Evidence for positive and negative transfer of abstract task knowledge

in adults and school-aged children

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This manuscript was submitted to Cognition on the 10th of October 2022. A revised manuscript was submitted on the 9th of October 2023.

Conflict of Interest Statement; We have no conflicts of interest to declare.

Acknowledgements; The research reported here was supported by a Grant-in-Aid for Japan Society for the Promotion of Science fellows (19J00130) to Kaichi Yanaoka, by Japan Society for the Promotion of Science KAKENHI (Grant No. JP20H01786) to Satoru Saito, and by a JSPS Bilateral Joint Research Project (JPJSBP120209916) to Satoru Saito and Christopher Jarrold.

Abstract

Engaging cognitive control is essential to flexibly adapt to constantly changing environments. However, relatively little is known about how prior task experience impacts on the engagement of cognitive control in novel task environments. We aimed to clarify how individuals learn and transfer the engagement of cognitive control with a focus on the hierarchical and temporal aspects of task knowledge. Highlighting two distinct cognitive control processes, the engagement of cognitive control in advance (proactive control) and in response to conflicts (reactive control), we conducted six preregistered online experiments with both adults (Experiment 1, 3, and 5: N = 71, N = 108, and N = 70) and 9- to 10-year-olds (Experiment 2, 4, 6: N = 69, N = 108, and N = 70). Using two different experimental paradigms, we demonstrated that prior task experience of engaging reactive control makes adults and 9-to 10-year-olds respond in a reactive way in a subsequent similar-structured condition with different stimuli in which proactive control could have been engaged. This indicates that individuals do learn knowledge about the temporal structure of task goal activation and, on occasion, negatively transfer this knowledge. Furthermore, individuals exhibited these negative transfer effects in a similar-structured condition with different task goals and stimuli, indicating that they learn hierarchically-structured task knowledge. The collective findings suggest a new way of understanding how hierarchical and temporal task knowledge influences the engagement of cognitive control and highlight potential mechanisms underlying the near transfer effects observed in cognitive control training.

Key words: task knowledge, proactive/reactive control, negative transfer, hierarchical structure, children

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It is essential for humans to flexibly adjust their goal-directed behaviors to constantly changing environments. Flexible implementation of goal-directed behaviors depends on cognitive control processes such as updating information stored in working memory, inhibiting prepotent responses, and switching to a new task (e.g., Engle & Kane, 2004; Miyake & Friedman, 2012; Monsell, 2003). The engagement of such cognitive control undergoes pronounced developmental improvements during childhood (e.g., Best & Miller, 2010; Diamond, 2013; Gathercole et al., 2004; Zelazo et al., 2013). Over the past two decades, considerable attention has been paid to how adults and children learn to engage cognitive control in studies of adaptive control (e.g., Abrahamse et al., 2016; Braem et al., 2019; Egner, 2014; Gonthier et al., 2021) and cognitive control training (Byrne et al., 2020, Fellman et al., 2020; Gathercole et al., 2019; Holmes et al., 2019; for a review von Bastian et al., 2022).

To clarify how individuals learn to engage cognitive control, previous studies have examined not only how individuals improve their performance during repetitions of a cognitive control task but also how they transfer such benefits to different task contexts (e.g., Braem et al., 2019; Gathercole et al., 2019). Thus, it is critically important to examine how individuals generalize and transfer task experience to the engagement of cognitive control in different task environments. The acquisition of long-term knowledge has emerged as one promising mechanism underlying such transfer effects, with various authors suggesting that transfer is supported by the acquisition of production rules (Anderson, 1982), cognitive skills (Taatgen, 2013), associations between control and stimulus-response mappings (Abarahamse et al., 2016), or cognitive routines (Gathercole et al., 2019). As individuals experience a task repeatedly, they begin to identify and learn abstract task knowledge that captures the regularities of the task environment beyond specific contexts (e.g., specific stimulus-response contingencies) (Bhandari & Badre, 2018; Collins & Frank, 2013; Franklin & Frank, 2018; Gershman et al., 2010; Rougier et al., 2005). Transfer arises when such task knowledge can be applied to different task environments. However, very few studies have systematically examined what aspects of a task individuals learn and transfer when engaging cognitive control. Classical schema theories would suggest that, through repeated experience, individuals are capable of learning hierarchical and temporal aspects of a task or an event and obtaining long-term knowledge about them (Lashley, 1951; Miller et al., 1960; Schank &

Abelson, 1977). Given this, we aimed to clarify how individuals learn and transfer the engagement of cognitive control with a focus on hierarchical and temporal aspects of task knowledge.

It is well known that a hierarchical structure promotes analogy and the application of existing knowledge at higher levels when encountering a similarly-structured task with different lower-level items (e.g., Gick & Holyoak, 1980, 1983). In line with this, many studies have shown that adults and children are aware that task environments have a hierarchical structure (Collins & Frank, 2013; Monsell, 2003; Munakata et al., 2012; Werchan et al., 2015, 2016; Zelazo, 2015). Specifically, individuals acquire knowledge of task representations, which is hierarchically composed of knowledge of a task goal and stimulus–response mappings that are tied to that goal. For example, in task-switching studies, participants are instructed to activate a particular task goal (e.g., sorting by either Feature A or Feature B), which enables them to process the relevant stimulus dimension (e.g., A or B), and select the correct stimulus-response mapping (e.g., pressing the "R" key when a stimulus is presented in a task A). Acquired knowledge of task representations allows adults to accommodate a novel set of stimulus–response mappings in a similarly-structured task, resulting in fast and accurate adaptation to different task environments (Badre & Frank, 2012; Badre et al., 2010; Dreisbach, 2012; Shahar et al., 2018). Among children, Werchan et al. (2015) showed that even infants spontaneously create hierarchical task representations during incidental learning. In addition, preschoolers not only benefit from incidental learning but also but also develop the ability to immediately represent, and maintain in working memory, task structures when task goals are explicitly conveyed via instruction (Munakata et al., 2012). Although infants and preschoolers therefore acquire knowledge of task representations in different ways, this knowledge allows them to generalize flexible goal-directed behaviors when presented with novel stimuli (Kharitonova et al., 2009; Kharitonova & Munakata, 2011; van Bers, Visser et al., 2014; van Bers, van Schijndel et al., 2020; Werchan et al., 2015, 2016). Given this, learning the hierarchical aspect of task knowledge, that is, knowledge of task representations, is likely to help both adults and children to engage cognitive control in subsequent similarly-structured conditions that employ different stimulus-response mappings.

On the other hand, researchers have paid less attention to how much individuals are aware that task environments have a dynamical structure, with events unfolding in a specific order, and with specific timings. However, individuals learn how to implement goal-directed behaviors in accordance with such temporal task structures. Such abstract task knowledge allows individuals to transfer an understanding of how to engage internal cognitive processing in accordance with temporal task structures to different task environments. The current study focused on knowledge of the temporal structure of the activation of task goals, which refers to individuals' knowledge about when to activate a task goal to engage cognitive control. Such knowledge differentiates two distinct cognitive control strategies, that is, proactive and reactive control (e.g., Braver, 2012; Chatham et al., 2009; Gonthier et al., 2016; Munakata et al., 2012). According to the Dual Mechanisms of Control theory (Braver, 2012), proactive control allows individuals to actively maintain goal-relevant information in a sustained manner before the occurrence of cognitively demanding events, to bias the cognitive system. By contrast, reactive control is mobilized only as needed after a high interference event is detected. For both adults and children, researchers have often employed several experimental paradigms to investigate whether either proactive or reactive control has been used, such as the AX-CPT task (e.g., Braver et al., 2007; Chatham et al., 2009), tests of working memory task (e.g., Bhandari & Badre, 2018; Cowan et al., 2021), and the cued task-switching paradigm (e.g., Chevalier et al., 2015; Elke & Weibe, 2017). Specifically, in the cued task-switching paradigm, proactive control requires goal activation based on contextual cue information *prior to* the onset of a bivalent target stimulus, whereas reactive control involves task goal activation *after* a bivalent target stimulus appears. Similarly, in a working memory context, proactive control (i.e., an input gating policy) requires participants to *first* activate a task goal based on contextual cue information *and then* subsequently update items in working memory based on the goal, whereas reactive control (i.e., an output gating policy) involves task goal activation *after* memorizing all available information and only then selecting those items relevant to goal completion. Thus, as individuals experience a cognitive control task repeatedly, they gain awareness of when they use cue information to activate a task goal and engage cognitive control.

A few studies have examined whether learning task knowledge of the temporal structure of the activation of task goals affects how individuals transfer cognitive control to different task environments (Bhandari & Badre, 2018, 2020; Gonthier et al., 2021; Sabah et al., 2021; Yanaoka et al., 2022). For example, Bhandari and Badre (2018) focused on proactive and reactive control strategies in a working memory task (i.e., input and output gating policies), demonstrating that adults show positive or negative transfer of a control strategy across working memory tasks that differ in their stimulus-response mappings. For children, a recent developmental study (Yanaoka et al., 2022) examined whether 5-year-olds, who are beginning to use proactive control, can learn to use proactive control, via the acquisition of knowledge of the temporal structure of goal activation, when engaging in cued task-switching. This study did not provide clear evidence that encouraging the use of proactive control leads to cognitive control being engaged more proactively in subsequent conditions with the same task structure but different stimulus-response mappings. This suggests that 5-year-olds, in contrast to adults, may have some difficulty in learning knowledge of the temporal structure of activation of task goals.

Summarizing the prior available evidence, it has been shown that both adults and children can learn and transfer hierarchical aspects of task knowledge. However, the transfer of temporal aspects of task knowledge has been demonstrated only in adults. Yanaoka et al. (2022) did not provide clear evidence that 5-year-olds can use their knowledge of the temporal structure of activation of task goals to support their subsequent engagement of proactive control. Nevertheless, given that 9- to 10-year-olds are more capable of engaging either proactive or reactive control mode depending on task demands than 3- to 5-year-olds (e.g., Chatham et al., 2009; Chevalier et al., 2015), it is possible that 9- to 10-year-olds would be sensitive to the temporal structure of task goal activation and learn knowledge of it from prior experience more efficiently than younger children. Therefore, we first aimed to examine whether 9- to 10-year-olds, as well as adults, can learn knowledge of the temporal structure of activation of task goals through experience with a cognitive control task and then reuse this in different task environments. To achieve the first aim, the present study explored two experimental paradigms which are used to measure whether individuals engage either proactive or reactive control (Experiment 1 and 2: the cued task-switching paradigm, Experiment 3 and 4: the AX-CPT). [1]

Alongside this first aim, we explored potential developmental differences in the learning of task knowledge of the temporal structure of the activation of task goals. Previous studies have demonstrated developmental improvements in learning knowledge of task representations (i.e., hierarchical complexity) from childhood to adolescence (e.g., Amso et al., 2014; van 't Wout et al., 2019; Verbruggen et al., 2018). We also expected potential developmental improvements in the degree of learning of the temporal aspects of task knowledge between school-aged children and adults (e.g., more pronounced transfer effects of task knowledge in adults) However, given that no previous

[1] Unger et al. (2016) reported that the working memory task used by Bhandari and Badre (2018) was relatively challenging for 7- to 11-year-olds. This is partly because that task requires participants to memorize target stimuli as well as contextual cue information, and so involves a high memory load. For that reason this task was not employed here.

studies have examined these temporal aspects of task knowledge in children, we did not have any firm predictions about these developmental differences. An exploratory analysis reported below directly compares the data from adults and children to explore any potential developmental differences.[2]

Second, we also aimed to clarify the hierarchical structure of the task knowledge underlying transfer of the engagement of cognitive control in both adults and school-aged children. Previous studies have argued that the more abstract structure task knowledge has, the more it supports broader generalizations (Badre & Frank, 2012; Botvinick et al., 2009; Schank & Abelson, 1977). Bhandari and Badre (2018) demonstrated that knowledge of task representations and knowledge of the temporal structure of the activation of task goals are independent of stimulus-response mappings. Given that a task goal is a higher-level concept that in turn governs sets of stimulus-response mappings (e.g., Monsell, 2003), we can further examine whether knowledge of task representation can accommodate different task goals as well as different stimulus-response mappings. Such an investigation stands to reveal whether the task knowledge that adults and school-aged children learn is specific to a

[2] Throughout our six experiments, we first investigated whether we obtained clear expected evidence in adults and then conducted the same-structured experiment for school-aged children to assess the extent to which the results replicated in children. Therefore, in line with manner in which each experiment was conducted, we report them separately rather than integrating them.

particular task goal or can be generalized to different task goals. Using the cued task-switching paradigm, Experiments 5 and 6 therefore aimed to identify how hierarchical knowledge of task representations is structured in adults and school-aged children by manipulating the overlap in key task features between the training and test phases.

Taken together, our six preregistered experiments aimed to examine whether adults and school-aged children are able to learn hierarchical and temporal structured task knowledge that supports subsequent cognitive control in different task environments.

Experiments 1 and 2

Experiments 1 and 2 employed a cued task-switching paradigm, in which participants are instructed to make either a color or shape judgement to a stimulus that appears along with informative cues that specify which sorting rule to use. To examine proactive and reactive control in the cued task-switching paradigm (Chevalier et al. 2015), we used Chevalier et al.'s two conditions that employ different cue-target intervals (see Figure 1) and have been repeatedly used for children (Chevalier et al., 2020; Elke & Weibe, 2017). First, in the "Proactive Possible" condition, the informative cue was shown at the same time as a pre-target stimulus (i.e., a gift box) and remained visible after target onset. In this way, proactive control was possible, but not necessary. In the "Proactive Impossible" condition, the informative cue was presented at the same time as the target, so that proactive cue processing was impossible and participants would have no option but to engage reactive control. These conditions constituted the two training groups as follows. In Experiments 1 and 2 (see Figure 1), participants in the proactive impossible training group performed the "Proactive Impossible" condition first in a training phase and performed the "Proactive Possible" condition using the same task goals but different stimuli in a subsequent test phase. Participants in the proactive possible training group first performed the "Proactive Possible" condition in a training phase and then were given a second "Proactive Possible" condition using the same task goals but different stimuli in a subsequent test phase. We employed this experimental design among adults (Experiment 1) and 9- to 10-year-olds (Experiment 2). To examine any negative transfer of the use of reactive control it was necessary to conduct experiments with participants who would normally be expected to perform tasks using a proactive control approach. Thus, we selected 9-to 10-year-old children as participants because they have been shown to rely on proactive control engagement when proactive preparation is possible, as do adults (e.g., Chatham et al., 2009; Chevalier et al., 2015).

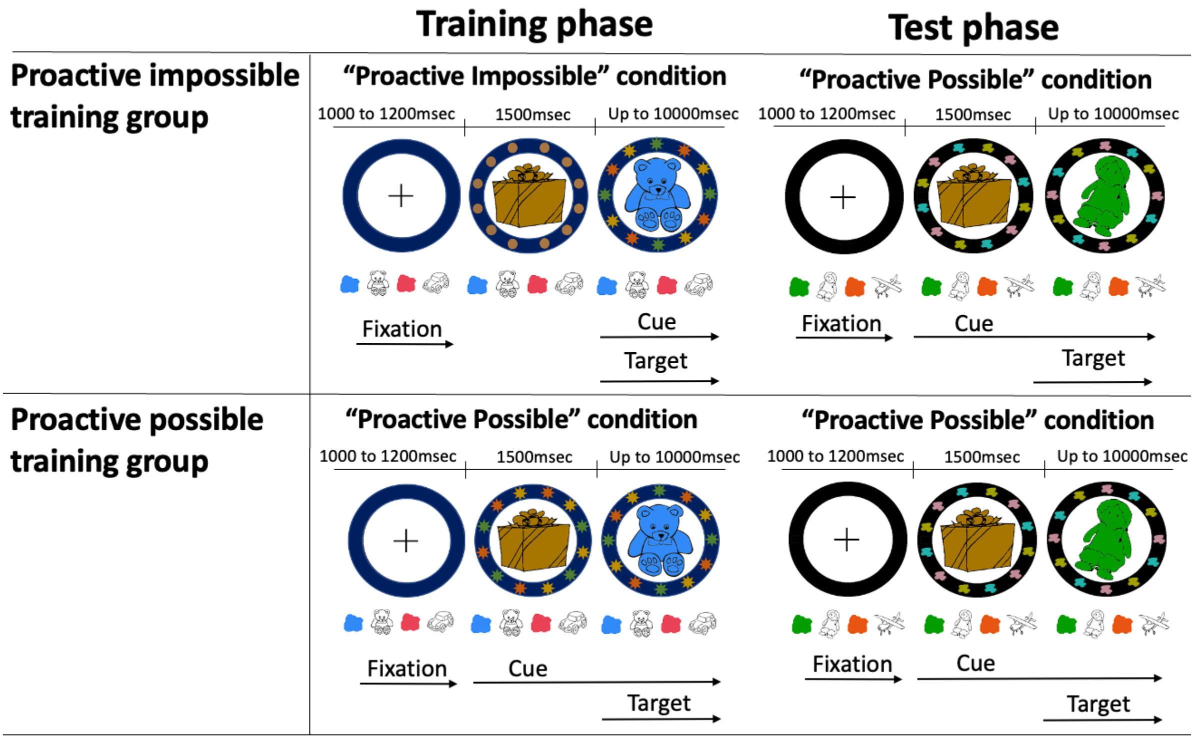

Figure 1. Illustration of the cued task-switching paradigm used in each condition. Participants sorted pictures by color and shape based on informative cues presented on the "circle" (i.e., 12 colorful patches or 12 gray geometrical shapes). In the "Proactive Impossible" condition, the informative cue was presented on target onset, whereas it appeared before the target in the "Proactive Possible" condition.

We tested three predictions through three planned contrasts. The first two predictions were prerequisites for testing the key prediction, which was prediction 3. First, we predicted that within the training phase adults (Experiment 1) and school-aged children (Experiment 2) in the proactive impossible training group would show slower response times than those in the proactive possible training group. This was based on the assumption that different cognitive control modes would be employed during the training phase between participants in the two training groups. Specifically, reactive control would be used in the "Proactive Impossible" condition and proactive control in the "Proactive Possible" condition. Second, we predicted that adults (Experiment 1) and school-aged children (Experiment 2) in the proactive possible training group would respond more quickly in the test phase than in the training phase, suggesting that they engage proactive control more efficiently at test following training; that is, positive transfer would occur. This second prediction is based on the evidence that practice with cued task-switching might simply help 5-year-olds shift towards proactive control in a subsequent cued task-switching condition (Yanaoka et al., 2022). While such positive transfer would be informative, it is potentially confounded with general training experience with the task and so this expected result would in and of itself not clearly determine what form of task knowledge individuals transferred.

With this in mind, our crucial, third prediction was that adults (Experiment 1) and school-aged children (Experiment 2) in the proactive impossible training group would show *slower response times* in the test phase in comparison to the performance of their peers in the proactive possible training group in the training phase. This prediction assumed that prior experience of engaging a reactive control mode (assessed by prediction 1) would make individuals respond more slowly in a subsequent similar-structured condition in which proactive control could have been engaged, despite the fact that prior task experience generally yields positive transfer effects (assessed by prediction 2). Thus, this predicted decrement in the test phase within the proactive impossible training group would provide direct evidence of negative transfer of knowledge of the temporal structure of activation of task goals.

Importantly, as suggested by Bhandari and Badre (2018), it is possible that both positive and negative transfer effects would transiently occur during the initial trials of the test phase and rapidly decrease across subsequent trials. Therefore, we preregistered the intention to take into account the effect of block in the training/test phase. Thus, we expected that the second and third predictions would at least be supported in the earlier block(s) in the training/test phase.

Furthermore, it was expected that response times on switch trials would be slower than those on no switch trials, indicating a switch cost. However, it was difficult to predict whether switch costs would be related to the transfer of task knowledge. Thus, we had two conflicting potential predictions: a) that switch costs would not be associated with the extent to which individuals positively or negatively transfer task knowledge, b) that switch costs would be mitigated when individuals positively or negatively transfer task knowledge.

Experiments 1 and 2 received approval from the institutional ethics review board of the University of Tokyo (19-334).

Experiment 1 (Method)

Participants. As specified in our preregistered plan (https://osf.io/erwm9), our target sample was 60 adults (i.e., 30 adults in the proactive impossible training group, 30 adults in the proactive possible training group). The participants were recruited to an online experiment and, given the possibility that some participants might not engage fully with an online study, we recruited 71 adults, aged between 19 and 30 years old, from a database of a research consulting company (Rakuten Insight, Inc. https://member.insight.rakuten.co.jp). All the participants were native Japanese speakers. All participants gave full informed consent before the experiment and were paid 1000 yen after completing all the task procedures. Despite the fact that most participants exhibited near perfect correct response rates (M = 95.2%, SD = 6.3%), Seven participants performed less than minus 3SD score of the mean accuracy (i.e., less than 76.2%) and were not included in the final analyses. Our final sample consisted of 32 adults in the proactive impossible training group (M = 25.93 years, SD = 3.16

years, 18 females and 14 males) and 32 adults in the proactive possible training group (M = 26.47 years, SD = 2.92 years, 15 females and 17 males).

Our target sample size was decided based on Yanaoka et al. (2022) (N = 58), which demonstrated that prior task experience increases 5-year-old children's use of proactive control with a similar experimental paradigm to this experiment. To ensure that the sample size in the previous study was adequately powered to detect the effect of task phase (training phase vs. test phase) on response times, we carried out power analyses using the simR package in R for generalized linear mixed effects models (Green & MacLeod, 2016). We focused on the effect of task phase on response times in the proactive possible training group as this was assumed to reflect children's changes in cognitive control mode (i.e., from reactive control to proactive control).[3] The simulation revealed that a sample of N = 58 participants yielded a power of 0.83 (95% CI [0.81, 0.85]) to detect the fixed-effect (β = -0.055) of the task phase in the proactive possible training group. Although the limitation of this power analysis was that it was conducted after this and the following experiments were completed, such power analysis suggests that the current experiment (sample size = 64) is not

[3] Although this previous effect reflects positive transfer, our current key prediction also focused on changes in cognitive control mode from the training phase to the test phase, thus we assume this power analysis provides an appropriate basis for evaluating the current sample size.

underpowered.

Materials. Our experiment was programmed in PsychoPy (Peirce et al., 2019) and exported and run as an PsychoJS experiment on Pavlovia (https://pavlovia.org/). The online experiment was run only with either Firefox or Chrome browsers.

To generate an experimental task for adult participants that could also be used with 9- to 10-year-olds we employed the cued task-switching paradigm previously revised for children (Chevalier et al., 2015). In line with Yanaoka et al. (2022), we replicated the stimuli used by Chevalier et al. (2015) as precisely as possible. There were two sets of targets, sized 8 × 8 cm, that varied on two dimensions (Set A; blue bear, blue car, pink bear, pink car, Set B; green airplane, green doll, yellow airplane, and yellow doll). These were surrounded by colored circles (Set A; blue, Set B; black) (see Figure 1a). There were also two types of informative task cues which were displayed around the target and signaled either a color sorting rule with 12 colorful patches or a shape sorting rule with 12 gray geometrical shapes (see Figure 1a). To aid responding, we constantly presented four 2 × 2 cm unidimensional response pictures (e.g., a bear, a red patch, a car, and a blue patch) and four response keys corresponding to each response picture (i.e., “R”, “T”, “O”, and “P”) below the target.

Procedure and experimental design. At the beginning of the experiment, participants provided information about their age and sex on a platform provided by the research consulting company, and were then informed about ethical information such as data confidentiality and their right to suspend the experiment. After they gave consent, they clicked on a link that took them to the main experimental task that was presented using Pavlovia. Participants were randomly assigned to either the proactive impossible training group or the proactive possible training group. Participants were introduced to the "Santa Claus Game", and told to assist Santa Claus by sorting a set of gifts according to either a color rule or a shape rule. They then performed two conditions of the cued task-switching paradigm (see Figure 1a). In the proactive impossible training group, participants experienced the "Proactive Impossible" condition in the training phase, followed by a "Proactive Possible" condition in the test phase that employed a different set of stimuli. Participants in the proactive possible training group experienced the "Proactive Possible" condition in the training phase, followed by a second "Proactive Possible" condition in the test phase that employed a novel set of stimuli.

Santa Claus Game. The onset of a trial in the "Santa Claus Game" was signaled by the appearance of a fixation cross displayed in the center of the screen within a colored circle. This was shown for 1000 to 1200 ms, after which a pre-target stimulus (i.e., a brown wrapped gift box) was displayed for 1500 ms. The pre-target was then replaced by a target (i.e., a gift) that remained on the screen until the participant's response or for a total of 10 seconds. The key manipulation was the onset of cue presentation displayed on the colored circle. In the "Proactive Impossible" condition, an uninformative cue (i.e., a set of 12 brown circles) was presented on the colored circle surrounding the pre-target and the informative cue appeared simultaneously with the target. As a result, there was no possibility of benefitting from the informative cue in advance. In contrast, in the "Proactive Possible" condition, the informative cue was already presented on the colored circle surrounding the pre-target and remained visible after the target appeared. In this latter condition participants could determine in advance which task goal they should activate based on the informative cue. However, they did not necessarily have to engage proactive preparation as they could also reactively process the informative cue that was displayed at the same time as the target onset.

The "Santa Claus Game" was composed of first practice, training, second practice, and test phases separated by a short break. To begin with, participants experienced the first practice phase, in which they were asked to sort bivalent gifts according to one of the task goals (either color or shape) based on an informative cue. Participants were also explicitly told that the informative cue would indicate which rule to use. They were also instructed to keep the index and middle fingers of each hand on four keys, which corresponded to unidimensional response pictures presented on the screen, and to respond with one of the four keys according to the current rule. Participants completed four practice trials with this first task, and were then given instructions for, and performed four practice trials with, the second task. The presentation order of the tasks was counterbalanced across participants. Next, participants were presented with 10 practice trials in a pseudorandom sequence that included five color trials and five shape trials. During these ten trials participants received feedback on their performance, and the sequence of ten trials was repeated if they made more than three errors.

During the training phase, participants completed three blocks of 21 trials separated by a short break; each block contained one start trial, 10 switch trials, and 10 no switch trials. Participants' performance of the start trials was excluded from the analyses. The switch and no switch trials were intermixed in a pseudorandom order, which was different in the training phase and the test phase.

Following the training phase, participants completed the second practice phase, followed by the test phase. In the second practice phase, participants were first introduced to a set of novel stimuli and were asked to perform four practice trials for each task goal (i.e., sorting a gift according to either a color or shape rule). For participants in the proactive impossible training group, the second practice phase was the first encounter with trials where the informative cue appeared in advance. However, they did not go on to extended practice with ten mixed trials. The test phase mirrored the training phase in number of trials, the proportion of trials on which a task switch occurred, and the absence of feedback. However, it is important to note that a different set of informative cue and target stimuli from that used in the training phase was employed across the second practice and the test phases. The two sets of stimuli used in training and test phases were counterbalanced across participants.

Data processing. The dependent measures from the cued task-switching paradigm were response times and correct response rates. Response times were examined for correct responses after discarding outliers, that is, values greater than median + 2.5 MAD (Median Absolute Deviation) and values lower than median – 2.5 MAD (Leys et al., 2013). This led to the exclusion of 5.4% of correct responses in the analyses of response times.

Data analysis. The study design, hypotheses, and analytic plan were preregistered in the Open Science Framework (https://osf.io/erwm9). We conducted regression analyses using generalized linear mixed-models (GLMMs) with a gamma distribution and log link function[4]. For correct response rates we also carried out generalized mixed-models logistic regression analysis. We employed the lme4 package (Bates et al., 2015) in the R system (R Core Team, 2013). To test the first and second predictions (see above), the following interdependent variables were used; training group (coded: 1 = proactive possible training group, -1 = proactive impossible training group), task phase (coded: 1 = test phase, -1 = training phase), trial type (coded: 1 = switch trial, -1 = no switch trial), block (coded -1 = block 1, 0 = block 2, 1 = block 3), and their interactions. We considered between-individual differences through the inclusion of a random intercept for participants for all the models. Given the complexity of the model, we did not include random slopes for the predictors. We compared the results of two regression models: one focal model with the two-way interaction between training group and task phase (or the three-way interaction between training

[4] The analysis presented here is broadly comparable to that specified in our pre-registration document but was adjusted during the analysis process to deal with exponential or logarithmic response time data because this is sensible. Furthermore, assuming a normal distribution for response times, we conducted regression analyses using linear mixed-models (LMMs), which also revealed mostly consistent findings concerning the three predictions.

group, task phase and block) and another model without the interaction. Regarding the two-way interaction, we examined two planned comparisons. First, to test whether individuals engage reactive control in the "Proactive Impossible" condition (prediction 1), a pairwise comparison was conducted to examine whether in the training phase individuals in the proactive impossible training group would respond more slowly than individuals in proactive possible training group. Second, to test whether a positive transfer effect occurs (prediction 2), a pairwise comparison was conducted to examine whether individuals in the proactive possible training group were faster in the test phase than in the training phase.

To test the crucial third prediction concerning negative transfer, we set up another model, including the factors of training group (coded: 1 = training phase performance of the proactive possible training group, -1 = test phase performance of the proactive impossible training group), trial type, block, and their interactions. We also included random intercepts for participants as random factors in the model. We also compared the results of two regression models: one focal model with the two-way interaction of training group and block vs. another model without the interaction. A pairwise comparison was conducted to examine whether individuals in the proactive impossible training group perform more slowly in the test phase than individuals in the proactive possible training group respond in the training phase (potentially only in earlier block(s)) (prediction 3). As specified in our preregistered analysis plan, if we did not find any clear negative/positive transfer effects in earlier block(s), we considered 5 trials as one mini-block and analyzed again.

We tested the predictors by making comparisons between the full model and the reduced model that lacked the predictor of interest. To evaluate the significance of the predictor, we reported the standardized coefficient, chi-square value, and *p*-value using the likelihood ratio test. Holm-corrected *p*-values with a family wise alpha of .05 are used throughout to adjust for pairwise comparisons.

Experiment 1 (Results and Discussion)

Cognitive control modes in the training phase and positive transfer effects of task knowledge (predictions 1 and 2)

Response times. Figure 2a depicts mean correct response times for each condition. Our focal comparison revealed a three-way significant interaction between task phase, training group, and block ($\beta = 0.07$, $t = 5.88$, $\chi^2 = 31.59$, $df = 1$, $p < .001$). The planned comparisons revealed the following two findings. First, as predicted, in the training phase participants in the proactive impossible training group were slower than participants in the proactive possible training group (β = -0.15, t = -5.71, p < .001), and such group differences did not significantly interact with block (β = 0.003, t = 0.43, p = .667). Second, according to pairwise comparisons with Holm correction, participants in the proactive possible training group were faster in the test phase than in the training phase but only in the first and second blocks (First block: β = -0.06, t = -6.77, p < .001, Second block: β = -0.06, t = -6.08, p < .001), whereas there were no significant differences in the third block (β = -0.002, t = -0.26, p = .797).

We also observed that trial type interacted significantly with training group (β = -0.04, t = -3.16, χ^2 = 8.90, df = 1, p = .003), revealing that participants in the proactive impossible training group experienced a switch cost (β = 0.03, t = 6.08, p < .001), whereas the switch cost for those in the proactive possible training group was not significant (β = 0.01, t = 1.60, p = .111). However, there were no other significant interactions with trial type.

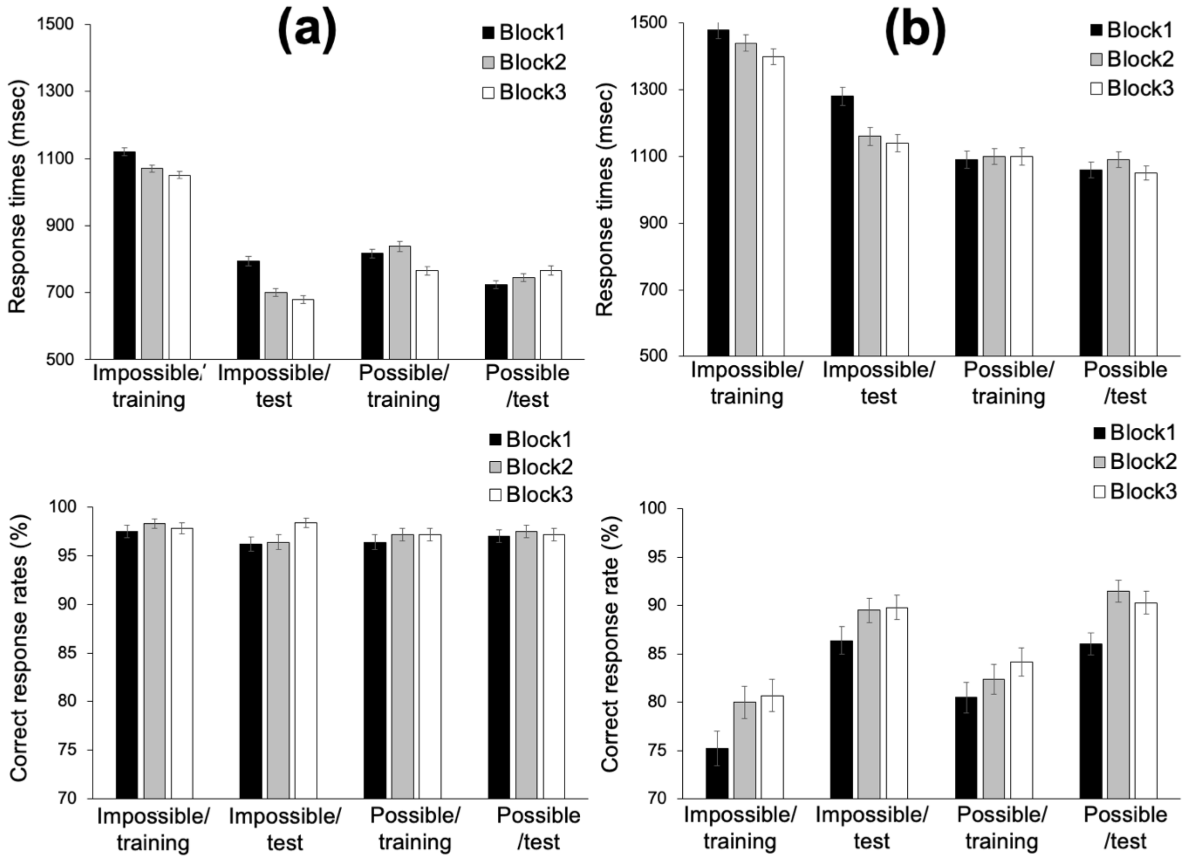

Figure 2. Mean response times and correct response rates in each condition. Error bars indicate standard errors. For adults, panel (a) shows response times (left upper) and correct response rates (left lower) in Experiment 1. For 9-to 10-year-olds, panel (b) shows response times (right upper) and correct response rates (right lower) in Experiment 2.

Correct response rates. Correct response rates were near ceiling (see Figure 2a), thus we did not consider them as a key measure for adults. Instead, we include the analysis for correct response rates in supplemental materials.

Negative transfer effects of task knowledge (prediction 3)

Response times. A key result was the expected significant interaction between training group and block ($\beta = 0.07$, $t = 3.86$, $\chi^2 = 14.86$, $df = 1$, p

< .001). Pairwise comparisons with Holm correction demonstrated that participants in the proactive impossible training group performed more *quickly* in the second block of the test phase relative to those in the proactive possible training group (Second block: $\beta = 0.10$, $t = 2.83$, $p = .014$), whereas we did not observe such differences in the first and third block (First block: $\beta = 0.01$, $t = 0.42$, $p = .678$; Third block: $\beta = 0.07$, $t = 2.04$, $p = .083$). We also observed that trial type interacted significantly with training group ($\beta = -0.05$, $t = -2.77$, $\chi^2 = 7.67$, $df = 1$, $p = .006$), revealing that participants in the proactive impossible training group experienced more of a switch cost in the test phase ($\beta = 0.04$, $t = 4.65$, $p < .001$), relative to the training phase performance of the proactive possible training group ($\beta = 0.01$, $t = 0.67$, $p = .502$).

According to our preregistered analysis plan, we broke the first block into four mini-blocks (5 trials in each mini-block) and examined a simple effect of training group in each mini-block using Holm correction. We found a significant expected pattern only in the first mini-block where participants in the proactive impossible training group performed more slowly in the test phase than did participants in the proactive possible training group in the training phase ($\beta = -0.10$, $t = -2.61$, $p = .036$). In contrast, no significant differences were observed in the second, third, and fourth mini-blocks (second mini-block: $\beta = 0.03$, $t = 0.74$,

p = .507, third mini-block: β = 0.03, t = 1.14, p = .507, fourth mini-block: β = 0.09, t = 2.21, p = .082) (see Figure 3a).

These findings reveal negative transfer effects in first mini-block of the test phase after the experience of the "Proactive Impossible" condition in the training phase. One may argue that slower response times in the test phase performance of the "Proactive Impossible" training group could reflect a fatigue effect as the "Proactive Impossible" training group has already completed another task beforehand. However, performance in the test phase would generally be expected to benefit from positive transfer. Indeed, when contrasting the test phase performance between two training groups, the group differences were clearly replicated. Specifically, the "Proactive Impossible" training group showed slower response times in the first mini-block than the "Proactive Possible" training group (β = -0.14, t = -3.67, p < .001).

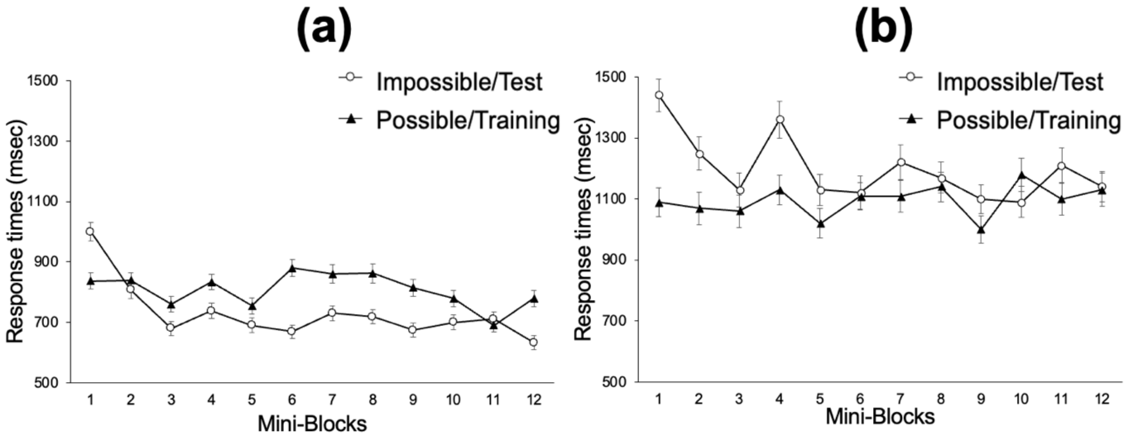

Figure 3. Mean response times for each mini-block. Error bars indicate standard errors. As seen in panel (a), which summarizes Experiment 1 in the first mini-block adults in the proactive impossible training group showed slower response

times in the test phase compared to the training phase performance of the proactive possible training group. Panel (b), which summarizes Experiment 2, indicates that during the first four mini-blocks 9- to 10-year-olds in the proactive impossible training group showed slower response times in the test phase in comparison to the training phase performance of the proactive possible training group.

Correct response rates. We include corresponding analyses for correct response rates in supplemental materials.

Summary of Experiment 1

We succeeded in conceptually replicating and extending Bhandari and Badre (2018)'s findings. Bhandari and Badre (2018) demonstrated that adults show transfer of task knowledge to task environments with different stimuli using a working memory task, whereas we observed similar results using the cued task-switching paradigm. Specifically, a positive transfer effect was observed across the training and test phase performance of the proactive possible training group, whereas a negative transfer effect was observed in the comparison of the test phase performance of the proactive impossible training group relative to the proactive possible training group's training phase performance. In particular, adults transferred knowledge of task management negatively only in the first mini-block (i.e., five trials) and rapidly adapted their cognitive control mode to new task demands.

Experiment 2 (Method)

Participants. We specified the target sample in our preregistered plan (https://osf.io/fwz4p). Our target sample was sixty 9-to 10-year-olds (i.e., thirty 9-to 10-year-olds in the proactive impossible training group, thirty 9-to 10-year-olds in the proactive possible training group). The logic behind a justification of the sample size is the same as for Experiment 1. We performed the online experiment for children with an expectation that some participants might be excluded due to low levels of performance indicative of guessing or non-engagement, or from quitting the experiment midway through. Thus, we recruited sixty-nine parents of a 9-to 10-year-old child from a database of a research consulting company (Rakuten Insight, Inc. https://member.insight.rakuten.co.jp). The parents reported that all the children were native Japanese speakers and did not have any history of neurological disorders, and both parents and children gave informed consent before participation in this experiment. A total of nine children were excluded (5 children did not finish all the blocks; 3 parents failed to send in photographs of their child performing the task as evidence of their participation (see below); one parent reported that they performed the task instead of their child). Our final sample was 29 school-aged children in the proactive impossible training group (*M* = 9.76 years, *SD* = 0.59 years, 15 girls and 14 boys) and 31 school-aged children in the proactive possible training group (*M* = 9.92 years, *SD* = 0.59 years, 19 girls and 12 boys). Parents were paid 2000 yen and a small gift of stationery was sent to the child as a reward. However, if children did not complete the training phase, they were not rewarded.

Materials and experimental design. The same materials used in the first experiment were employed. As in Experiment 1, children were randomly assigned to either the proactive impossible training group or the proactive possible training group.

Procedure and Santa Claus Game. In line with Experiment 1, on a platform of the research consulting company, parents provided information about children's age, sex, and their history of neurological disorders, and then parents and their children were informed about relevant ethical information. After providing informed consent, they clicked on a link that took them to the main experimental task that was presented using Pavlovia. We asked parents to stay at their child's side in case any technical difficulties arose. Children read through the instructions of the "Santa Claus Game" by themselves, and if they did not understand the instructions, we asked their parents to explain them verbally.

The sequence of each trial and the composition of the first practice, training, second practice, and test phases were the same as in Experiment 1. However, Experiment 2 included two additional procedures that were conducted by parents. First, we asked parents to take pictures of the PC screen and their children during a short break between blocks. Parents were instructed to take this picture from behind the child to preserve anonymity. We had three blocks for each phase, thus they needed to take four pictures in total (i.e., two pictures in the training phase and two pictures in the test phase) and then send the pictures to the first author after completing the experiment. The pictures were considered evidence of the child's participation in the experiment. Second, after children completed the experiment, we asked parents whether their child carried out all the blocks, noting that they could receive rewards even if it was reported that parents performed the task instead of their child. As mentioned above, three parents did not send four pictures and one parent reported that they performed the task instead of their child. Data from these children were excluded from final analyses.

Data processing. The key dependent measures were response times and correct response rates. Following the same procedure as Experiment 1, response times greater than median + 2.5 MAD and values lower than median – 2.5 MAD were excluded (Leys et al., 2013). As a result, 5.6% of correct responses were not included in the analyses of response times.

Data analysis. The study design, hypotheses, and analytic plan were preregistered in the Open Science Framework (https://osf.io/fwz4p). For Experiment 2, we employed the same analytic plan as Experiment 1.

Experiment 2 (Results and Discussion)

Cognitive control modes in the training phase and positive transfer effects of task knowledge (predictions 1 and 2)

Response times. Figure 2b depicts mean correct response times for each condition. As expected, our analysis showed significant interactions between task phase and training group ($\beta = 0.08$, $t = 9.00$, $\chi^2 = 80.94$, $df = 1$, $p < .001$). The planned comparisons revealed the following two findings: First, training phase response times were slower in the proactive impossible training group than in the proactive possible training group ($\beta = -0.16$, $t = -4.09$, $p < .001$), which replicated the behavioral finding of Chevalier et al. (2015). Second, children in the proactive possible training group showed faster response times in the test phase than in the training phase ($\beta = -0.01$, $t = -2.10$, $p = .036$).

The main effect of trial type was also significant ($\beta = 0.04$, $t = 3.97$, $\chi^2 = 16.22$, $df = 1$, $p < .001$), but it did not interact significantly with the other factors. Thus, we found a switch cost in response times.

Correct response rates. Correct response rates for each condition are shown in Figure 2b. We found significant main effects of task phase (*Odds ratio* = 1.48, 95% CI: 1.38-1.60, $z = 10.63$, $\chi^2 = 117.03$, $df = 1$, $p < .001$), trial type (*Odds ratio* = 0.91, 95% CI: 0.85-0.98, $b = -0.10$, $z = -2.57$, $\chi^2 = 6.68$, $df = 1$, $p = .010$), and block (*Odds ratio* = 1.22, 95% CI: 1.12-1.34, $z = 4.49$, $\chi^2 = 20.02$, $df = 1$, $p < .001$). Furthermore, task phase did not interact significantly with training group (*Odds ratio* = 0.96, 95% CI: 0.89-1.03, $\chi^2 = 1.05$, $df = 1$, $p = .305$).

Negative transfer effects of task knowledge (prediction 3)

Response times. There was an expected significant interaction between training group and block ($\beta = 0.04$, $t = 3.55$, $\chi^2 = 12.59$, $df = 1$, $p < .001$). Pairwise comparisons with Holm correction demonstrated that children in the proactive impossible training group performed more slowly in the first block of the test phase relative to the proactive possible training group's performance in the first block of the training phase ($\beta = -0.12$, $t = -2.49$, $p = .039$). By contrast, we did not observe significant differences in the second and third blocks (second block: β = -0.04, t = -0.77, p = .510, third block: β = -0.05, t = -1.14, p = .510) (see Figure 3b).

There was a significant main effect of trial type (β = 0.04, t = 3.40, χ^2 = 11.54, df = 1, p = .001), but it did not interact significantly with the negative transfer effects.

Consistent with Experiment 1, we contrasted the test phase performance of the two training groups to exclude the possibility that slower response times in the test phase performance of the "Proactive Impossible" training group could reflect a fatigue effect. The analysis revealed that the "Proactive Impossible" training group showed slower response times in the first block than the "Proactive Possible" training group (β = -0.12, t = -2.61, p = .027), thus the negative transfer effects remained.

Correct response rates. The main effect of training group (*Odds ratio* = 0.81, 95% CI: 0.58-1.16, z = -1.19, χ^2 = 1.38, df = 1, p = .240) and its interaction with block (*Odds ratio* = 0.98, 95% CI: 0.87-1.12, z = -0.24, χ^2 = 0.06, df = 1, p = .811) were not significant. There was no significant main effect of trial type (*Odds ratio* = 0.95, 95% CI: 0.86-1.06, z = -0.90, χ^2 = 0.78, df = 1, p = .377), nor any significant interactions involving trial type.

Summary of Experiment 2

Experiment 2 produced similar findings in school-aged children to those seen in adults in Experiment 1. Specifically, children positively transferred a collective body of task knowledge, resulting in faster response times in the test phase than in the training phase with different stimuli. A key finding was expected negative transfer of the engagement of cognitive control in the different task environments, suggesting that children learn knowledge of the temporal structure of activation of task goals. This negative transfer of knowledge of task management was found only in the first block of trials, after which children may have adopted a proactive control mode to meet the demands of the new task.

Experiments 3 and 4

Experiments 1 and 2 demonstrated that school-aged children as well as adults can learn task knowledge and transfer it to different task environments positively and negatively. The key finding, across both of these previous experiments, was that performance in the test phase of the proactive impossible training group was slower than performance in the training phase of the proactive possible training group, despite this analysis comparing two “Proactive Possible” conditions. However, one might potentially question the extent to which such negative transfer effects unequivocally index knowledge of the temporal structure of the activation of task goals. For example, apparent negative transfer effects could potentially be attributed to an element of surprise with the task caused by a switch from the training phase to the test phase. In other words, the costs associated with getting accustomed to a different task environment might lead to a temporary slowing down of participants' responses, resulting in the apparent negative transfer effects. If so, then slower response times seen in the cued task-switching paradigm may not necessarily be an indication of "more reactive control" or "less proactive control", making it challenging to identify the precise control mechanism underlying the negative transfer effect.

To address this issue, Experiments 3 and 4 aimed to replicate and extend the findings of Experiments 1 and 2 using the AX-CPT (Braver et al, 2007; Chatham et al., 2009), which has been used in the majority of past research investigating proactive and reactive control. In the AX-CPT, the use of proactive/reactive control is signaled by the comparison of responses across different trial types, rather than overall response times. Thus, any negative transfer effect observed in the AX-CPT as a result of less use of proactive control, cannot be explained by a temporary slowing of overall response times caused by a surprising switch from the training phase to the test phase. Thus, Experiments 3 and 4 employed the AX-

CPT to establish the relation between negative transfer effects and proactive/reactive control.

In the AX-CPT, participants are required to respond with a target key when they detect the AX sequence (i.e., an A cue followed by an X probe). Non-target responses are provided to other cue–probe sequences (an A cue followed by an Y probe, an B cue followed by an X probe, or an B cue followed by an Y probe). Asymmetry in trial type frequency is critical to revealing distinct behavioral profiles for proactive versus reactive control. A traditional version of the AX-CPT is composed of 70% AX trials, 10% AY trials, 10% BX trials, and 10% BY trials in each task block and hereafter is referred to as AX-CPT (70AX). Due to the large proportion of AX trials (e.g., 70%), participants who use proactive control tend to prepare a target response whenever the cue is an A, which elicits slowed response times and elevated error rates on AY trials. On the other hand, these participants answer quickly and accurately on trials when the cue is a B by virtue of preparing a non-target response in advance, even when the cue is followed by a X (i.e., BX trials). A different pattern is observed for participants who use reactive control. Such participants show fast response times and low error rates on AY trials, but they show slowed response times and elevated error rates on BX trials. Given this, the AX-CPT allows for a clear dissociation between proactive and reactive control patterns of behavioral performance across trial types.

Different variants of the AX-CPT have been already developed through the manipulation of trial type frequency. Richmond et al. (2015) used a modified version of the AX-CPT to equate the frequency of both the cue and the probe as follows; 40% AX trials, 10% AY trials, 10% BX trials, and 40% BY trials. This version allowed Richmond et al. to control potential sources of variance related to the typical infrequency of both the B cue and the Y probe, although their AX-CPT (40AX) yielded comparable results to the traditional AX-CPT (70AX). Redick et al. (2014) developed a version of the AX-CPT in which preparing an advance response based on the A cue was counterproductive. Their version was composed of 40% AX trials, 40% AY trials, 10% BX trials, and 10% BY trials; hereafter termed AX-CPT (40AY). In contrast to more traditional tasks where the A cue predicts a target response with high conditional probability, in the AX-CPT (40AY) the A cue predicts target and non-target responses with equal probability, encouraging reactive control.

We took advantage of the additional insights into cognitive control mode provided by these previous versions of the AX-CPT to produce three versions of the task; the exact proportion of each trial type was modified slightly to account for the total number of trials used in each task. In line with studies using the traditional version of the AX-CPT, we generated a ‘traditional condition’, which was composed of 62.5% AX trials, 12.5% AY trials, 12.5% BX trials, and 12.5% BY trials in each task block. Following the AX-CPT (40AX) developed by Richmond et al. (2015), we created a ‘balanced condition’, which was composed of 37.5% AX trials, 12.5% AY trials, 12.5% BX trials, and 37.5% BY trials in each task block. Finally, as a modified version of the task used by Redick et al. (2014), we included a ‘reactive encouraged condition’, which was composed of 37.5% AX trials, 37.5% AY trials, 12.5% BX trials, and 12.5% BY trials in each task block. Although several studies (Richmond et al.,2015; Gonthier et al., 2016, 2019) using the AX-CPT have demonstrated that the balanced condition shows a similar pattern to that observed in the traditional condition, the balanced condition has been less widely used, compared to the traditional condition. Thus, we included both the traditional and the balanced conditions to extend our evidence and to facilitate comparisons to the broader literature on the AX-CPT, although we had the same prediction for the contrast with the reactive encouraged condition for each condition.

Experiments 3 and 4 each compared three training groups in which these different conditions of the AX-CPT were employed in a training phase and in which the balanced condition (Richmond et al., 2015) was always employed in a test phase (see Figure 5). Different stimuli were employed in the training phase and the test phase. In the traditional training group, adults (Experiment 3) and school-aged children (Experiment 4) first experienced the traditional condition in the training phase, followed by the balanced condition in the test phase. In the balanced training group, adults (Experiment 3) and children (Experiment 4) first experienced the balanced condition in the training phase, followed again by the same condition in the test phase. In the reactive encouraged training group, adults (Experiment 3) and children (Experiment 4) first experienced the reactive encouraged condition in the training phase, followed by the balanced condition in the test phase.

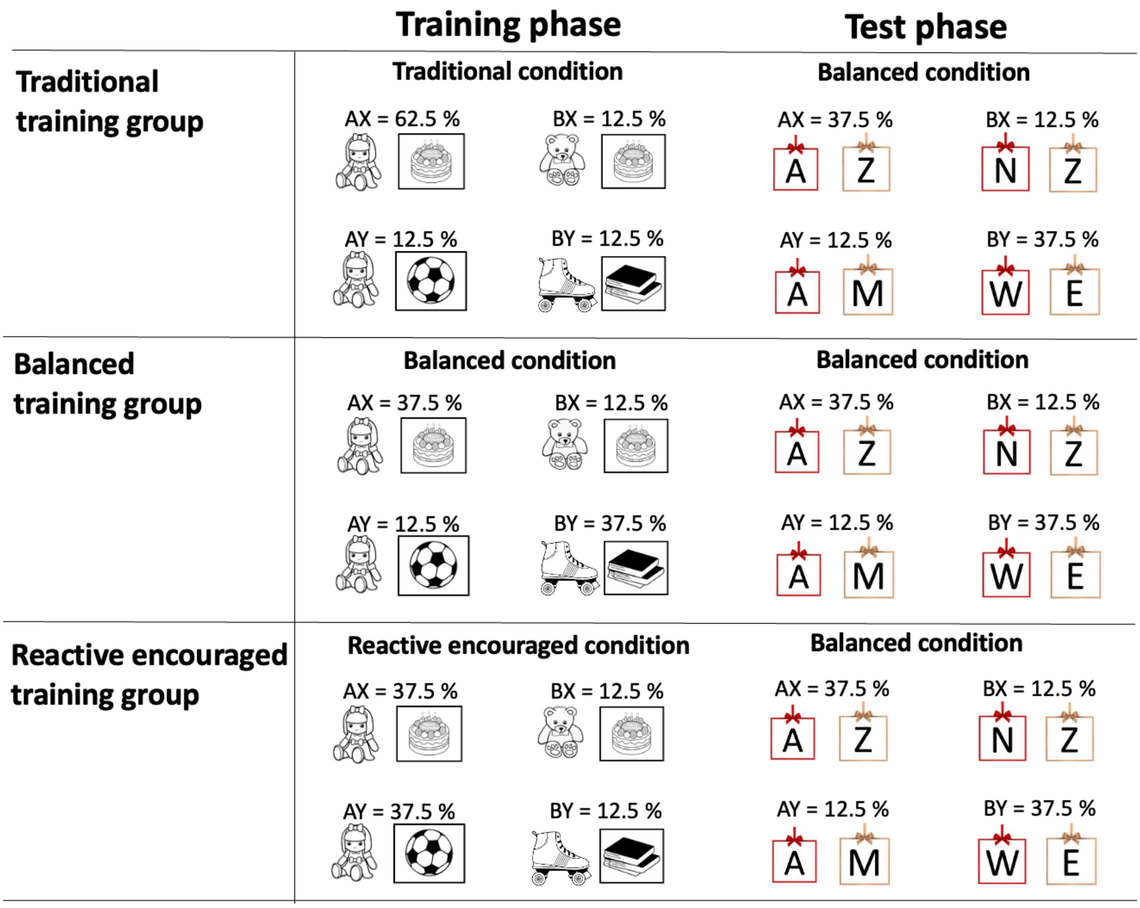

Figure 5. Illustration of the AX-CPT used in each condition. Participants pressed a target key only when an “A” cue (e.g., a doll or letter A) was followed by the presence of an “X” probe (e.g., a cake or letter Z). For all other trial type (i.e., AY, BX, and BY trials), participants responded by pressing a non-target key. The cue “B” and the probe “Y” were chosen from 12 stimuli (e.g., a bear, a soccer ball). Each condition differed in terms of trial type frequency. In the traditional condition, AX targets occurred on 62.5% of all cue-probe trials, and the remaining non-target trial types (AY, BX, BY) each occurred on 12.5% each of cue-probe trials. In the balanced condition, the frequencies of AX targets and BY non-targets were equal (i.e., 37.5%), and the remaining non-target trial types (AY, BX) each occurred on 12.5% of trials. In the reactive encouraged condition, the frequencies of AX targets and AY non-targets were equal (i.e., 37.5%), and the remaining non-target trial types (AY, BX) each occurred on 12.5% of trials.

We again tested three predictions. As before, the first two predictions were prerequisites for testing the third, key prediction. In the training phase, we predicted that adults (Experiment 3) and school-aged children (Experiment 4) in the reactive encouraged training group would show less engagement of proactive control than participants in the traditional and balanced training groups. We tested this prediction in two complementary ways. One is whether the reactive encouraged training group have less of a tendency to show slower response times and/or higher error rates on AY trials than on BX trials when compared to the other two training groups. The other one is whether the reactive encouraged training group show weaker patterns of using proactive control across the three indices of control that we extracted from each study (see below). Our second prediction was that adults (Experiment 3) and children (Experiment 4) in both the traditional and balanced training groups would engage more proactive control, as indexed by positive transfer effects. This second prediction stems from the evidence that practice in the AX-CPT promotes a shift towards proactive control in the subsequent AX-CPT (older adults: Paxton et al., 2006, school-aged children: Gonthier & Blaye, 2022). Specifically, we expected that both training groups would show slower response times and/or higher error rates on AY trials than BX trials, coupled with stronger patterns of using proactive control in other derived indices, in the test phase as compared to the training phase. Note that this positive transfer effect is potentially confounded with general training experience with the task.

Third, our key prediction was that performance in the test phase of adults (Experiment 3) and children (Experiment 4) in the reactive encouraged training group would exhibit less evidence of proactive control than the training phase performance of participants in the traditional and balanced training groups. As already noted, comparisons between AY and BX trials reveal the tendency to utilize proactive or reactive control, thus the AX-CPT allows us to find negative transfer effects that cannot be explained simply by slower overall response times that result from a surprising switch between the training to test phases. Specifically, we expected that the reactive encouraged training group would show less of a tendency towards slower response times and/or higher error rates on AY trials than on BX trials and some weaker patterns of engaging proactive control in other derived indices in the test phase, when compared to the other two training groups in the training phase.

Taken together, using the AX-CPT, we reexamined whether adults and school-aged children learn task knowledge and transfer it to a subsequent similar-structured condition with different stimuli. The following two experiments

(Experiments 3 and 4) received approval from the institutional ethics review board of the University of Tokyo (21-274).

Experiment 3 (Method)

Participants. As specified in our preregistered plan (https://osf.io/yfte6), our target sample was 96 adults (traditional training group = 32, balanced training group = 32, reactive encouraged training group = 32). The age range was from 19-year-olds to 50-year-olds. We decided on the sample size based on Experiment 1 (32 participants per group) and recruited one hundred eight adults from a database of a research consulting company (Lancers, Inc. https://www.lancers.jp). All the participants were native Japanese speakers. All participants gave full informed consent before the experiment and were paid 600 yen after completing all the task procedures. Six participants had very high error rates (four made errors on more than half of AX trials and two had 100% errors on AY trials), thus they were not included in the final analyses. Our final sample consisted of 39 adults in the traditional training group (M = 40.33 years, SD = 6.49 years, 17 females and 22 males), 31 adults in the balanced training group (M = 39.13 years, SD = 6.83 years, 14 females and 17 males), and 32 adults in the reactive encouraged training group (M = 41.03 years, SD = 6.31 years, 18 females and 14 males).

Materials and Procedure. The task setting was the same as Experiment 1. The experiment was programmed in PsychoPy (Peirce et al., 2019) and exported and run as an PsychoJS experiment on Pavlovia (https://pavlovia.org/).

The task procedure was adapted from Richmond et al. (2015) and Gonthier et al. (2019). However, the cover story was a “Santa Claus Game” in which participants selected a particular combination of Christmas gifts to help Santa Claus so that the task would be set in a familiar context for children in Experiment 4. Different sets of 8 × 8 cm stimuli (i.e., picture stimuli and letter stimuli) were prepared for the training and test phases. Participants were first shown that each trial started with a cue stimulus that was displayed at the center of the screen for 1000 ms, followed by a 4000 ms interstimulus interval. Subsequently, a probe stimulus with a surrounding black square was presented for 500 ms and then a fixation cross appeared during the 1000 ms inter-trial interval. At the time of probe onset, two response keys (“G” and “J”) were simultaneously presented at the bottom of the screen Thus, responses to the probe stimuli were recorded with a time limit of 1500 ms. All participants used the index fingers of the left and right hand to respond to non-targets and targets, respectively.

Furthermore, participants were made aware that there were 4 different trial types: AX, AY, BX, and BY. They were instructed to press the G key only when an "A" cue (e.g., a doll or letter A) was followed by the presence of an "X" probe (e.g., a cake or letter Z) (i.e. AX equivalent trials). For all other trial type (i.e., AY, BX, and BY equivalent trials), participants were instructed to respond by pressing the J key. For trial types other than AX, 12 stimuli were used (e.g., a bear, a car, a train, a soccer ball, a tennis racket, a camera, a watch, a video game console, a piano, a book, a telescope, shoes; letter B, C, E, F, M, N, O, T, V, W, and X).

Following instructions, participants completed eight practice trials in a pseudorandom sequence that included two trials for each trial type. During these eight trials participants received feedback on their performance, and the sequence of eight trials was repeated if they made more than two errors. Participants then completed three blocks of 32 trials, which were separated by a short break, with no feedback. This procedure was identical in the training and test phases, which were also separated by a short break. It is important to note that different sets of stimuli were used in the training and test phases (e.g., picture stimuli in the training phase and letter stimuli in the test phase), and stimulus sets were counterbalanced across participants.

Experimental design. As already mentioned, we developed three task versions by manipulating trial type frequency, that is, the traditional, the balanced, and the reactive encouraged conditions. Participants were randomly assigned to either the traditional training group, the balanced training group, or the reactive encouraged training group. Each group experienced one of the different conditions of the AX-CPT in the training phase, followed by the balanced condition in the test phase.

Data processing. The dependent variables were response times and error rates in the AX-CPT. Trials with response times of less than 200 ms were excluded. Furthermore, three additional indices reflecting the use of proactive control were of interest. That is, the Proactive Behavioral Index (PBI), the d'-context, and the A-cue bias. The PBI (Braver et al., 2009) was calculated as (AY − BX)/(AY + BX) for both response times and error rates. Furthermore, a composite PBI can be computed by averaging the PBIs obtained for response times and error rates after standardization. This index reflects the relative balance of interference between AY and BX trials: a positive PBI reflects higher interference on AY trials, indicating proactive control, whereas a negative PBI reflects higher interference on BX trials, indicating reactive control. In order to correct for trials where hit rates were equal to 1 or false alarm rates equal to 0, a log-linear correction [hit rate = (number of hits + 0.5)/(number of trials + 1) and false alarm rate = (number of false alarms + 0.5)/(number of trials + 1)] was applied to all error data prior to computing the PBI scores (as in Braver et al., 2009; Hautus, 1995).

As with the PBI score, the d'-context, and the A-cue bias, we had almost consistent findings. To avoid making this section more complex than needed, only the PBI scores are reported in the following results section. Explanations for d'-context and A-cue bias indices and their results are reported in supplementary materials (see., Experiment 3: d'-context and A-cue bias, Experiment 4: d'-context and A-cue bias).

Data analysis. The study design, hypotheses, and analytic plan were preregistered in the Open Science Framework (https://osf.io/yfte6). Using the lme4 package (Bates et al., 2015) in the R system (R Core Team, 2013), we conducted regression analyses with GLMMs with a gamma distribution for response times. For error rates, we also used GLMMs analysis with a logit link function. Multiple regression analyses were also conducted with the PBI scores as the dependent variable. In the main text, we only report the analyses for the PBI scores computed for response times and error rates. We report all the results of analyses for response times and error rates (which are highly consistent with the analyses for the PBI scores) in supplemental material (see Experiment 3: Response times and error rates).

To test the first and second predictions for the PBI scores, the regression model contained the factors of training group (traditional training group, balanced training group, and reactive encouraged training group), task phase (training and test phase), and their two-way interactions. We were interested in the significance of the two-way interaction (training group × task phase).

We focused on the following two planned comparisons. First, pairwise comparisons were conducted to examine whether in the training phase individuals in the reactive encouraged training group would have lower PBI scores, compared to individuals in the traditional and balanced training groups (prediction 1). Second, pairwise comparisons were conducted to examine whether individuals in the traditional and balanced training groups showed higher PBI scores in the test phase, compared to in the training phase (prediction 2).

To test the key third prediction concerning negative transfer for PBI scores we focused on the significance of the main effect of training group (corresponding to test phase performance in the reactive encouraged training group, training phase performance in the traditional and balanced training groups). Pairwise comparisons were conducted to examine whether individuals in the reactive encouraged training group had lower PBI scores in the training phase, compared to the training phase performance of individuals in the traditional and balanced training groups.

Experiment 3 (Results and Discussion)

Cognitive control modes in the training phase and positive transfer effects of task knowledge (predictions 1 and 2)

Descriptive statistics and analysis for response times and error rates are reported in supplemental material (see Experiment 3: Response times and error rates). Hereafter we refer to the effect of contrasting the reactive encouraged training group with the traditional training group as a ‘traditional group’ factor and the effect of contrasting the reactive encouraged training group with the balanced training group as a ‘balanced group’ factor.

PBI scores for response times For the PBI score computed for response times (see Figure 6a), our focal comparison showed that training group factors did not significantly interact with task phase (traditional group × task phase: β = -0.01, t = -0.06, p = .950, balanced group × task phase: β = 0.18, t = 1.02, p = .307). However, significant main effects were observed for the traditional group factor (β = 0.71, t = 4.36, p < .001) and the balanced group factor (β =

0.53, t = 3.06, p = .003), indicating that adults in the reactive encouraged training group showed lower PBI scores computed for response times, compared to adults in the traditional and balanced training groups, regardless of task phase. We then focused on the main effect of task phase in the traditional and balanced training groups to examine positive transfer effects. According to pairwise comparisons, there was no significant effect of task phase in the traditional training group (β = -0.02, t = -0.19, p = .847) or in the balanced training group (β = 0.16, t = 1.36, p = .356).

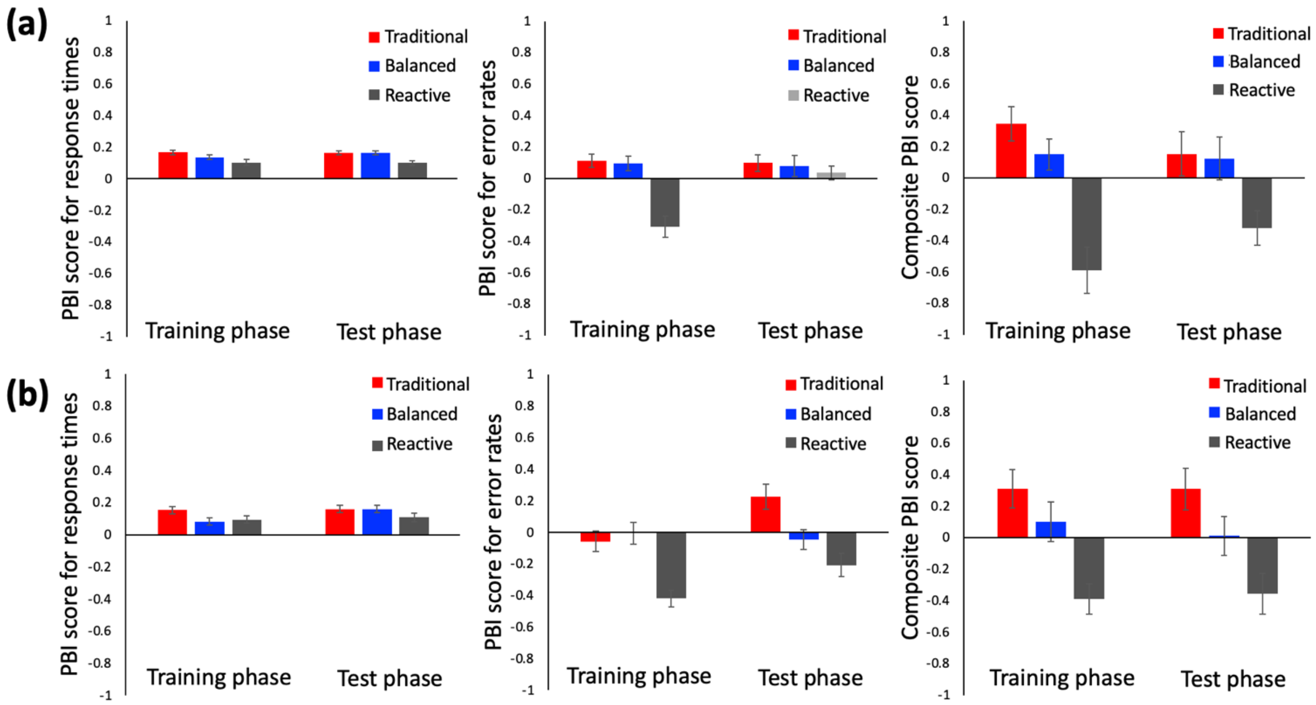

Figure 6. Mean PBI scores in each condition. Error bars indicate standard errors. Panel (a) shows adult data (Experiment 3), whereas panel (b) shows data from 9- to 10-year-olds (Experiment 4). Panels on the left show the PBI score for response times, panels in the center show the PBI score for error rates, and panels on the right show the composite PBI score.

PBI scores for error rates. For the PBI score computed for error rates (see Figure 6a), our focal comparison revealed significant two-way interactions between training group and task phase (traditional group × task phase: $\beta = -0.52$, $t = -3.34$, $p = .001$, balanced group × task phase: $\beta = -0.53$, $t = -3.23$, $p = .001$). These interactions were explored further via planned comparisons. First, in the training phase there were significant main effects of the traditional group factor ($\beta = 0.60$, $t = 5.56$, $p < .001$) and the balanced group factor ($\beta = 0.55$, $t = 5.12$, $p < .003$), indicating that during the training phase adults in the reactive encouraged training group showed lower PBI scores computed for error rates than adults in the traditional and balanced training groups. Second, there were no significant changes in the PBI score computed for error rates between training and test phases in both the traditional training group ($\beta = -0.02$, $t = -0.18$, $p = .860$) and the balanced training group ($\beta = -0.03$, $t = -0.21$, $p = .832$).

Composite PBI score. Figure 6a depicts the composite PBI score for each group. Our focal comparison revealed that training group factors did not significantly interact with task phase (traditional group × task phase: $\beta = -0.19$, $t = -1.84$, $p = .067$, balanced group × task phase: $\beta = -0.29$, $t = -1.13$, $p = .262$). However, we found significant main effects of the traditional group factor ($\beta = 0.89$, $t = 5.63$, $p < .001$) and the balanced group factor ($\beta = 0.75$, $t = 4.50$, p

< .001), indicating that adults in the reactive encouraged training group showed lower composite PBI score, compared to adults in the traditional and balanced training groups, regardless of task phase. In terms of positive transfer effects, pairwise comparisons showed no significant main effect of task phase in the traditional training group (β = -0.12, t = 1.13, p = .535) or the balanced training group (β = -0.02, t = -0.15, p = .880).

Negative transfer effects of task knowledge (prediction 3)

The analysis for response times and error rates is reported in supplemental material (see Experiment 3: Response times and error rates).

PBI scores for response times. Our analysis for the PBI score computed for response times revealed a significant main effect of the traditional group factor (β = 0.75, t = 3.20, p = .002), indicating that adults in the reactive encouraged training group showed lower PBI scores computed for response times in the test phase, compared to adults in the traditional training group in the training phase. Conversely, the main effect of the balanced group factor was not significant (β = 0.41, t = 1.65, p = .103).

PBI scores for error rates. Our analysis for the PBI score computed for error rates showed that neither the main effect of the traditional group factor (β = 0.22, t = 1.20, p = .232) nor that of the balanced group factor (β = 0.18, t = 0.91,

p = .365) was significant. Thus, PBI score computed for error rates did not differ among the three training groups.

Composite PBI score. Our analysis revealed significant main effects of the traditional group factor (β = 0.84, t = 4.40, p < .001) and the balanced group factor (β = 0.60, t = 2.99, p = .004). Adults in the reactive encouraged training group showed lower composite PBI score in the test phase, compared to adults in the traditional and balanced training groups in the training phase.

One may argue that lower PBI scores in the test phase performance of the reactive encouraged training group than in the training phase performance of the traditional and balanced training groups may reflect a fatigue effect as the reactive encouraged training group, unlike the other two groups, had already completed another task. To examine this possibility, in non-preregistered exploratory analyses presented in our supplemental material (see Experiment 3: Test phase comparison) we contrasted the test phase performance of the three training groups. This showed that in the test phase, the reactive encouraged training group showed a significantly lower PBI score computed for response times and a significantly lower composite PBI score than the traditional and balanced training groups. These findings are consistent with the results of our preregistered analyses, and confirm that fatigue cannot account for our results.

Summary of Experiment 3

We succeeded in extending the findings of Experiment 1, which used a cued task-switching paradigm, to the AX-CPT. A key result was that a negative transfer effect was observed in the comparison of the test phase performance of the reactive encouraged training group relative to the training phase performance of the traditional and balanced training groups. This negative transfer reflected less use of proactive control in the AX-CPT. These findings also conceptually replicate and extend Bhandari and Badre (2018)'s work. In contrast, we found no evidence of positive transfer effects from training to test phases in the traditional training group or the balanced training group.

Experiment 4 (Method)

Participants. As specified in our preregistered plan (https://doi.org/10.17605/OSF.IO/BM329), our target sample was 96 school-aged children (traditional training group = 32, balanced training group = 32, and reactive encouraged training group = 32). We decided on the sample size based on Experiment 2 (32 participants per one group) and recruited one hundred and eight 9- to 10-year-olds from a database of a research consulting company (ASMARQ, Co., Ltd. https://www.asmarq.co.jp). All the children were native

Japanese speakers and did not have any history of neurological disorders. Both parents and children gave informed consent. In total, six children were excluded (three children did not finish all the blocks; three parents failed to send in the child's photographs showing them performing the task). Hence, our final sample consisted of 35 children in the traditional training group (M = 9.73 years, SD = 0.50 years, 20 girls and 15 boys), 35 children in the balanced training group (M = 9.74 years, SD = 0.55 years, 18 girls and 17 boys), and 32 children in the reactive encouraged training group (M = 9.77 years, SD = 0.54 years, 18 girls and 14 boys). Parents and children were paid 2000 yen for their participation. However, if children did not complete the training phase, they were not rewarded.

Materials and Procedure. The materials and the composition of practice, training, and test phases were the same as in Experiment 3. However, there were two changes from Experiment 3. First, following Experiment 2, children read through the instructions of the AX-CPT by themselves, and if they did not understand the instructions, we asked their parents to explain them verbally. Furthermore, we asked parents to take pictures of the PC screen and their child during a short break between blocks (i.e., two pictures in the training phase and two pictures in the test phase). Second, in terms of the sequence of each trial, a cue stimulus was displayed for 1000 ms, followed by a 1500 ms interstimulus interval. Subsequently, a probe stimulus with a surrounding black square was presented until children responded or until a response deadline of 3500 ms had passed.

Experimental design. As in Experiment 3, children were randomly assigned to either the traditional training group, the balanced training group, or the reactive encouraged training group.

Data processing. The dependent measures were response times and error rates. Trials with response times faster than 200 ms were excluded. We also report PBI scores, which directly reflect whether children use either proactive or reactive control.

Data analysis. The study design, hypotheses, and analytic plan were preregistered in the Open Science Framework (https://doi.org/10.17605/OSF.IO/BM329). We employed the same analytic plan as in Experiment 3.

Experiment 4 (Results and Discussion)

Cognitive control modes in the training phase and positive transfer effects of task knowledge (predictions 1 and 2)

Descriptive statistics and analysis for response times and error rates are reported in supplemental material (see Experiment 4: Response times and error rates).

PBI scores for response times. For the PBI scores computed for response times (see Figure 6b), our focal comparison showed that training group factors did not significantly interact with task phase (training group × task phase: β = 0.23, t = 1.37, p = .173, balanced group × task phase: β = -0.03, t = -0.18, p = .859). However, there was a significant main effect of the training group factor (β = 0.41, t = 2.39, p = .018), indicating that children in the reactive encouraged training group showed lower PBI scores computed for response times, compared to children in the traditional training group, regardless of task phase. In contrast, there was no significant difference between the training phase performance of the balanced and reactive encouraged training groups. Next, in terms of positive transfer effects, pairwise comparisons revealed that the main effect of task phase was significant in the balanced training group (β = 0.29, t = 2.43, p = .033), but not in the traditional training group (β = 0.02, t = 0.20, p = .839). Thus, children in the balanced training group showed higher PBI scores computed for response times in the test phase compared to the training phase.

PBI scores for error rates. For the PBI scores computed for error rates (see Figure 6b), our focal comparison revealed no significant two-way interactions between training group and task phase (traditional group × task phase: $\beta = 0.08$, $t = 0.53$, $p = .599$, balanced group × task phase: $\beta = -0.29$, $t = -1.83$, $p = .069$). Conversely, we observed significant main effects of the traditional group factor ($\beta = 0.92$, $t = 5.85$, $p < .001$) and the balanced group factor ($\beta = 0.67$, $t = 4.24$, $p < .001$). Thus, regardless of task phase, children in the reactive encouraged training group showed lower PBI scores computed for error rates, compared to children in the traditional and balanced training groups. Furthermore, to examine positive transfer effects, pairwise comparisons were conducted. The main effect of task phase was significant in the traditional training group ($\beta = 0.32$, $t = 3.00$, $p = .007$), but not in the balanced training group ($\beta = -0.04$, $t = -0.43$, $p = .669$). Thus, children in the traditional training group showed higher PBI scores computed for error rates in the test phase compared to the performance in the training phase.

Composite PBI score. Figure 6b depicts the composite PBI score for each group. Our focal comparison revealed that training group did not significantly interact with task phase (traditional group × task phase: $\beta = -0.08$, $t = -0.50$, $p = .616$, balanced group × task phase: $\beta = -0.02$, $t = -0.15$, $p = .880$). However, there were significant main effects of the traditional group factor (β = 0.91, t = 5.54, p < .001) and of the balanced group factor (β = 0.57, t = 3.48, p = .005), indicating that children in the reactive encouraged training group showed lower composite PBI scores, compared to children in the traditional and balanced training groups, regardless of task phase. In terms of positive transfer effects, pairwise comparison did not find any significant main effects of task phase in the traditional training group (β = -0.001, t = -0.01, p = .999) or in the balanced training group (β = -0.06, t = -0.53, p = .999). Thus, the composite PBI score did not differ across the training phase and test phase in the two training groups.

Negative transfer effects of task knowledge (prediction 3)

The analyses for response times and error rates are reported in supplemental material (see Experiment 4: Response times and error rates).

PBI scores for response times. Our analysis for the PBI score computed for response times revealed that neither the main effect of the traditional group factor nor the main effect of the balanced group factor was significant (traditional group; β = -0.19, t = -0.79, p = .435, balanced group; β = 0.33, t = 1.33, p = .186).

PBI scores for error rates. Our analysis for the PBI scores computed for error rates showed the main effect of the balanced group factor was significant (β

= 0.47, t = 2.09, p = .039), indicating that children in the reactive encouraged training group showed lower PBI scores computed for error rates in the test phase, compared to children in the balanced training group in the training phase. In contrast, the main effect of the traditional group factor was not significant (β = 0.36, t = 1.58, p = .119).

Composite PBI score. Our analysis revealed significant main effects of the traditional group (β = 0.89, t = 3.75, p < .001) and balanced group (β = 0.61, t = 2.57, p = .012) factors; children in the reactive encouraged training group showed lower composite PBI scores in the test phase, relative to the training phase composite PBI scores of children in the traditional and balanced training groups.

In line with Experiment 3, we contrasted the test phase performance of the three training groups to examine the effect of fatigue (see Experiment 4: Test phase comparison). These additional analyses showed, firstly, that in the test phase the reactive encouraged training group showed significantly lower composite PBI scores than the traditional and balanced training groups. Furthermore, in the test phase the traditional training group also showed significantly higher PBI score computed for error rates than the reactive encouraged training group. These results are largely compatible with the results of our preregistered analyses, indicating that the suggestion of a fatigue effect alone cannot explain our results.

Summary of Experiment 4

Experiment 4 produced a key finding in school-aged children that paralleled that seen in adults in Experiment 3. Specifically, children in the reactive encouraged training group successfully learnt knowledge of the temporal structure of activation of task goals and then negatively transferred this knowledge to a different task environment (as shown in the analysis of PBI composite scores). Furthermore, children showed evidence of positive transfer effects in the AX-CPT, in contrast to adults in Experiment 3. Children in the traditional and balanced training groups showed more evidence of the engagement of proactive control in the test phase compared to the preceding training phase that employed different stimuli.

Experiments 5 and 6

The fifth and sixth experiments aimed to clarify the hierarchical structure of task knowledge underlying the transfer of the engagement of cognitive control in both adults and school-aged children. Therefore, we further extended the findings reported above by examining whether task knowledge could be transferred by adults and 9- to 10-year-olds – both positively and negatively – to the engagement of cognitive control in a subsequent environment that included different task goals as well as different stimuli. While Experiments 1-4 used different stimuli between training and test phases, Experiment 5 and 6 used a different set of task goals between the two phases (e.g., color and shape tasks in a training phase, size and orientation tasks in a test phase) as well as different stimuli in the cued task-switching paradigm (see Figure 7). We focused on the hierarchical structure of the cued task-switching paradigm, which is composed of layers of a task goal, bidimensional stimuli based on the goal, and corresponding keys based on stimulus-response mappings. Thus, the cued task-switching paradigm enables us to manipulate task goals and stimuli separately, whereas this would be challenging in the AX-CPT in which a task goal is tied to particular stimuli (e.g., press the G key only when a doll was followed by a cake). Thus, Experiments 5 and 6 employed the cued task-switching paradigm. This is the first direct assessment of whether task knowledge is tied to particular task goals or can be generalized to different task goals. Specifically, we tested three predictions as in Experiments 1 and 2. Experiments 5 and 6 received approval from the institutional ethics review board of the University of Tokyo (19-334).

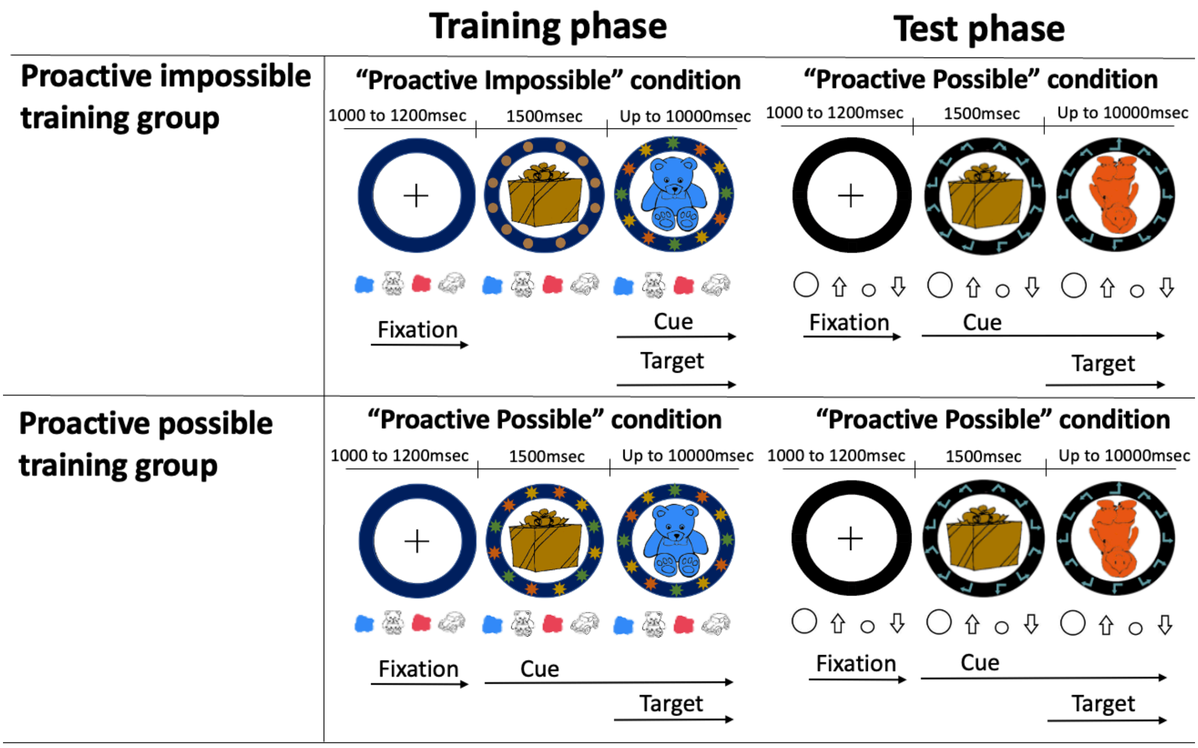

Figure 7. Illustration of the cued task-switching paradigm used in each condition. Participants sorted pictures by color and shape based on informative cues presented on the "circle" (i.e., 12 colorful patches or 12 gray geometrical shapes). In the "Proactive Impossible" condition, the informative cue was presented on target onset, whereas it appeared before the target in the "Proactive Possible" condition.

Experiment 5 (Method)

Participants. As specified in our preregistered plan (https://osf.io/npjmr), our target sample was 60 adults (30 adults in the proactive impossible training group, 30 adults in the proactive possible training group). We decided on this sample size based on Experiment 1 and recruited 70 adults, whom were 19-year-olds to 30-year-olds who had not participated in Experiment 1, from a database of a research consulting company (Rakuten Insight, Inc. https://member.insight.rakuten.co.jp). All the participants were native Japanese speakers, and they gave informed consent and were paid 1000 yen after completing all the task procedures. Consistent with Experiment 1, most participants exhibited near perfect correct response rates (*M* = 94.5%, *SD* = 7.6%), and 8 participants performed outside 3SD of the mean for overall accuracy (i.e., less than 71.6%) and were therefore not included in the final analyses. Our final sample was 31 adults in the proactive impossible training group (*M* = 25.78 years, *SD* = 2.39 years, 15 females and 16 males) and 31 adults in the proactive possible training group (*M* = 25.22 years, *SD* = 3.08 years, 17 females and 14 males).

Materials and experimental design. In addition to a set of 8 × 8 cm targets varying on color and shape dimensions, we prepared another set of 8 × 8 cm targets varying on size and orientation dimensions (size: large doll and small doll, orientation: upright doll and inverted doll) (see Figure 1b). Another set of informative cues was prepared, which signaled either a size sorting rule by virtue of showing 12 ovals of various sizes or an orientation sorting rule indicated by 12 crooked arrows of various orientations (see Figure 1b). We constantly presented four 2 × 2 cm unidimensional response pictures (e.g., a large circle, a small circle, an upward arrow, and a downward arrow). As in Experiment 1, adults were randomly assigned to either the proactive impossible training group or the proactive possible training group.

Procedure and Santa Claus Game. The procedure, the sequence of each trial, and the composition of the first practice, training, second practice, and test phases were the same as in Experiment 1. However, unlike in Experiment 1, in Experiment 5 the set of task goals and stimuli used in the test phase was different from that used in the training phase. For example, after participants were asked to make either a color or shape judgement to one set of bidimensional gifts (e.g., a pink bear) in the training phase, they were then asked to make either a size or orientation judgement to another set of bidimensional gifts (e.g., a small inverted doll) in the test phase. The sets of task goals used in either the training or test phases were counterbalanced across participants.

Data processing. The dependent measures were response times and correct response rates. Following the same procedure as Experiment 1 (Leys et al., 2013), resulted in the removal of 5.6% of correct responses from the analyses of response times.

Data analysis. The study design, hypotheses, and analytic plan were preregistered in the Open Science Framework (https://osf.io/npjmr). We used the same analytic plan as in Experiment 1.

Results and Discussion (Experiment 5)

Cognitive control modes in the training phase and positive transfer effects of task knowledge (predictions 1 and 2)

Response times. Figure 8a depicts mean correct response times for each condition. Our preregistered model failed to converge, thus we dropped any interactions related to the factor of block. Our key comparison showed significant interactions between task phase and training group (β = 0.18, t = 15.40, χ^2 = 237.07, df = 1, p < .001). According to our planned comparisons, in the training phase adults in the proactive impossible training group performed more slowly than those in the proactive possible training group (β = -0.18, t = -6.32, p < .001). We also found that adults in the proactive possible training group performed more quickly in the test phase than in the training phase (β = -0.02, t = -7.56, p <.001).

There was also a significant switch cost in response times (β = 0.07, t = 5.75, χ^2 = 33.01, df = 1, p < .001), but no significant interactions with switch cost.

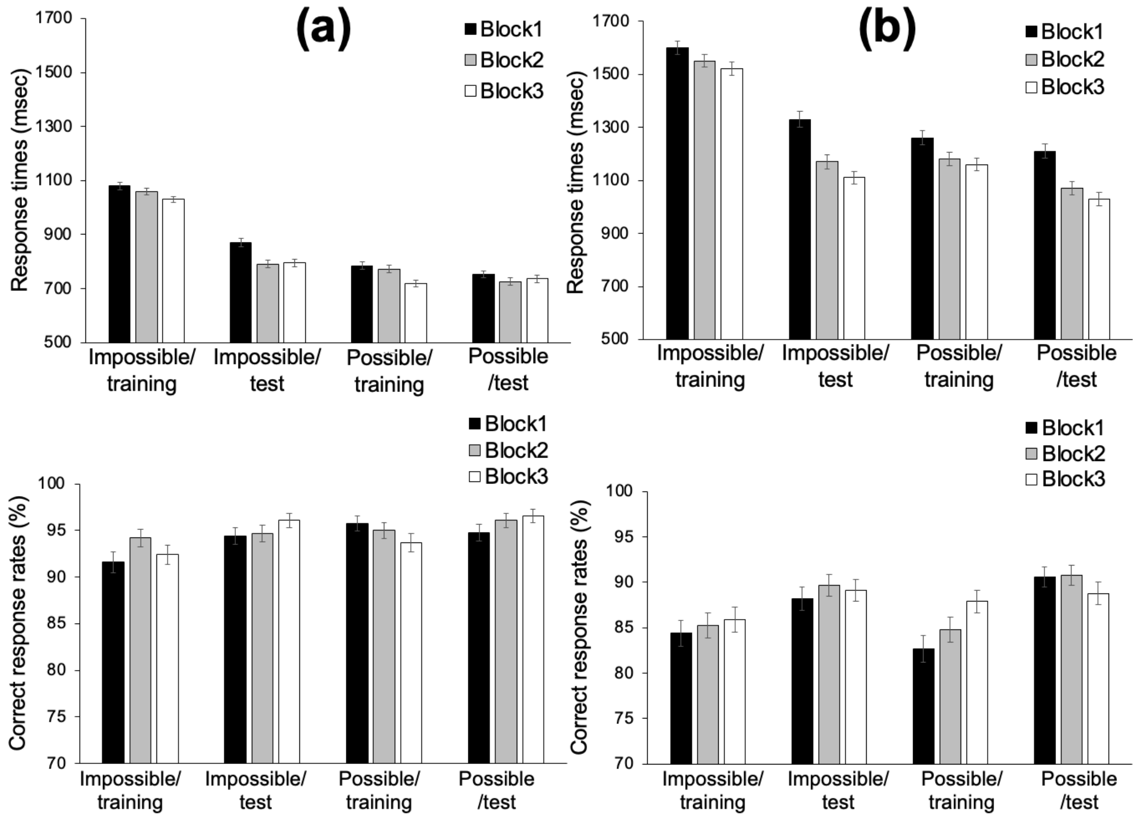

Figure 8. Mean response times and correct response rates in each condition. Error bars indicate standard errors. For adults, panel (a) shows response times (left upper) and correct response rates (left lower) in Experiment 5. For 9-to 10-year-olds, panel (b) shows response times (right upper) and correct response rates (right lower) in Experiment 6.

Correct response rates. In line with Experiment 1, correct response rates were near ceiling (see Figure 8a), thus we did not consider them as a key measure for adults. We include the analysis for correct response rates in supplemental materials.

Negative transfer effects of task knowledge (prediction 3)

Response times. Contrary to our prediction, we did not observe the expected significant interaction between training group and block (β = 0.03, t = 1.86, χ^2 = 3.47, df = 1, p = .063). According to the preregistered analysis plan, we broke three blocks into twelve mini-blocks and examined a simple effect of training group in first four mini-blocks using Holm correction. We found the same pattern as in Experiment 1. That is, response times were slower in the test phase performance of the proactive impossible training group than in the training phase performance of the proactive possible training group only in the first mini-block (β = -0.11, t = -2.54, p = .044). In contrast, no significant differences were observed in the second, third, and fourth mini-blocks (second mini-block: β = -0.06, t = -1.52, p = .383, third mini-block: β = -0.06, t = -1.38, p = .383, fourth mini-block: β = -0.005, t = -0.12, p = .907) (see Figure 9a).

There was a significant main effect of trial type (β = 0.06, t = 3.67, χ^2 = 13.44, df = 1, p < .001), but it did not interact significantly with the negative transfer effect.

Consistent with Experiment 1, faster overall response times were observed in the test phase, thus the effect of fatigue is less likely to affect slower response times in the "Proactive Impossible" training group. Indeed, when we contrasted the test phase performance of the "Proactive possible" training group with that of the “Proactive Impossible” training group, the “Proactive Impossible” training group showed significantly slower response times in the first mini block (β = -0.15, t = -3.44, p = .002).

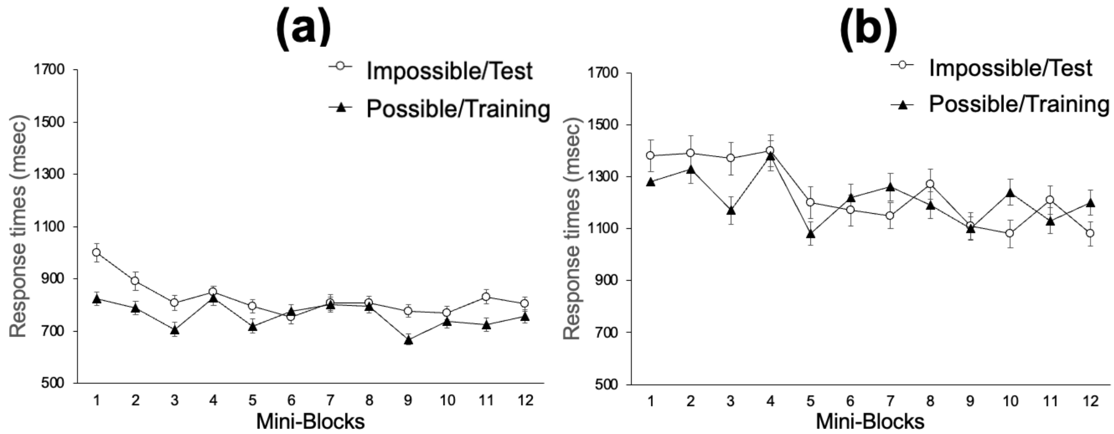

Figure 9. Mean response times for each mini-block. Error bars indicate standard errors. As seen in panel (a) (left), which summarizes Experiment 5 in the first mini-block adults in the proactive impossible training group showed slower response times in the test phase compared to the training phase performance of the proactive possible training group. Panel (b) (right), which summarizes Experiment 6, indicates that among 9- to 10-year-olds there were no significant differences in response times between the test phase performance of the proactive impossible training group and the training phase performance of the proactive possible training group even in the first mini-block.

Correct response rates. In line with Experiment 1, we also include the analysis for correct response rates in supplemental materials.

Summary of Experiment 5

Experiment 5 succeeded in its aim of substantially extending the results of Experiment 1 (and by implication those of Bhandari & Badre, 2018) by exploring the transfer of task knowledge when not just the stimuli, but also the task goals, changed between training and test. Adults in the proactive impossible training group responded more slowly in the test phase than did adults in the proactive possible training group in the training phase, even though different task goals and stimuli were used between the two phases. This finding suggests that adults can adapt knowledge of task management to exert cognitive control across task environments with different task goals and stimuli. This provides the first evidence that the knowledge of task management that adults learn can be generalized to different task goals. Furthermore, although negative transfer was observed initially among participants in the proactive impossible training group, it was very short-lived as these participants rapidly switched to a proactive control strategy in the test phase.

Experiment 6 (Method)

Participants. As specified in our preregistered plan (https://osf.io/5d4xu), our target sample was sixty 9-to 10-year-olds (i.e., thirty 9-to 10-year-olds in the proactive impossible training group, thirty 9-to 10-year-olds in the proactive possible training group). We decided on the sample size based on Experiment 2 (N = 60) and recruited seventy 9-to 10-year-olds, who did not participate in Experiment 2, from a database of a research consulting company (Rakuten

Insight, Inc. https://member.insight.rakuten.co.jp). All the children were native Japanese speakers and did not have any history of neurological disorders. Both parents and children gave informed consent. In total, 4 children were excluded (one child did not finish all the blocks; two parents failed to send in the child's photographs showing them performing the task; one parent reported that they performed the task instead of their child). Hence, our final sample was 33 school-aged children in the proactive impossible training group (*M* = 9.91 years, *SD* = 0.54 years, 16 girls and 17 boys) and 33 school-aged children in the proactive possible training group (*M* = 9.90 years, *SD* = 0.57 years, 14 girls and 19 boys). Parents were paid 2000 yen and a small gift of stationery was sent to the child as a reward. However, if children did not complete the training phase, they were not rewarded.

Materials and experimental design. The materials were same as Experiment 5. Children were randomly assigned to either the proactive impossible training group or the proactive possible training group.

Procedure and Santa Claus Game. The procedure, the sequence of each trial, and the composition of practice, training, and test phases were the same as in Experiment 2. However, critically, as in Experiment 5, the task goals and stimuli used in the test phase were different from those in the training phase. These tasks and stimuli were identical to those used in Experiment 5.

Data processing. The dependent measures were response times and correct response rates. Following the same procedure as Experiment 1 (Levy et al., 2013), we excluded 5.4% of correct responses from the analyses of response times.

Data analysis. The study design, hypotheses, and analytic plan were preregistered in the Open Science Framework (https://osf.io/5d4xu). We employed the same analytic plan as in Experiment 1.

Results and Discussion (Experiment 6)

Cognitive control modes in the training phase and positive transfer effects of task knowledge (predictions 1 and 2)

Response times. Figure 8b depicts response times for each condition. As expected, our analysis showed significant interactions between task phase and training group (β = 0.07, t = -4.25, χ^2 = 73.73, df = 1, p < .001). According to the planned comparisons, in the training phase children in the proactive impossible training group responded more slowly compared to children in the proactive possible training group (β = -0.15, t = -3.82, p < .001). We also found that children in the proactive possible training group showed faster response times in the test phase relative to the training phase (β = -0.05, t = -7.58, p < .001).

There was also a significant switch cost in response times (β = 0.07, t = 9.28, χ^2 = 86.03, df = 1, p < .001). There were no significant interactions with switch cost.

Correct response rates. Correct response rates by condition are shown in Figure 8b. There was a significant three-way interaction between task phase, training group, and block (*Odds ratio* = 0.91, 95% CI: 0.83-0.99, z = -2.14, χ^2 = 4.50, df = 1, p = .034). Our planned comparisons first compared the training phase performance of the reactive and proactive possible training groups, revealing no significant group differences (*Odds ratio* = 1.09, 95% CI: 0.82-1.58, z = 0.50, p = .616). Training group did not significantly interact with block (*Odds ratio* = 1.12, 95% CI: 0.92-1.11, z = 1.76, p = .078). We also conducted planned comparison between the training and test phase performance of the proactive possible training group, using Holm correction, demonstrating better correct response rates in the test phase than in the training phase within the first and second blocks (first block: *Odds ratio* = 1.57, t = 4.76, p < .001, second block: *Odds ratio* = 1.44, t = 3.77, p < .001), whereas the effect of task phase was not significant in the third block (*Odds ratio* = 1.02, z = 0.21, p = .831).

We found significant a main effect of trial type (*Odds ratio* = 0.91, 95% CI: 0.85-0.98, z = -2.45, χ^2 = 5.87, df = 1, p = .015). There were no significant interactions with switch cost.

Negative transfer effects of task knowledge (prediction 3)

Response times. As expected, we found that training group interacted with block significantly (β = 0.04, t = 3.49, χ^2 = 12.16, df = 1, p < .001). Pairwise comparisons with Holm correction demonstrated no significant differences across training groups in all the blocks (first block: β = -0.05, t = -1.15, p = .745, second block: β = -0.01, t = -0.21, p = .999, third block: β = 0.01, t = 0.14, p = .999). According to the preregistered analysis plan, we broke each block into four mini-blocks and examined the first four mini-blocks as in our previous experiments. Using Holm correction, it was revealed that there were no significant simple effects of training group in each mini-block (first mini-block: β = -0.08, t = -1.45, p = .438, second mini-block: β = -0.02, t = -0.37, p = .999, third mini-block: β = -0.10, t = -1.94, p = .212, fourth mini-block: β = -0.02, t = -0.36, p = .999) (see Figure 9b).

There was a significant main effect of trial type (β = 0.07, t = 5.82, χ^2 = 33.83, df = 1, p < .001), but it did not interact significantly with the negative transfer effects.

Correct response rates. We found that the main effect of training group (*Odds ratio* = 0.93, 95% CI: 0.65-1.35, z = -0.38, χ^2 = 0.14, df = 1, p = .705) and its interaction with block (*Odds ratio* = 1.13, 95% CI: 0.99-1.29, z = 1.91, χ^2 = 3.50, df = 1, p = .061) were not significant.

Summary of Experiment 6

Experiment 6 extended the findings of Experiment 2 by revealing that school-aged children can show positive transfer effects across task environments with different task goals and stimuli. This finding suggests that a collective body of task knowledge that children learn is independent of specific stimulus-response mappings and specific task goals. In contrast, they did not show negative transfer effects of task knowledge across task environments with different task goals as well as different stimuli, thus their knowledge of task management is not generalized to different task goals. We discuss the asymmetrical pattern observed in 9- to 10-year-olds (i.e., positive transfer effects were present, but negative transfer effects were absent) in the General Discussion section.

Direct Comparisons Between Adults and School-aged Children

To explore potential developmental differences in negative transfer effects of task knowledge, we conducted a set of direct comparisons between the data for adults and school-aged children. We added a factor of experiment (i.e., Experiment 1 vs. 2, Experiment 3 vs. 4, and Experiment 5 vs. 6) and its related interactions to the above-mentioned regression models examining negative transfer effects. In terms of Experiments 1 and 2 and Experiments 5 and 6 we compared the results of two regression models with response times as a dependent variable: one focal model with the three-way interaction (experiment × training group × block) and another model without the three-way interaction. In terms of Experiments 3 and 4, adults and school-aged children showed negative transfer effects on the composite PBI score, thus we compared the results of two regression models with the composite PBI score as the dependent variable. One focal model contained the two-way interaction (experiment × training group) while the second model omitted this interaction. In both analyses, a pairwise comparison of the interaction was conducted to examine whether adults differ from school-aged children in the extent to which they showed negative transfer effects. Response times were standardized for each adult and school-aged children prior to statistical analyses. In the following section, we only report targeted significant effects and interactions with the experimental factor as we have already reported the other aspects of these analyses.

In the comparison between Experiments 1 and 2, training group interacted significantly with block (β = -0.02, t = 5.24, χ^2 = 27.49, df = 1, p < .001), but did not interact significantly with the experimental factor (β = -0.003, t = -0.40, χ^2 = 0.15, df = 1, p = .697). Pairwise comparisons revealed that the training group differences were not significant in the first block (β = -0.11, t = -1.79, p = .073), but that in the first mini-block individuals in the proactive impossible training group performed more slowly in the test phase than did individuals in the proactive possible training group in the training phase (β = -0.27, t = -4.07, p < .001). Therefore, although both adults and school-aged children exhibited negative transfer effects in the first mini-block, there were not developmental differences in the degree of these negative transfer effects.

In the comparison between Experiments 5 and 6, training group interacted significantly with block (β = 0.03, t = 3.45, χ^2 = 11.93, df = 1, p = .001), but did not interact with the experimental factor (β = -0.01, t = -0.78, χ^2 = 0.60, df = 1, p = .438). According to a pairwise comparison, in the first block individuals in the proactive impossible training group showed performed more slowly in the test phase relative to the training phase performance of the proactive possible training group (β = -0.11, t = -1.97, p = .049). Importantly, the absence of reliable interactions with the experimental factor implies that there were no developmental differences in the degree of the negative transfer effects. Our previous analyses suggested that adults in Experiment 5 showed negative transfer effects across task environments with different task goals as well as different stimuli, whereas children in Experiment 6 did not show such negative transfer effects. However, the results of the direct comparison of these experiments indicate that this difference across participant groups is, itself, not reliable, as apparent developmental differences disappeared. Instead, the key finding was that all individuals showed negative transfer in the first block.

Finally, in the comparison between Experiments 3 and 4, the experimental factor did not interact significantly with the traditional group factor (β = 0.001, t = 0.008, p = .993) or the balanced group factor (β = 0.01, t = 0.08, p = .938). Instead, there were significant main effects of the traditional group factor (β = 0.66, t = 5.72, p < .001) and the balanced group factor (β = 0.46, t = 3.86, p < .001). Therefore, both adults and school-aged children in the reactive encouraged training group showed lower composite PBI scores in the test phase than those in the traditional and balanced training groups showed in the training phase. Furthermore, the degree of such negative transfer effects did not differ between adults and school-aged children.

Overall, therefore, our exploratory analyses revealed no reliable developmental differences in the degree of negative transfer of task knowledge between adults and 9- to 10-year-olds.

General Discussion

The current study investigated adults' and children's ability to transfer hierarchical and temporal structured task knowledge to the engagement of cognitive control in novel task environments. A set of six preregistered experiments examined whether school-aged children as well as adults can learn knowledge about the temporal structure of task goal activation and transfer it to different task environments. The experiments further aimed to examine the nature of task knowledge with regards to its hierarchical structure. Findings from all the experiments are summarized in Tables 1 and 2. The most important finding is that prior task experience of engaging reactive control makes adults and 9-to 10-year-olds respond reactively in a subsequent but similar-structured condition with different stimuli in which proactive control could have been engaged.

Table 1. Summary of predictions and findings from Experiments 1, 2, 5, and 6

		Prediction	Adults	Children
			Experiment 1	Experiment 2
Same task goals Different stimuli		**Cognitive control mode effect (Different cognitive control modes between the two training groups)**		
	RTs	In the training phase, *slower RTs* in the proactive impossible training group than proactive possible training group.	✓	✓
		Positive transfer effect (Changes in response times and error rates in the proactive possible training group)		
	RTs	*Faster RTs* in the test phase than in the training phase.	✓ First and second blocks	✓
	Error rates	*Lower error rates* in the test phase than in the training phase.	×	✓
		Negative transfer effect (Transfer of task knowledge of using reactive control)		
	RTs	*Slower RTs* in the test phase of the proactive impossible training group than in the training phase of the proactive impossible training group	✓ First "mini" block	✓ First block
			Experiment 5	Experiment 6
Different task goals Different stimuli		**Cognitive control mode effect (Different cognitive control modes between the two training groups)**		
	RTs	In the training phase, *slower RTs* in the proactive impossible training group than proactive possible training group.	✓	✓
		Positive transfer effect (Changes in response times and error rates in the proactive possible training group)		
	RTs	*Faster RTs* in the test phase than in the training phase.	✓	✓
	Error rates	*Lower error rates* in the test phase than in the training phase.	✓	✓ First and second blocks
		Negative transfer effect (Transfer of task knowledge of using reactive control)		

RTs	*Slower RTs* in the test phase of the proactive impossible training group than in the training phase of the proactive impossible training group	✓ First "mini" block	×

Note. Significant effects are represented by "✓" and non-significant effects are represented by "×".

Table 2. Summary of predictions and findings from Experiments 3 and 4

		Prediction	Adults Experiment 3	Children Experiment 4
Same task goals Different stimuli		**Cognitive control mode effect (Different cognitive control modes between the two training groups)**		
	PBI (RTs)	In the training phase, *lower PBI scores* in the reactive encouraged training group than the traditional and balanced training groups.	✓	traditional vs. reactive ✓ balanced vs. reactive ×
	PBI (error rates)		✓	✓
	Composite PBI		✓	✓
		Positive transfer effect (Changes in the degree of proactive control engagement in the traditional and balanced training groups)		
	PBI (RTs)	*Higher PBI scores* in the test phase than in the training phase.	×	traditional × balanced ✓
	PBI (error rates)		×	traditional ✓ balanced ×
	Composite PBI		×	×
		Negative transfer effect (Transfer of task knowledge of using reactive control)		
	PBI (RTs)	*Lower PBI scores* in	traditional vs. reactive ✓ balanced vs. reactive	

		×	×
PBI (error rates)	the test phase of the reactive encouraged training group than in the training phase of the traditional and balanced training groups	×	traditional vs. reactive × balanced vs. reactive ✓
Composite PBI		✓	✓

Note. Significant effects are represented by "✓" and non-significant effects are represented by "×".

Cognitive control modes in the training phase

Our manipulation in the training phase of each experiment succeeded in inducing individuals to engage cognitive control either reactively or less proactively as predicted. Four experiments using the cued task-switching paradigm robustly demonstrated that in a training phase in which participants learn an initial task, participants in a proactive impossible training group who are unable to engage in proactive control responded more slowly than those in the proactive possible training group where proactive control was possible. In other words, both adults and 9- to 10-year-olds engage proactive control when cue-based proactive preparation is possible, whereas they engage reactive control when the informative cue is presented simultaneously with the target onset (see Table 1). Given that Chevalier et al. (2015) found a similar result in 10-year-olds, Experiments 2 and 6 with children replicate this finding and Experiments 1 and 5 extend it to adult participants.

Two experiments using the AX-CPT developed modified versions of the paradigm through the manipulation of trial type frequency (Braver et al. 2007; Redick et al. 2014; Richmond et al. 2015). Redick et al. (2014) equalized the frequencies of AX and AY trials, forcing participants to rely on the probe letter when deciding their response following an A cue. Our reactive encouraged condition was akin to Redick et al.'s (2014) version. We demonstrated that participants exhibited less of a tendency to engage proactive control (at least as measured by response times, error rates, and PBI scores) in the reactive encouraged training group than in the traditional and balanced conditions where the A cue predicts a specific response with a high conditional probability. That is, both adults and 9- to 10-year-olds engage proactive control when the task cue serves as a valid cue for deciding a response, whereas they engage reactive control when the task cue is non-predictive. The results of Experiment 3 with adults were consistent with those of Redick et al. (2014) while Experiment 4 with children extended these findings to school-aged children.

Positive transfer effects of task knowledge

In the studies employing the cued task-switching paradigm, we found clear positive transfer effects from the training phase to the test phase among the proactive possible training groups. These positive transfer effects in adults were observed in response times in Experiments 1 and 5 and in correct response rates in Experiment 5; positive transfer effects in 9- to 10-year-olds were observed in response times and correct response rates in Experiments 2 and 6 (see Table 1). Consistent with previous studies (e.g., Bhandari & Badre, 2018; Sabah et al., 2021; Yanaoka et al., 2022), Experiments 1 and 2 demonstrated that both adults and children show positive transfer effects across common task environments with different stimuli. Although these transfer effects are potentially confounded with any underlying practice effects, we assume that in these experiments both adults and 9- to 10-year-olds are able to learn a collective body of task knowledge, which includes knowledge of task representations and knowledge of the temporal structure of task goal activation. Such task knowledge helps both adults and children to exert cognitive control more efficiently in the test phase with different materials, compared to in the training phase. Specifically, *knowledge of task representations* concerns knowledge of a task goal and stimulus–response mappings that are tied to that goal. Conversely, *knowledge of the temporal structure of the activation of task goals* concerns knowledge about when individuals activate a task goal to engage cognitive control. However, on the basis of this particular result it is difficult to specify precisely what type of task knowledge is positively transferred to support the engagement of cognitive control (e.g., knowledge of task representations vs. knowledge of the temporal structure of task goal activation). Given this limitation, it is important that Experiments 5 and 6 revealed the novel finding that both adults and 9- to 10-year-olds showed positive transfer effects across task environments with both different stimuli and different task goals. We can therefore argue that any collective body of task knowledge is distinct from specific task goals and stimulus-response mappings.

Experiments 3 and 4 provide further evidence that clarifies how learning a collective body of task knowledge positively affects cognitive control in a subsequent condition. In Experiment 4, we observed that school-aged children showed positive transfer effects on direct measures of using proactive/reactive control in the AX-CPT. Specifically, in the test phase children in the traditional and balanced training groups showed more of a tendency to engage proactive control (i.e., higher PBI scores) compared to in the training phase. Thus, it appears that learning a collective body of task knowledge leads to a further shift towards engaging proactive control as well as efficient engagement of cognitive control (e.g., faster response times) in the similar-structured task with different stimuli. Indeed, recent studies showed that prior task experience boosts proactive control engagement in 5-year-olds who begin to engage proactive control

(Yanaoka et al., 2022) and in 4- to 6-year-olds (Gonthier & Blaye, 2022). In contrast, Experiment 3 did not observe consistent positive transfer effects in adults across training and test phases (i.e., no significant differences in PBI scores). However, consistent with the experiments using the cued task-switching paradigm, adults' overall performance was faster in the test phase than in the training phase. Therefore, although prior task experience made their performance more efficient, it might not have changed their cognitive control mode. One potential explanation for the discrepancy between the results of Experiments 3 and 4 is that there might be no room to further increase the use of proactive control, especially for adults who engage proactive control by default.

The absence of consistent evidence of positive transfer across Experiments 3 and 4 means that we cannot strongly argue from this particular aspect of the data that learning a collective body of task knowledge necessarily supports a further shift to proactive control. Rather, the overall pattern of results from the experiments that employed the cued task-switching paradigm provides strong evidence that learning a collective body of task knowledge supports efficient engagement of cognitive control in task environments with different task goals and stimuli.

Negative transfer effects of task knowledge

The most critical finding of the current set of studies was that both adults and 9- to 10-year-olds did show negative transfer effects. Specifically, Experiments 1 and 2, in which the cued task-switching paradigm was employed, revealed slower response times in the test phase performance of the proactive impossible training group than observed in the training phase performance of the proactive possible training group, despite the fact that this analysis compares two "Proactive Possible" conditions. Furthermore, in Experiments 3 and 4, which employed the AX-CPT, there was less evidence of a tendency to engage proactive control in the test phase performance of the reactive encouraged training group than in the training phase performance of the traditional and balanced training groups, despite the fact that these analyses again compare the identical balanced condition.

These consistent findings suggest that both adults and 9- to 10-year-olds do learn knowledge about the temporal structure of task goal activation from prior experience and transfer it to the engagement of cognitive control in different task environments. Specifically, participants in the proactive impossible training groups and in the reactive encouraged training groups appear to learn to activate a task goal at the time of target (probe) onset during the first training phase and continue to exert reactive control in the subsequent test phase. We have therefore demonstrated that both adults and 9- to 10-year-olds learn what approach they take to engage cognitive control from the repetition of task performance and so acquire knowledge of the temporal structure of task goal activation. In terms of adults, these findings are consistent with, and go beyond, previous studies (e.g., Bhandari & Badre, 2018; Sabah et al., 2021). Those studies demonstrated negative transfer effects using a working memory task, whereas we have extended this work by showing comparable results using the cued task-switching paradigm and the AX-CPT. In terms of developmental differences, the current study provides the first evidence of the successful learning of task knowledge of the temporal structure of activation of task goals in children, albeit among relatively old (9-to 10-year-old) children. Compared with adults, the degree of negative transfer seen in children was similar. Thus, it appears that by the middle school ages, children are capable of learning the temporal structures of a cognitive control task and using this knowledge to regulate their cognitive control engagement in a similar task. Given the absence of age differences, it is possible that this abstract task knowledge is learnt implicitly and automatically triggers the engagement of cognitive control (see, Botvinick et al., 2001; Gonthier et al., 2021). Indeed, recent studies of adaptive control have demonstrated that school-aged children as well as preschoolers can implicitly learn the probability of occurrence of incongruent/switch trials and use this information to adjust their level of control (e.g., Gonthier et al., 2021; Lucenet & Blaye, 2023). Future work could examine whether the findings of this study are applicable to preschoolers, and whether acquiring task knowledge about cognitive control engagement is truly implicit, as appears to be the case for the learning mechanism behind adaptive control.

Another issue for further consideration is whether a switch from the training phase to the test phase temporarily delays participants' overall response times, which potentially leads to what might appear to be negative transfer effects being observed in the cued task-switching paradigm. However, the AX-CPT allows us to index the use of proactive/reactive control through a comparison of responses across specific trial types, not overall response times. Thus, even accounting for the possibility of a surprising element of the switch from the training phase to the test phase, our findings with the AX-CPT established a direct link between observed negative transfer effects and the use proactive/reactive control.

Conversely, one might argue that when participants recognize that tasks used in the training and test phases are not subjectively different, changes in performance from the training phase to the test phase cannot be described as 'transfer'. For example, participants could not be aware of forthcoming changes in trial type frequencies in the AX-CPT before starting the test phase, and might take time to notice any change in frequency as the test phase progresses. However, awareness of the differences between the training and test phase is not a requirement for the establishment of transfer. That is, regardless of whether participants recognize the differences between the training and test phase, transfer arises when they apply an approach learned in the training phase to a subsequent test phase with different stimuli. Therefore, our findings with the cued task-switching and the AX-CPT can be regarded as evidence for positive and negative transfer effects.

This work also found clear evidence for the hierarchical structure of task knowledge. Specifically, Experiments 5 and 6 demonstrated that adults showed significant negative transfer effects across task environments with different task goals and stimuli, while 9- to 10-year-olds did not. However, further exploratory analyses revealed no significant developmental differences in the degree of these negative transfer effects. We therefore discuss findings from Experiment 5 and 6 with a view of general cognitive processes, not through the lens of developmental differences. The cued task-switching paradigm used in the current work has a hierarchical structure. The highest level is using a contextual cue that indicates a task goal, a middle level is performing a task to sort bidimensional stimuli based on the goal, and a lower level is selecting one corresponding key based on stimulus-response mappings. Learning knowledge of the temporal structure of task goal activation requires participants to learn the pattern of when they activate task goals based on the cue, which happens at the top level of this task structure. Furthermore, to transfer knowledge of the temporal structure of task goal activation to task environments with different task goals and stimuli, individuals are further required to update and maintain abstract representations of task goals (middle level) and stimulus-response mappings (lower level). It can therefore be inferred that individuals update and maintain abstract representations of all levels of the hierarchical task structure while performing the cued task-switching paradigm. As a result, they learn hierarchical task knowledge, which is independent from specific task goals and stimulus-response mappings, and transfer this knowledge (on occasion, negatively) to a similar-structured condition with different task goals and stimuli.

It is worth noting that the degree of negative transfer effects differed between the cued task-switching paradigm and the AX-CPT. Negative transfer effects within the cued task-switching paradigm were clearly present at earlier trials, but they reduced very quickly in adults, and in 9-to 10-year-olds in Experiment 2. In contrast, negative transfer effects within the AX-CPT did not change in size across blocks. It is possible that the size of the negative transfer effect depends on how easy it is for participants to notice the effectiveness of using proactive control during the test phase. Specifically, within the test phase of a cued task-switching paradigm, cue stimuli are always valid and available, thus it may be relatively easy for participants to notice the effectiveness of processing the cue in advance. As a result, it is possible that participants in the current study recognized that using reactive control was not the most adaptive strategy in the latter "Proactive Possible" condition and switched to using proactive control to be more adaptive to the environment. Consistent with this possibility, it has been demonstrated that both adults and school-aged children are capable of engaging in metacognitive processes, in which they judge whether to use a cognitive strategy depending on its effectiveness for solving a problem (e.g., Chevalier et al., 2020; Niebaum et al., 2019, 2021; O'Leary & Sloutsky, 2017). In contrast, as mentioned above, in the test phase of the AX-CPT, it might be difficult to be aware of changes in the proportion of trial type frequency as such awareness presumably requires the integration of information across a series of successive trials. As a result, participants may never recognize that using reactive control is not the most adaptive strategy in the latter balanced condition. Perhaps implementing more trials would help participants evaluate the effectiveness of a cognitive control strategy, leading to the eventual reduction of negative transfer effects. These findings therefore indicate the need to consider the relation between the degree of transfer effects and experimental paradigms in future studies.

Clarifying the nature of task knowledge (i.e., the extent to which it is hierarchically and temporally structured) provides two theoretical and practical implications for cognitive control training studies. First, focusing on the temporal structure of task knowledge encourages attention to negative as well as positive transfer effects. Most cognitive control training studies have explored whether or not cognitive training leads to positive transfer effects. However, the current work and other recent studies have demonstrated that repeated practice of a cognitive task does not necessarily bring positive outcomes when considering the validity of newly acquired task-specific skills (Bustamante et al., 2021; Ni et al., 2023). These findings confirm that acquiring knowledge of the temporal structure of task goal activation impairs task performance in any subsequent condition where such knowledge is not optimal. Thus, when researchers and practitioners build a training program, they need to consider how individuals approach the process of cognitive control in accordance with dynamical task structures and whether acquired task knowledge can be successfully used in any subsequent condition. Such investigations of negative transfer effects would have important practical implications for the application of cognitive control training programs to educational and clinical fields.

Second, one can analyze whether transfer effects occur or not from the perspective of the nature of task knowledge. Cognitive control training studies often report that benefits from training a cognitive control task extend only to different tasks with structures similar to those of the training task, that is near transfer effects (e.g., Holmes et al., 2019; Melby-Lervåg & Hulme, 2013; Soveri et al., 2017). Therefore, it is useful to consider what factors determine the similarity of task structure to clarify the cognitive mechanism underlying near transfer effects. Based on our findings, hierarchical and temporal features will be factors that determine the similarity of task structures. Specifically, even if a trained task and a transferred task appear to be very similar, their different temporal structures may impair near transfer. In contrast, a similar hierarchical structure will promote near transfer, even if the trained task and the transferred task look very different. Although recent studies have started to focus on the hierarchical structure of tasks (Byrne et al., 2020; Holmes et al., 2019; Rennie et al., 2021), more work considering the temporal aspects of task knowledge is needed. Specifically, one might examine whether cross-paradigm transfer effects occur between different experimental paradigms that share temporal aspects of task knowledge (e.g., the AX-CPT and the cued task-switching paradigm). Although it makes more sense to establish transfer within a paradigm before investigating cross-paradigm transfer, this investigation would be an interesting next step to further clarify the cognitive mechanisms underlying the transfer of cognitive control training.

Conclusion

The current work provides a set of novel findings. In both the cued task-switching paradigm and the AX-CPT, prior task experience supports efficient engagement of cognitive control in task environments with different stimuli in both adults and 9- to 10-year-olds, that is, positive transfer effects are seen. A key finding was that prior task experience of engaging reactive control makes both adults and 9- to 10-year-olds respond in a reactive manner in a subsequent similar-structured task with different stimuli, in which they could otherwise engage proactive control. The degree of such negative transfer effects depends on the nature of the experimental paradigm. These findings suggest that individuals learn knowledge of the temporal structure of task goal activation through previous task experience and, on occasions, negatively transfer such knowledge.

Furthermore, even when different task goals and stimuli are employed, individuals can transfer task knowledge of how to engage cognitive control positively and negatively, indicating the hierarchical structure of task knowledge. Taken together, these novel findings substantially extend our understanding of the mechanisms supporting the transfer of prior task knowledge to novel situations in adults and children.

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