

1 Evidence accumulation modelling offers new insights into the cognitive mechanisms that  
2 underlie linguistic and action-based training

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## Abstract

21 Evidence accumulation modelling has been shown to uncover new insights into the cognitive  
22 mechanisms that underlie decision making from behavioural data. By jointly modelling  
23 reaction time and accuracy data, such decision models estimate latent variables that  
24 represent distinct computational processes, such as stimulus encoding, response caution and  
25 the quality of information processing. In this study we use an evidence accumulation model,  
26 the Linear Ballistic Accumulator (LBA), to shed new light into the mechanisms that underlie  
27 learning based on linguistic and action-based training. The LBA model is applied to  
28 behavioural data from a previously published training study where participants learn to  
29 name, tie or name and tie a set of knots. Our results show that training is multifaceted and  
30 associated with an increase in stimulus-encoding time, a reduction in response caution, as  
31 well as an increase in the speed of information accumulation. Furthermore, the results  
32 showed that there was an added benefit to the rate of evidence accumulation when naming  
33 and tying experience were combined. This latter finding suggests that performance benefits  
34 from multi-modal training may be instantiated in computational processes that are  
35 associated with the quantity and quality of information accumulation during decision making.  
36 Overall, in applying this computational approach to accuracy and reaction time data, we  
37 uncover new insights into the mechanisms that govern experience-dependent plasticity.

38 *Public significance statement:* The results of this study show that multi-modal training,  
39 which spans linguistic and action-based content, increases the quality of information that is  
40 gained through perception to make a decision. These results provide a novel computational  
41 account of performance benefits that are often observed from multi-modal training, which  
42 will aid theory development on learning and plasticity within cognitive science.

43 *Keywords:* evidence accumulation modelling, training, learning, action, naming,  
44 cognitive mechanisms, plasticity

45 Word count: 6703

46

## Introduction

47 Evidence accumulation models are a class of computational models used to understand  
48 the latent cognitive processes that underlie human decision making. Typically, these models  
49 use accuracy and reaction times collected in speeded choice tasks to draw insights about the  
50 psychological mechanisms that underlie those decisions. The application of this modelling  
51 approach within the domain of cognitive psychology has led to a number of novel insights  
52 about the mechanisms that underlie processes such as lexical decision making (Wagenmakers,  
53 Ratcliff, Gomez, & McKoon, 2008), ageing (Ratcliff, Thapar, & McKoon, 2001, 2010) and  
54 perceptual discrimination (Ratcliff & McKoon, 2008). Importantly, these insights are often  
55 not evident from more conventional analyses of accuracy and reaction time data. Given  
56 these characteristics, we applied an evidence accumulation model, the Linear Ballistic  
57 Accumulator (LBA; Brown and Heathcote (2008)), to behavioural data from a prior  
58 published study that used neuroimaging to examine the effects of different types of training  
59 on object knowledge and perception (Cross et al., 2012). In contrast to the original study's  
60 analysis, which analysed accuracy and reaction time separately, in this paper we apply an  
61 evidence accumulation model to uncover novel insights into the latent computational  
62 processes that underlie linguistic and action-based learning.

63

Whilst it is common for researchers to draw conclusions from a separate analysis of  
accuracy and reaction time, it is unclear how to combine these measures into a single  
measure by which to quantify task difficulty or subject ability (Wagenmakers, Van Der Maas,  
& Grasman, 2007). Consider, for example, a perceptual discrimination task that requires  
participants to indicate whether two images are of the same or different objects (Cross et al.,  
2012; Weisberg, van Turennout, & Martin, 2007). Objects could belong to two categories of  
training, one where the participants learn to name the object (name-based) and the other  
where the participant interacts physically with the object (action-based). Objects that are  
subject to name-based training are discriminated faster but with more errors, than objects

72 that are the subject of action-based training. It is unclear from a separate analysis of  
73 accuracy and reaction time data in which condition performance is superior. This is because  
74 without a principled way to combine accuracy and RT, these measures are incommensurable.  
75 While this example demonstrates the well-documented speed-accuracy trade-off, where less  
76 cautious responding is associated with faster, but more error prone responding, and more  
77 cautious responding is associated with slower but more accurate responses, this is just one of  
78 the many ways in which accuracy and reaction times can interact (Ratcliff & Rouder, 1998).

79 Evidence accumulation models provide a principled way to combine accuracy and  
80 reaction time, enabling direct insight into the processes that underlie speeded decisions  
81 (Brown & Heathcote, 2008; Ratcliff, 2002). They do so by combining accuracy and the  
82 distribution of RT for correct and error responses in order to estimate parameters of a model  
83 that can separate the effects of response caution from difficulty. While there are many  
84 different varieties of evidence accumulation model, they all share a similar basic framework  
85 (Donkin, Averell, Brown, & Heathcote, 2009). Namely, these models all assume that when  
86 making a decision, evidence is sampled from the environment and that information is used as  
87 evidence for one of the potential responses. As soon as evidence in favour of a particular  
88 response reaches a threshold, the decision process is terminated and the corresponding  
89 response is made.

90 All evidence accumulation models aim to provide estimates of four common aspects of  
91 the decision making process: the rate at which evidence accumulates in favour of a decision  
92 (drift rate), how much evidence is required before a response is reached (threshold), the  
93 amount of evidence in favour of a response that exists at the outset of a decision (start point  
94 noise) and the amount of time it takes to complete all processes that are thought to fall  
95 outside the decision, including stimulus encoding and motor responding (non-decision time).  
96 These parameters quantify the latent variables of the decision-making process. Threshold,  
97 for example, measures the amount of evidence necessary to make a response. As threshold

98 increases, responses take longer but are more likely to be correct. In this way, threshold can  
99 account for differences in response caution. Drift rate, on the other hand, is thought to  
100 reflect the signal-to-noise ratio of the stimulus. In this way, drift rate quantifies the  
101 deterministic component of the accumulation process. Drift rate, therefore, measures both  
102 the quantity and the quality of information in the system and can provide a direct measure  
103 of task difficult or subject ability (Lewandowsky & Oberauer, 2018).

104 Assessing how parameters vary as a function of experimental conditions has the  
105 potential to reveal more about the mechanisms that underlie the decision-making process  
106 than is apparent from an analysis of accuracy and RT alone (Donkin et al., 2009; Dutilh et  
107 al., 2019; Evans, 2019; Evans & Wagenmakers, 2020). Perhaps one of the most persuasive  
108 examples of this approach comes from the ageing literature. One typical finding within the  
109 ageing research is that response times increase with increasing age, a finding that led to the  
110 conclusion that there is a cognitive decline associated with ageing (Salthouse, 1996).

111 Application of an evidence accumulation model to data from such tasks, however, reveals  
112 that rather than older adults performing more poorly on speeded response time tasks than  
113 younger adults, differences in responses are actually due to differences in response caution  
114 (Ratcliff, Thapar, Gomez, & McKoon, 2004). That is, older adults are more cautious  
115 responders than younger adults, requiring a higher level of evidence to trigger a response.  
116 Importantly, this inference was not available from a traditional analysis of accuracy and RT.  
117 This is just one example in which evidence accumulation modelling has allowed researchers  
118 to draw inferences that were unavailable in a traditional analysis of behavioural data (White  
119 & Kitchen, 2022). Evidence accumulation modelling thus provides us with an opportunity to  
120 interrogate behavioural data to uncover novel insights into the latent variables that underlie  
121 decision making in a way that a traditional analysis cannot.

122 In the present paper, we use the evidence accumulation approach to shed new light on  
123 the mechanisms that underlie two kinds of learning based on different types of training

experience. Specifically, we apply the Linear Ballistic Accumulator (LBA) (Brown & Heathcote, 2008) to behavioural data from an existing multi-session training dataset that taught participants how to tie and name novel knots (Cross et al., 2012). In making use of existing data not only do we provide novel insights into the mechanisms that underlie different types of training, but we also demonstrate how computational modelling can lead to conclusions that are not readily apparent from a traditional analysis of accuracy and RT alone.

In the domain of training, the most typical behavioural finding is that with increased repetition of a task response times decrease and accuracy increases (Simons et al., 2016; von Bastian et al., 2022). While this finding is most commonly interpreted as evidence of improved task performance, it provides few insights about the latent processes that underlie training-related changes. Evidence accumulation modelling of training effects, on the other hand, has shown that task repetition can influence the rate at which information accumulates, the amount of evidence needed to trigger a response and non-decision time (Dutilh, Krypotos, & Wagenmakers, 2011; Dutilh, Vandekerckhove, Tuerlinckx, & Wagenmakers, 2009; Reinhartz, Strobach, Jacobsen, & von Bastian, 2023). Studies that have used these computational modelling techniques to investigate how task repetition improves response times report an increase in the rate of information accumulation associated with repeated performance of the same speeded task (Dutilh et al., 2011; Dutilh et al., 2009; Liu & Watanabe, 2012; Ratcliff, Thapar, & McKoon, 2006; Zhang & Rowe, 2014).

These studies have also found that while the rate of information accumulation increases during practice, these effects are also associated with decreased boundary separation (Dutilh et al., 2011; Dutilh et al., 2009; Liu & Watanabe, 2012; Zhang & Rowe, 2014). That is, with increased repetition of a task, participants require less evidence to trigger a decision. This finding has led some authors to suggest that training effects may elicit a shift in response caution, leading people to prioritise speed over accuracy. The

150 influence of training on non-decision time has less consistently been reported in the  
151 literature, with some studies suggesting that training decreases non-decision timing (Dutilh  
152 et al., 2011; Dutilh et al., 2009) and other studies reporting no influence on this parameter  
153 (Strobach, Liepelt, Pashler, Frensch, & Schubert, 2013). Dutilh and colleagues (2011; 2009),  
154 for example, found that improved performance on a repeated lexical decision task was  
155 associated with faster drift rates, lower response caution and a decrease in non-decision time.  
156 This finding led the authors to conclude that training effects were multifaceted.

157 These conclusions, however, have been drawn from a limited number of perceptual  
158 discrimination tasks, with the vast majority of studies using either random dot motion  
159 (Cochrane, Sims, Bejjanki, Green, & Bavelier, 2023) or lexical discrimination tasks (Dutilh et  
160 al., 2011). Similarly, these studies typically investigate training related changes that are  
161 induced by task repetition (Dutilh et al., 2011; Dutilh et al., 2009). In contrast, we applied  
162 evidence accumulation modelling to understand and compare the mechanisms that underlie  
163 different types of training during a complex real-word perceptual discrimination task.

164 Cross and colleagues (2012), across five days, taught knot-naïve participants to tie or  
165 name a set of knots that were previously unknown to them. Performance on, and neural  
166 activity during, a perceptual discrimination task was then measured. Participants were  
167 required to discriminate whether two images were of the same or different knots. Stimuli fell  
168 into one of four training categories; training about how to name and tie the knot, knowledge  
169 of how to name the knot only (linguistic-based training), training in how to tie the know  
170 only (action-based training) and no training of the knot. Consistent with typical training  
171 effects the authors reported a decrease in response times as training days progressed. A  
172 somewhat surprising effect of training type on response times also emerged, with participants  
173 performing the perceptual discrimination task faster for untrained compared to trained  
174 knots. There were no effects of training in terms of accuracy data. The authors concluded  
175 that these behavioural findings were suggestive that the newly formed linguistic and action

knowledge that was developed via training was taking time to process when presented with a familiar set of knots. This conclusion, however, is based upon a traditional analysis of observed variables where reaction times reflect the total time taken to complete the decision-making process, including stimulus processing and motor responding. Application of evidence accumulation modelling, on the other hand, provides us with an opportunity to break down a decision into the latent variables that underlie the acquisition of linguistic and action-based knowledge induced by training.

The aim of the present study was to investigate to what extent parameters in the LBA model vary by each type of training. Given previous studies have suggested that increased drift rate, decreased response caution and decreased non-decision time (Dutilh et al., 2011; Dutilh et al., 2009; Zhang & Rowe, 2014) are all associated with training-related changes, we hypothesised that improvements in perceptual discrimination due to training would be associated with (1) an increase in drift rate; (2) a decrease in response caution; (3) a decrease in non-decision time or (4) some combination of these factors. Furthermore, it was also possible that the extent to which these parameters varied by training type (naming, tying, naming & tying, untrained) may differ, although we had no specific predictions about the direction of this hypothesis.

## Methods

### Transparency and Openness Statement

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study (Simmons, Nelson, & Simonsohn, 2012). In addition, the hypotheses and planned analysis for this paper were preregistered in advance (see our pre-registration here: <https://aspredicted.org/6ztj-45s5.pdf>). We deviated from our pre-registration in one way. Originally, we had intended to include in our model data from both a pre- and post-training session. That is, we intended to compute the difference in parameter estimates between the pre- and post-training variable. Instead, we only included

202 data from the post-training session in our final analysis. This deviation from preregistration  
203 was necessary as the model building process could not be completed with both pre- and  
204 post-training session variables included, due to the large number of parameters being fit and  
205 the model failing to converge. By removing the pre-training session data, the number of  
206 parameters was reduced by half. As a result, the model could converge and we were able to  
207 successfully complete the model building process.

208 Importantly, given that we were interested in the mechanisms that underlie training  
209 vs. no-training, as well as comparisons between different types of training (linguistic  
210 vs. action vs. both), only the post-training session was necessary to capture and quantify  
211 these effects. Indeed, Cross and colleagues (2012), in their original study, included only  
212 results from the post-training session in their final analysis, as this session is thought to be  
213 more consistent and reflect the participants' learned state (Weisberg et al., 2007). All other  
214 aspects of the pre-registration were unchanged. In addition, all of the analysis code used in  
215 this paper have been made available on the open science framework (<https://osf.io/ea6gk/>).  
216 Given that the data were collected several years before 2012, it was not yet routine to  
217 request explicit consent to share data publicly. Therefore, the raw data are only available  
218 from the authors upon request. Since the current manuscript was written in R using the  
219 `papaja()` package (Aust & Barth, 2023), it is also computationally reproducible and available  
220 via GitHub ([https://github.com/rich-ramsey/knot\\_dmc](https://github.com/rich-ramsey/knot_dmc)).

## 221 Dataset

222 We applied the LBA model to a previously published dataset from Cross and  
223 colleagues (2012). This study used fMRI to examine brain activity whilst participants  
224 completed a speeded perceptual discrimination task before and after training. The data used  
225 in the current study, therefore, were collected in or before 2012. Training consisted of  
226 participants learning to name 10 knots, tie 10 knots and name and tie a further 10 knots,  
227 while a final 10 knots remained untrained (i.e., no information about how to tie the knot or

228 what it was called was experienced during the training period). Before and after the knot  
229 training portion of the study, participants were required to complete 80 trials of a perceptual  
230 discrimination task. In this task, participants had to decide whether two photographs were  
231 of the same or different knots. Each pair of knots was selected from the same learning class  
232 (i.e., name, tie, both name and tie or untrained knots). When photographs were of the same  
233 knot, the viewing angle of the two photographs differed, so the stimuli presented were never  
234 identical. Of the 80 trials, 50% of the knots were the same and 50% of the knots were  
235 different. Both accuracy and response times (ms) of the perceptual discrimination task were  
236 recorded. As we were interested in modelling only the behavioural results of the perceptual  
237 discrimination task, we summarise the aspects of the dataset relevant to the present study  
238 below and refer readers to the original paper for all other details (see Cross et al., 2012).

239 The data included in the present paper differed from that reported by Cross and  
240 colleagues (2012) in a number of key ways. First, while 30 participants took part in the  
241 behavioural portion of the original study, only data from the 20 participants who comprised  
242 the final fMRI sample were available for re-analysis. The decision to include only the final  
243 training session in the LBA model meant that a further two participants were excluded from  
244 modelling as they did not complete the final session of the perceptual discrimination task.  
245 Therefore, 18 participants were included in the present study ( $M = 19.4$  years, age ranged  
246 from 17 – 27 years). Second, unlike Cross and colleagues who included the post-training  
247 session across all five days in their analysis of accuracy and RT, we included only the  
248 post-training session on the final day of training (Day 5 post-training). Given the aim of our  
249 study was to use evidence accumulation modelling to examine the cognitive mechanisms  
250 underlying linguistic and action-based training, it was sufficient to use the training effects  
251 evident on the last day of training for our analysis. That is, general training effects could be  
252 compared via a comparison between the untrained and trained conditions, and between each  
253 type of training category (e.g. linguistic vs. action vs. both). The benefit of including only  
254 the final post-training sessions was a computationally simpler model.

The present study therefore had a single within-subjects factor of training type with four levels (naming/tying/both/untrained). During naming training, participants were shown a video of a knot being rotated through 360 degrees with the name displayed in the top right-hand corner of the screen. During tying training, participants were shown a video of how to tie the knot from a first-person perspective and instructed to correctly tie each of the knots in this category by following along with the video at least once per day of training. During both naming and tying training participants were shown a video of how to tie the knot with the name of the knot displayed in the top right-hand corner of the screen and were instructed to correctly tie each of the knots in this category at least once per day of training. Knots in the untrained condition were unfamiliar to participants. Assignment of each of the 40 knots was counterbalanced across training condition and participant.

## LBA data analysis

**Model Specification.** We fit the LBA model to each participants' data for the final post-training session. The LBA model has one accumulator for each response, each with potentially different parameter values. In this design, that meant that there was one accumulator for pairs of knots that were the same and another accumulator for pairs of knots that were different. Each accumulator possessed the following parameters; start point noise ( $A$ ), representing the amount of information in each accumulator at the beginning of a decision; threshold ( $b$ ) which represents the amount of evidence necessary in order to trigger a decision (in the present study this was represented in terms of the difference between the top of the start point distribution and the response threshold ( $B = b - A \geq 0$ )); drift rate ( $v$ ) the rate at which evidence accumulates for each response; and non-decision time ( $Ter \geq 0$ ) the amount of time it takes to complete all other processes that fall outside the decision making process, including stimulus encoding and motor responding. We allowed the threshold parameter to vary by Training Type (name, tie, both, untrained) and Response (participant's response as to whether the two knots match vs. no-match). The drift rate

parameter was allowed to vary by Training Type and an accumulator match factor, which denotes the match between the accumulator and the stimulus. Specifically, if the stimulus displayed two of the same knots, then the accumulator for the “match” response was the TRUE or matching accumulator, whereas the accumulator for the “no match” response would be the FALSE or mismatching accumulator. In this way the difference between the TRUE and FALSE accumulator captures both the quantity and quality of information accumulating about the stimulus. The larger the difference between the TRUE and FALSE accumulators, the higher the quality of information accumulating in favour of that response (Lewandowsky & Oberauer, 2018). Given this, we operationalised drift rate as the difference between the TRUE and FALSE accumulator. The standard deviation for the TRUE accumulator was allowed to vary by the accumulator match factor, whereas the standard deviation for the FALSE accumulator was fixed at 1 to make the model identifiable (Donkin et al., 2009). The non-decision time parameter was allowed to vary by Training Type, while the standard deviation of non-decision time was fixed at 0. We fixed a single value for start point noise (A).

**Model estimation.** Model estimation was carried out in a Bayesian statistical framework using the Dynamic Models of Choice software that is written in the R programming language (Heathcote et al., 2019). Full details of priors and sampling methods are provided in supplementary materials. Following prior work (Castro, Strayer, Matzke, & Heathcote, 2019), priors were selected using a weakly informative approach. That is, priors were chosen to have little influence on estimation (graphical summaries of how posteriors were updated relative to priors are provided in supplementary materials). Sampling occurred in two steps. First, sampling was carried out separately for each individual participant. The results of this step then provided the starting points for the full hierarchical model. Inspection of graphical summaries confirmed that the model provided an adequate account for all major aspects of the data. Cumulative distribution functions comparing data with the model are provided in supplementary materials.

308       **Parameter Estimates.** In order to make inferences about the mechanisms that  
309 underlie different types of training, we compared the influence of training type in the final  
310 post-training session across different parameter estimates. Specifically, the threshold, drift  
311 rate difference and non-decision time parameters were estimated for each training type  
312 (untrained, naming, tying, both). Each posterior sample for each individual participant was  
313 then averaged across individuals to obtain the distribution of group average differences for  
314 each parameter. Pairwise comparisons on these posterior distributions were then computed  
315 between each training type and the untrained condition, as well as between each training  
316 type. To summarise the distribution of parameters of interest we report the median of the  
317 posterior distribution together with 95% quantile intervals of the distribution in square  
318 brackets.

## 319                  Results

### 320       Analysis of Observed Variables

321       Prior to conducting evidence accumulation modelling, we first analysed accuracy and  
322 reaction time separately. The purpose of this analysis was primarily to assess the effect of  
323 training as in the original paper (Cross et al., 2012). In particular, given that the data  
324 included in our analysis differed in a number of ways to that reported by Cross and  
325 colleagues, we sought to estimate the size of training effects evident in a separate analysis of  
326 accuracy and RT. These analyses were conducted using a Bayesian estimation approach to  
327 multilevel modelling. As these analyses were not the main focus of this paper, we report  
328 them briefly below. Full details, however, can be found in supplementary materials.

329       There was some evidence of an effect of training type on accuracy (see Figure 1A).  
330      Relative to the untrained condition ( $M = 87.4$ ,  $SD = 33.3$ ) accuracy was higher for knots  
331 that received both naming and tying training ( $M = 88.9$ ,  $SD = 31.5$ ), but was lower in both  
332 the tying ( $M = 85.1$ ,  $SD = 35.6$ ) and naming conditions ( $M = 83.8$ ,  $SD = 36.9$ ). There also  
333 appeared to be an effect of training type in RT (see Figure 1B) relative to knots that

334 received no training ( $M = 1139$  ms,  $SD = 345$  ms), participants responded faster to knots  
 335 that received naming training ( $M = 1055$  ms,  $SD = 347$  ms), tying training ( $M = 1119$  ms,  
 336  $SD = 356$  ms) and knots that received both naming and tying training tying training ( $M =$   
 337  $1082$  ms,  $SD = 344$  ms).

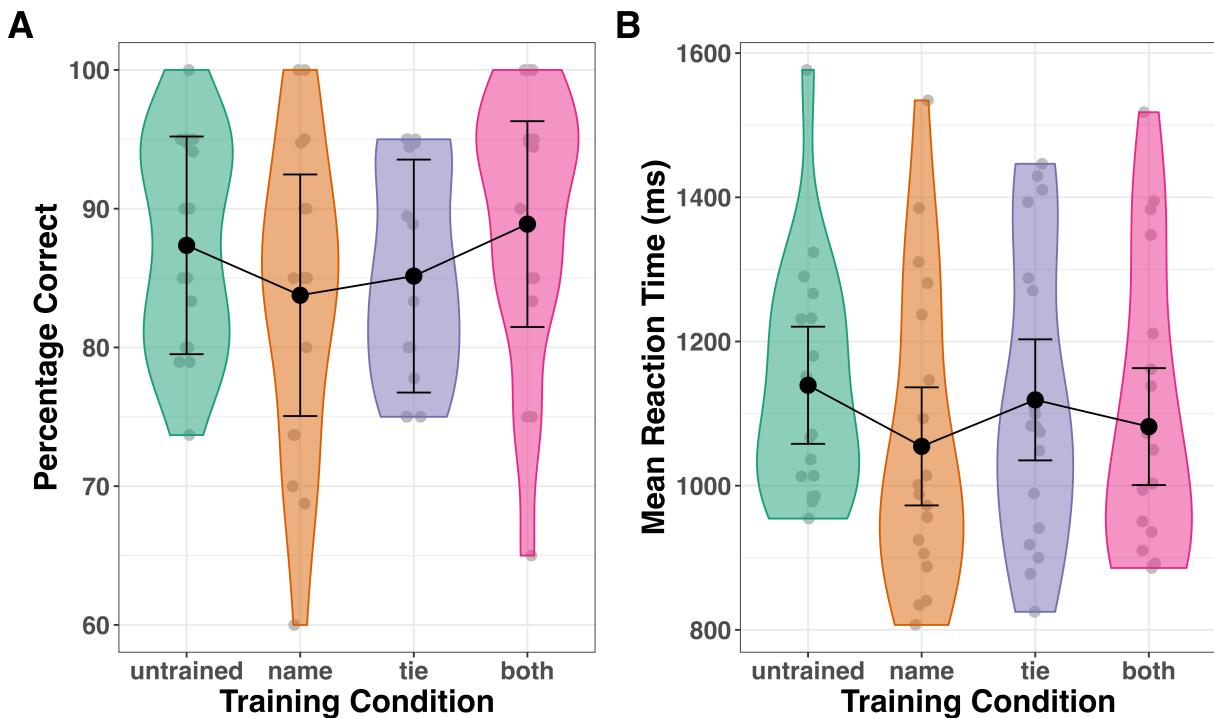


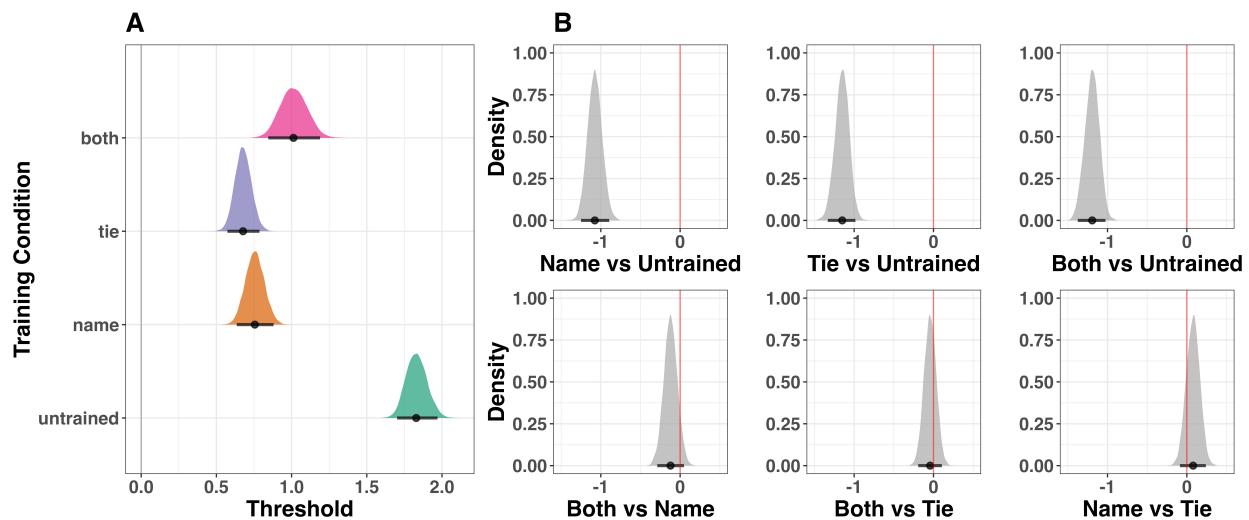
Figure 1. Accuracy and Reaction Time by Training Type and Session. (A) Percent correct on the perceptual discrimination task by training type. (B) Mean reaction time (ms) on the perceptual discrimination task by training type. Black points denote group means, while error bars represent within subjects' standard errors of the mean. Grey points denote individual subject means.

### 338 Evidence Accumulation Modelling

339       **Thresholds.** Inspection of the posterior distributions for the threshold parameter of  
 340 the LBA model revealed evidence to suggest that thresholds significantly differed by Training  
 341 Type. Specifically, thresholds were lower in all three training conditions, naming (0.76 [0.64,

342 0.88]), tying, (0.68 [0.57, 0.79]) and both naming and tying training (1.01 [0.84, 1.19])  
 343 relative to the untrained condition (2.80 [2.60, 3.03]) (see Figure 2A).

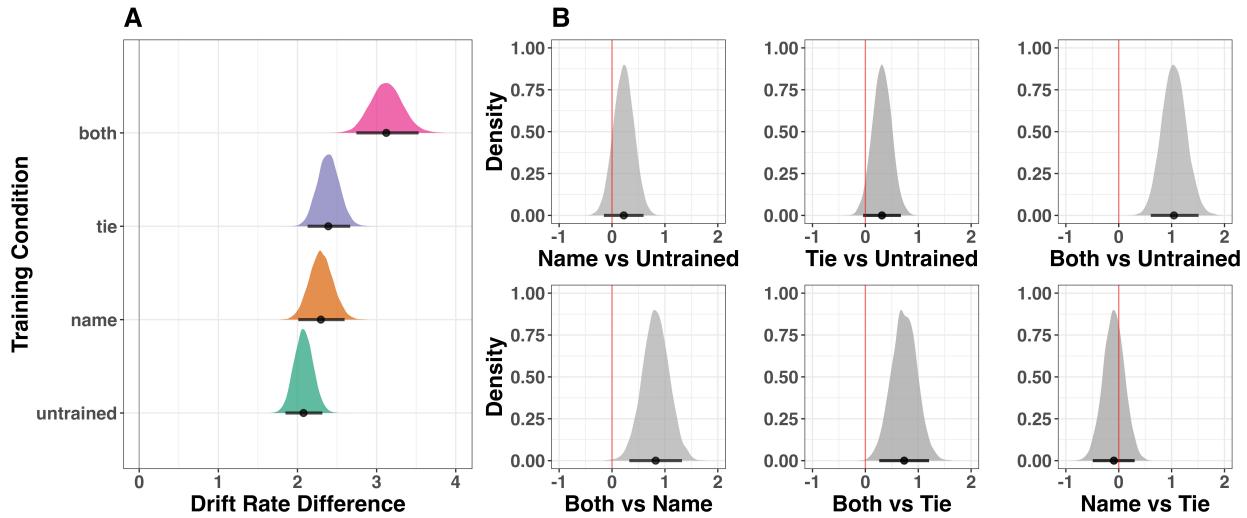
344 Pairwise comparisons between each training condition and the untrained condition  
 345 confirmed that there was a substantial reduction in thresholds in all three trained conditions  
 346 compared to the untrained condition (see top row of Figure 2B). In contrast, pairwise  
 347 comparisons between each type of training revealed little evidence to suggest that thresholds  
 348 differed substantially by type of training (see bottom row of Figure 2B). Therefore, these  
 349 results suggest that participants were substantially less cautious when responding to all  
 350 trained knots compared to untrained knots.



*Figure 2.* Posterior Distributions for the Threshold Parameter by Training Condition and Pairwise Differences between Training Conditions. (A) This panel demonstrates the posterior distributions for the threshold parameter of the LBA model by training condition. (B) This panels shows the difference in the posterior distribution for the threshold parameter between each training condition relative to the untrained condition (top row) and between each training condition (bottom row). In all graphs, black points represent the median value of the posterior distribution, while thick black lines represent the 95% quantile interval of the distribution. In difference graphs, the red line represents the zero point of the distribution.

351       **Drift rate.** In order to quantify the influence of training type on the quality and  
352 quantity of information accumulating from the stimulus, we computed the difference between  
353 the TRUE and FALSE drift rate (drift rate difference). As can be seen in Figure 3A drift  
354 rate difference appeared substantially higher for knots that received both tying and naming  
355 training (3.12 [2.74, 3.53]), relative to naming (2.30 [2.01, 2.60]), tying (2.39 [2.13, 2.67]) and  
356 untrained conditions (2.08 [1.85, 2.31]). Pairwise comparisons between training conditions  
357 confirmed that there was evidence to suggest that the quality of evidence accruing was  
358 higher for knots that received both naming and tying training relative to knots that received  
359 naming, tying and no training (See Figure 3B). The posterior distributions for each of these  
360 comparisons was positive and with values entirely above zero.

361       As can be seen in Figure 3B there was also evidence that the drift rate difference was  
362 greater for knots that received naming training relative to no training and tying training  
363 relative to no training, respectively. The posterior distributions for each of these comparisons  
364 was largely positive, with most values falling above zero. In contrast, there was no evidence  
365 to suggest that drift rate differed between the naming and tying conditions (bottom  
366 right-hand graph in Figure 3B), with the difference centred around zero, with values falling  
367 both above and below zero.



*Figure 3.* Posterior Distributions for the Drift Rate Difference Parameter by Training Condition and Pairwise Differences between Training Conditions. (A) This panel demonstrates the posterior distributions for the drift-rate parameter of the LBA model by training condition. (B) This panels shows the difference in the posterior distribution for the drift-rate parameter between each training condition relative to the untrained condition (top row) and between each training condition (bottom row). In all graphs, black points represent the median value of the posterior distribution, while thick black lines represent the 95% quantile interval of the distribution. In difference graphs, the red line represents the zero point of the distribution.

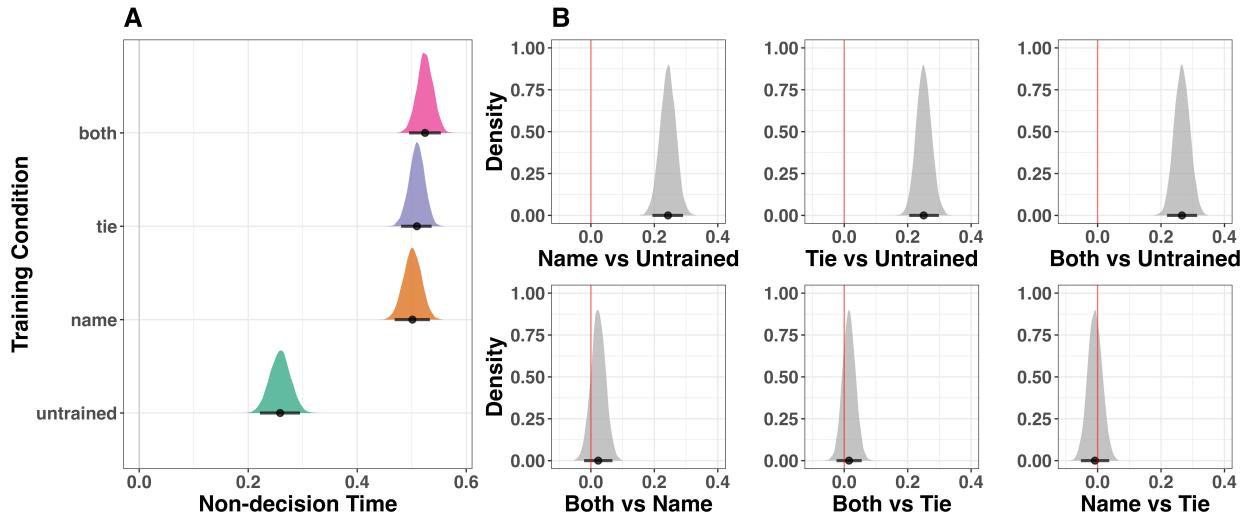
368 In summary, a clear benefit emerged in terms of the quality and quantity of  
 369 information processing during task performance following training that jointly involved both  
 370 types of learning (naming and typing). A smaller benefit was observed for information  
 371 processing when only one type of training was provided (naming or tying). In other words,  
 372 all types of training, albeit to different degrees, made the drift-rate parameter associated  
 373 with the accurate response steeper than the incorrect response. All things being equal, the  
 374 benefit of such drift-rate effects to performance would be faster and more accurate responses.

375 **Non-decision time.** As Figure 4 demonstrates, relative to the untrained condition  
 376 (0.26 [0.22, 0.29]) non-decision time was significantly higher for knots that received naming

<sup>377</sup> (0.50 [0.47, 0.53]), tying (0.51 [0.48, 0.54]) and both naming and tying training (0.52 [0.50,  
<sup>378</sup> 0.55]).

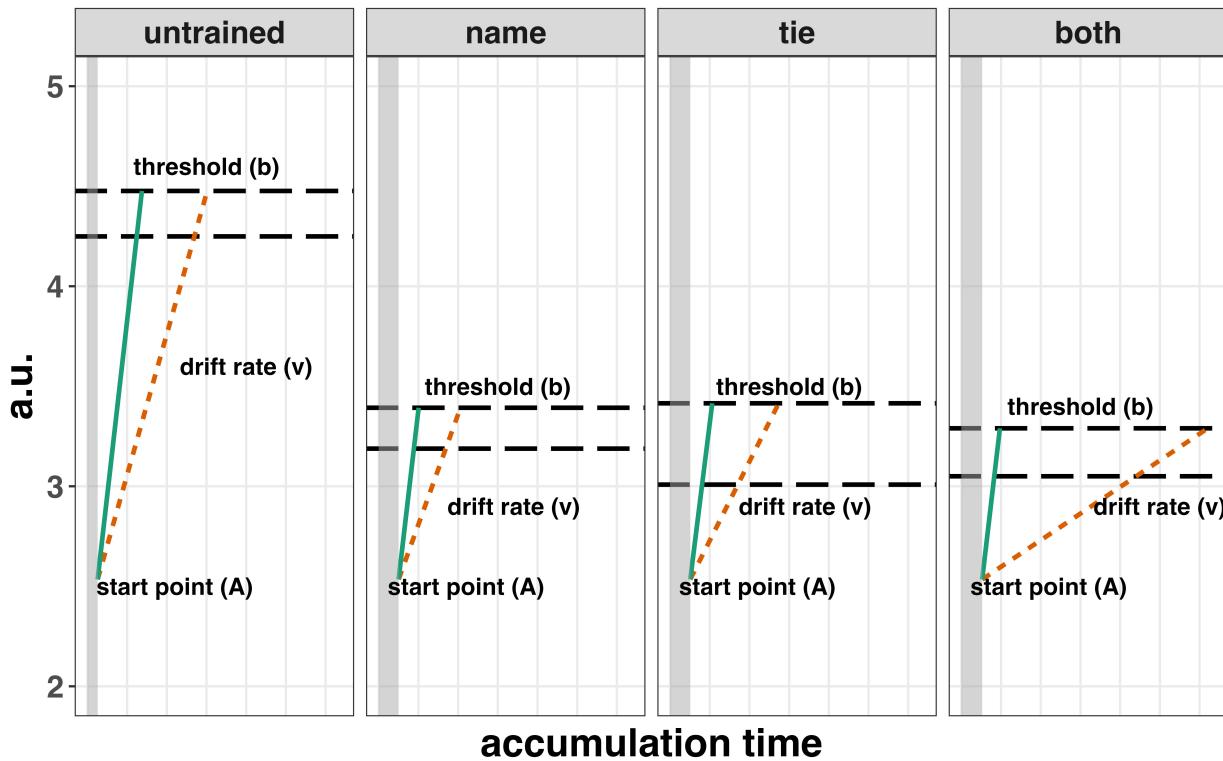
<sup>379</sup> Pairwise comparisons showed that non-decision time was substantially higher in all  
<sup>380</sup> three training conditions relative to the untrained condition with difference values being  
<sup>381</sup> positive and entirely above zero. In contrast, pairwise comparison revealed there to be no  
<sup>382</sup> evidence to suggest that non-decision time differed by training type, with difference values  
<sup>383</sup> centered around zero (see Figure 4B).

<sup>384</sup> Given that motor preparation for such a simple key-pressing task is unlikely to be  
<sup>385</sup> affected by this type of training, we suggest that these results must reflect the longer time  
<sup>386</sup> taken to encode the stimulus following the development of newly acquired linguistic or action  
<sup>387</sup> knowledge.



*Figure 4.* Posterior Distributions for the Non-decision Time (ndt) Parameter by Training Condition and Pairwise Differences between Training Conditions. (A) This panel demonstrates the posterior distributions for the ndt parameter of the LBA model by training condition. (B) This panel shows the difference in the posterior distribution for the ndt parameter between each training condition relative to the untrained condition (top row) and between each training condition (bottom row). In all graphs, black points represent the median value of the posterior distribution, while thick black lines represent the 95% quantile interval of the distribution. In difference graphs, the red line represents the zero point of the distribution.

388       **Summary.** To help visualise the pattern of results across conditions, in Figure 5 we  
 389 plot the mean values of each parameter and each condition using the structure of a decision  
 390 model plot. This plot does not form part of our inferential analytical approach. Instead, the  
 391 plot provides a visual aid to highlight differences between conditions, as well as how the  
 392 parameters may combine together within one particular condition. For example, we think  
 393 that the plot nicely illustrates the differences between conditions in non-decision time (grey  
 394 rectangle), thresholds (dashed black lines) and drift rate (solid green and dashed orange  
 395 lines).



*Figure 5.* A summary of the key findings visualised using the structure of a decision model plot. Each panel represents an experimental condition and displays the same information. The grey column represents non-decision time (ndt) with its thickness representing the amount of ndt. Start point (A) was fixed across conditions and does not vary. For ease of presentation, two thresholds (b, dashed black lines) are displayed per condition. The lower threshold represents a mismatch between the displayed knots and the higher threshold represents a match between the displayed knots on a given trial. The mean drift rate (v) for true (solid green) and false (dashed orange) responses are also displayed.

396

## Discussion

397

The aim of the present study was to use evidence accumulation modelling to

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investigate the cognitive mechanisms that underlie linguistic and action-based training in a simple knot-tying and knot-naming task. Our results revealed that the effects of training are multifaceted, in terms of the latent cognitive processes involved. In other words, training

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400

401 impacted several cognitive sub-processes that, in combination, determine subsequent task  
402 performance. In addition, an added benefit was observed for the speed of information  
403 accumulation when naming and tying experience were combined. This latter finding suggests  
404 that a multi-modal training protocol can aid the quantity and quality of information  
405 processing during decision making. Below, we discuss several ways in which our findings  
406 advance our understanding of how cognitive systems are shaped by different types of  
407 knowledge acquisition and experience. More generally, we also outline why future work may  
408 benefit from taking a more computational approach to understand the effects of training on  
409 learning and performance.

410 **Training leads to general decreases in response caution and general increases in  
411 non-decision time**

412 As predicted, our results showed that relative to the untrained condition, response  
413 caution was lower in all of the training conditions. That is, participants required less  
414 evidence to trigger a decision in the perceptual discrimination task when presented with any  
415 of the trained knots compared to untrained knots. This finding is in consistent with other  
416 studies that have found task repetition to be associated with decreased response caution  
417 (Dutilh et al., 2011; Dutilh et al., 2009; Liu & Watanabe, 2012; Zhang & Rowe, 2014).  
418 Extending these previous studies, our results also suggest that this decrease in response  
419 caution is a general effect and does not differ by type of training. Specifically, we found no  
420 evidence to suggest that changes in response caution differed whether knots received naming  
421 or tying training, or a combination of both. Given that lower response caution signals a  
422 tendency to prioritise the speed over the accuracy of responses, these results suggest that  
423 training, in part, provides a general bias to favour quicker responses.

424 The effects of training on non-decision time were consistent with the behavioural  
425 findings reported in the original study (Cross et al., 2012). Specifically, the original authors  
426 found reaction times to be higher in all three training conditions relative to the untrained

427 condition. In the current study, we found all types of training to be associated with an  
428 increase in non-decision time. That is, participants took approximately twice as long to  
429 complete all other mechanisms that fall outside the decision-making process, such as  
430 stimulus encoding and motor responding, when presented with a trained compared to an  
431 untrained knot. We found no evidence to suggest that the non-decision time parameter was  
432 modulated by training type. When these results are taken on their own, and given that  
433 motor preparation for such a simple key-pressing task is unlikely to be affected by this type  
434 of training, we infer that these results reflect the longer time taken to encode the stimulus  
435 following the development of newly acquired linguistic or action knowledge. In other words,  
436 we consider these effects to reflect the added cognitive processes that are triggered by  
437 viewing a stimulus that has been in some way enriched by training experience.

438 As a point of comparison, however, it is noteworthy that other training studies have  
439 either failed to find an association between training and non-decision time (Strobach et al.,  
440 2013) or they have reported training to decrease non-decision time (Dutilh et al., 2011;  
441 Dutilh et al., 2009). These prior studies used largely different forms of training to the  
442 current study. For example, Dutilh and colleagues (2009) trained participants on a lexical  
443 decision task. The lexical task involved making a word vs non-word judgment to strings of  
444 text and training involved repeatedly performing the same task across several days.  
445 Therefore, it is currently unclear how different types of training and experience may impact  
446 non-decision time, but it seems a valuable component to include when building models of the  
447 computational processes involved in experience-dependent plasticity.

448 **The combination of linguistic and action-based training increases the quality of  
449 information accumulation**

450 We found evidence to support the hypothesis that training increases the rate at which  
451 evidence accumulates. Relative to knots that were untrained, there was an increase in the  
452 rate at which evidence accumulated following all training conditions (naming, tying and

453 both). The finding that training generally increases the rate at which evidence accumulates  
454 is consistent with previous studies that have found repeatedly completing speeded tasks to  
455 be associated with an increase in the rate at which information accumulates (Dutilh et al.,  
456 2011; Dutilh et al., 2009; Liu & Watanabe, 2012; Ratcliff et al., 2006; Zhang & Rowe, 2014).  
457 Thus, de novo acquisition of linguistic and action knowledge made it easier to quickly and  
458 accurately arrive at a perceptual judgment.

459 In an extension of these studies, however, the increase in drift rate was substantially  
460 higher for knots that received both naming and tying training, compared to untrained knots  
461 and knots that received either type of training alone. A such, the ability to reach a decision  
462 quickly and correctly was made easier by a training regime that combined two types of  
463 training knowledge. We consider two ways to interpret the added benefit of multi-modal  
464 training. First, it is possible that the increase in drift-rate represents a dose-response effect,  
465 rather than being due to the unique combination of two types of training. That is, knots  
466 that received both training types received more training overall than knots that received only  
467 naming training or only tying training. Even so, it is still noteworthy that such a  
468 dose-response effect was specific to the drift-rate parameter and not evident in either the  
469 threshold or non-decision time parameter.

470 A second interpretation is that the unique combination of linguistic and action-based  
471 training may somehow enhance the quality and quantity of information accumulation during  
472 decision making. Such a qualitative interpretation would be consistent with prior studies  
473 that have reported multi-modal training protocols to lead to greater improvements in  
474 cognitive functions such as visuospatial working and episodic memory, executive functioning  
475 and the speed of information processing than single-function training protocols, as well as  
476 studies that report multi-model training protocols to engage a broad network of sensorimotor  
477 brain regions more than unimodal training protocols (Kirsch & Cross, 2015). In the present  
478 study, we were unable to tease apart whether the results reflect a dose-response effect or

479 instead reflect a qualitatively different impact of multi-modal training. We encourage future  
480 studies to systematically manipulate the combination of training types to determine whether  
481 increased exposure to training and/or different types of training influence the quality and  
482 rate at which evidence accumulates about a decision.

483 **Implications for understanding the effects of training and experience**

484 The results of this study have a number of implications for our understanding of how  
485 training influences cognitive processes during a perceptual decision making. First, on a more  
486 general level, our key inferences about the mechanisms that underlie training would not be  
487 possible from a more conventional and separate analysis of accuracy and RT (Parker &  
488 Ramsey, 2023). The results of the present study, therefore, make it clear that the application  
489 of evidence accumulation modelling to behavioural data from a previously published training  
490 paradigm or a future training study can uncover new insights about the cognitive  
491 mechanisms responsible for learning and the acquisition of object knowledge.

492 Second, consistent with prior studies, our results revealed training effects to be  
493 multifaceted. That is, training effects were evident across a number of parameters of the  
494 LBA model, rather than a single parameter (Dutilh et al., 2011; Dutilh et al., 2009;  
495 Reinhartz et al., 2023). This suggests that improvements in task performance that are  
496 associated with training can be attributed to a number of underlying mechanisms. It may  
497 also be one reason for the wide variety of training-induced outcomes that are observed across  
498 different tasks and training protocols, as it is possible that different types and amounts of  
499 training can impact underlying cognitive processes in different ways. And this is one clear  
500 benefit to understanding cognitive processes that is provided by taking a more mathematical  
501 approach to theory building in psychology and cognitive neuroscience, as it forces a more  
502 explicit formulation of the relationship between parts of a system that are under  
503 investigation (Hintzman, 1991; Yarkoni, 2022/ed).

504        Third, in an extension to previous studies, which typically administer one type of  
505        training (Dutilh et al., 2011; Dutilh et al., 2009; Reinhartz et al., 2023), we found no  
506        evidence to suggest that training effects differ by training type (linguistic: learning names  
507        vs. motor: learning to tie). This finding is noteworthy to consider in the context of the  
508        neuroimaging results of the original study, which found action-based training to be uniquely  
509        associated with activation in the anterior intraparietal sulcus, a brain region associated with  
510        object manipulation (Cross et al., 2012). On the face of it, therefore, these results suggest  
511        that there are some unique training-specific contributions that shape cognitive and brain-based  
512        mechanisms, but our analytical approach was insensitive to such training-type differences.  
513        Taken together, these results highlight the value of using multi-method approaches to tackle  
514        research questions in cognitive neuroscience, as we are able to provide empirical support for  
515        domain-general as well as domain-specific effects of training.

### 516        **Limitations and constraints on generality**

517        While we modelled behavioural data collected from one perceptual discrimination task  
518        completed on the final day of training, it is possible that there were session-by-session and  
519        trial-by-trial training effects that were not captured in the present study. In a recent  
520        application of evidence accumulation modelling to trial-by-trial data from a learning study,  
521        for example, the authors reported that training effects were best characterised as a  
522        continuous changing in drift rate, and a day-by-day variability in response caution (Cochrane  
523        et al., 2023). Future studies should, therefore, look to collect enough data per session to  
524        enable a computational modelling approach that can examine the time course of learning at  
525        both the trial and session level.

526        It is also important to acknowledge constraints on the generality of our findings  
527        (Simons, Shoda, & Lindsay, 2017). While we interpret the results of our study as indicative  
528        of the mechanisms that underlie training effects broadly, we cannot rule out the possibility  
529        that these effects are specific to the type, amount and duration of training used in the

530 original studies training paradigm. Future studies should look to systematically manipulate  
531 the type and amount of training participants receive, across a range of tasks in order to  
532 further understand the cognitive mechanisms that underlie different forms of training.

533

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