Motor demands in catogory learning during task switching

Matthew J. Crossley[1, 2], Hannah Arnold[1], David M. Kaplan[1, 2], and F. Gregory Ashby [3]

[1]School of Psychological Sciences, Macquarie University, Sydney, Australia

[2]Macquarie University Performance and Expertise Research Centre, Macquarie University, Sydney, Australia

[3]Department of Psychological & Brain Sciences, University of California, Santa Barbara

Correspondence: Matthew J. Crossley, PhD, School of Psychological Sciences, Macquarie University, Australian Hearing Hub, 16 University Ave, Macquarie University, NSW 2109, Australia. Email: matthew.crossley@mq.edu.au

Abstract

Procedural category learning involves forming many-to-one stimulus-response (SR) associations through trial-and-error feedback. While single-task contexts suggest these associations are linked to motor goals (e.g., pressing a button on the left) rather than specific motor effectors (e.g., pressing with a particular finger), it is unknown if this holds in task-switching contexts. In this study, we investigated whether category learning during task-switching relies on motor goal-based SR associations or shifts to an effector-specific level. Participants learned two category structures while switching tasks from the beginning of training. Our results revealed that learning was more effective when stimuli from a specific region of stimulus space were mapped to different fingers on the same hand, as opposed to different fingers on opposite hands. Nonetheless, significant learning occurred in both cases. These findings suggest that procedural category learning during task switching involves forming SR associations tied to both motor goals and, to some extent, motor effectors.

Introduction

In task-switching experiments, participants are asked to perform two distinct tasks in a pseudo-random interleaved order (Kiesel et al., 2010; Monsell, 2003). Most studies have focused on switching between well-learned tasks that can be performed with high accuracy in isolation. Little attention has been given to how task switching operates when tasks must be learned simultaneously.

We are aware of only two lines of research that have begun to explore simultaneous learning of new tasks during task switching. First, Collins and colleagues have studied simple tasks with highly discernible stimuli and straightforward response rules (Collins, 2017; Collins & Frank, 2013; Collins et al., 2014; Collins & Frank, 2016a, 2016b). These tasks, due to their simplicity, are rapidly learned, limiting the scope for investigating how task switching interacts with the learning process itself. Moreover, these tasks rely heavily on declarative memory and explicit reasoning. The question of how task switching impacts procedural learning remains largely unexplored.

Our lab has begun to address this gap by examining task switching with more complex, procedural category learning tasks that do not lend themselves to rapid learning (**crossley_switch_2023**; Crossley et al., 2018; Turner et al., 2017). A key finding from this research is that learning under task switching is only reliably successful when the motor responses for each task are distinct (**crossley_switch_2023**).

Procedural category learning involves forming stimulus-response (SR) associations through trial-and-error feedback. Ashby, Ell, and Waldron (2003) provided key evidence for procedural learning in certain categorization tasks. They showed that performance was unaffected by switching hands but was impaired by switching key locations, suggesting that SR associations are linked to motor goals (e.g., pressing a key on the left) rather than motor effectors (e.g., pressing with a specific finger).

While this suggests that the SR associations in single-task contexts operate at the motor goal level, it remains unclear whether this holds while task switching. In this study, we investigated whether procedural category learning during task switching occurs at the level of motor goals or whether it occurs at the level of motor effectors.

Methods

Design

We examined category learning while participants switched on a random trial-by-trial basis between two different categorization tasks. Each task was an information-integration (II) category-learning task, in which the optimal strategy is similarity based, and for which no simple verbal rule (Ashby & Gott, 1988; Ashby et al., 1998) can achieve perfect accuracy. On every trial in both tasks, the participant was instructed to assign the single presented stimulus to its correct category. The stimuli in both tasks were circular sine-wave gratings that varied across trials in their spatial frequency and their orientation. Gratings in the first task were presented on a gray square background on top of a black screen, whereas gratings in the second task were presented on a gray diamond background on top of a black screen. See Figure 1 for examples.

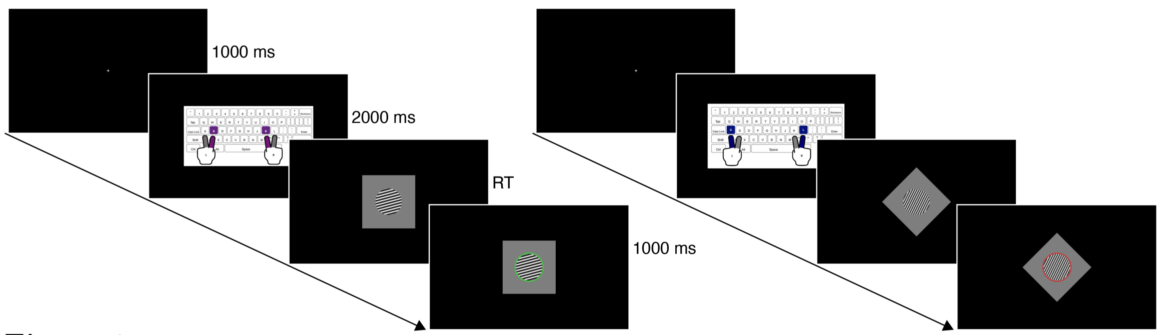

Figure 1

Left: *Example Square subtask trial in which a correct response was given.* ***Right:*** *Example Diamond subtask trial in which an incorrect response was given.*

Subjects were randomly assigned to one of two conditions – Congruent or Incongruent. The Congruent is named to reflect the nature of how stimuli were assigned to specific fingers. In particular, stimuli from different tasks but from the same regions of stimulus space were assigned to fingers on the same hand. In the Incongruent condition, participants were required to use the same set of keys as in the Congruent condition. However stimuli from different tasks but from the same regions of stimulus space were to fingers on different hands. This is the sense in which the Congruent condition is congruent and the Incongruent condition is incongruent. Please see Figure 1 for an illustration of the exact mappings used.

Participants

We recruited 91 participants to serve as participants. One participant was excluded from the analysis for failing to follow the instructions regarding which fingers and keys to use to indicate category responses. The remaining 90 participants were either first-year undergraduate psychology students from Macquarie University recruited via the Sona system (n = 28) or individuals from the general community (n = 62), recruited via direct invitation from the researchers. All Macquarie University undergraduate participants completed the study and received course credit for their participation. All other participants volunteered with no compensation. All participants were between 18 to 30 years of age, fluent in English, had normal or corrected-to-normal vision and hearing and no history of neurological impairments. Each participant was randomly assigned to one of 2 conditions (named Congruent and Incongruent). Of the 45 incongruent participants there were 12 males and 31 females. Their ages ranged from 18 to 27 years old ($M = 19.6$, $SD = 1.7$). Of the 45 congruent participants there were 16 males and 29 females. Their ages ranged from 18 to 30 years old ($M = 22.5$, $SD = 2.3$).

Stimuli and Categories

The stimuli were circular sine wave gratings that varied in spatial frequency and orientation. Stimuli coordinates were generated by first sampling points in polar coordinates and then converting them into Cartesian coordinates. Specifically, a radius values r were sampled from a uniform distribution on the interval $[0, 1]$, and angle values θ were sampled uniformly on $[0, 2\pi]$. These polar coordinates (r, θ) were then transformed into Cartesian coordinates (x, y) using the equations $x = r\cos(\theta)$ and $y = r\sin(\theta)$. This resulted in a set of (x, y) coordinates uniformly distributed within a circle of radius 1 and centered at the origin. Next, (x, y) coordinates were transformed from a circular uniform distribution to an elliptical uniform distribution with it's major axis along the horizontal axis by multiplying the x values by 124.02 and the y values by 28.44. Finally, the resulting coordinates were rotated by 45°and translated by $(40, 60)$ for half the stimuli and by $(60, 40)$ for the other half. The resulting stimuli distributions are shown in Figure **??**.

Procedure

Participants were first given a paper information and consent form and were required to sign and date the form before proceeding. They were also given an optional demographic questionnaire to complete. Participants were then given verbal instructions with the aid of slides (see the Appendix). Briefly participants in all conditions were told that they were to categorize circular sine wave gratings on the basis of their spatial frequency and orientation, and that each category was equally likely. They were also instructed that gratings presented on a square background may or may not require a different response policy than gratings presented on a diamond background.

Each participant completed a single session consisting of 400 trials, with each task (square or diamond) interleaved psuedo-randomly. On each trial, participants viewed a fixation cross (1000 ms), followed by a cue image that indicated the correct finger-key mapping for the upcoming task (2000 ms), followed by a response-terminated stimulus, and then feedback (1000 ms). Responses were given via the "a", "s", "k" and "l" keys as indicated by the cue image (see Figure **??**. Feedback following correct responses was a green circle that appeared around the stimulus, and feedback following incorrect responses was a red circle. See Figure 1 an illustration of example trials.

Statistical Analysis

We performed a logistic regression to examine learning as a function of condition (Congruent vs Incongruent), best-fitting decision-bound model (rule-based vs procedural), and log trial. All categorical predictors (i.e., condition and best-fitting decision-bound

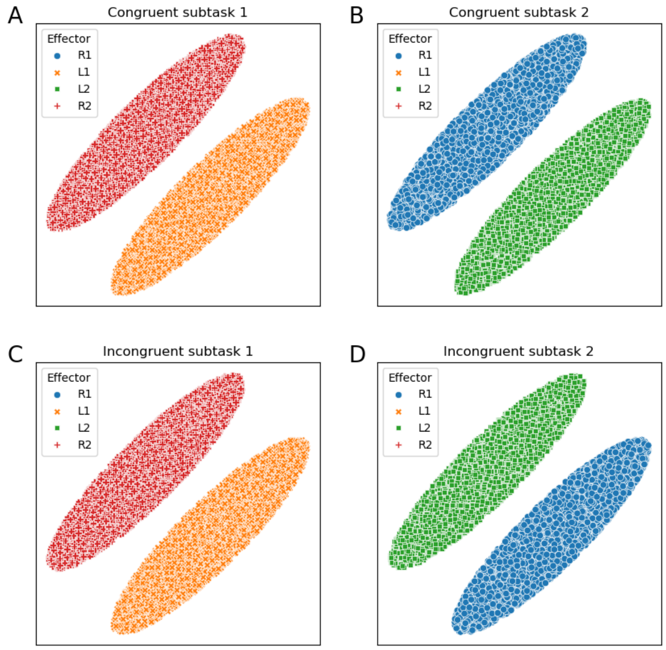

Figure 2

A: *Stimuli distributions for the Square task in the Congruent condition.* ***B:*** *Stimuli distributions for the Diamond task in the Congruent condition.* ***C:*** *Stimuli distributions for the Square task in the Incongruent condition.* ***D:*** *Stimuli distributions for the Diamond task in the Incongruent condition. In all panels, the colour of the points indicates the effector – and thus the response key – that indicates the correct category for that stimulus. R1 stands for the right index finger, R2 for the right middle finger, L1 for the left index finger, and L2 for the left middle finger. The key feature of the Incongruent condition is that stimuli from the same region of stimulus space are assigned to different hands in different subtasks.*

model) were dummy coded. Log trial number was used rather than trial number to account for the fact that the learning apparent in Figure 3 is non-linear, with more rapid initial improvements followed by slowed improvements as the task progresses. To assess whether there were differences in the proportion of participants best fit by a rule-based or procedural decision-bound model in each condition, we conducted a χ^2 test. To assess switch costs, we computed the difference in accuracy and RT between switch trials and stay trials for all trials across the entire experiment for each participant. We then conducted a 2 (condition) x 2 (best-fitting decision-bound model) ANOVA on the resulting switch costs.

Decision-Bound Analysis

To identify the decision strategy used by each participant, we fit decision-bound models (Ashby & Gott, 1988; Maddox & Ashby, 1993) to the trial-by-trial response data from the final 100 trials of the experiment separately for each subtask. We examined 1-dimensional rule-based models and 2-dimensional procedural models. The rule-based models assumed participants established a criterion on a single stimulus dimension and then categorized stimuli based on whether they exceeded this criterion. These models had two free parameters. One parameter that determined the criterion value and a second parameter that determined the variance of perceptual and criterial noise. The 2-dimensional procedural models – i.e., general linear classifier (GLC) – assumed that participants used a linear decision boundary with an arbitrary slope and intercept. Stimuli were categorized based on their position relative to this boundary. The GLC has three free parameters. One parameter that determined the slope of the boundary, a second parameter that determined the intercept of the boundary, and a third parameter that determined the variance of perceptual and criterial noise. For details, see Ashby and Valentin (2017).

Results

Learning Curves

Figure 3A shows the mean accuracy per trial averaged over all participants for each condition. The semi-transparent lines show performance separately for each subtask and the solid lines show performance averaged over both subtasks. This figure clearly indicates that learning proceeded more quickly and to a larger extent in the Congruent condition than in the Incongruent condition. Figure 3B shows the results for participants best fit by a rule-based decision-bound model and Figure 3C shows the results for participants best fit by a procedural decision-bound model (see the "Decision Bound Models" section for details). The trend in both of these panels is the same as that observed when considering all participants regardless of best-fitting model (Figure 3A).

We conducted a logistic regression to examine the effects of experimental condition (Congruent vs. Incongruent), decision-bound model (DBM: rule-based vs. procedural), and their interactions on accuracy. The results are summarized in Table **??**. See the "Statistical Analysis" section for details. The effect of log(trial) was significant ($\beta = 0.4775$, SE $= 0.026$, $z = 18.211$, $p < .001$), indicating that accuracy increased across trials. The effect of Condition was not statistically significant ($\beta = 0.2289$, SE $= 0.205$, $z = 1.119$, $p = .263$), indicating that overall accuracy in the Congruent and Incongruent conditions was similar. However, the interaction between Condition and log(trial) was significant ($\beta = -0.1321$, SE $= 0.041$, $z = -3.205$, $p = .001$), indicating that accuracy improved across trialsl more rapidly for the Congruent condition than in the Incongruent condition. The three-way interaction of Condition, best-fitting decision-bound, and log(trial) was also significant ($\beta = 0.1361$, SE $= 0.050$, $z = 2.735$, $p = .006$), indicating that the rate of improvement in accuracy across trials was greater in the Congruent condition than in the Incongruent condition but only for participants best fit by a procedural model. Overall accuracy was also significantly greater for participants best fit by a procedural model than for participants best fit by a rule-based model ($\beta = 0.9020$, SE $= 0.167$, $z = 5.386$, $p < .001$) Participants best fit by a procedural model also showed a greater improvement in accuracy

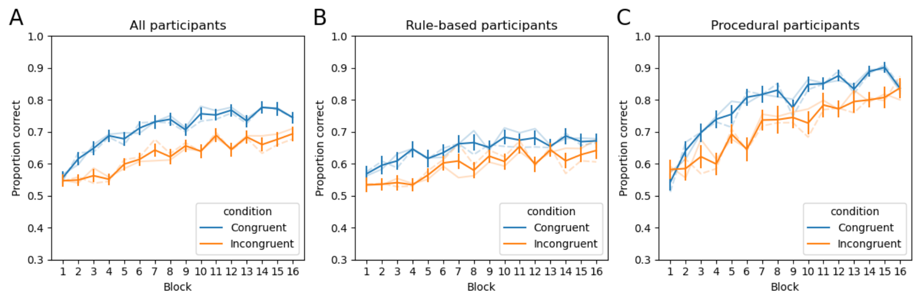

Figure 3

A: *Mean accuracy per block in averaged over all participants.* ***B:*** *Mean accuracy per block in averaged over participants best fit by a rule-based decision-bound model.* ***C:*** *Mean accuracy per block in averaged over participants best fit by a procedural decision-bound model. In all panels, blue lines correspond to the Congruent condition and orange lines correspond to the Incongruent condition. The semi-transparent lines show the performance in each subtask, and the solid lines show the performance averaged over both subtasks. Error bars are standard errors of the mean.*

across trials than participants best fit by a rule-based model ($\beta = -0.3348$, SE = 0.034, $z = -9.937$, $p < .001$). The interaction between Condition and best fitting decision-bound model was not significant ($\beta = -0.4712$, SE = 0.249, $z = -1.895$, $p = .058$).

Task Switching

Figure 4 shows switch costs for for accuracy and RT for Congruent and Incongruent conditions for all participants, participants best fit by a rule-based decision-bound model, and participants best fit by a procedural decision-bound. A 2 (condition) x 2 (best-fitting decision-bound model) ANOVA revealed that the effect of condition was significant ($F(1, 86) = 8.74, p < .001, \eta^2 = 0.09$), indicating that switch costs were greater in the Incongruent condition than in the Congruent condition (see Figure 4). However, the difference in switch cost between participants best fit by a procedural model and participants best fit by a rule-based model was not significant $F(1, 86) = 0.02, p = .88, \eta^2 = 0.00$. The interaction term was also non-significant, $F(1, 86) = 0.01, p = .93, \eta^2 = 0.00$.

Decision Bound Models

Figure **??** panels A, B, D, and E show the decision bounds from the best-fitting decision-bound models in both conditions overlaid on the underlying category distribution for each subtask. Figure **??** panels C and F show the proportion of participants whose responses were best fit by each type of model in each condition. For this analysis, we coded each particpant as a procedrual model user if they were best by a GLC model on both subtasks, or as a rule-based model user if they were best fit by a RB model on either subtask. This figure clearly shows that there were more procedural users in the Congruent condition than in the Incongruent condition. The results of Pearson's Chi-Squared test revealed that there were signifcantly more participants best fit by a procedural model in

	coef	std err	z	P> |z|	[0.025	0.975]
Intercept	-1.0034	0.129	-7.796	0.000	-1.256	-0.751
Condition	0.2289	0.205	1.119	0.263	-0.172	0.630
DBM	0.9020	0.167	5.386	0.000	0.574	1.230
Condition:DBM	-0.4712	0.249	-1.895	0.058	-0.959	0.016
log(trial)	0.4775	0.026	18.211	0.000	0.426	0.529
condition:log(trial)	-0.1321	0.041	-3.205	0.001	-0.213	-0.051
DBM:log(trial)	-0.3348	0.034	-9.937	0.000	-0.401	-0.269
Condition:DBM:log(trial)	0.1361	0.050	2.735	0.006	0.039	0.234

Table 1

Logistic regression results. Condition is dummy coded with the Incongruent condition as the reference. Decidion-bound model (DBM) is dummy coded with the rule-based model as the reference.

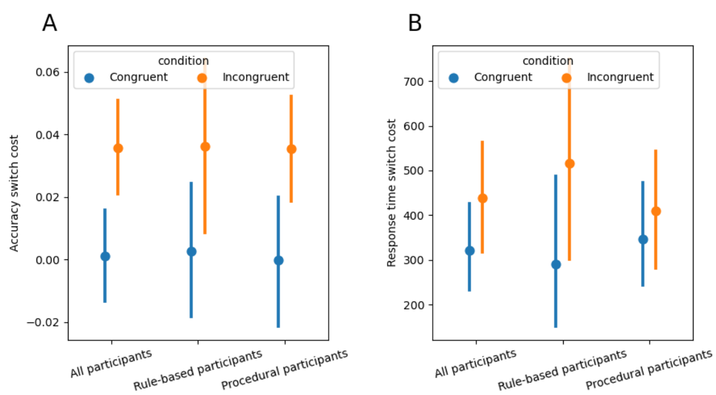

Figure 4

*Accuracy switch costs **A** and RT switch costs **B** for both Congruent (blue) and Incongruent (orange) conditions for all participants, participants best fit by a rule-based decision-bound model, and participants best fit by a procedural decision-bound model.*

the Congruent condition than in the Incongruent condition ($\chi^2(1, N = 200) = 4.48, p = .034, \text{Cramer's}V = 0.16$).

Discussion

Procedural category learning involves the gradual formation of many-to-one stimulus-response (SR) associations through trial-and-error feedback. Previous research in single-task contexts suggests that these associations are linked to motor goals (e.g., pressing a button on the left) rather than specific motor effectors (e.g., pressing a button with a particular finger). The current study aimed to extend this finding to task-switching contexts, investigating whether SR associations remain goal-based or shift to an effector-specific level when tasks are switched. Participants learned two category structures while switching be-

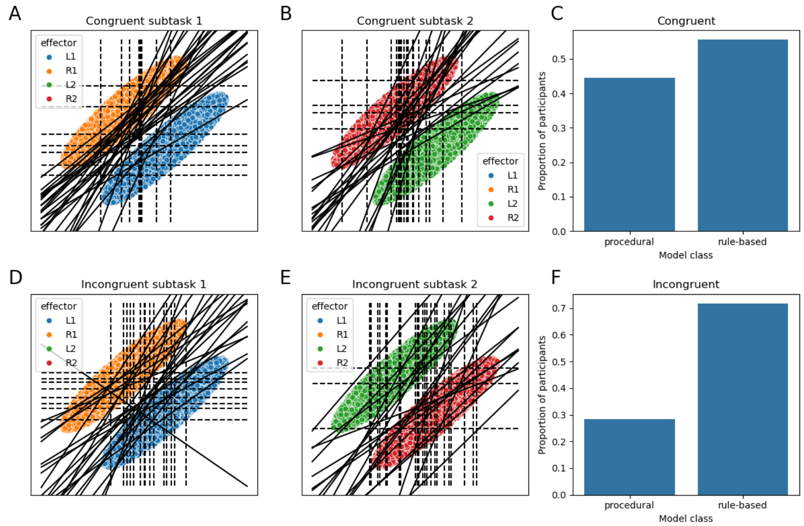

Figure 5

Category structures and decision bounds from the best-fitting decision bound model for each participant and subtask in each condition during the final 100 trials of training. A: Decision bounds for the Square task in the Congruent condition. B: Decision bounds for the Diamond task in the Congruent condition. C: Proportion of participants best fit by a procedural model in each condition. D: Decision bounds for the Square task in the Incongruent condition. E: Decision bounds for the Diamond task in the Incongruent condition. F: Proportion of participants best fit by a procedural model in each condition.

tween tasks from the start of training, with motor responses varying across tasks. Our results showed more effective learning when stimuli from the same region of stimulus space were mapped to responses on the same hand (Congruent condition), compared to when different hands were used (Incongruent condition). These findings suggest that procedural category learning continues to rely primarily on motor goal-based SR associations during task switching. However, the fact that learning also occurred in the Incongruent condition indicates that effector-specific associations may also play a role.

Context cues and response generalization

A more refined interpretation of our results can be gleaned by considering how participants used (or failed to use) the context cue meant to differentiate between the two tasks. There are three main possibilities: (1) the context cue was used perfectly, enabling participants to form independent, context-specific SR associations; (2) the context cue was entirely ignored; or (3) it was used imperfectly, leading to some degree of generalization or interference between contexts.

First, if participants had successfully formed independent SR associations for each task, we would expect no difference in learning performance between the Congruent and Incongruent conditions. Each task would have been learned in isolation, with no interference or generalization across contexts. However, given the significant difference in learning outcomes between the two conditions, this explanation is inconsistent with our findings. Second, if participants entirely ignored the context cue, there would be no cost associated with switching between contexts. Yet, our data show clear switch costs in both conditions, making it unlikely that participants disregarded the context cue, and thus, we can rule out this possibility. Third, if participants did form separate SR associations for each task but these associations were subject to some degree of generalization or interference across contexts, several possibilities emerge.

If learning and generalization occurred at the motor goal level rather than the effector level, we would expect strong learning in the Congruent condition. This is because stimuli from the same region of stimulus space would consistently be associated with the same motor goal (e.g., pressing a left-hand button) across both tasks. Learning in the Incongruent condition, however, would be impaired relative to the Congruent condition – depending on the extent of generalization between contexts – because stimuli from the same region of stimulus space would be associated with different motor goals in each task. This possibility aligns well with our findings.

If learning and generalization occurred at the effector level, the degree of generalization between effectors would dictate learning outcomes. Without any generalization, learning would fail in both conditions. This is because stimuli from the same region of stimulus space would require different motor responses across tasks. However, if generalization occurred between fingers on the same hand, learning could still succeed in the Congruent condition but not in the Incongruent condition. If generalization extended to mirrored fingers on opposite hands, learning would also occur in the Incongruent condition. Thus, our results suggest that there may be a higher degree of generalization between fingers on the same hand and, to a lesser extent, between mirrored fingers on opposite hands.

In summary, our findings imply that if the response component of the SR associations driving procedural category learning operate at the motor goal level, there is some degree of generalization between contexts such that the goal associations learned in one context can be used or must be overcome in another context. Conversely, if the response component operates at the effector level, our results suggest greater generalization occurs between fingers on the same hand than between mirrored fingers on opposite hands. This interpretation broadly aligns with anatomical evidence showing that finger representations in M1 – while somatotopic – widey overlap for neighboring fingers (REFS).

Relation to existing lines of research

This study builds upon our previous investigation into the effects of motor planning on task-switching in novel and attention-demanding tasks (**crossley_switch_2023**; Crossley et al., 2018; Turner et al., 2017). In that earlier work, we were among the first to explore task switching when the tasks are not only new to participants but also challenging to learn. One of the key findings was that learning while task-switching was only possibly when each task involved unique motor responses. In the present study, we extend this line of inquiry by showing that the stimulus-response (SR) associations formed during task switching are primarily at the motor goal level, but also at the effector level.

A line of studies from Collins and colleagues is also relevant to our current results (Collins, 2017; Collins & Frank, 2013; Collins et al., 2014; Collins & Frank, 2016a, 2016b). In particular Collins and Frank (2016a) showed that when task switching, humans prefer hierarchical rules in which the motor responses used for within a task are adjacent. However, it is not simple to connect our results to theirs since their studies used relatively simple tasks characterized by easily discernible stimuli and straightforward response rules, whereas ours was difficult to learning and relied on procedural learning.

Conclusions

Put smart and important sounding stuff here.

Authors' contributions

MJC wrote the paper, designed the experiments, performed all data analysis and modelling, and and oversaw data collection; HA wrote the paper and collected all data. DMK wrote the paper and oversaw data collection; FGA wrote the paper and designed the experiments.

References

Ashby, F. G., Alfonso-Reese, L. A., Turken, A. U., & Waldron, E. M. (1998). A neuropsychological theory of multiple systems in category learning. [Publisher: American Psychological Association]. *Psychological Review*, *105*(3), 442–481.

Ashby, F. G., & Gott, R. E. (1988). Decision rules in the perception and categorization of multidimensional stimuli. *Journal of experimental psychology. Learning, memory, and cognition*, *14*(1), 33–53. https://doi.org/10.1037/0278-7393.14.1.33

Ashby, F. G., & Valentin, V. V. (2017). Multiple systems of perceptual category learning: Theory and cognitive tests. In H. Cohen & C. Lefebvre (Eds.), *Handbook of categorization in cognitive science, Second Edition* (pp. 157–188). New York: Elsevier.

Collins, A. G. E. (2017). The Cost of Structure Learning. *Journal of Cognitive Neuroscience*, *29*(10), 1646–1655. https://doi.org/10.1162/jocn_a_01128

Collins, A. G. E., Cavanagh, J. F., & Frank, M. J. (2014). Human EEG Uncovers Latent Generalizable Rule Structure during Learning. *The Journal of Neuroscience*, *34*(13), 4677–4685. https://doi.org/10.1523/JNEUROSCI.3900-13.2014

Collins, A. G. E., & Frank, M. J. (2013). Cognitive control over learning: Creating, clustering, and generalizing task-set structure. *Psychological Review*, *120*(1), 190–229. https://doi.org/10.1037/a0030852

Collins, A. G. E., & Frank, M. J. (2016a). Motor Demands Constrain Cognitive Rule Structures (J. Daunizeau, Ed.). *PLOS Computational Biology*, *12*(3), e1004785. https://doi.org/10.1371/journal.pcbi.1004785

Collins, A. G. E., & Frank, M. J. (2016b). Neural signature of hierarchically structured expectations predicts clustering and transfer of rule sets in reinforcement learning. *Cognition*, *152*, 160–169. https://doi.org/10.1016/j.cognition.2016.04.002

Crossley, M. J., Roeder, J. L., Helie, S., & Ashby, F. G. (2018). Trial-by-trial switching between procedural and declarative categorization systems. *Psychological Research*, *82*(2), 371–384. https://doi.org/10.1007/s00426-016-0828-4

Kiesel, A., Steinhauser, M., Wendt, M., Falkenstein, M., Jost, K., Philipp, A. M., & Koch, I. (2010). Control and interference in task switching—A review. *Psychological Bulletin*, *136*(5), 849–874. https://doi.org/10.1037/a0019842

Maddox, W. T., & Ashby, F. G. (1993). Comparing decision bound and exemplar models of categorization. *Perception & Psychophysics*, *53*(1), 49–70. https://doi.org/10.3758/BF03211715

Monsell, S. (2003). Task switching. *Trends in Cognitive Sciences*, *7*(3), 134–140. https://doi.org/10.1016/S1364-6613(03)00028-7

Turner, B. O., Crossley, M. J., & Ashby, F. G. (2017). Hierarchical control of procedural and declarative category-learning systems. *NeuroImage*, *150*, 150–161. https://doi.org/10.1016/j.neuroimage.2017.02.039