problems for which participants tried their best to select the better rounding strategies. Therefore, we compared ERPs for correctly solved homogeneous and heterogeneous problems. Following Grabner and De Smedt (2011), we grouped lateral electrodes into eight clusters: left and right prefrontal, left and right frontal, left and right parietal, and left and right occipitoparietal cortices (see Figures 2 and 3). Using a combination of statistical analyses (\( t \)-tests) of every 50 ms and visual inspection, we defined three windows of interest: 0–200, 400–600, and 800–1,000. No effects came out significant between 1,000 and 1,500 ms. We conducted ANOVAs on mean amplitudes of electrophysiological activities, while participants solved homogeneous and heterogeneous problems in these three windows. In our design, participants had to respond out loud when they had the answer to the problem. We cannot know exactly when participants’ vocalizations started because it depends on many parameters and we did not collect latencies of first vocalizations. However, given estimation latencies (5,413 ms for homogeneous problems and 6,160 ms for heterogeneous problems), it is reasonable to think that participants did not speak during the first

**Table 1**

<table>
<thead>
<tr>
<th>Type of problems</th>
<th>Mean percentages of better strategy selections</th>
<th>Mean solution latencies</th>
<th>Mean percentages of errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homogeneous problems</td>
<td>94.5</td>
<td>5,413</td>
<td>6.8</td>
</tr>
<tr>
<td>Heterogeneous problems</td>
<td>67.2</td>
<td>6,160</td>
<td>6.3</td>
</tr>
</tbody>
</table>

**Fig. 2.** Schematic display of event-related potential electrodes positions.
Fig. 3. Visualization of event-related potential analysis of variance results for time windows (Potential is the mean potential in each time windows.).

1,000–1,500 ms. Furthermore, we rejected all epochs with movement artifacts.

0–200 ms
ANOVAs revealed a significant effect in the right, $F(1, 18) = 5.11$, $MSE = 0.73$, $\eta^2_p = .27$, $p = .02$, and left parietal, $F(1, 18) = 7.24$, $MSE = 0.46$, $\eta^2_p = .29$, $p = .01$. Effects were also significant in the right, $F(1, 18) = 6.53$, $MSE = 0.69$, $\eta^2_p = .27$, $p = .02$, and left occipitoparietal, $F(1, 18) = 8.78$, $MSE = 0.64$, $\eta^2_p = .33$, $p = .01$. ERPs were significantly more positive in these regions, while participants solved homogeneous problems than while solving heterogeneous problems.

400–600 ms
ANOVAs revealed significant more positive activities for heterogeneous than for homogeneous problems in the left parietal, $F(1, 18) = 10.8$, $MSE = 0.32$, $\eta^2_p = .37$, $p = .01$, and in the left occipitoparietal, $F(1, 18) = 5.37$, $MSE = 0.45$, $\eta^2_p = .23$, $p = .04$.

800–1,000 ms
ANOVAs revealed significant more positive activities for homogeneous problems than for heterogeneous problems in the right, $F(1, 18) = 5.41$, $MSE = 0.92$, $\eta^2_p = .21$, $p = .07$, and left parietal, $F(1, 18) = 7.88$, $MSE = 0.85$, $\eta^2_p = .3$, $p = .01$. Activities were also significantly more positive in the left occipitoparietal, $F(1, 18) = 6.03$, $MSE = 1.28$, $\eta^2_p = .25$, $p = .03$, and marginally significantly more positive in the right occipitoparietal, $F(1, 18) = 4.13$, $p = .057$, $MSE = 1.07$, $\eta^2_p = .19$, $p = .05$.

Examples of wave amplitudes during homogeneous and heterogeneous problems for each cluster are presented in
**Fig. 4.** Wave amplitudes during homogeneous (blue) and heterogeneous problems (red) for left and right (a) prefrontal, (b) frontal, (c) parietal, and (d) occipitoparietal.

Figure 4, and scalp maps of the three windows of interest are presented in Figure 5.

**DISCUSSION**

This study aimed to further our understanding of mechanisms underlying strategy selection processes using ERP and behavioral data. We pursued this goal in the context of a computational estimation task in which participants had to choose the better of two rounding strategies on each problem to provide estimates for two-digit multiplication problems. Participants chose the better strategy more often on homogeneous than on heterogeneous problems. We also found more positive ERPs, while participants solved homogeneous problems than while they solved heterogeneous problems from 0 to 200ms and from 800 to 1,000ms after problem display. Moreover, cerebral activities were more positive for heterogeneous than for homogeneous problems from 400 to 600ms following problem display.

In this experiment, we replicated the robust findings that participants choose the better strategy more often on homogeneous than on heterogeneous problems, previously reported in numerous studies of computational estimation (e.g., LeFevre et al., 1993; Lemaire & Leclère, 2014a, 2014b; Lemaire et al., 2004). This result was expected because characteristics of homogeneous problems (i.e., size of unit digits) allow to easily determine which strategy is the better one. In contrast, characteristics of heterogeneous problems are less salient. Thus, the better strategy is more difficult to find, and participants selected it less often. Analyses of solution times showed that participants were faster to solve homogeneous than heterogeneous problems, although error rates were the same for both types of problems.

The main goal of collecting ERP data was to test differences in the time course of mechanisms underlying the better strategy selection. We found more positive cerebral activities while participants were solving homogeneous problems compared with heterogeneous problems during early stage of problem solving (i.e., from 0 to 200ms after stimulus presentation). Previous ERP findings (e.g., Dehaene et al., 1999) suggest that this is a window during which participants encode problems. Our early difference in ERPs for homogeneous and heterogeneous problems during encoding of problems may result from participants’ quickly activating the rule for determining the better strategy on
homogeneous problems. That is, while participants were encoding operands of homogeneous problems, they quickly noticed that unit digits of both operands were either smaller or larger than 5. This enabled them to quickly decide that the better strategy is RD when both unit digits are smaller than 5 and is RU when both unit digits are larger than 5. Unknown is whether participants strategically aimed at first examining the size of unit digits to quickly decide which strategy is the better strategy before finishing to encode the decade digits of the operands and rounding them up or down, or whether they fully encoded both operands before further analyzing the size of unit digits and, subsequently, selected the better strategy. Future work could test these two possibilities. This could be performed by comparing ERPs of each type of problem when participants are explicitly instructed to apply the first versus the second approach. Eye movements would enable researchers to ensure that participants comply with instructions to use each strategy on all problems.

The next interesting and original findings in our ERP data was the more positive cerebral activities for homogeneous than for heterogeneous problems between 800 and 1,000 ms after problem presentation. Such later differences in ERPs may correspond to participants’ being already engaged in the strategy execution phase on homogeneous problems. Also, participants may be continuing to figure out the better strategy on heterogeneous problems. They could try to do this by calculating the sum of unit digits and by comparing this sum to 10. An interesting follow-up study to test this possibility would be to manipulate distance between sum of unit digits and 10 and to determine whether ERP differences would arise as a function of such distance.

We observed an interesting final difference between homogeneous and heterogeneous problems (i.e., more positive activities for heterogeneous problems) that occurred between 400 and 600 ms after problem display. This difference may reflect the greater difficulty of selecting the better strategy on heterogeneous problems. Recall that a more complex rule must be used by participants to select the better strategy on these problems. That is, participants needed to calculate the sum of unit digits on heterogeneous problems before being able to decide which is the better strategy. The better strategy is RD if this sum is smaller than 10 and RU if it is larger than 10. Calculating the sum of unit digits was not necessary on homogeneous problems. Such extraprocessing steps may have generated larger positive cerebral activities between 400 and 600 ms post-heterogeneous problems display.

The issue raised by our findings concerns whether both our behavioral and ERP results reflect differences in difficulty for strategy selection or more general difficulty effects. First, mean correct products were statistically nondifferent between homogeneous and heterogeneous problems. This was necessary for the difficulty of determining which strategy is the better strategy on each problem to be unconfounded with the difficulty of calculating correct products. Second, as postulated by models of strategy selection, participants solve these problems by using the same set of processes. They first encode problems before adding both unit digits to finally compare this sum with 10. The difference in difficulty between homogeneous and heterogeneous arises from the fact that the sum of unit digits is closer to 10 for heterogeneous problems. Therefore, if our results reflect only a general difficulty effect, the difference between the two types of problems would influence participants when comparing the sum with 10, a process known to occur after 250 ms (e.g., El Yagoubi et al., 2003). In contrast, the present findings revealed an early ERP difference (i.e., 0–200 ms) between homogeneous and heterogeneous problems.

All together, our data suggest that characteristics of problems are crucial in strategy selection, especially when these characteristics are highly correlated with accuracy as is the case in our computational estimation task. When
characteristics of problems are salient, participants can use rules to figure out the better strategy. These rules can be easy, like on homogeneous problems, or more difficult, like on heterogeneous problems. Our ERP data were crucial in revealing different time courses for each type of strategy selection processes.

At a more general level, the present findings have theoretical implications regarding strategy selection models such as Payne, Bettman, and Johnson’s adaptive decision maker (1993); Siegler and Shipley’s adaptive strategy choice model (ASCM) (1995); Lovett and Andon’s adaptive control of thought–rational (ACT–R) (1996); Lovett and Schunn’s RCCL (1999); Siegler and Araya’s SCADS (2005); and Rieskamp and Otto’s SSL model (2006). First, models assumed that participants need to fully encode the problem before activating available strategies in working memory. Our results suggest that it is possible that participants activated available strategies during encoding of problems especially when salience of problem features enables to quickly and easily select the better available strategy.

Second, models also assumed that strategy choices involve the same set of processes when selecting different strategies on different items. However, the present findings suggest that participants use different sets of strategy selection processes depending on the type of problems. By implementing different sets of strategy selection processes, computational models of strategy selection will further our understanding of mechanisms underlying strategy selection and specify the dynamics of these strategy selection processes.

Finally, our results also have several implications regarding both cognitive development and education. First, as discussed in detail by many researchers (e.g., Siegler, 1996), it is important to take into account multiple-strategy use and children’s skills at selecting the best strategy on each problem when thinking about what changes in children with age as well as how such changes occur. Indeed, what may change with age, among others, are mechanisms underlying strategy selection. Such changes may concern the type of strategy selection mechanisms or how executing each mechanism changes with age and/or schooling. An interesting follow-up of the present approach would be to collect ERPs in children of different age groups while they are solving different types of problems. Of interest would be whether, like here, ERPs would reveal different types of strategy selection mechanisms and ERPs with different time courses in each group of children. Moreover, it would be interesting to adapt the present approach to better inform how different cultural backgrounds and instruction methods influence age-related changes in children or adults while they select the best strategy on each problem. Previous studies found many cultural differences regarding strategy selection processes in both children and adults (e.g., Campbell & Xue, 2001; Xu et al., 2014). For example, Xu et al. recently found that Chinese-educated participants were more likely to choose the best strategy than Canadian-educated participants in the context of computational estimation tasks like those used in this study. It would be interesting to determine whether differences in ERPs for homogeneous and heterogeneous problems are found in both groups of participants like here or if these two groups of participants who have learned arithmetic in different education systems show different patterns of ERPs when they select the best strategy on each problem. In other words, it would be interesting to determine how different education systems shape the type of strategy selection mechanisms used by participants when they try to select the best strategy on each item. More generally, it would be of interest to further analyze if education-related and age-related differences in both adults and children are specific to some symbolic systems (like arithmetic studied here) or if they generalize across different domains of cognition, some heavily influenced by education (like reading, mathematics) and others less influenced (like executive control, working memory).

REFERENCES


