Manuscript accepted for publication at *Journal of Experimental Psychology: General*.

Manuscript accepted for publication at *Journal of Experimental Psychology: General*.

Interference and Integration in Hierarchical Task Learning

Woo-Tek Lee[1,2,3], Eliot Hazeltine[1,2] and Jiefeng Jiang[1,2]

[1]Cognitive Control Collaborative, University of Iowa, Iowa City, IA 52242

[2]Department of Psychological and Brain Sciences, University of Iowa, Iowa City, IA 52242

[3]Behavioral-biomedical Interface Training Program, University of Iowa, Iowa City, IA 52242

Corresponding author:

Jiefeng Jiang, PhD

Department of Psychological and Brain Sciences

Cognitive Control Collaborative

University of Iowa

Iowa City, IA 52242

jiefeng-jiang@uiowa.edu

Author note

All data ana analysis scripts related to this paper are available in Open Science Framework at (https://osf.io/pu2fw/?view_only=43227ca6ef4149e9a9ef9ff011daae09). The authors declare there is no prior dissemination of the data and there is no known conflict of interest to disclose.

Acknowledgment

We thank the members of the Cognitive Control Collaborative for helpful discussions.

Word Count: 11,921

Abstract

A key feature of human task learning is shared task representation: Simple, subordinate tasks can be learned and then shared by multiple complex, superordinate tasks as building blocks to facilitate task learning. An important yet unanswered question is how superordinate tasks sharing the same subordinate task affects the learning and memory of each other. Leveraging theories of associative memory, we hypothesize that shared subordinate tasks can cause both interference and facilitation between superordinate tasks. These hypotheses are tested using a novel experimental task which trains participants to perform superordinate tasks consisting of shared, trained subordinate tasks. Across three experiments, we demonstrate that sharing a subordinate task can (1) impair the memory of previously learned superordinate tasks and (2) integrate learned superordinate tasks to facilitate new superordinate task learning without direct experience. These findings shed light on the organizational principles of task knowledge and their consequences on task learning.

Keywords: Task learning, generalization, integration, proactive interference, retroactive interference

Introduction

Humans are able to learn and retain a large number of tasks. Each of us is proficient in a wide array of tasks and can leverage this knowledge to acquire new skills. In fact, most new skills we develop involve components of already mastered abilities. For example, learning to play pickle ball may tap our knowledge of tennis and volleyball and learning how to use new teleconference software is faster for a person who already knows how to use a webcam. However, how the memory of tasks is organized to support the efficient transfer of task learning remains largely unknown.

In theory, learned tasks can be used as building blocks to accelerate the learning of more complex tasks (Musslick & Cohen, 2021; Musslick et al., 2017). Moreover, reusing learned task knowledge can reduce redundancy in task representation (e.g., remove the need to store a separate copy of the knowledge of webcam operation for every task using a webcam). This organizational principle that superordinate tasks can share subordinate tasks leads to a hierarchical architecture of task representations, similar to hierarchical representation of knowledge within a task (Collins, Cavanagh, & Frank, 2014; Kikumoto & Mayr, 2018; Schumacher & Hazeltine, 2016) and the proposed hierarchical organization of the prefrontal cortex (Badre, 2008; Badre & Nee, 2017; Koechlin & Summerfield, 2007). However, little empirical work has examined how shared components of tasks affects their learning.

Sharing a subordinate task representation makes superordinate tasks interdependent. It is currently unknown whether/how this interdependency affects memory organization of superordinate tasks. Conceptually, a superordinate task should consist of associations among subordinate tasks. Therefore, leveraging concepts from the associative memory literature, we hypothesize that two mnemonic effects will occur when superordinate tasks share subordinate tasks. First, sharing a subordinate task may cause interference between superordinate tasks, as

in memory interference effects (e.g., Badre & Wagner, 2005; Bramao, Jiang, Wagner, & Johansson, in press; Darby & Sloutsky, 2015; Martínez, Villar, Ballarini, & Viola, 2014; Underwood, 1957; Wixted, 2004). Specifically, if two superordinate tasks are learned sequentially, the memory of the first superordinate task may interfere with the learning of the second superordinate task, a phenomenon termed proactive interference. Moreover, the learning of the second superordinate task may also impair the memory of the first superordinate task, a phenomenon termed retroactive interference.

Second, sharing a subordinate task may cause the integration of the two superordinate tasks, leading to (indirect) associations among their non-overlapping subordinate tasks, analogous to computational simulations of partially overlapping associative memories (Kumaran & McClelland, 2012). This integration may facilitate the learning of a new superordinate task consisting of the non-overlapping subordinate tasks. In this way, task learning can occur without direct experience (i.e., transfer or zero-shot learning, see Bejjani, Zhang, & Egner, 2018; Jiang et al., 2020; Koster et al., 2018; Kuhl, Shah, DuBrow, & Wagner, 2010; Shohamy & Wagner, 2008; Wimmer & Shohamy, 2012; Zeithamova, Dominick, & Preston, 2012; Zeithamova & Preston, 2010). For example, superordinate tasks AB (i.e., consisting of subordinate tasks A and B) and BC can be integrated by their shared subordinate task B. This integration will facilitate the learning of a new superordinate task AC, as A and C have been associated by integration.

To test these hypotheses, we designed a novel hierarchical task learning paradigm with superordinate tasks that consist of shared subordinate tasks (Figs. 1 and 2). We first validate the learning of subordinate and superordinate tasks in Experiment 1. Importantly, we demonstrate that learning of superordinate tasks involves encoding of associations between involved subordinate tasks. We then show retroactive interference and integration effects in

hierarchical task learning in Experiment 2a. The findings are replicated in Experiment 2b. These findings further demonstrate how partially overlapping between-subordinate task associations, established from superordinate task learning, can affect the learning and memory of complex tasks. Taken together, we extend classic effects in declarative memory (e.g., association, interference and generalization) to memory of skills. These findings indicate that the two different types of memory may share similar underlying mechanisms. These findings also shed light on the organizational principles of task knowledge and their consequences on task learning.

Experiment 1

In a hierarchical organization of task knowledge, learning of superordinate task can benefit from reusing knowledge of learned subordinate tasks. It remains unclear whether learning occurs at the superordinate task level. On the one hand, the superordinate task can be viewed as a collection of subordinate tasks. If all subordinate tasks are learned, no learning is needed at the superordinate task level. On the other hand, superordinate task may maintain a task structure of compositional relations to subordinate tasks. Performing superordinate tasks may cause learning at the superordinate task level (e.g., strengthening compositional relations). We address this question by testing (1) whether participants can learn the subordinate and superordinate tasks with the experimental procedure and (2) whether the learning of superordinate tasks occurs at the superordinate level (e.g., not only due to performance improvement in subordinate tasks) while controlling for performance at subordinate level and stimulus and response configuration learning. To preview the results, our findings are consistent with both forms of learning. To our knowledge, this provides the first evidence supporting the notion that the learning of complex tasks involves strengthening of their

compositional information at superordinate level and learning at subordinate task level, thus supporting the proposal that tasks can be hierarchically represented.

Method

Participants.

For this experiment, the target sample size was 50 based on a previous study on generalization effect of cognitive control (Jiang et al., 2020). A total of 58 participants completed the experiment through Amazon's Mechanical Turk online, with monetary compensation of $8 for the whole experiment. Eight participants were removed from analysis due to technical difficulty during data transmission (1 participant), low accuracy (below 60%) in either phase (5 participants), in test stage, or due to more than half of trials in any of the blocks in superordinate task phase being removed in data trimming process (2 participants; see below). The final sample consisted of 50 participants (21 females, 29 males; age: M = 34.80 years, sd = 9.75). The study was approved by the University of Iowa Institutional Review Board.

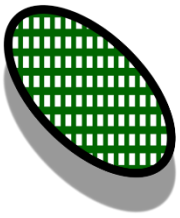
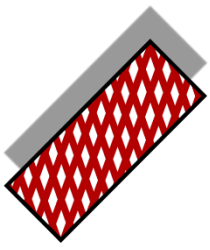
Features	Word Cues	Image Cues	Sample Target Stimuli
1. Shape	Oval or Rectangle		
2. Outline	Thick or Thin		
3. Color	Green or Red		
4. Fill	Parallel or Diagonal		
5. Shadow	Down or Up		
6. Tilt	Left or Right		

Figure. 1. Stimulus features and cues and target stimuli used in all experiments. There were six stimulus features with two possible values each. Cue stimuli indicated one stimulus feature presented as text or image. The presentation type (text or image) was randomized on each trial. Target stimuli (see rightmost column for two examples) consisted of all six stimulus features.

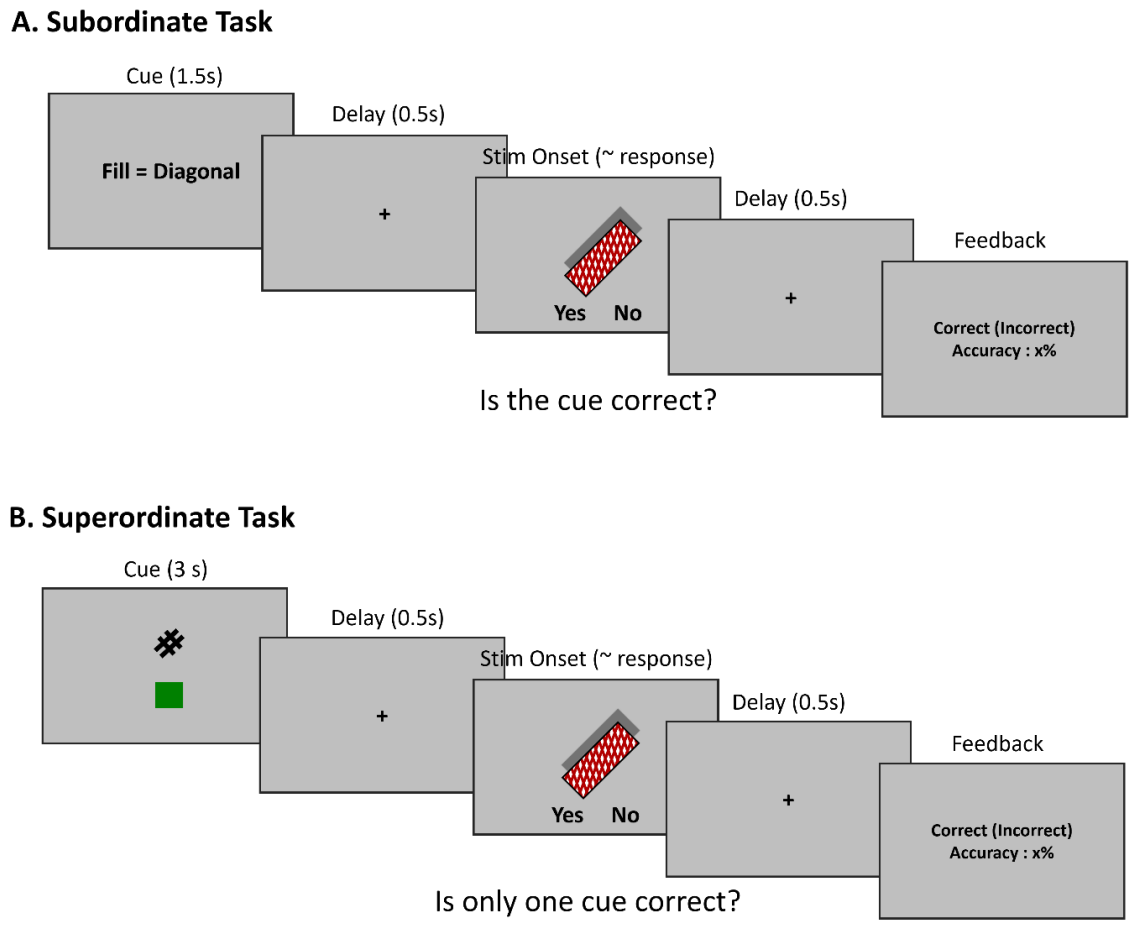


Figure 2. Trial structure of subordinate and superordinate tasks. (A) Illustration of a subordinate task. In subordinate tasks, participants first encounter a single cue that contains prediction of upcoming stimulus. After 0.5 s, participants see the actual stimulus and decide whether the cue correctly described the stimulus by pressing 'D' or 'F' key. After the response, visual feedback is provided. (B) Illustration of a superordinate task. Here, participants encounter two cues simultaneously, and each cue contain different feature

prediction of upcoming stimulus. After a 0.5 s delay, participants see the stimulus and decide whether only one cue is correct. The rest of the design is identical to the subordinate task.

Stimuli

The stimuli consisted of six features, each with two possible values (Fig. 1). The features and their possible values were: shape (oval or rectangle), color (green or red), outline (thick or thin), shadow (cast upward or downward), tilt (clockwise or counterclockwise) and fill pattern (parallel or diagonal). The cue stimuli indicated the value of one feature. The task stimuli are combinations of all six features. This design leads to 64 (2^6) unique target stimuli. The size of the target stimuli was 177 (width) by 280 (height) pixels. The size of image cues was approximately 43 (width) by 58 (height) pixels. The size of font for text cues was 40 pixels.

Procedure

Four features were randomly chosen from the six features as task-relevant features for each participant, so only four subordinate tasks were used. Participants started the experiment by reading the instructions presented on the screen with multiple slides. They then completed two phases: a subordinate task phase (4 blocks of 64 trials each) followed by a superordinate task phase (6 blocks of 48 trials each). The blocks were separated by a self-paced rest period and then a 5-second on-screen countdown to the next block.

For the subordinate task phase, each trial started with the presentation of a cue stimulus indicating a single feature value for 1,500 ms (Fig. 2A). This cue could be an image or text. Two cue types were used to make the experiment compatible with future neuroimaging research with decoding analysis as we assume that using two cue types will prevent visual

information of cues from confounding decoding results. Note that we do not expect any behavioral effects influenced by using different cue types in this research. The cue type was randomized on a trial-by-trial basis. The cue stimulus was followed by a blank screen delay of 500 ms. The target stimulus was then presented in the center of the screen and remained until a response was detected.

Participants were required to report whether the cue stimulus correctly predicted the feature in the target stimulus by pressing the appropriate keyboard button ('correct' = 'D', and 'incorrect' = 'K'). This response mapping was constant across-subjects. After the response, a blank screen was presented for 500 ms followed by a feedback screen. The feedback presented the word 'correct' or 'incorrect' based on the correctness of the response. Additionally, starting from the second block, the screen also displayed the participant's overall accuracy in this phase.

For all experiments, subordinate tasks were evenly distributed within each block so that no subordinate task was practiced more than any other. The subordinate task phase trained participants to perform subordinate tasks, which were match/mismatch tasks defined by the cued feature (Fig. 2A shows a fill pattern match/mismatch task).

Note that the subordinate tasks can be represented as either rules or collections of individual cue-stimulus-response associations (Sloman, 1996). However, given the large number of unique cue-stimulus combinations (4 cue dimensions × 2 levels/cue × 64 stimuli), rule representations are more likely used in this study. We assume that, for the subordinate tasks, practice improves the application of these rules to the current stimulus to facilitate performance (Brass, Liefooghe, Braem, & De Houwer, 2017). The rules specify which stimulus features are task relevant and thus can guide cognitive control to direct selective attention to the appropriate feature. Recent theoretical accounts posit that cognitive control is

dynamic and adapts to specific task demands (Ritz, Leng, & Shenhav, 2021; Shenhav, Botvinick, & Cohen, 2013). Within this framework, an important part of learning the subordinate tasks is the optimization of cognitive control of selective attention. Better applied cognitive control will consequently improve performance. Other learning occurring may involve more efficient processing of stimulus and response generation.

The trial structure in the superordinate task phase was identical to the subordinate task phase except for two changes (Fig. 2B). First, two cue stimuli were presented simultaneously instead of one. They predicted the values of two distinct features of the upcoming target stimulus. The presentation duration increased to 3,000ms to give participants more time to process the additional cue. Second, participants were required to make a response using the "exclusive or" rule, that is, whether one and only one of the two cues correctly predicted the target stimulus. In other words, if both cues were correct or if both were incorrect, participants should press the 'K' button. Otherwise, participants were required to press the 'D' button. This rule was chosen to ensure that participants must perform both subordinate tasks (i.e., evaluating both cues) to make the correct response. Tasks performed in this phase were superordinate tasks, which were built upon two practiced subordinated tasks (e.g., Fig. 2B shows a fill pattern-color superordinate task).

The superordinate task phase was further divided into two stages: a learning stage (block 1-4) and a test stage (block 5-6) (Fig. 3A). The structure of the trials was identical for the two stages; only the task combinations differed. In the learning stage, participants performed two superordinate tasks (denoted AB and CD, indicating the subordinate tasks involved) each composed of two of the four subordinate tasks trained in the subordinate task phase (denoted A-D). For all experiments, superordinate tasks were evenly distributed within a block to avoid familiarity with subordinate tasks from confounding performance in superordinate

tasks. In the test stage, participants had already learned superordinate tasks (AB and CD), as well as new superordinate tasks (AC, AD, BC and BD). Learned and new tasks were evenly distributed in this stage to avoid differences in the degree of exposure to subordinate tasks from confounding the superordinate task performance. Importantly, the learned and new superordinate tasks shared the same subordinate tasks and only differed in the composition of their subordinate tasks. Therefore, behavioral difference between learned and new superordinate tasks can only be attributed to the superordinate level of the task representation hierarchy.

The superordinate task was designed to simulate real-life tasks that require completing multiple sub-tasks (e.g., making coffee involves sub-tasks of grinding coffee beans and boiling water.). A key form of learning that is unique to superordinate tasks is the association between subordinate tasks. Specifically, during the execution of a superordinate task, the co-occurrence of the two subordinate tasks will trigger binding between them (DuBrow & Davachi, 2016; Eichenbaum, 2014; Zeithamova & Preston, 2017). The association between subordinate tasks provides structural information for cognitive control to optimize the coordination and execution of the subordinate tasks, leading to performance improvement. Much of the previous research has employed hierarchical rules in which a higher-level rule determines which of the several lower-level rules will be used to generate response (e.g., Badre, Hoffman, Cooney, & D'esposito, 2009; Collins et al., 2014; Theves, Neville, Fernández, & Doeller, 2021). The branching at the higher-level rule will result in only a part of lower-level rules being executed. As our goal is to establish an association between subordinate tasks, we applied an exclusive or rule to ensure that both subordinate tasks must be executed to determine the correct response. As with subordinate tasks, the large number of cue-stimulus combinations make it more likely for the participants to associate the two

subordinate tasks than encoding individual cue-stimulus-response associations.

Data Analyses. We first removed trials that exceed 4,000ms or less than 300ms/500ms for subordinate/superordinate task in response time (RT). Additionally, within each participant, slow trials that had RT above 3 standard deviations from the median were removed. The remaining trials were used in the accuracy analysis. For the RT analysis, only correct trials were used. In all experiments, all statistical tests were two-tailed.

To test the learning effect of subordinate and superordinate tasks, analyses were performed collapsed across tasks. Trimmed data from the subordinate task phase and the learning stage of the superordinate task phase were analyzed using linear mixed model analysis and R software version 4.1.0 (R Core Team, 2020) with lme4 (Bates, Kliegl, Vasishth, & Baayen, 2015). The formula for this analysis is as follows:

$$y_i = (\beta_0 + u_{i1}) + (\beta_1 + u_{i2})x + \epsilon_i$$

where y_i refers to a value of behavior measures (either RT or accuracy) for a participant i. β_0 and β_1 each represent fixed effects for the intercept (β_0) and slope (β_1) that are consistent among participants. Additionally, u_{i1} and u_{i2} represent random effects for the intercept and slope that can vary randomly for each participant. The term x represents block, and ϵ_i reflects a residual effect. In this model, the effect of interest was the fixed-effect of slope, β_1, that indicates how the behavioral measure changes over blocks. Additionally, we conducted logistic mixed effect model analysis to test the learning effect in accuracy over trials more thoroughly (Table S1). Overall, we replicated all the findings from the linear mixed-effect model with averaged accuracy data (see Table S1 in the online supplemental material).

To test the possibility of exponential trend in learning curve, we conducted a non-linear mixed effect model using simple exponential function. The formula for this analysis is

as follows:

$$y_i = (\beta_0 + u_{i1}) - (\beta_1 + u_{i2}) * e^{(\beta_2 + u_{i3}) * x} + \epsilon_i$$

where y_i refers to a value of behavior measures (either RT or accuracy) for a participant i. β_0, β_1, and β_2 each represent fixed effects for the intercept (β_0), saturation point (β_1), and learning rate (β_2) that are consistent among participants. Additionally, u_{i1} , u_{i2}, and u_{i3} represent random effects for the intercept, saturation point, and learning rate that can vary randomly for each participant. The term x represents block, and ϵ_i reflects a residual effect. In this model, the effects of interest were the fixed-effects β_0, β_1, and β_2 that indicate how the behavioral measure changes over blocks. Overall, the non-linear model provided a better fit of the subordinate task RT in Exp1 and Exp2a, and accuracy in Exp 2b. Additionally, we found a better fit of superordinate tasks for RTs in odd blocks of Exp2b. In all other cases, the linear model provided a better fit than the non-linear model. (See Table S2 and S3 in the online supplemental materials). Therefore, there is no conclusive evidence supporting a better fit for the non-linear model.

Crucially, learning of superordinate tasks was further tested between learned and new superordinate tasks in the test stage. To this end, we first tested accuracy between learned and new superordinate tasks using paired t-tests. For RT, a trial-level approach was applied using Matlab 2019b. First, we built a nuisance effect matrix, each row of which represented the trial-wise status of response, response repetition, post-error, cue modality (text or image), task repetition, and cue modality repetition. To remove the influence of individual differences in subordinate tasks and their temporal change on superordinate task RT, eight additional regressors, encoding whether each of the four subordinate tasks was performed on each trial and their temporal drift, were also included in the nuisance effect matrix. The nuisance effect matrix was then regressed against trial-wise RT. To control for the non-normal distribution of

RTs while making the results more interpretable, we computed the median of the residuals for learned and new superordinate tasks for each participant and used the medians of the residuals for paired t-tests. Note that although in theory this trial-level analysis can be applied to accuracy data using logistic regression, the high overall accuracy did not provide sufficient error trials to obtain robust estimates for logistic regression.

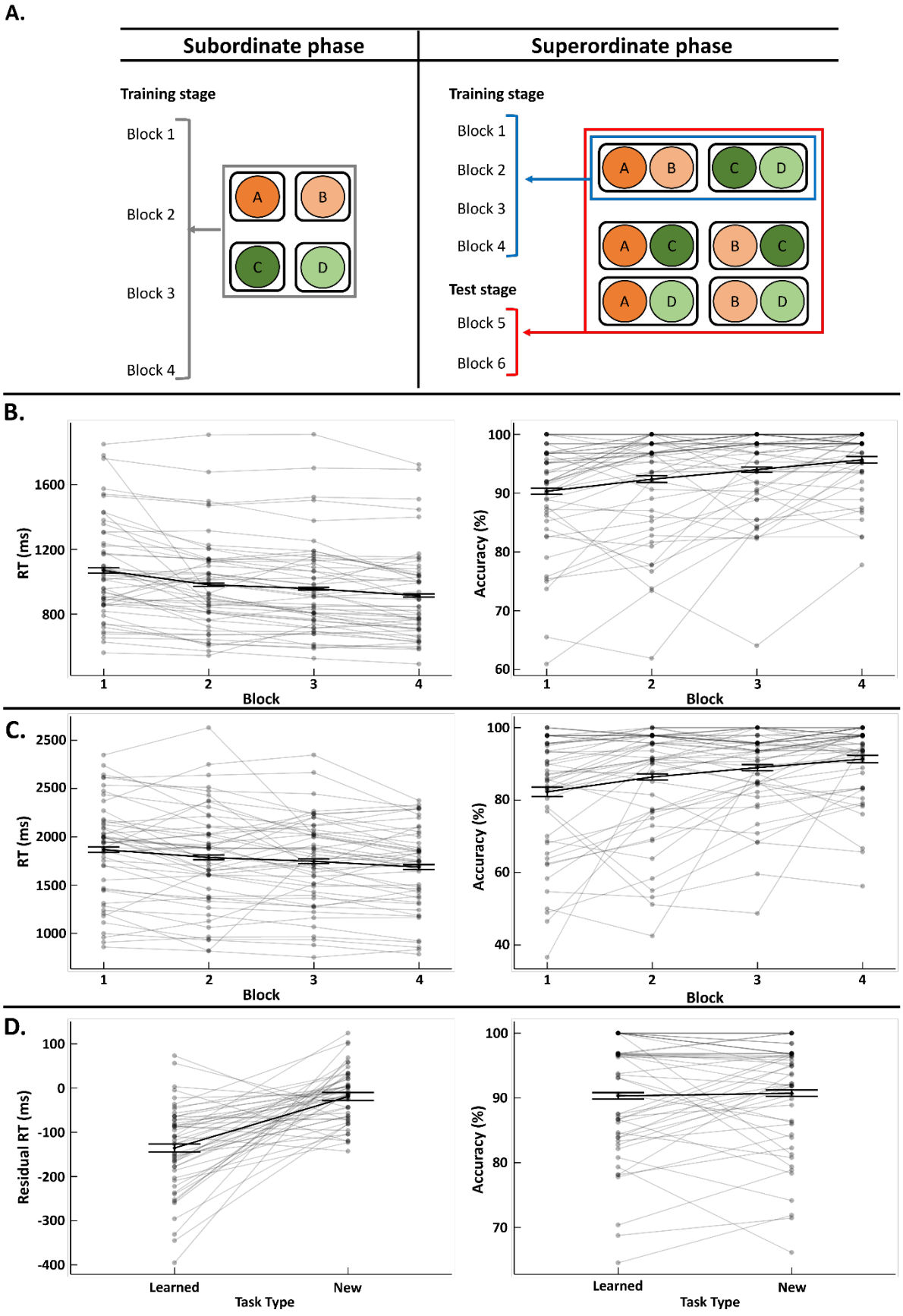

A.
Subordinate phase
Superordinate phase
Training stage
Block 1
Block 2
Block 3
Block 4
A
B
C
D
Training stage
Block 1
Block 2
Block 3
Block 4
Test stage
Block 5
Block 6
A
B
C
D
A
C
B
C
A
D
B
D
B.
RT (ms)
1600
1200
800
1
2
3
4
Block
Accuracy (%)
100
90
80
70
60
1
2
3
4
Block
C.
RT (ms)
2500
2500
2000
1500
1000
1
2
3
4
Block
Accuracy (%)
100
80
60
40
1
2
3
4
Block
D.
Residual RT (ms)
100
0
-100
-200
-300
-400
Learned
New
Task Type
Accuracy (%)
100
90
80
70
Learned
New
Task Type

Figure 3. Design and results of Experiment 1. (A) Illustration of experimental design. (B) Individual RT (left) and accuracy (right) in subordinate task phase, imposed with group mean and SEM plotted as a function of block. (C) Data from the training stage of the superordinate task phase. Panel arrangements are identical to (B). (D) Individual RT (left) and accuracy (right) at the test stage of the superordinate task phase, imposed with group mean and SEM plotted as a function of experimental condition (learned or new tasks).

Table 1.

Exp	Task	Behavior	Training								Test	
			1 Block	2 Block	3 Block	4 Block	5 Block	6 Block	7 Block	8 Block	Learned/Gen	New/Con
Exp1	Sub	RT (ms)	1069.61 (17.11)	981.64 (9.80)	957.00 (8.13)	914.51 (9.95)	NA	NA	NA	NA	NA	NA
		Acc (%)	89.10 (0.55)	91.69 (0.61)	94.04 (0.46)	95.73 (0.60)	NA	NA	NA	NA	NA	NA
	Sup	RT (ms)	1867.59 (29.36)	1786.67 (24.68)	1747.27 (24.24)	1687.70 (25.39)	NA	NA	NA	NA	-135.46 (8.98)	-19.18 (8.98)
		Acc (%)	82.29 (1.29)	86.39 (0.86)	88.97 (0.86)	91.35 (1.02)	NA	NA	NA	NA	90.31 (0.49)	90.72 (0.49)
Exp2a	Sub	RT (ms)	1046.12 (23.50)	952.10 (23.51)	867.62 (11.72)	846.01 (12.34)	820.24 (9.33)	831.64 (8.98)	798.45 (12.23)	781.14 (13.14)	NA	NA
		Acc (%)	87.08 (1.01)	90.01 (0.70)	90.25 (0.50)	90.94 (0.64)	92.44 (0.60)	92.71 (0.57)	92.79 (0.50)	93.48 (0.52)	NA	NA
	Sup	RT (ms)	1811.19 (25.95)	1752.69 (25.59)	1739.49 (15.76)	1667.07 (17.21)	1699.61 (22.29)	1573.45 (21.01)	1624.94 (18.42)	1554.71 (16.59)	-87.36 (10.18)	-43.32 (10.18)
		Acc (%)	81.30 (1.43)	86.24 (1.29)	88.58 (0.82)	89.75 (0.97)	88.55 (0.76)	90.64 (0.85)	88.81 (0.84)	91.61 (0.83)	87.03 (0.44)	86.72 (0.44)
Exp2b	Sub	RT (ms)	1291.88 (17.09)	1144.30 (13.86)	1134.05 (10.68)	1107.70 (9.16)	1077.94 (11.58)	1064.67 (10.93)	1041.96 (14.62)	1052.33 (12.23)	NA	NA
		Acc (%)	90.92 (0.74)	92.79 (0.49)	94.12 (0.33)	93.47 (0.39)	94.24 (0.35)	94.76 (0.41)	93.88 (0.46)	95.06 (0.44)	NA	NA
	Sup	RT (ms)	2130.24 (27.78)	1995.89 (34.40)	2018.85 (22.07)	1911.98 (14.20)	1976.36 (22.07)	1884.62 (18.10)	1973.40 (19.39)	1908.01 (17.87)	-75.67 (11.30)	-47.19 (11.30)
		Acc (%)	86.89 (0.89)	91.89 (0.47)	89.46 (0.55)	92.17 (0.60)	90.53 (0.53)	92.50 (0.50)	91.52 (0.72)	91.90 (0.60)	89.06 (0.40)	88.63 (0.40)

Summary statistics of behavioral performance as a function of block (for training stage) and condition (for test stage). For test phase, residual RTs are shown. NA = not appliable; Sub = subordinate task phase; Sup = superordinate task phase; Learned = learned superordinate tasks in Exp 1; New = new superordinate tasks in Exp 1; Gen = generalizable superordinate tasks in Exp 2a and 2b; Con = control superordinate tasks in Exp 2a and 2b.

Results

Subordinate task phase.

Figure 3B and Table 1 show performance change as a function of block in subordinate task phase. A linear mixed-effect model analysis revealed significant negative slope of RT (t_{50} = -6.76, $p < .001$, Cohen's d = 0.97) and positive slope of accuracy (t_{50} = 5.37, $p < .001$, Cohen's d = 0.76) as a function of block, indicating improved performance over time. A logistic mixed effect model with trial-wise accuracy data also showed same result (z_{50} = 6.61, $p < .001$, Cohen's d = 0.94). Additionally, a nonlinear mixed-effect model analysis with exponential function also revealed significant saturation point and learning rate for RTs , but not for accuracy. Statistics are provided in the online supplemental materials (Table S2 and S3).

Superordinate task phase.

Figure 3C and Table 1 show performance change as a function of block in the learning stage (block 1-4) of superordinate task phase. Overall, participants' performance improved across blocks, supported by a linear mixed-effect model analysis showing statistically significant decrease in RT (t_{50} = -3.22, p = .002, Cohen's d = 0.46) and increase in accuracy (t_{50} = 4.45, $p < .001$, Cohen's d = Cohen's d = 0.64) over time. A logistic mixed effect model with trial-wise accuracy data showed same result (z_{50} = 5.47, $p < .001$, Cohen's d = 0.78). Additionally, a

nonlinear mixed-effect model analysis with exponential function revealed significantly different saturation point from zero for both RTs and accuracy but only significantly different learning rate from zero for RTs. Additional analysis on Akaike information criteria (AIC) and Bayesian information criteria (BIC) showed better fitness of linear model than exponential model in all types of blocks in superordinate tasks (Table S3). Statistics are provided in the online supplemental materials (Table S2 and S3).

Critically, we compared performance between learned and new superordinate tasks in the test stage (block 5-6) of the superordinate task phase (Fig. 3D, Table 1). Participants showed significantly faster residual RTs for learned than new superordinate tasks (t_{49} = -6.54, $p < .001$, Cohen's d = 0.93). Accuracy showed no significant difference between conditions (t_{49} = -0.42, p = .677, Cohen's d = 0.06). Given that the learned and new superordinate tasks were built upon the same subordinate tasks, shortened RT in learned subordinate tasks provides strong support for learning at the superordinate task level and the encoding of associations between included subordinate tasks during the learning of a superordinate task.

To rule out the possibility that participants learned superordinate tasks independent of subordinate tasks rather than forming a hierarchy in task representations, we compared performance of the learned superordinate tasks in block 2 and new superordinate tasks in block 5. Specifically, if superordinate task learning occurred independently from subordinate task learning and the learning of other superordinate tasks, performance of new superordinate task in block 5 should not benefit from the extra practice of subordinate tasks in blocks 1-4 of the superordinate task stage. Consequently, task performance for new superordinate tasks in block 5 would be expected to be comparable to that of learned superordinate task performance in block 2. A simple t-test for this hypothesis did not support the independent learning hypothesis, as it showed significantly higher accuracy for new superordinate tasks in

block 5 than the learned superordinate tasks in block 2 (t_{49}=2.31, p = .025), while showing non-significant difference in RTs (t_{49}=-0.67, p>.50). This analysis further supported the hypothesis that participants learned superordinate tasks by leveraging learned subordinate task knowledge.

However, one could also argue that better performance in the new superordinate tasks in block 5 compared to the learned superordinate tasks in block 2 might stem from subjects have more exposure to the superordinate task procedure in block 5 than in block 2. To rule out this possibility, we conducted Experiment S1. Experiment S1 further supported hierarchical task representation hypothesis by showing significantly higher accuracy (t_{24} = 2.31, p = .030) in a superordinate task that consisted of already learned subordinate tasks compared to a superordinate task that consisted of new subordinate tasks. Residual RTs showed a non-significant difference (t_{24} = -0.31, p = .760) between two conditions (Fig S1). See Exp. S1 and Fig. S1 in the online supplemental material for detailed information.

The finding that task learning occurs at both superordinate and subordinate levels also provides to our knowledge the first direct evidence for the encoding of association between subordinate tasks in hierarchical task representation. Thus, Experiment 1 set the stage for using task associations to investigate the organizational principles of complex task representations (e.g., how does sharing a subordinate task affect the learning and memory of superordinate tasks?).

Experiment 2a

In Experiment 2a, we built on the findings from Experiment 1 that supported associations between subordinate tasks and investigated how these associations can organize the memory

of superordinate tasks by testing the task interference and integration hypotheses. That is, we examined whether two superordinate tasks sharing a subordinate task (e.g., AB and BC) (1) interfere with the learning of each other and (2) link their non-overlapping subordinate tasks (e.g., A and C) to facilitate the learning of a new superordinate task (e.g., AC) consisting of these non-overlapping subordinate tasks.

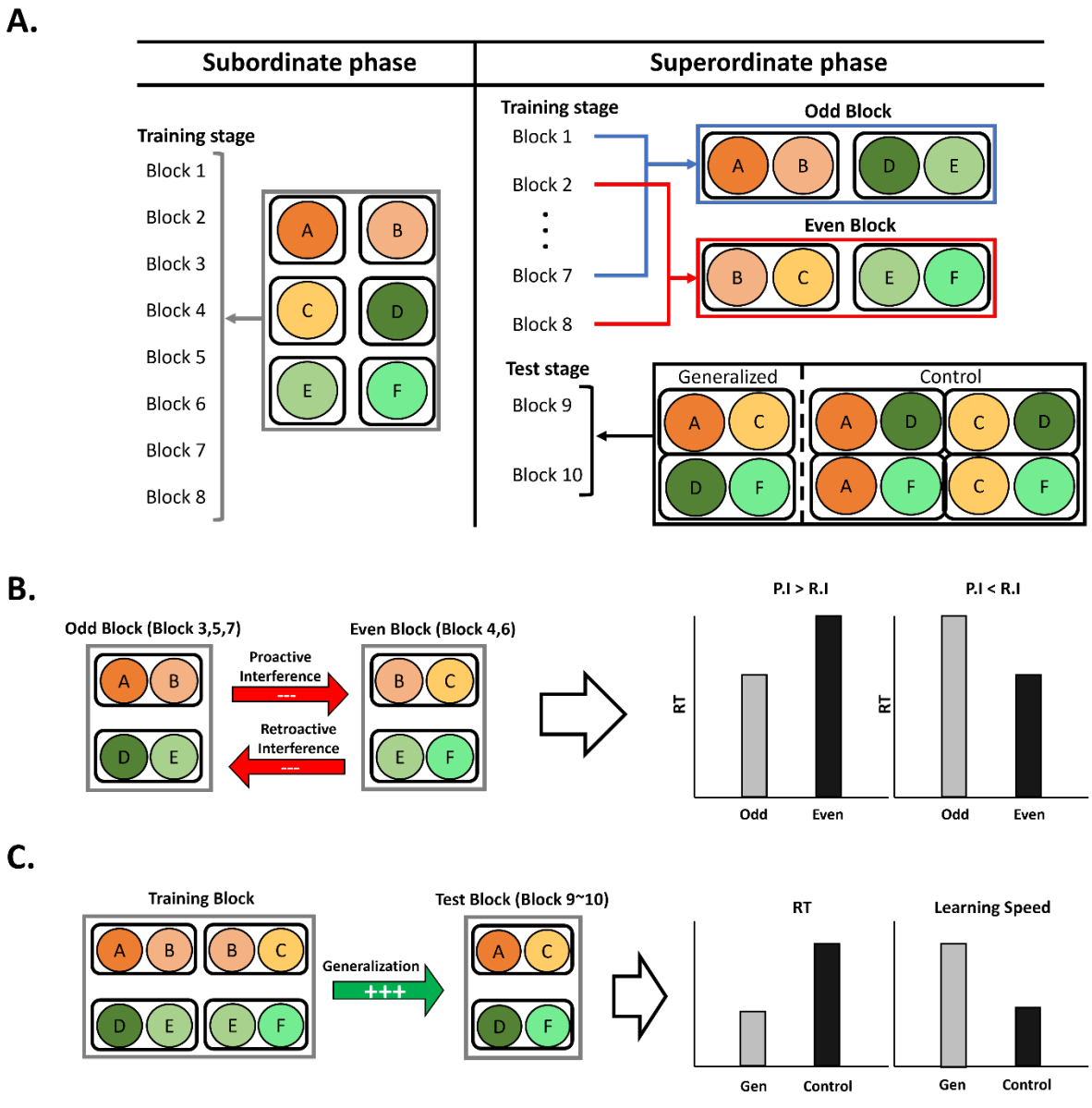


Figure 4. Design and illustration of predictions of Experiment 2a and 2b. (A) Illustration of experimental design. (B) Predictions for proactive and retroactive interference effect in

training stage of superordinate phase. If proactive interference is stronger than retroactive interference, there should be higher RT for even than odd blocks, and the opposite if retroactive interference is stronger. (C) Predictions for generalization effect in test stage. If generalization facilitates learning new tasks as predicted by integration, faster RT in and faster learning speed are expected in generalizable tasks than control tasks. P.I. = proactive interference; R.I. = retroactive interference.

Method

Participants

The target sample size was 50 as in Experiment 1. A total of 68 participants completed the experiment through Amazon's Mechanical Turk online, with monetary compensation of $12 for the whole experiment. Eighteen participants were removed from analysis due to technical difficulty during data transmission (3 participant), low accuracy (below 60%) in either phase (6 participants), in test stage (2 participants), or due to more than half of trials in any of the blocks in superordinate task phase is removed in data trimming process (7 participants). The final sample consisted of 50 participants (25 females, 25 males; age: M = 31.06 years, sd = 11.36). The study was approved by the University of Iowa Institutional Review Board.

Stimuli

The stimuli were identical to Experiment 1.

Procedure

The same six subordinate tasks from Experiment 1 were used for all participants. The phases in the experiment were identical to Experiment 1 except for the number of blocks and trials.

Participants completed 8 blocks of 64 trials each for the subordinate task phase and 10 blocks of 48 trials each for the superordinate task phase. The superordinate task phase was divided into two separate stages: a learning stage (block 1-8), and a test stage (block 9-10) (Fig. 4A). In the learning stage, participants encountered two superordinate tasks in each block, and the composition of superordinate tasks alternated between odd (AB and DE) and even blocks (BC and EF). The interleaving procedure allows us to test proactive interference (how AB and DE impair performance of BC and EF) and retroactive interference (how BC and EF impair performance of AB and DE).

Because superordinate tasks AB and BC share the subordinate task B, we predict that the learning of AB and BC will cause A and C to be linked and that this will lead to facilitation in the learning of superordinate task AC (i.e., generalization). Similarly, we predict that task DF is generalizable from learning DE and EF based on the shared subordinate task E. This prediction was tested in the test stage, in which participants encountered two generalizable superordinate tasks (AC and DF). They also performed control superordinate tasks (AD, AF, CD, and CF), whose composition of subordinate tasks is not predicted by integration. Importantly, both the generalizable and control superordinate tasks were never presented to participants prior to the test stage. Furthermore, both generalizable and control superordinate tasks shared the same subordinate tasks and were evenly distributed within each block. Therefore, the generalizable and control superordinate tasks only differed in their composition of subordinate tasks (i.e., whether the composition can be inferred from learned superordinate tasks).

Data Analyses. Analyses on learning effects in subordinate task phase and learning stage of subordinate task phase were identical to those in Experiment 1 with one exception: We separated odd blocks and even blocks in learning stage for linear mixed-effect model analysis

due to the interleaved design.

To test interference effects, we compared performance between odd (AB and DE tasks) and even (BC and EF tasks) blocks in the learning stage of the superordinate task phase (Fig. 4B). Better performance in odd than even blocks would support the notion of proactive interference (e.g., task AB, which was learned earlier, impairs the learning of task BC). The opposite pattern can be viewed as evidence for retroactive interference (e.g., learning of task BC compromises memory of task AB). Note that this analysis tests the net effect of proactive and retroactive interference. That is, while a significant result will support the presence of one interference effect, it does not rule out the presence of the other interference. In this analysis, the first two blocks were excluded to remove the confound of initial learning of the superordinate tasks. The last block was removed to balance the temporal order of odd and even blocks. In other words, blocks 3-7 were used so that both odd and even blocks had the same temporal center (i.e., both odd and even blocks centered at block 5), thereby controlling for the potential confound of time. Difference in accuracy between odd and even blocks was tested using paired t-test at the group level. For RT analysis, as in Experiment 1, trial-wise status of response, response repetition, post-error, cue modality (text or image), task repetition, and cue modality repetition were regressed out. The difference in the RT residuals between odd and even blocks was tested using paired t-tests. Note that regressors encoding subordinate tasks and their temporal change were not used in the regression, as they are perfectly correlated with the effect of interests (i.e., regressors encoding task A and D also encode odds blocks, and regressors encoding task C and F also encode even blocks). Within each participant, this perfect correlation may suggest that the odd vs. even block comparison reflects performance differences in subordinate tasks involved. However, this perfect correlation is unlikely to confound the main result at the group level, because tasks order was

randomized for each participant.

One possible confounding factor for interpreting the interference effect is a non-linear learning curve for RT. Specifically, if the exponential learning effect caused robust reduction of RT in early 3rd to 4th blocks and smaller reductions in the later blocks, then RT would be faster in even blocks than odd blocks. To test this hypothesis, we first fitted the RTs of 3rd to 7th blocks with nonlinear mixed-effect model with the exponential model used in the Exp 1. Furthermore, we conducted additional linear mixed effect model analysis for the data and compared the fitness of the linear model to the exponential model. Even though neither of the single linear model nor the single exponential model is our hypothesized interference model, the analysis was conducted to test the plausibility of the exponential model since exponential learning might produce a pattern of RTs that would contaminate our measure of the relative influence of proactive and retroactive interference.

As in the learning stage, new associations between subordinate tasks in the test stage are formed and strengthened for each of the new superordinate tasks. Furthermore, associative learning theories (e.g., Rescorla, 1972) posit that the strength of these associations will increase with repeated exposure (i.e., practice). Accordingly, we further hypothesized that the generalization will affect the learning of associations in two possible time courses: at the beginning of test phase and throughout the test phase. Consistent with the second time course, it has been reported that performance of generalized tasks improve gradually over trials (Vaidya, Jones, Castillo, & Badre, 2021). Instead of comparing generalizable and control superordinate tasks over all trials, we accounted for the different time course effects with three predictions of the generalization effect: First, the generalization effect may grant generalizable superordinate tasks a head start at the beginning of the test phase, leading to better performance than control superordinate tasks (Fig. 4C). Second, the generalization

effect may promote the learning of generalizable superordinate tasks, leading to faster performance improvement than control superordinate tasks (Fig. 4C). Third, related to increased performance improvement, generalizable superordinate tasks may show better performance in the later part of the test phase than control superordinate tasks.

To test the predictions, we first regressed out the confounding factors from trial-wise RTs using all nuisance regressors as in Experiment 1. We then compared accuracy and residual RTs separately between generalizable and control superordinate tasks using paired t-tests. The first two predictions were tested using trial-level RT analyses. Specifically, we fit a design matrix, which consisted of binary regressors marking generalizable and control superordinate tasks (to estimate RT at the beginning of test phase) and their temporal order (i.e., a value n indicates the n-th occurrence of the task; the regressors were used to estimate RT improvement over time) against the residual RTs. We then compared the resulting regression coefficients of estimated starting RT and estimated RT improvement over time between regressors representing generalizable and control superordinate tasks. To test the last prediction, we compared residual RTs between generalizable and control superordinate tasks from block 10 using a paired t-test.

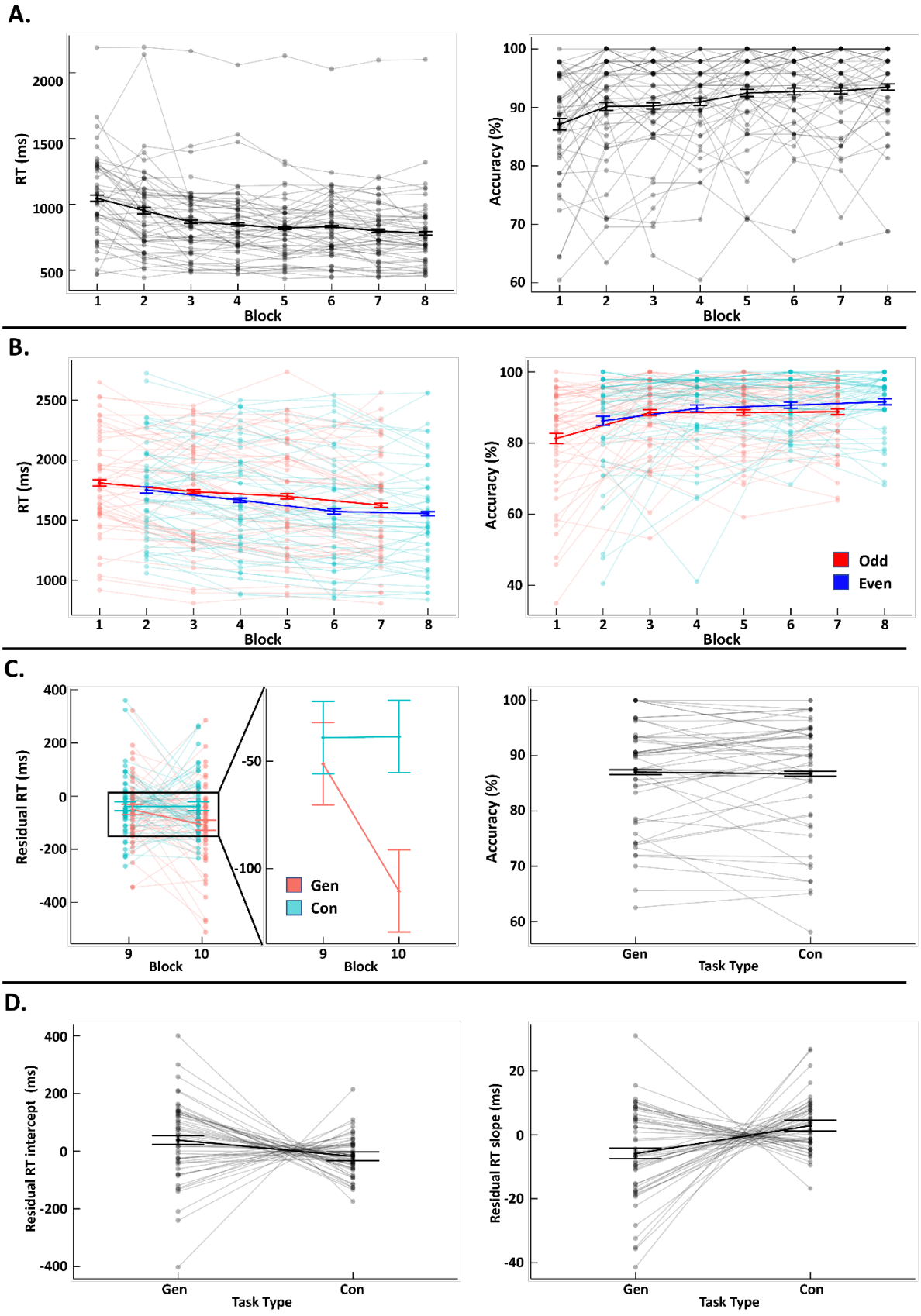


Figure 5. Results from Experiment 2a. (A) Individual RT (left) and accuracy (right) in

subordinate task phase, imposed with group mean and SEM plotted as a function of block. (B) Data from the training stage of the superordinate task phase. Panel arrangements are identical to (A). (C) Behavioral measures in the test stage of the superordinate task phase. On the left, Individual residual RT (left), group mean residual RT (right) with SEM plotted as a function of block and experimental condition (generalizable or control superordinate task). On the right, individual accuracy imposed with group mean and SEM plotted as a function of experimental condition. (D) Individual intercepts (left) and slopes (right) for residual RT in the test stage of the superordinate task phase imposed with group mean and SEM plotted as a function of condition (generalizable or control superordinate task).

Results

Subordinate task phase.

Figures 5A and Table 1 show performance as a function of block in subordinate task phase. As in Experiment 1, a linear mixed-effect model analysis showed significant negative slope of RT (t_{50} = -9.69, $p < .001$, Cohen's d = 1.38) and positive slope of accuracy (t_{50} = 5.91, $p < .001$, Cohen's d = 0.84) as a function of block, indicating an increase in performance over time. A logistic mixed effect model with trial-wise accuracy data showed the same result (z_{50} = 8.21, $p < .001$, Cohen's d = 1.17). Additionally, a nonlinear mixed-effect model analysis using an exponential function also revealed significant saturation point and learning rate for both RTs and accuracy. Statistics are provided in the online supplemental materials (Table S2 and S3).

Superordinate task phase.

Figure 5B and Table 1 show performance change during the superordinate task phase as a function of block in the learning stage (block 1-8). Overall, performance improved over the

blocks for both odd and even blocks, supported by a linear mixed-effect model analysis showing a statistically significant decrease in RT (Odd: t_{50} = -5.32, p < .001, Cohen's d = 0.76; Even: t_{50} = -6.45, p <. 001, Cohen's d = 0.92) and increase in accuracy (Odd: t_{50} = 3.56, p = .001, Cohen's d = 0.51; Even: t_{50} = 2.92, p = .005, Cohen's d = 0.42) over block, thus replicating the learning effect on superordinate tasks in Experiment 1. A logistic mixed effect model analysis with trial-wise accuracy data also showed same result (Odd: z_{50} = 3.91, p < .001, Cohen's d = 0.56; Even: z_{50} = 2.04, p = .042, Cohen's d = 0.29). Additionally, a nonlinear mixed-effect model with an exponential function showed a significantly different saturation point from zero for both RTs and accuracy. However, learning rate was not significantly different from zero for both RTs and accuracy in all types of blocks except for RTs in odd block (Table S2), suggesting that the exponential model does not provide significantly better explanation for the data compared to the linear mixed-effect model. Additional analysis that shows fitness of models further supported these findings by showing better fit for the linear model than the exponential model in all types of blocks (Table S3). Statistics are provided in the online supplemental materials (Table S2 and S3). To test the relative effects of proactive and retroactive interference, we compared performance between odd (block 3, 5, and 7) and even (block 4 and 6) blocks. Residual RT was significantly slower in odd (task AB and DE) than even (task BC and EF) blocks (t_{49} = 2.39, p = 0.021, Cohen's d = 0.34), consistent with the prediction of retroactive interference (i.e., later learned tasks impairs the memory of previously learned tasks). Accuracy did not show statistically significant difference (t_{49} = 1.23, p > 0.22, Cohen's d = 0.17), with odd blocks numerically less accurate than even blocks (Fig. 5A-B).

To test the possible confounding effect of an exponential learning curve on the interference effect, we conducted a nonlinear mixed-effect model analysis with exponential

model using RTs of 3rd to 7th blocks. The result showed non-significant fixed effect for both saturation point (t_{198} = -1.45, p = .148) and learning rate (t_{198} = 0.76, p = .446). Further model comparison between linear model and exponential model showed a better fit for linear model over exponential model, which justifies our interpretation of the interference effect.

As a coarse test of generalization effect, we compared performance between generalizable and new superordinate tasks (Fig. 5C). Accuracy was similar between two types of tasks (t_{49} = 0.36, p > 0.71, Cohen's d = 0.05). Consistent with the generalization effect, RT in generalizable superordinate tasks was significantly shorter than control superordinate tasks (t_{49} = 2.19, p = 0.034, Cohen's d = 0.31).

We further tested generalization in three ways (Fig. 5D; see Methods). First, surprisingly, estimated residual RT at the beginning of the test phase showed a trend of slowing for generalizable than control superordinate tasks (t_{49} = 1.90, p = 0.062, Cohen's d = 0.27). Second, consistent with our prediction, residual RT improved faster in generalizable than control superordinate tasks, indicated by a larger slope of residual RT decreasing over time (t_{49} = 2.67, p = 0.010, Cohen's d = 0.38). Finally, supporting the notion that the faster reduction in residual RT was indeed linked to better residual RT in generalizable than control superordinate tasks later in the test phase, we found that, in block 10, the trials were faster for generalizable than control superordinate tasks (t_{49} = 2.30, p = 0.026, Cohen's d = 0.33). Collectively, the findings support the generalization hypothesis, such that generalizable superordinate tasks showed faster RT improvement over time and faster RT after the beginning of the test phase.

In summary, our findings supported retroactive interference and integration when the two superordinate tasks shared a subordinate task. The findings suggest that compositional information, possibly in the form of associations between simple tasks included in the same

complex task, is used to organize the memory of complex task representations.

Experiment 2b

In this experiment, we aimed to replicate the findings of interference and generalization effects in Experiment 2a using a well-powered sample.

Method

Participants

The target sample size was 84, calculated based on the weakest effect of interest (the RT difference in residual RTs between generalizable and control superordinate tasks, Cohen's d = 0.31), alpha level of 0.05, and statistical power of 0.8. A total of 133 participants completed the experiment through Amazon's Mechanical Turk online, with monetary compensation of $13 for the whole experiment. Forty-nine participants were removed from analysis due to low accuracy in either phase (14 participants), low accuracy in test stage (5 participants), or more than half of trials in any of the blocks in superordinate task phase is removed in data trimming process (30 participants). The final sample consisted of 84 participants (24 females, 60 males; age: M = 35.40 years, sd = 8.94). The study was approved by the University of Iowa Institutional Review Board.

Stimuli

The stimuli used were identical to Experiment 1.

Procedure

The procedure was identical to Experiment 2a, except that participants were required to rest for at least 7 minutes (enforced as countdown on the screen) following the learning stage of

the superordinate task phase. The rest period was included to promote memory replay and integration (Roscow, Chua, Costa, Jones, & Lepora, 2021).

Data Analyses. All analytic procedures were identical to Experiment 2a.

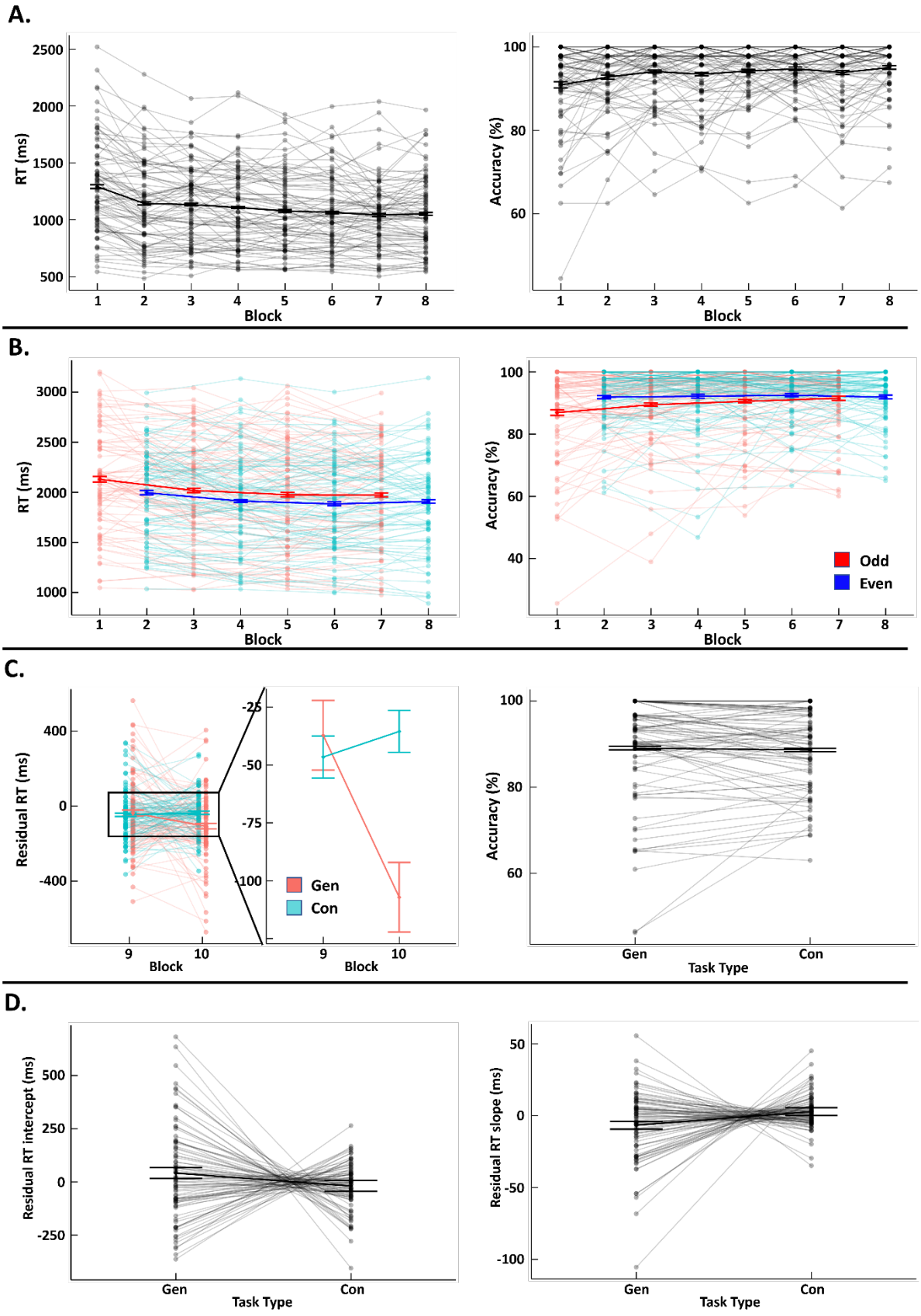


Figure 6. Results of Experiment 2b. Panel arrangements are identical to Fig. 5.

Results

Subordinate task phase.

Figures 6A and Table 1 show performance change as a function of block in subordinate task phase. As in Experiment 1, a linear mixed-effect model analysis showed significant negative slope of RT (t_{84} = -8.85, $p < .001$, Cohen's d = 0.97) and positive slope of accuracy (t_{84} = 3.23, p= .002, Cohen's d = 0.84) as a function of block, indicating increase in performance over time. A logistic mixed effect model with trial-wise accuracy data showed the same result (z_{84} = 5.23, $p < .001$, Cohen's d = 0.57). Additionally, a nonlinear mixed-effect model with an exponential function also revealed significant saturation point and learning rate for both RTs and accuracy. Statistics are provided in the online supplemental materials (Table S2 and S3).

Superordinate task phase.

Figure 6B and Table 1 show performance change as a function of block in the learning stage (block 1-4) of the superordinate task phase. Overall, performance improved over blocks for both odd and even blocks, supported by linear mixed-effect model analysis showing statistically significant decrease in RT (Odd: t_{84} = -3.65, $p < .001$, Cohen's d = 0.40; Even: t_{84} = -2.68, p =. 009, Cohen's d = 0.29) and increase in accuracy (Odd: t_{84} = 3.17, p = .002, Cohen's d = 0.35; Even: t_{84} = 0.12, p = .909, Cohen's d = 0.01) over block, thus replicating the learning effect on superordinate tasks. A logistic mixed effect model analysis with trial-wise accuracy data also showed the same result (Odd: z_{84} = 4.01, $p < .001$, Cohen's d = 0.44; Even: z_{84} = -1.00, p = .316, Cohen's d = 0.11). Additionally, a nonlinear linear mixed-effect model with an exponential function showed significantly different saturation point from zero for both RTs and accuracy except for accuracy in even blocks. However, learning rate was not significantly different from zero for both RTs and accuracy in all types of blocks, which suggests that the exponential model does not provide significantly better explanation for the

data compared to the linear mixed-effect model. Additional analysis that shows fitness of models partly supported these findings by showing better fitness of linear model than exponential model in accuracy only, but not in RTs (Table S3).

Replicating the findings supporting retroactive interference in Experiment 2a, we again observed slower residual RTs in odd than even blocks ($t_{83} = 3.01$, $p = 0.004$, Cohen's $d = 0.33$). Numerically, accuracy in the odd blocks was lower than the even blocks. However, this difference was not statistically significant ($t_{83} = 1.65$, $p > 0.10$, Cohen's $d = 0.18$).

To test the possible confounding effect of exponential learning curve on the interference effect, we conducted nonlinear mixed-effect model with an exponential function on the RTs of 3rd to 7th blocks. The result showed a non-significant fixed effect for saturation point ($t_{334} = 1.21$, $p = .23$) but a significant fixed effect for learning rate ($t_{334} = -3.17$, $p = .002$). Further model comparisons between linear model and exponential model showed a better fit for linear model over exponential model, which justifies our analysis of the interference effect.

In the test phase, accuracy was not significantly different between generalizable and control superordinate tasks (Fig. 6C; $t_{83} = 0.53$, $p > 0.59$, Cohen's $d = 0.06$). Across the whole test phase, residual RT was numerically shorter in generalizable than control superordinate tasks, although the difference was not statistically significant (Fig. 6c; $t_{83} = 1.27$, $p > 0.20$, Cohen's $d = 0.14$). All the remaining tests replicated the findings from Experiment 2a (Fig. 6D). Specifically, estimated residual RT at the beginning of the test phase was marginally slower in generalizable than control superordinate tasks ($t_{83} = 1.68$, $p > 0.098$, Cohen's $d = 0.18$). Crucially, residual RT again decreased faster in generalizable than control superordinate tasks ($t_{83} = 2.45$, $p = 0.017$, Cohen's $d = 0.27$). Consistent with this finding, the remaining trials were faster for generalizable than control superordinate tasks in block 10 ($t_{83} = 2.32$, $p = 0.020$, Cohen's $d = 0.26$). Thus, the findings support the generalization hypothesis

by replicating faster RT improvement in generalizable than control superordinate tasks, which was accompanied by faster RT later in the test phase, despite of a trend of slower RT in the beginning.

Discussion

This study investigated the effects of shared task representations on task learning and memory within the superordinate level of a task hierarchy. To address this question, we first applied the classic theories of associative memory (for review, see H. Eichenbaum, 2017), which focus on items, to the learning of tasks. We predicted that a crucial part of complex task learning is to establish associations among the subordinate tasks. To test this prediction, we designed a novel experimental paradigm with six subordinate tasks in the form of a one-feature match/mismatch task on multi-feature objects. Participants exhibited robust learning of the subordinate tasks in all experiments (Figs. 3B, 5A, 6A).

To investigate how the hierarchical organization of task knowledge can enable task learning without direct experience, we then tested whether subordinate tasks are associated during superordinate task learning to facilitate generalization to novel superordinate tasks. To this end, subjects learned superordinate tasks consisting of two learned subordinate tasks (Fig. 2B). The “exclusive or” rule ensured that both subordinate tasks were performed to produce the correct response for the superordinate tasks. Learning was first demonstrated by robust performance increases over time for superordinate tasks (Figs. 3C, 5B, 6B). Critically, performance for in learned superordinate tasks was better than performance for new superordinate tasks that differed from learned superordinate tasks only in the composition of subordinate tasks, thus controlling for subordinate task performance. The data analysis further controlled for potential confounding factors involving stimulus and response

configuration learning. Participants showed significant RT decrease in learned than new superordinate tasks (Fig. 3D). To our knowledge, these findings are the first to demonstrate task learning at both superordinate and subordinate levels, thus providing strong support for the hierarchical organization of tasks and the encoding of associations between subordinate tasks during superordinate task learning.

Notably, the association between subordinate tasks included in the same superordinate tasks is similar to relational processing in several aspects. First, under the framework of configurational processing of face perception (Maurer, Le Grand, & Mondloch, 2002; Mercure, Dick, & Johnson, 2008), there are two orders of configural processing. First-order configural processing involves the relationship between items (e.g., mouth is below nose), similar to associations between subordinate tasks within a superordinate task. Nevertheless, the relations in face perception are often directional, whereas in the current experiments, the order of the two cues in superordinate tasks was randomized, making the relationship between the two subordinate tasks nondirectional. Second-order configural processing includes the distance between features (e.g., distance between mouth and nose). Its counterpart in the present experiments would be the strength of association between subordinate tasks, which may be tested by manipulating association strength via statistical contingency (e.g., probability of subordinate tasks being included in a superordinate task).

Second, compared to item-specific processing, relational processing focuses more on the relationship between items (Burns, 2006; Humphreys, 1976; Hunt & Einstein, 1981). In the context of Experiment 1, item-specific processing is equivalent to subordinate task-level learning effect. Only relational processing would predict that the learned superordinate task, which encodes the practiced relation between subordinate tasks, will outperform new superordinate tasks (Fig. 3D).

Finally, the hierarchical organization of tasks is also similar to levels of abstraction in categorization (Jolicoeur, Gluck, & Kosslyn, 1984). In categorization, a decision can be made at a subordinate (i.e., more concrete) or a superordinate (i.e., more abstract) level. For example, instead of identifying an animal as a cat, the response can be subordinate (e.g., British Shorthair) or superordinate (e.g., mammal). Importantly, the mechanisms of selecting the most suitable level of abstraction (e.g., D'Lauro, Tanaka, & Curran, 2008) may share the mechanisms of determining which task representation to activate (e.g., when to switch from a superordinate task representation of making coffee to a subordinate task of grinding beans and vice versa). In general, future studies may examine whether and how theories of relational processing may apply to hierarchical task representations and the memory organization of task knowledge.

Our focus was the performance of superordinate tasks while maintaining the level of exposure of subordinate task constant across conditions (e.g., AC vs DF), However, another approach to understanding superordinate task representations would be to investigate the difference of behavioral performance between superordinate tasks as a function of expertise of consisting subordinate tasks. Specifically, if participants indeed build superordinate task representations by associating pre-existing subordinate tasks together, then one would expect a better behavioral performance on superordinate tasks consisting of more trained subordinate tasks then superordinate tasks with less trained subordinate tasks. Testing this hypothesis would provide strong evidence that subordinate task representations are basic building blocks of superordinate task representations.

With the current experimental paradigm, we investigated how superordinate tasks are organized in learning and memory by associations between their consisting subordinate tasks in Experiment 2a and 2b. Specifically, we tested two hypotheses: sharing the same

subordinate task will induce both interference and integration between superordinate tasks. Although the memory of tasks, which involves semantic and procedural memory, is different from the memory of items both conceptually and in their neural basis (Squire, 2004), our findings showed that task learning, similar to item learning, exhibited interference and integration, thus suggesting similarities in the organizational principles of the memories of items and tasks.

We showed empirical evidence that interference due to shared task representations occurs during task learning and when superordinate tasks are performed separately. Specifically, we observed retroactive interference (i.e., impaired memory of learned superordinate task, Fig. 5B, 6B). Intriguingly, computational modeling work has also shown that multitasking performance is impaired among superordinate tasks sharing the same subordinate task following task learning (Musslick & Cohen, 2019; Musslick et al., 2017; Sagiv, Musslick, Niv, & Cohen, 2020). In a connectionist view (e.g., McClelland, McNaughton, & O'Reilly, 1995), learning is achieved by changing connectivity between neural computing units. Therefore, interference may result from superordinate tasks competing for the connectivity patterns of the shared subordinate task. An important future research question is whether/how shared task representations can become exclusive in order to reduce interference (Sagiv et al., 2020). For this purpose, the theory of multiple memory traces (Nadel, Samsonovich, Ryan, & Moscovitch, 2000) may provide a mechanism for obtaining multiple representations of the same task to reduce task representation sharing (e.g., high demand of a task may lead to replication of the task representation). The possible mechanisms of interference may include impaired memory trace (e.g., the memory strength of superordinate task AB decreases when performing superordinate task BC) and slowed prospective learning (e.g., performing task BC in block 4 reduces the learning of task AB in

block 5). Due the lack of proper control condition (e.g., not-interleaved superordinate task condition) in the present study, we were unable to determine the mechanism. Future research may adjudicate the two hypotheses using two tests: The impaired memory trace hypothesis may be tested by comparing task performance before and after interference (e.g., task performance at the end of block 3 vs. task performance at the beginning of block 5). The slowed learning hypothesis may be tested via derived learning parameters (e.g., slope, learning rate).

Note that the retroactive interference effect may have masked a weaker proactive interference effect in the learning stage of the superordinate phase. In both Experiment 2a and 2b, we observed a trend of slower RTs to generalizable than control superordinate tasks at the beginning of test phase (Fig. 5D, 6D). In an exploratory analysis, we combined the datasets and found this effect to be statistically significant ($t_{133} = 2.35$, $p = 0.020$, Cohen's $d = 0.20$). This may reflect stronger proactive interference in generalizable than control superordinate tasks. That is, in generalizable superordinate tasks, both subordinate tasks (e.g., A and C) reactivate the same associated subordinate task (e.g., B), leading to stronger interference (e.g., the reactivation of B interferes the execution of A and C). This potential proactive interference effect (worse performance for generalizable tasks) may have cancelled out the expected generalization effect (better performance for generalizable tasks) at the beginning of the test phase and confounded the contrast between generalizable and control superordinate tasks' test phase performance. Future studies should test whether shared subordinate tasks produce proactive interference.

Experiment 2a and 2b also supported the integration hypothesis and demonstrated how task learning can occur without direct experience. Specifically, the learning of two superordinate tasks AB and BC that shared subordinate task B facilitated the learning of a

new superordinate task AC, as shown by faster improvement in RT (Fig. 5D, 6D) and faster RT in the later part of the test stage (Fig. 5C, 6C). This finding is conceptually consistent with studies showing inferential preference to AC item pairs after learning AB and BC item pairs (e.g., Wimmer & Shohamy, 2012; Zeithamova & Preston, 2010) and extends the findings to task learning. This finding also suggests that the task representation may be organized to facilitate the encoding of potential related tasks (e.g., through partially overlap associations of subordinate tasks such as AB and BC)(Bar, 2009) and proactively facilitate these inferred tasks.

It may seem counterintuitive to observe both a beneficial integration effect and a detrimental interference effect within the same experiment. A crucial distinction between the two effects is the tasks involved: the integration effect benefits the learning of a new superordinate task (e.g., AC) that does not include the shared subordinate task (e.g., B), whereas the interference effect affects learned superordinate tasks that share the subordinate task (e.g., AB and BC). We view these effects as two sides of the same coin: Without shared task representation, neither interference nor integration would occur. In this way, integration may be viewed as a benefit at the cost of interference. We further speculate that integration occurs with the resolution of interference. Recall that in Experiment 2a and 2b the partially overlapping superordinate tasks (e.g., AB and BC, and DE and EF) were interleaved. The interleaved design has been shown to be able to prevent old knowledge from being catastrophically overwritten by new knowledge (McClelland et al., 1995). From the connectionist perspective, by interleaving superordinate tasks, connectivity patterns of a shared subordinate task may iteratively converge to a state that works for both superordinate tasks, thus resolving the interference as well as providing the common ground for integration.

This finding is also in line with a recent paper (Flesch et al., 2018) reporting clearer

segregation of categorization rules between two different object categorization tasks with a blocked training design than an interleaved training design, while interleaved training design promoted integration of categorization rules from both human participants and deep neural network agents. We extended this finding by showing that this result can be generalized to abstract, complex task representations. In our experiments, participants might be impaired in the suppression of similar superordinate tasks in previous block during training, which may induce interference effect, but also might help to integrate two similar superordinate tasks, allowing for generalization.

More broadly, this study connects cognitive control and long-term memory. First, cognitive control, which is defined as a set of cognitive mechanisms that align thinking and behavior to internal goals (Egner, 2017; Miller & Cohen, 2001), is central to task performance. Recent studies have begun to investigate how humans learn and remember cognitive control settings for single tasks (for reviews, see Bugg & Crump, 2012; Chiu & Egner, 2019; Egner, 2014). However, it remains underexplored how memories of multiple tasks are organized and how the organization of the tasks in memory affects their performance. Here, we demonstrate that tasks can be associated with each other. These associations form a network of tasks, such that multiple associations can interfere with each other and also facilitate future learning of tasks through generalization.

These findings also extended the boundary conditions of associative memory. Specifically, associative memory has been extensively studied with declarative memory tasks. We showed that well-established associative memory effects, such as interference and inference, also exist in memory of skills. Although declarative memory and skill memory are historically viewed as different memory types (Gabrieli, 1998; Squire, Knowlton, & Musen, 1993), our findings suggest that they may share similar organizational principles.

Specifically, the associations between tasks may serve as a foundation to support relational memory that reconstructs or infers relations (e.g., temporal order, hierarchy and shared context) between tasks (Buckmaster, Eichenbaum, Amaral, Suzuki, & Rapp, 2004; Fortin, Agster, & Eichenbaum, 2002; McKenzie et al., 2014). Relational memory of tasks may further lead to higher-order associations (Curran, 1997; Garvert, Dolan, & Behrens, 2017; Schapiro, Rogers, Cordova, Turk-Browne, & Botvinick, 2013; Schapiro, Turk-Browne, Norman, & Botvinick, 2016). Importantly, these associations may be extended to cognitive maps for task knowledge organization, similar to studies showing that abstract information can be represented in cognitive maps (Constantinescu, O'Reilly, & Behrens, 2016; Park, Miller, Nili, Ranganath, & Boorman, 2020).

In sum, the framework of a cognitive map may capture task organization in long-term memory, such that tasks are represented as nodes (e.g., cities on a map) and their associations serve as links between nodes (e.g., roads connecting cities). This map provides a direction of task learning through practice, such that procedural task memory (e.g., how cognitive control is applied) changes through practice to benefit multitasking of or switch between strongly associated tasks (e.g., the association effect and the generalization effect). As a trade-off, tasks linked to multiple other tasks would suffer interference due to competition among its linked tasks. This framework may have practical implications on how to adjust training procedures (e.g., how to use different equipment to run different experiments in a laboratory, how to use different tools to repair different parts of a car) to reduce interference and improve generalization.

In conclusion, we demonstrated that shared subordinate tasks can induce both interference and integration in the learning and memory of superordinate tasks. These findings shed light on the organizational principles of task knowledge in the brain and their

consequences on task learning. The findings also have practical implications for how to leverage the principles of task representations to improve the organization of study materials and activities in skill training.

Context

Compared to other species and artificial intelligence agents, humans learn and retain multiple tasks remarkably efficiently. This is due in part to the fact that we can reuse acquired task knowledge. That is, learned tasks can be used as shared resources to construct new, more complex tasks. However, how task knowledge is shared across tasks during learning is largely unknown. Here, we employ a novel task design to demonstrate that this sharing can be a double-edged sword. On the one hand, sharing a simple task can facilitate the learning of complex tasks through the integration of previously acquired knowledge about the simple tasks. On the other hand, sharing can also cause interference between the memories of complex tasks. This study sheds light on the organizational principles of task knowledge in the brain and motivates further research on how to leverage these organizational principles to facilitate task learning.

References

Badre. (2008). Cognitive control, hierarchy, and the rostro-caudal organization of the frontal lobes. *Trends Cogn Sci, 12*(5), 193-200. doi:10.1016/j.tics.2008.02.004

Badre, & Nee, D. E. (2017). Frontal Cortex and the Hierarchical Control of Behavior. *Trends Cogn Sci*. doi:10.1016/j.tics.2017.11.005

Badre, & Wagner, A. D. (2005). Frontal lobe mechanisms that resolve proactive interference. *Cereb Cortex, 15*(12), 2003-2012.

Badre, D., Hoffman, J., Cooney, J. W., & D'esposito, M. (2009). Hierarchical cognitive control deficits following damage to the human frontal lobe. *Nat Neurosci, 12*(4), 515-522.

Bar, M. (2009). The proactive brain: memory for predictions. *Philosophical Transactions of the Royal Society B:*

Biological Sciences, 364(1521), 1235-1243.

Bates, D., Kliegl, R., Vasishth, S., & Baayen, H. (2015). Parsimonious mixed models. *arXiv preprint arXiv:1506.04967*.

Bejjani, C., Zhang, Z., & Egner, T. (2018). Control by association: Transfer of implicitly primed attentional states across linked stimuli. *Psychon Bull Rev, 25*(2), 617-626. doi:10.3758/s13423-018-1445-6

Bramao, I., Jiang, J., Wagner, A., & Johansson, M. (in press). Testing theories of forgetting: The effect of memory suppression strategies on associative memory. *Cereb Cortex*.

Brass, M., Liefooghe, B., Braem, S., & De Houwer, J. (2017). Following new task instructions: Evidence for a dissociation between knowing and doing. *Neuroscience & Biobehavioral Reviews, 81*, 16-28.

Buckmaster, C. A., Eichenbaum, H., Amaral, D. G., Suzuki, W. A., & Rapp, P. R. (2004). Entorhinal cortex lesions disrupt the relational organization of memory in monkeys. *Journal of Neuroscience, 24*(44), 9811-9825.

Bugg, J. M., & Crump, M. J. (2012). In support of a distinction between voluntary and stimulus-driven control: A review of the literature on proportion congruent effects. *Front Psychol, 3*, 367.

Burns, D. J. (2006). Assessing distinctiveness: Measures of item-specific and relational processing. *Distinctiveness and memory*, 109-130.

Chiu, Y. C., & Egner, T. (2019). Cortical and subcortical contributions to context-control learning. *Neurosci Biobehav Rev, 99*, 33-41. doi:10.1016/j.neubiorev.2019.01.019

Collins, A. G., Cavanagh, J. F., & Frank, M. J. (2014). Human EEG uncovers latent generalizable rule structure during learning. *Journal of Neuroscience, 34*(13), 4677-4685.

Constantinescu, A. O., O'Reilly, J. X., & Behrens, T. E. (2016). Organizing conceptual knowledge in humans with a gridlike code. *Science, 352*(6292), 1464-1468.

Curran, T. (1997). Higher-order associative learning in amnesia: Evidence from the serial reaction time task. *J Cogn Neurosci, 9*(4), 522-533.

D'Lauro, C., Tanaka, J. W., & Curran, T. (2008). The preferred level of face categorization depends on discriminability. *Psychon Bull Rev, 15*(3), 623-629.

Darby, K. P., & Sloutsky, V. M. (2015). The cost of learning: interference effects in memory development. *Journal of Experimental Psychology: General, 144*(2), 410.

DuBrow, S., & Davachi, L. (2016). Temporal binding within and across events. *Neurobiology of learning and memory, 134*, 107-114.

Egner, T. (2014). Creatures of habit (and control): a multi-level learning perspective on the modulation of

congruency effects. *Front Psychol, 5*, 1247. doi:10.3389/fpsyg.2014.01247

Egner, T. (2017). *The Wiley handbook of cognitive control*. Southern Gate, Chichester, West Sussex, UK: Wiley Blackwell.

Eichenbaum, H. (2014). Time cells in the hippocampus: a new dimension for mapping memories. *Nature reviews neuroscience, 15*(11), 732-744.

Eichenbaum, H. (2017). Memory: Organization and Control. *Annu Rev Psychol, 68*, 19-45. doi:10.1146/annurev-psych-010416-044131

Fortin, N. J., Agster, K. L., & Eichenbaum, H. B. (2002). Critical role of the hippocampus in memory for sequences of events. *Nat Neurosci, 5*(5), 458-462.

Gabrieli, J. D. (1998). Cognitive neuroscience of human memory. *Annual review of psychology, 49*(1), 87-115.

Garvert, M. M., Dolan, R. J., & Behrens, T. E. (2017). A map of abstract relational knowledge in the human hippocampal–entorhinal cortex. *Elife, 6*, e17086.

Humphreys, M. S. (1976). Relational information and the context effect in recognition memory. *Memory & Cognition, 4*(2), 221-232.

Hunt, R. R., & Einstein, G. O. (1981). Relational and item-specific information in memory. *Journal of Verbal Learning and Verbal Behavior, 20*(5), 497-514.

Jiang, J., Bramao, I., Khazenzon, A., Wang, S. F., Johansson, M., & Wagner, A. D. (2020). Temporal Dynamics of Memory-guided Cognitive Control and Generalization of Control via Overlapping Associative Memories. *J Neurosci*. doi:10.1523/JNEUROSCI.1869-19.2020

Jolicoeur, P., Gluck, M. A., & Kosslyn, S. M. (1984). Pictures and names: Making the connection. *Cogn Psychol, 16*(2), 243-275.

Kikumoto, A., & Mayr, U. (2018). Decoding hierarchical control of sequential behavior in oscillatory EEG activity. *Elife, 7*, e38550.

Koechlin, E., & Summerfield, C. (2007). An information theoretical approach to prefrontal executive function. *Trends Cogn Sci, 11*(6), 229-235. doi:10.1016/j.tics.2007.04.005

Koster, R., Chadwick, M. J., Chen, Y., Berron, D., Banino, A., Duzel, E., . . . Kumaran, D. (2018). Big-Loop Recurrence within the Hippocampal System Supports Integration of Information across Episodes. *Neuron, 99*(6), 1342-1354 e1346. doi:10.1016/j.neuron.2018.08.009

Kuhl, B. A., Shah, A. T., DuBrow, S., & Wagner, A. D. (2010). Resistance to forgetting associated with hippocampus-mediated reactivation during new learning. *Nat Neurosci, 13*(4), 501-506.

doi:10.1038/nn.2498

Kumaran, D., & McClelland, J. L. (2012). Generalization through the recurrent interaction of episodic memories: a model of the hippocampal system. *Psychol Rev, 119*(3), 573-616. doi:10.1037/a0028681

Lee, W. T. (2022). https://osf.io/pu2fw/?view_only=43227ca6ef4149e9a9ef9ff011daae09.

Martínez, M. C., Villar, M. E., Ballarini, F., & Viola, H. (2014). Retroactive interference of object-in-context long-term memory: role of dorsal hippocampus and medial prefrontal cortex. *Hippocampus, 24*(12), 1482-1492.

Maurer, D., Le Grand, R., & Mondloch, C. J. (2002). The many faces of configural processing. *Trends Cogn Sci, 6*(6), 255-260.

McClelland, J. L., McNaughton, B. L., & O'Reilly, R. C. (1995). Why there are complementary learning systems in the hippocampus and neocortex: insights from the successes and failures of connectionist models of learning and memory. *Psychol Rev, 102*(3), 419-457. doi:10.1037/0033-295X.102.3.419

McKenzie, S., Frank, A. J., Kinsky, N. R., Porter, B., Rivière, P. D., & Eichenbaum, H. (2014). Hippocampal representation of related and opposing memories develop within distinct, hierarchically organized neural schemas. *Neuron, 83*(1), 202-215.

Mercure, E., Dick, F., & Johnson, M. H. (2008). Featural and configural face processing differentially modulate ERP components. *Brain Res, 1239*, 162-170.

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annu Rev Neurosci, 24*, 167-202. doi:10.1146/annurev.neuro.24.1.167

Musslick, S., & Cohen, J. D. (2019). *A Mechanistic Account of Constraints on Control-Dependent Processing: Shared Representation, Conflict and Persistence.* Paper presented at the CogSci.

Musslick, S., & Cohen, J. D. (2021). Rationalizing constraints on the capacity for cognitive control. *Trends Cogn Sci*.

Musslick, S., Saxe, A., Özcimder, K., Dey, B., Henselman, G., & Cohen, J. D. (2017). *Multitasking capability versus learning efficiency in neural network architectures*.

Nadel, L., Samsonovich, A., Ryan, L., & Moscovitch, M. (2000). Multiple trace theory of human memory: computational, neuroimaging, and neuropsychological results. *Hippocampus, 10*(4), 352-368.

Park, S. A., Miller, D. S., Nili, H., Ranganath, C., & Boorman, E. D. (2020). Map making: constructing, combining, and inferring on abstract cognitive maps. *Neuron, 107*(6), 1226-1238. e1228.

Rescorla, R. A. (1972). A theory of Pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. *Current research and theory*, 64-99.

Ritz, H., Leng, X., & Shenhav, A. (2021). Cognitive control as a multivariate optimization problem. *arXiv preprint arXiv:2110.00668*.

Roscow, E. L., Chua, R., Costa, R. P., Jones, M. W., & Lepora, N. (2021). Learning offline: memory replay in biological and artificial reinforcement learning. *Trends in neurosciences*.

Sagiv, Y., Musslick, S., Niv, Y., & Cohen, J. D. (2020). Efficiency of learning vs. processing: Towards a normative theory of multitasking. *arXiv preprint arXiv:2007.03124*.

Schapiro, A. C., Rogers, T. T., Cordova, N. I., Turk-Browne, N. B., & Botvinick, M. M. (2013). Neural representations of events arise from temporal community structure. *Nat Neurosci, 16*(4), 486-492.

Schapiro, A. C., Turk-Browne, N. B., Norman, K. A., & Botvinick, M. M. (2016). Statistical learning of temporal community structure in the hippocampus. *Hippocampus, 26*(1), 3-8.

Schumacher, E. H., & Hazeltine, E. (2016). Hierarchical task representation: Task files and response selection. *Current Directions in Psychological Science, 25*(6), 449-454.

Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). The expected value of control: an integrative theory of anterior cingulate cortex function. *Neuron, 79*(2), 217-240. doi:10.1016/j.neuron.2013.07.007

Shohamy, D., & Wagner, A. D. (2008). Integrating memories in the human brain: hippocampal-midbrain encoding of overlapping events. *Neuron, 60*(2), 378-389. doi:10.1016/j.neuron.2008.09.023

Sloman, S. A. (1996). The empirical case for two systems of reasoning. *Psychol Bull, 119*(1), 3.

Squire, L. R. (2004). Memory systems of the brain: a brief history and current perspective. *Neurobiology of learning and memory, 82*(3), 171-177.

Squire, L. R., Knowlton, B., & Musen, G. (1993). The structure and organization of memory. *Annual review of psychology, 44*(1), 453-495.

Theves, S., Neville, D. A., Fernández, G., & Doeller, C. F. (2021). Learning and representation of hierarchical concepts in hippocampus and prefrontal cortex. *Journal of Neuroscience, 41*(36), 7675-7686.

Underwood, B. J. (1957). Interference and forgetting. *Psychol Rev, 64*(1), 49.

Vaidya, A. R., Jones, H. M., Castillo, J., & Badre, D. (2021). Neural representation of abstract task structure during generalization. *Elife, 10*, e63226.

Wimmer, G. E., & Shohamy, D. (2012). Preference by association: how memory mechanisms in the hippocampus bias decisions. *Science, 338*(6104), 270-273. doi:10.1126/science.1223252

Wixted, J. T. (2004). The psychology and neuroscience of forgetting. *Annu. Rev. Psychol., 55*, 235-269.

Zeithamova, D., Dominick, A. L., & Preston, A. R. (2012). Hippocampal and ventral medial prefrontal activation during retrieval-mediated learning supports novel inference. *Neuron, 75*(1), 168-179. doi:10.1016/j.neuron.2012.05.010

Zeithamova, D., & Preston, A. R. (2010). Flexible memories: differential roles for medial temporal lobe and prefrontal cortex in cross-episode binding. *J Neurosci, 30*(44), 14676-14684. doi:10.1523/JNEUROSCI.3250-10.2010

Zeithamova, D., & Preston, A. R. (2017). Temporal proximity promotes integration of overlapping events. *J Cogn Neurosci, 29*(8), 1311-1323.

Supplemental Materials

Interference and Integration in Hierarchical Task Learning

Woo-Tek Lee[1,2], Eliot Hazeltine[1,2] and Jiefeng Jiang[1,2]

[1]Cognitive Control Collaborative, University of Iowa, Iowa City, IA 52242

[2]Department of Psychological and Brain Sciences, University of Iowa, Iowa City, IA 52242

Supplementary Experiment

Experiment S1

Method

Participants.

For this experiment, the target sample size was 25 based on the size of the hierarchical task learning effect (i.e., effect between training and new superordinate tasks) in Experiment 1 with an alpha level of 0.05 and a beta level of 0.9. A total of 35 participants completed the experiment through Amazon's Mechanical Turk online with monetary compensation of $6 for the whole experiment. Ten participants were removed from analysis due to low accuracy (below 60%) in either phase (9 participants) or to more than half of trials in any of the blocks in the superordinate task phase being removed in the data trimming process (1 participant; see below). The final sample consisted of 25 participants (7 females, 18 males; age: M = 37.00 years, sd = 9.22). The study was approved by the University of Iowa Institutional Review Board.

Stimuli

The stimuli were identical to Experiment 1.

Procedure

The procedure was the same as Experiment 1 except for the following changes. Participants completed two phases: a subordinate task phase (2 blocks of 64 trials each) followed by a

superordinate task phase (2 blocks of 48 trials each). In the subordinate task phase, only two subordinate tasks were used for training (A & B). In the superordinate task phase, participants performed two superordinate tasks: one that consisted of already learned subordinate tasks (AB) and the other that consisted of new subordinate tasks (CD). Before the subordinate task phase, participants performed 24 training trials consisting of four possible subordinate tasks (A, B, C, D).

Data Analyses.

Data processing was identical to the Experiment 1 with one exception: The regressors representing individual subordinate tasks were removed when computing RT residuals because the experimental design leads to perfect collinearity between subordinate and superordinate task regressors. For this analysis, we compared behavioral performance (residual RTs, accuracy) between the learned (AB) and new superordinate tasks (CD) using paired t-test.

Results

We compared performance between superordinate tasks consisting of already learned subordinate tasks (AB) and superordinate tasks consisting new subordinate tasks (CD) using paired t-test (Fig S1). We did not find significant differences in residual RTs (t_{24} = -0.31, p = .760) between the two conditions, but we found significantly higher accuracy (t_{24} = 2.31, p = .030) in the learned condition (AB) than the new condition (CD). Thus, this experiment supports the notion of hierarchical task learning, that is, knowledge of subordinate tasks is re-used during the learning of superordinate task.

Supplementary Figure

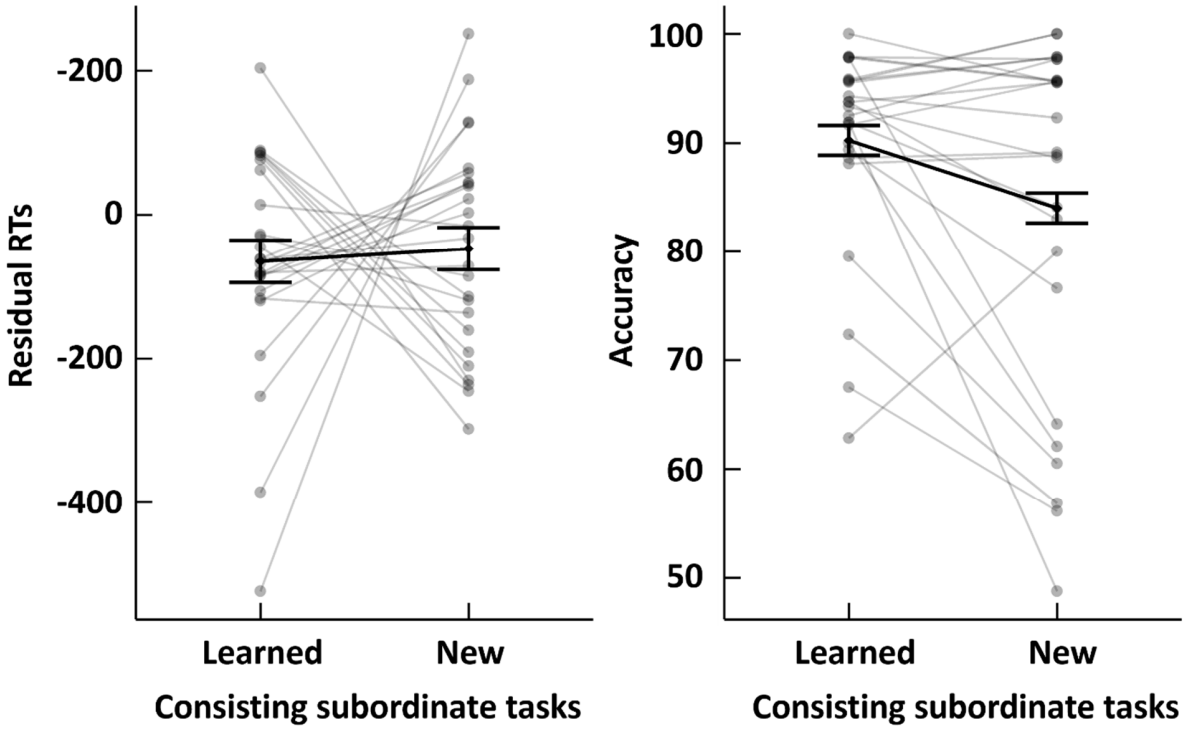


Figure S1. Results of Experiment S1. Individual RT (left) and accuracy (right) at the superordinate task phase, imposed with group mean and SEM plotted as a function of experimental condition (superordinate tasks consisted of already learned subordinate tasks or new subordinate tasks).

Supplementary Table

Table S1. Summary statistics of logistic mixed-effect model analysis for accuracy

	Subordinate	Superordinate
Exp 1	z_{50} = 6.61, p < .001, Cohen's d = 0.94	z_{50} = 5.47, p < .001, Cohen's d = 0.78
Exp 2a	z_{50} = 8.21, p < .001, Cohen's d = 1.17	Odd: z_{50} = 3.91, p < .001, Cohen's d = 0.56 Even: z_{50} = 2.04, p = .042, Cohen's d = 0.29
Exp 2b	z_{84} = 5.23, p < .001, Cohen's d = 0.57	Odd: z_{84} = 4.01, p < .001, Cohen's d = 0.44 Even: z_{84} = -1.00, p = .316, Cohen's d = 0.11

Note. Each cell includes group-mean value with standard error in parentheses, z- statistic and p-value. Cells are organized based on experimental phase, parameter and dependent variable.

Detailed statistics of logistic mixed-effect model analysis for accuracy. Overall, logistic mixed effect model analysis with trial-wise accuracy data replicated all the results using linear-mixed effect model analysis with averaged accuracy data.

Table S2. Summary statistics of nonlinear mixed-effect model with exponential function

		Subordinate		Superordinate	
		saturation (‘β_1’)	Learning rate (‘β_2’)	saturation (‘β_1’)	Learning rate (‘β_2’)
Exp 1	RTs	-0.13 (0.02) t_{148} = -5.52, p < .001	1.86 (0.48) t_{148} = 3.88, p < .001	-0.36 (0.11) t_{148} = -3.39, p < .001	0.44 (0.14) t_{148} = 3.11, p = .002
	Accuracy	0.21 (0.48) t_{148} = 0.44, p = .663	0.11 (0.34) t_{148} = 3.08, p = .748	0.20 (0.09) t_{148} = 2.14, p = .034	0.30 (0.41) t_{148} = .74, p = .458
Exp 2a	RTs	-0.47 (0.05) t_{148} = -8.77, p < .001	0.41 (0.07) t_{148} = 5.62, p < .001	Odd: 2.37 (0.22) t_{148} = 2.58, p = .01 Even: -0.28 (0.13) t_{148} = -2.24, p = .027	Odd: -0.09 (0.03) t_{148} = -3.46, p = .007 Even: 0.44 (0.37) t_{148} = 1.20, p = .232
	Accuracy	-0.12 (0.04) t_{148} = -2.51, p = .012	-0.05 (0.02) t_{148} = -3.36, p = .001	Odd: 0.07 (0.01) t_{148} = 5.27, p < .001 Even: 0.06 (0.02) t_{148} = 2.64, p = .001	Odd: 4.12 (11.76) t_{148} = 0.35, p = .727 Even: 0.92 (0.92) t_{148} = 1.00, p = .318
Exp 2b	RTs	-0.23 (0.02) t_{148} = -15.22, p < .001	0.62 (0.10) t_{148} = 5.92, p < .001	Odd: -0.15 (0.04) t_{148} = -3.87, p < .001 Even: -0.10 (0.03) t_{148} = -3.35, p < .001	Odd: 2.09 (1.09) t_{148} = 1.92, p = .056 Even: 3.02 (3.38) t_{148} = 0.92, p = .360
	Accuracy	0.04 (0.01) t_{148} = 3.54, p < .001	0.52 (0.07) t_{148} = 7.76, p < .001	Odd: 0.05 (0.02) t_{148} = 2.13, p = .033 Even: 0.003 (0.01) t_{148} = 0.40, p = .690	Odd: 0.59 (0.60) t_{148} = 0.98, p = .329 Even: 4.05 (143.91) t_{148} = 0.03, p = .978

Note. Each cell includes group-mean value with standard error in parentheses, t- statistic and p-value. Cells are organized based on experimental phase, parameter and dependent variable.

Detailed statistics of nonlinear mixed-effect model analysis with exponential function. In case of subordinate tasks, both saturation points and learning rate showed significant fixed effect for both RTs and accuracy in all three experiments. On the other hand, superordinate tasks showed mixed results. Superordinate tasks in Exp 1 showed significant fixed effect of saturation point for both RTs and accuracy, and significant fixed effect of learning rate for RTs only. In Exp 2a, saturation points showed significant fixed effect in RTs and accuracy for both odd and even blocks, while learning rate showed non-significant fixed effects except in RTs for odd blocks. Exp 2b showed significant fixed effects of saturation point except for accuracy in even blocks, and non-significant fixed effect of learning rate in all cases.

Table S3. Description for the fitness of models in all conditions.

		Subordinate (AIC / BIC)		Superordinate (AIC / BIC)	
		Linear	exponential	linear	exponential
Exp 1	RTs	-189.71 / -169.92	-211.18 / -188.09	68.38 / 88.17	75.37 / 98.46
	Accuracy	-599.43 / -579.64	-569.10 / -546.01	-348.21 / -328.42	-319.19 / -296.10
Exp 2a	RTs	-376.38 / -352.43	-436.19 / -408.25	Odd: 23.41 / 43.20 Even: 16.52 / 36.31	Odd: 27.23 / 50.32 Even: 18.94 / 42.03
	Accuracy	-1140.03 / -1116.08	-1113.72 / -1085.78	Odd: -349.45 / -329.66 Even: -372.59 / -352.80	Odd: -347.73 / -324.65 Even: -356.98 / -333.89
Exp 2b	RTs	-565.68 / -538.62	-544.07 / -512.50	Odd: 231.53 / 254.43 Even: 94.78 / 117.68	Odd: 227.44 / 254.1557 Even: 91.00 / 117.72
	Accuracy	-2121.42 / -2094.36	-2163.96 / -2132.39	Odd: -669.26 / -646.35 Even: -816.12 / -793.22	Odd: -623.45 / -596.73 Even: -800.88 / -774.16

Note. Each cell includes Akaike Information Criteria (AIC) / Bayesian Information Criteria (BIC) values as measures for fitness of models.

Detailed model fitting values of linear mixed-effect model and nonlinear mixed-effect model with exponential function. In case of subordinate tasks, both Exp 1 and Exp 2b showed better fitness of RTs for linear model than exponential model while showing better fitness of accuracy for exponential than linear model. However, Exp 2b presented opposite trend by showing better fit of RTs for linear model and better fitness of accuracy for exponential model. Superordinate tasks showed better fit of linear model than exponential model in all cases except RTs in Exp 2b, which showed better fitness of exponential model than linear model. Overall, exponential models did not outperform linear models in explaining performance improvement in participants.

Table S4. Summary statistics of nonlinear mixed-effect model analysis with exponential function in superordinate tasks using RTs of 3rd to 7th blocks.

	Saturation point ('β_1')	Learning rate ('β_2')
Exp 2a	-0.18 (0.12) t_{198} = -1.45, p = .148	0.33 (0.43) t_{198} = 0.76, p = .446
Exp 2b	0.18 (0.15) t_{334} = 1.21, p = .23	-0.06 (0.02) t_{334} = -3.17, p = .002

Note. Each cell includes average value with standard error in the upper row, and t-test statistics in the bottom row.

Detailed statistics of nonlinear mixed-effect model analysis with exponential function. Saturation points did not show significant fixed effect in both experiments. Learning rate did not significantly differ from 0 in Exp 2a, or even showed statistically significant result in direction opposite to prediction in Exp 2b. Together these results do not support the hypothesis that the faster RTs in even blocks than odd blocks are an effect of exponential learning curve.

Table S5. Description for the fitness of models in superordinate tasks using RTs of 3rd to 7th blocks.

	Linear (AIC / BIC)	Exponential (AIC / BIC)
Exp 2a	17.48/38.61	18.72 / 43.37
Exp 2b	197.61 / 221.86	211.97 / 240.25

Note. Each cell includes AIC / BIC values as an index for fitness of models.

Detailed model fitting values of linear mixed-effect model and nonlinear mixed-effect model with exponential function. Linear model showed better fitness than exponential model in all two experiments, which do not support the exponential model hypothesis.