

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

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Abstract

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

37 *Keywords:* evidence accumulation modelling, training, learning, action, naming,
38 cognitive mechanisms, plasticity

39 Word count: 6967

40 Introduction

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

57 Whilst it is common for researchers to draw conclusions from a separate analysis of
58 accuracy and reaction time, it is unclear how to combine these measures into a single
59 measure by which to quantify task difficulty or subject ability (Wagenmakers, Van Der Maas,
60 & Grasman, 2007). Consider, for example, a perceptual discrimination task that requires
61 participants to indicate whether two images are of the same or different objects (Cross et al.,
62 2012; Weisberg, van Turennout, & Martin, 2007). Objects could belong to two categories of
63 training, one where the participants learn to name the object (name-based) and the other
64 where the participant interacts physically with the object (action-based). Objects that are
65 subject to name-based training are discriminated faster but with more errors, than objects

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

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

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

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

98 Assessing how parameters vary as a function of experimental conditions has the
99 potential to reveal more about the mechanisms that underlie the decision-making process
100 than is apparent from an analysis of accuracy and RT alone (Donkin et al., 2009; Dutilh et
101 al., 2019; Evans, 2019; Evans & Wagenmakers, 2020). Perhaps one of the most persuasive
102 examples of this approach comes from the ageing literature. One typical finding within the
103 ageing research is that response times increase with increasing age, a finding that led to the
104 conclusion that there is a cognitive decline associated with ageing (Salthouse, 1996).
105 Application of an evidence accumulation model to data from such tasks, however, reveals
106 that rather than older adults performing more poorly on speeded response time tasks than
107 younger adults, differences in responses are actually due to differences in response caution
108 (Ratcliff, Thapar, Gomez, & McKoon, 2004). That is, older adults are more cautious
109 responders than younger adults, requiring a higher level of evidence to trigger a response.
110 Importantly, this inference was not available from a traditional analysis of accuracy and RT.
111 This is just one example in which evidence accumulation modelling has allowed researchers
112 to draw inferences that were unavailable in a traditional analysis of behavioural data (White
113 & Kitchen, 2022). Evidence accumulation modelling thus provides us with an opportunity to
114 interrogate behavioural data to uncover novel insights into the latent variables that underlie
115 decision making in a way that a traditional analysis cannot.

116 In the present paper, we use the evidence accumulation approach to shed new light on
117 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

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

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

158 Cross and colleagues (2012), across five days, taught knot-naïve participants to tie or
159 name a set of knots that were previously unknown to them. Performance on, and neural
160 activity during, a perceptual discrimination task was then measured. Participants were
161 required to discriminate whether two images were of the same or different knots. Stimuli fell
162 into one of four training categories; training about how to name and tie the knot, knowledge
163 of how to name the knot only (linguistic-based training), training in how to tie the know
164 only (action-based training) and no training of the knot. Consistent with typical training
165 effects the authors reported a decrease in response times as training days progressed. A
166 somewhat surprising effect of training type on response times also emerged, with participants
167 performing the perceptual discrimination task faster for untrained compared to trained
168 knots. There were no effects of training in terms of accuracy data. The authors concluded
169 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>). Given that we used secondary data in this study, we did not have a stopping rule in terms of data collection because we did not collect any data. Instead, we simply aimed to use as much of the existing data as possible based on availability.

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

Importantly, given that we were interested in the mechanisms that underlie training vs. no-training, as well as comparisons between different types of training (linguistic vs. action vs. both), only the post-training session was necessary to capture and quantify these effects. Indeed, Cross and colleagues (2012), in their original study, included only results from the post-training session in their final analysis, as this session is thought to be more consistent and reflect the participants' learned state (Weisberg et al., 2007). All other aspects of the pre-registration were unchanged. In addition, the analysis code used in this paper is available online, and the manuscript was written in R using the `papaja()` package (Aust & Barth, 2023), which means it is computationally reproducible. The code and manuscript are available via GitHub (https://github.com/rich-ramsey/knot_dmc). Given that the data were collected several years before 2012, it was not yet routine to request explicit consent to share data publicly. Therefore, the raw data are only available from the authors upon request.

Dataset

We applied the LBA model to a previously published dataset from (Cross et al., 2012). Cross and colleagues (2012) used fMRI to examine brain activity whilst participants completed a speeded perceptual discrimination task before and after training. The data used

in the current study, therefore, were collected in 2006. Training consisted of participants learning to name 10 knots, tie 10 knots and name and tie a further 10 knots, while a final 10 knots remained untrained (i.e., no information about how to tie the knot or what it was called was experienced during the training period). Before and after the knot training portion of the study, participants were required to complete 80 trials of a perceptual discrimination task. In this task, participants had to decide whether two photographs were of the same or different knots. Each pair of knots was selected from the same learning class (i.e., name, tie, both name and tie or untrained knots). When photographs were of the same knot, the viewing angle of the two photographs differed, so the stimuli presented were never identical. Of the 80 trials, 50% of the knots were the same and 50% of the knots were different. Both accuracy and response times (ms) of the perceptual discrimination task were recorded. As we were interested in modelling only the behavioural results of the perceptual discrimination task, we summarise the aspects of the dataset relevant to the present study below and refer readers to the original paper for all other details (see Cross et al., 2012).

The data included in the present paper differed from that reported by Cross and colleagues (2012) in a number of key ways. First, while 30 participants took part in the behavioural portion of the original study, only data from the 20 participants who comprised the final fMRI sample were available for re-analysis. The decision to include only the final training session in the LBA model meant that a further two participants were excluded from modelling as they did not complete the final session of the perceptual discrimination task. Therefore, 18 participants, all right-handed (Oldfield, 1971) and neurologically healthy undergraduate and graduate students, were included in the present study ($M = 19.4$ years, age ranged from 17 – 27 years). We do not have access to information on the gender of participants, but we note from the original publication that of the 20 participants that completed the fMRI component of the study, 14 were female (Cross et al., 2012). This means that our sample of 18 participants is predominantly female.

248 Second, unlike Cross and colleagues who included the post-training session across all
249 five days in their analysis of accuracy and RT, we included only the post-training session on
250 the final day of training (Day 5 post-training). Given the aim of our study was to use
251 evidence accumulation modelling to examine the cognitive mechanisms underlying linguistic
252 and action-based training, it was sufficient to use the training effects evident on the last day
253 of training for our analysis. That is, general training effects could be compared via a
254 comparison between the untrained and trained conditions, and between each type of training
255 category (e.g. linguistic vs. action vs. both). The benefit of including only the final
256 post-training sessions was a computationally simpler model.

257 The present study therefore had a single within-subjects factor of training type with
258 four levels (naming/tying/both/untrained). During naming training, participants were
259 shown a video of a knot being rotated through 360 degrees with the name displayed in the
260 top right-hand corner of the screen. During tying training, participants were shown a video
261 of how to tie the knot from a first-person perspective and instructed to correctly tie each of
262 the knots in this category by following along with the video at least once per day of training.
263 During both naming and tying training participants were shown a video of how to tie the
264 knot with the name of the knot displayed in the top right-hand corner of the screen and were
265 instructed to correctly tie each of the knots in this category at least once per day of training.
266 Knots in the untrained condition were unfamiliar to participants. Assignment of each of the
267 40 knots was counterbalanced across training condition and participant.

268 LBA data analysis

269 **Model Specification.** We fit the LBA model to each participants' data for the final
270 post-training session. The LBA model has one accumulator for each response, each with
271 potentially different parameter values. In this design, that meant that there was one
272 accumulator for pairs of knots that were the same and another accumulator for pairs of
273 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.

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

Results

Analysis of Observed Variables

Prior to conducting evidence accumulation modelling, we first analysed accuracy and reaction time separately. The purpose of this analysis was primarily to assess the effect of training as in the original paper (Cross et al., 2012). In particular, given that the data included in our analysis differed in a number of ways to that reported by Cross and

327 colleagues, we sought to estimate the size of training effects evident in a separate analysis of
328 accuracy and RT. These analyses were conducted using a Bayesian estimation approach to
329 multilevel modelling. As these analyses were not the main focus of this paper, we report
330 them briefly below. Full details, however, can be found in supplementary materials.

331 There was some evidence of an effect of training type on accuracy (see Figure 1A).
332 Relative to the untrained condition ($M = 87.4$, SEM = 7.84) accuracy was higher for knots
333 that received both naming and tying training ($M = 88.9$, SEM = 7.42), but was lower in
334 both the tying ($M = 85.1$, SEM = 8.40) and naming conditions ($M = 83.8$, SEM = 8.71).
335 There also appeared to be an effect of training type in RT (see Figure 1B) relative to knots
336 that received no training ($M = 1139$ ms, SEM = 81.2 ms), participants responded faster to
337 knots that received naming training ($M = 1055$ ms, SEM = 81.9 ms), tying training ($M =$
338 1119 ms, SEM = 83.9 ms) and knots that received both naming and tying training tying
339 training ($M = 1082$ ms, SEM = 81.1 ms).

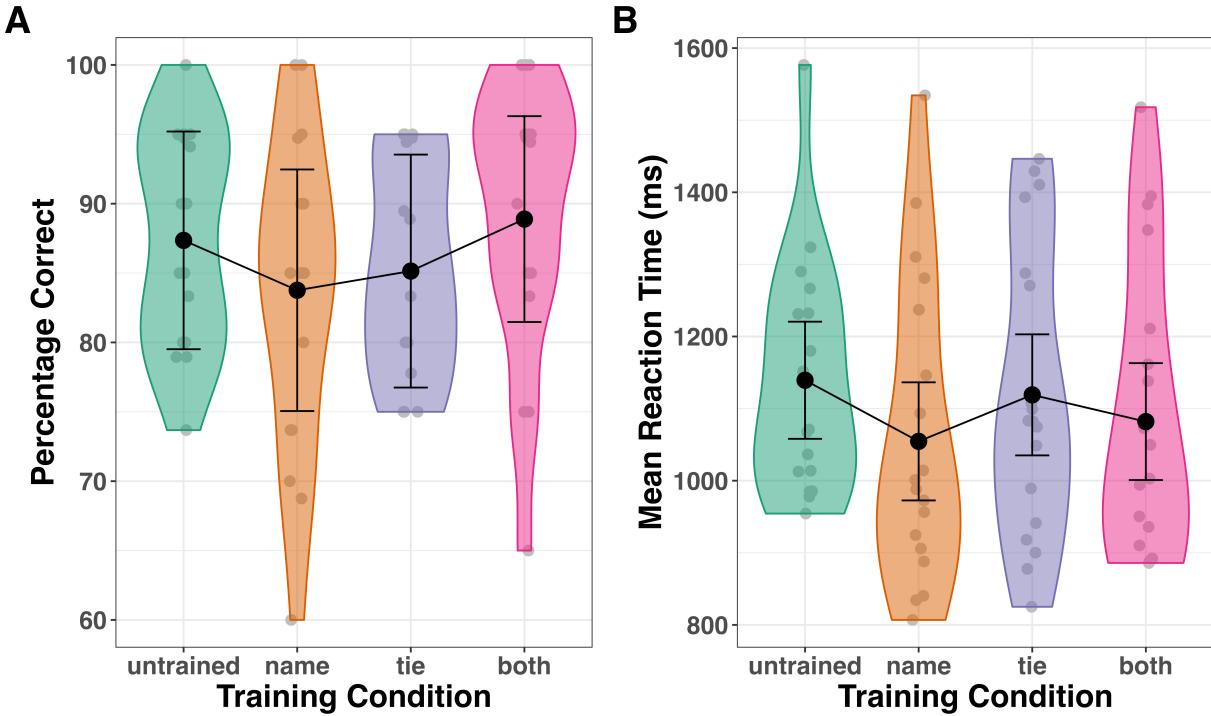


Figure 1. Accuracy and Reaction Time by Training Type and Session. (A) Percent correct on the perceptual discrimination task by training type. (B) Mean reaction time (ms) on the perceptual discrimination task by training type. Black points denote group means, while error bars represent within subjects'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

340 Evidence Accumulation Modelling

341 **Thresholds.** Inspection of the posterior distributions for the threshold parameter of
 342 the LBA model revealed evidence to suggest that thresholds differed by Training Type.
 343 Specifically, thresholds were lower in all three training conditions, naming (0.76 [0.64, 0.88]),
 344 tying, (0.68 [0.57, 0.79]) and both naming and tying training (1.01 [0.84, 1.19]) relative to
 345 the untrained condition (2.80 [2.60, 3.03]) (see Figure 2A).

346 Pairwise comparisons between each training condition and the untrained condition
 347 confirmed that there was a substantial reduction in thresholds in all three trained conditions

348 compared to the untrained condition (see top row of Figure 2B). In contrast, pairwise
 349 comparisons between each type of training revealed little evidence to suggest that thresholds
 350 differed substantially by type of training (see bottom row of Figure 2B). Therefore, these
 351 results suggest that participants were substantially less cautious when responding to all
 352 trained knots compared to untrained knots.

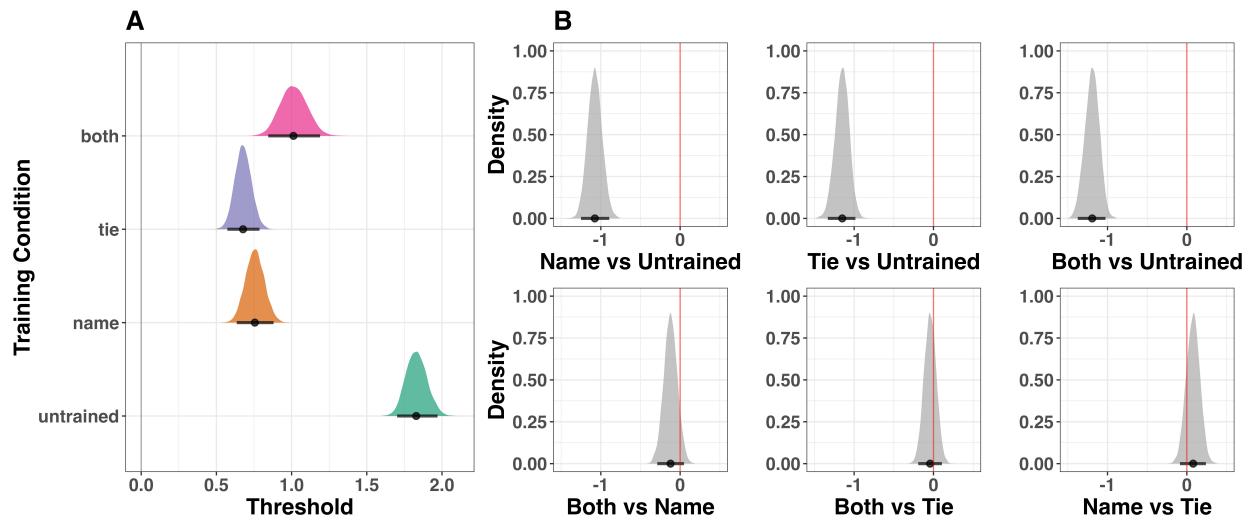


Figure 2. Posterior Distributions for the Threshold Parameter by Training Condition and Pairwise Differences between Training Conditions. (A) This panel demonstrates the posterior distributions for the threshold parameter of the LBA model by training condition. (B) This panels shows the difference in 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.

353 **Drift rate.** In order to quantify the influence of training type on the quality and
 354 quantity of information accumulating from the stimulus, we computed the difference between
 355 the TRUE and FALSE drift rate (drift rate difference). As can be seen in Figure 3A drift
 356 rate difference appeared substantially higher for knots that received both tying and naming

357 training (3.12 [2.74, 3.53]), relative to naming (2.30 [2.01, 2.60]), tying (2.39 [2.13, 2.67]) and
358 untrained conditions (2.08 [1.85, 2.31]). Pairwise comparisons between training conditions
359 confirmed that there was evidence to suggest that the quality of evidence accruing was
360 higher for knots that received both naming and tying training relative to knots that received
361 naming, tying and no training (See Figure 3B). The posterior distributions for each of these
362 comparisons was positive and with values entirely above zero.

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

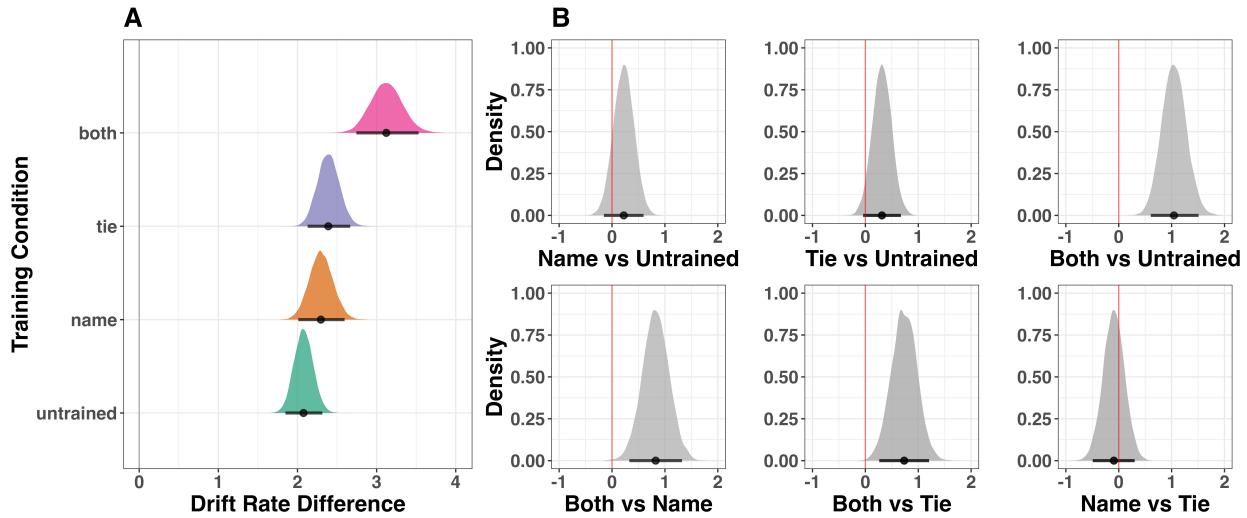


Figure 3. Posterior Distributions for the Drift Rate Difference Parameter by Training Condition and Pairwise Differences between Training Conditions. (A) This panel demonstrates the posterior distributions for the drift-rate parameter of the LBA model by training condition. (B) This panels shows the 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.

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

377 **Non-decision time.** As Figure 4 demonstrates, relative to the untrained condition
 378 (0.26 [0.22, 0.29]) non-decision time was significantly higher for knots that received naming

379 (0.50 [0.47, 0.53]), tying (0.51 [0.48, 0.54]) and both naming and tying training (0.52 [0.50,
380 0.55]).

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

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

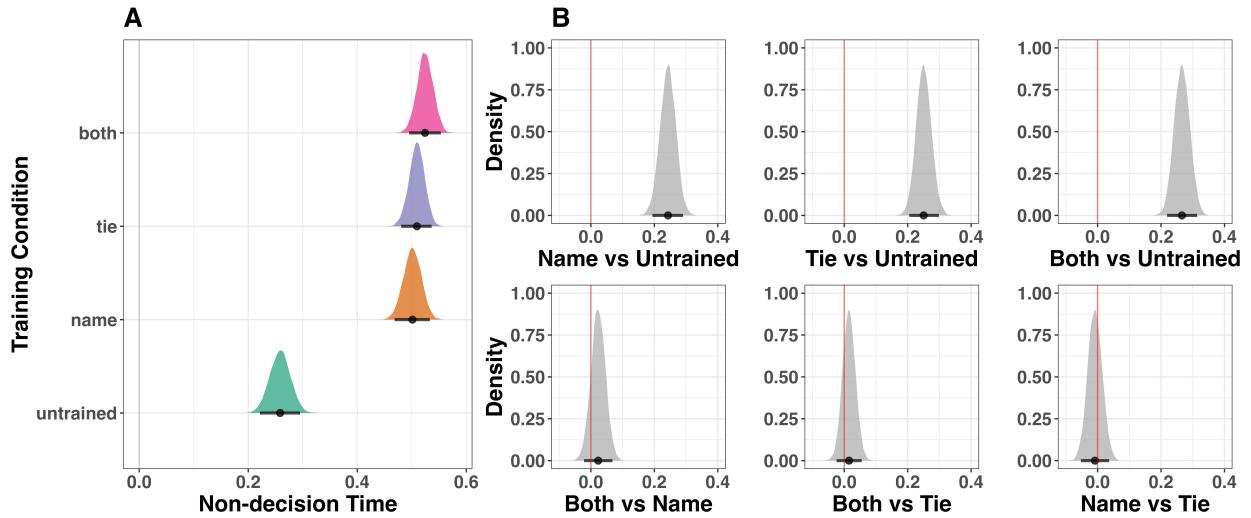


Figure 4. Posterior Distributions for the Non-decision Time (ndt) Parameter by Training Condition and Pairwise Differences between Training Conditions. (A) This panel demonstrates the posterior distributions for the ndt parameter of the LBA model by training condition. (B) This panel shows the difference 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.

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

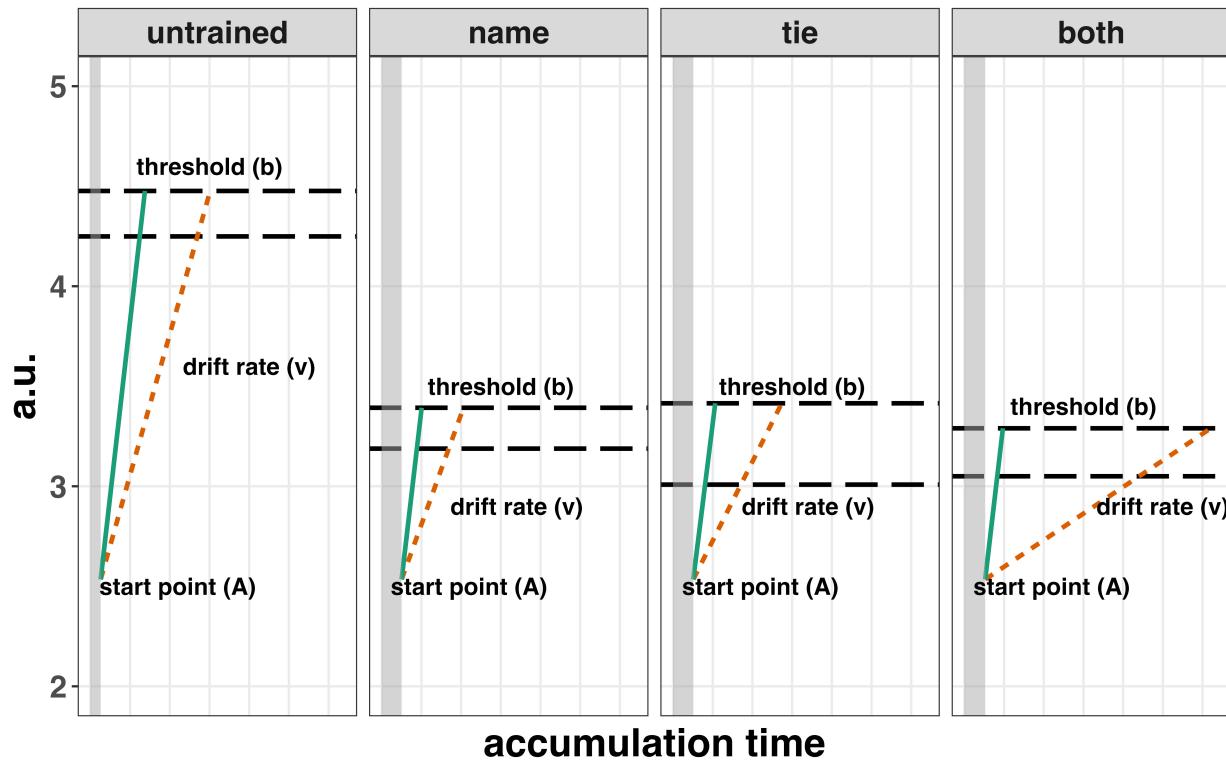


Figure 5. A summary of the key findings visualised using the structure of a decision model plot. Each panel represents an experimental condition and displays the same information. The grey column represents non-decision time (ndt) with its thickness representing the amount of ndt. Start point (A) was 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.

398

Discussion

399 The aim of the present study was to use evidence accumulation modelling to investigate
 400 the cognitive mechanisms that underlie linguistic and action-based training in a knot-tying
 401 and knot-naming task. Our results revealed that the effects of training are multifaceted, in
 402 terms of the latent cognitive processes involved. In other words, training impacted several

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

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

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

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

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

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

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

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

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

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

471 A second interpretation is that the unique combination of linguistic and action-based
472 training may lead to a qualitative difference in information accumulation during decision
473 making. Such a qualitative interpretation would be consistent with prior studies that have
474 shown that compared to uni-modal training protocols, multi-modal training leads to greater
475 improvements in cognitive domains such as working memory and problem solving (Ward et
476 al., 2017), as well as greater engagement of a broad network of sensorimotor brain regions
477 (Kirsch & Cross, 2015). In the present study, we were unable to tease apart whether the
478 results reflect a dose-response effect or instead reflect a qualitatively different impact of
479 multi-modal training. We encourage future studies to systematically manipulate the
480 combination of training types to determine whether increased exposure to training and/or

481 different types of training influence the quality and rate at which evidence accumulates
482 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).

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 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 Similarly, while we had originally planned to model the difference between the pre- and
527 post-training data for each participant, due to model complexity we were limited to
528 including the post-training session only. It is possible, therefore, that improved post-training
529 scores in the trained conditions, rather than reflecting the operation of training, may instead
530 be due to unbalanced pre-test scores between these conditions. However, it should be noted
531 that there were no clear and obvious differences in RT or accuracy in the day 1, session 1

532 data (i.e., before any training had started; see supplementary materials). Therefore, we
533 consider it quite unlikely that random variation in pre-training differences between
534 conditions could account for our findings.

535 In using secondary data analysis in the present study, we were also limited in what
536 data was available for analysis. Indeed, we determined our sample size by aiming to use as
537 much of the existing data as was possible. Consequently, the likely precision of our
538 parameter estimates is unknown. Given this limitation, it's important for future studies look
539 to replicate the findings in the present study.

540 It is also important to acknowledge constraints on the generality of our findings
541 (Simons, Shoda, & Lindsay, 2017). While we interpret the results of our study as indicative
542 of the mechanisms that underlie training effects broadly, we cannot rule out the possibility
543 that these effects are specific to the type, amount and duration of training used in the
544 original studies training paradigm. Future studies should look to systematically manipulate
545 the type and amount of training participants receive, across a range of tasks in order to
546 further understand the cognitive mechanisms that underlie different forms of training.

547

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