

When past actions complicate new choices: A computational perspective on adaptive behavior

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When past actions complicate new choices: A computational perspective on adaptive behavior

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Abstract

Adaptive behavior requires integrating information from preceding actions with current demands. Yet, how this information configures subsequent decisions remains unclear. We applied drift-diffusion modelling to twelve datasets with a combined analyzed sample size of $N=863$, spanning diverse stimulus materials, response mappings, and laboratory and online settings. This breadth allowed us to identify recurring computational signatures across experimental implementations and examine their generality across task families. Across the core stimulus–response binding tasks, partial repetitions consistently biased the initial decision state away from the currently required response and reduced the evidence threshold for commitment. These effects were largely uncorrelated across participants, supporting distinguishable influences on response preference and evidential requirements. Evidence accumulation rate showed less consistent effects, although its changes covaried with both initial settings of the decision process. The pattern extended less uniformly to visual search, flanker, task-switching, and response–response binding tasks, indicating dependence on task demands. Yet, convergence across varied implementations supports an account in which preceding actions shape specifically the starting conditions of subsequent decisions. When past and present demands partially overlap, an inappropriate response tendency can coincide with reduced evidential requirements for commitment. By connecting action-control theory with computational decision models, these findings help explain how continuity between successive actions can compromise adaptive responding.

Introduction

While goal-directed behavior appears to be implemented effortlessly, the selection of the most appropriate action in a given situation requires complex cognitive operations and overcoming several concurring action tendencies. Importantly, such tendencies can arise from previously conducted actions. These tendencies in the sense of sequence effects can lead to improvements in performance, for instance when it comes to conflict adaptation[1] or post-error adjustments[2]. However, in some cases, the influence of a previous action in a certain situation can cause impairment of a subsequent action in a similar situation, for instance, if the action that is now required differs slightly (but not completely) from the previous one. Particularly these costs of partially repeating stimulus-response links have been subject to ideomotor-inspired theories such as the Theory of Event Coding (TEC[3]) and the Binding and Retrieval in Action Control (BRAC[4]) framework. Both these theories explain sequential effects in terms of binding the characteristics (or features) of stimuli, responses, and effects of responses together in a common structure, the event-file[5–7], which initially remains active in the working memory[8,9]. As such an event-file is suggested to be a network-like structure, the reoccurrence of one of those features can trigger the retrieval or reactivation of the whole event-file, making it easy to respond in the same way, that is, with the same response features, given the same stimulus features recur as well. However, if confronted with changes in this feature structure, actions become costly, both with respect to speed and accuracy (so-called *partial repetition costs*[7]).

These symptomatic performance costs have been at the core of year-long and extensive research on action control mechanisms (for a collection of related articles, see [10], and [5], for a paper on consensus definitions) that inspired research in neurophysiological[11], developmental [e.g., 12,13], and psychiatric fields [e.g., 14,15]. Across this literature, however, retrieval itself has typically served as the explanatory endpoint rather than a starting point for further mechanistic inquiry: a pattern of impaired reaction times and/or error rates on partial-repetition trials is taken as evidence that an event-file was retrieved and compared against the current situation, but what happens to the unfolding decision process once this comparison reveals a mismatch – how retrieved information actually translates into the specific behavioral costs observed – has rarely been addressed directly. Intriguingly, while particularly the BRAC framework[4] poses the most elaborated model to date, distinguishing binding and retrieval as separate processes in perception-action-integration and including top-down and bottom-up influencing factors modulating both processes separately, it too does not yet provide a statement on how things proceed after the retrieval of an event-file. While in the case of a full repetition

of the feature set retrieval alone can explain how the correct action is implemented, the model misses specific explanations for those critical occasions when a mismatch between the action coded in the retrieved event-file and the appropriate action in the given situation occurs.

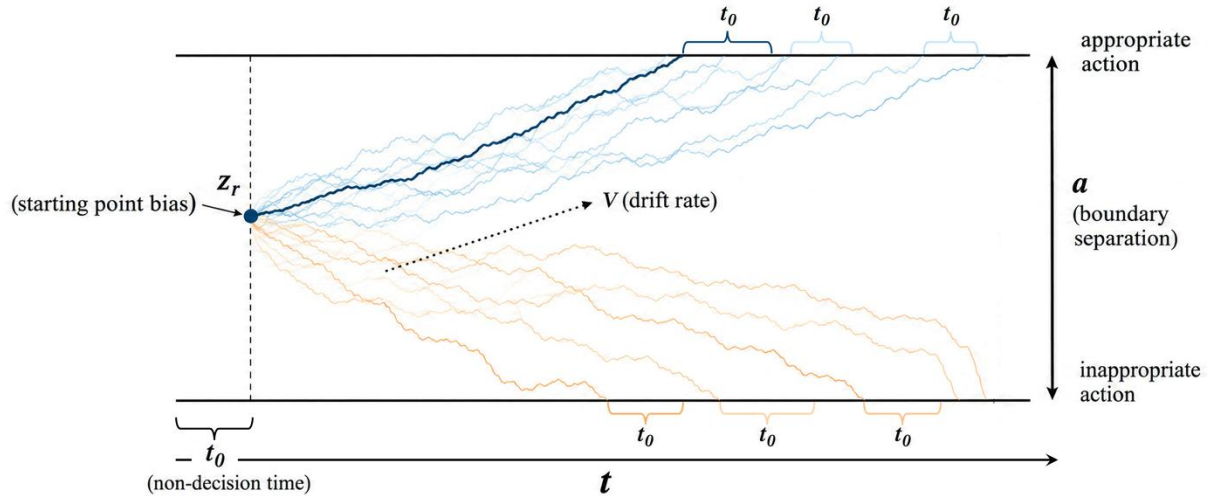
Previous accounts have frequently invoked a process of *reconfiguration* to explain what happens when a retrieved event-file only partially matches the currently required action. In classical event-coding approaches, partial repetitions are assumed to require the updating or rebinding of previously established feature relations before the currently appropriate action can be selected[7,16]. More recent neurophysiological work has provided converging evidence that partial mismatches recruit processing beyond mere retrieval. Conditions requiring changes to established perception–action relations have been associated with distinct theta- and alpha-band dynamics and have consequently been interpreted as reflecting the reconfiguration of event-file representations[17–21]. At the same time, the precise nature of this reconfiguration remains unresolved. For example, evidence argues against the strong assumption that partial repetition costs necessarily arise because previously bound feature codes must first be completely unbound before entering a new event-file[22]. Thus, although reconfiguration provides a useful functional description of the processes required after a retrieval mismatch, it does not yet specify how the retrieved information alters the unfolding decision process.

What, then, does reconfiguration entail computationally? A retrieved response could alter the decision process in several fundamentally different ways: it could bias response readiness before evidence accumulation begins, change the amount of evidence required for commitment, alter the efficiency or direction of evidence accumulation itself, or affect several of these components simultaneously. One established technique to disentangle the cognitive processes that underly decision making is drift-diffusion modeling (DDM[23,24]; see **Figure 1**): The DDM assumes a decision process between two concurring responses, which are carried out if enough evidence for one of the alternatives is accumulated. The amount of required evidence is reflected in the boundary parameter a of the DDM, reflecting how cautiously the response selection is done, sometimes suggested to reflect the speed-accuracy trade-off. The speed of evidence accumulation is coded in the drift rate v , which can be affected by the quality of information and perceptual quality. In addition to his decision process for one or the other boundary, perceptual encoding and motor execution processes are accounted for by estimating a non-decision time t_0 that is not subject to the evidence accumulation process. Together, these parameters can be used to compute at which time point which of the boundaries will be hit, in other words, the reaction time and the accuracy of each trial. However, there are other parameters that can be estimated using DDM which might affect this seemingly simple process.

One of them is the bias z_r of the starting point of the evidence accumulation, that is, how inclined the decision process is already to one of the boundaries. In this way, this bias can influence the likelihood of hitting one or the other boundary.

Figure 1

The decision process in the drift-diffusion model.



Note. Schematic illustration of the drift diffusion process and its four estimated parameters. t_0 represents the time required for non-decisional components before and after the decision process, z_r denotes the relative starting point of the diffusion process between the two response boundaries R1 and R2, a reflects the amount of evidence required to reach a decision, and v represents the mean rate and direction of evidence accumulation toward the decision boundaries.

Given this role of the starting point bias, it is likely that this parameter is biased in the context of sequential task structures and sequences of actions. Based on the previous action and the previous stimulus set, the starting point bias might vary, reflecting the notion of the BRAC framework[4] that full repetitions might promote carrying out the appropriate action, while partial repetitions might hamper appropriate acting while leaning more towards the previous action tendency which might be wrong in the current situation. Importantly, as the starting point bias is set right after the encoding of the stimulus set at the beginning of the decision process, it might reflect the retrieval process. If so, full repetitions should be associated with a higher starting point bias (that is, being closer to the boundary marking the appropriate action), while partial repetitions should be related to lower starting point biases.

Intriguingly, also the boundary separation is set right after the encoding and at the beginning of the decision process. Thus, also the boundary separation might reflect retrieval, however, perhaps a different facet of retrieval than the starting point bias. Given that boundary separation is commonly linked to response caution, one plausible hypothesis, inspired by classical conflict-monitoring accounts [e.g., 25], is that a retrieved but currently inappropriate response should increase caution, reflected in a wider boundary separation during partial

repetitions. Alternatively, boundary separation could instead track something other than deliberate caution – for instance, an unintended consequence of the retrieval conflict itself.

Crucially, when assuming that both parameters reflect the same process, they should be correlated with each other. While boundary separation and starting point bias might thus reflect retrieval, the drift rate might be related to the processes necessary for overcoming the retrieved action tendency in case it is inappropriate. Thus, it might reflect the reconfiguration of an inappropriate response tendency once bias and boundary have already been shaped by retrieval.

Lastly, assuming that retrieval is reflected in the starting point bias and the boundary separation, that is, the parameters at the kick-off of the decision process, the non-decision time should be less affected by sequential effects. The non-decision time parameter (t_0) captures processes outside evidence accumulation, particularly stimulus encoding and response execution[26,27]. Accordingly, t_0 is not a fixed motor constant but can vary with perceptual encoding demands or response preparation[28–30]. In the present context, repetitions or changes of event features could therefore facilitate or impair processing before response selection begins. If partial-repetition costs partly reflect such non-decisional processes, binding effects should also emerge in t_0 ; their absence would instead support the view that retrieval primarily alters the decision process itself.

To test these assumptions, we reanalyzed twelve datasets spanning both classical event-file paradigms and further sequential-action paradigms, decomposing the decision process that unfolds in action episode n once the event-file from episode $n-1$ is retrieved into its constituent DDM parameters. We demonstrate that binding effects robustly occur on the starting point bias z_r and the boundary separation a , while binding effects on these parameters were uncorrelated. However, while binding effects on the drift rate v were not consistently significant, they were correlated with the binding effects on z_r and a . Thus, the results suggest that retrieval configures decision making through two separable components, a response-specific starting-point bias and a relaxation of the decision criterion under retrieval conflict, while subsequent reconfiguration processes largely depend on these initial settings.

Methods

We reanalyzed twelve datasets from experiments that employed sequential response displays with orthogonally varied prime–probe relations of stimuli and responses (cf. **Figure 2**). Four of these datasets follow the logic of the classical S1R1–S2R2 paradigm[6] (see **Box 1**), and four follow the logic of the distractor–response binding (DRB) paradigms[31] (see **Box 1**) – together representing the paradigms most directly designed to examine event-file binding

and retrieval. The remaining four datasets are drawn from paradigms not traditionally associated with event-file research but that nonetheless involve sequences of stimulus–response episodes: a visual search task, a flanker task, a task-switching paradigm, and a response–response binding task. The latter paradigm originates from the event-file literature as well, but targets bindings between successive responses rather than between a stimulus and a response[32]. Including these four additional paradigms allowed us to test whether the decision-level signatures of event-file retrieval identified in the classical paradigms generalize to sequential action control more broadly. Data collected in the laboratory is marked with a superscript a (“^a”), and data collected online is marked with a superscript b (“^b”). The distinction between symbolic and figurative tasks refers to the stimulus material used (*symbolic* for letters and *figurative* for non-letter stimuli, e.g., geometric shapes or pictures).

=====Box 1=====

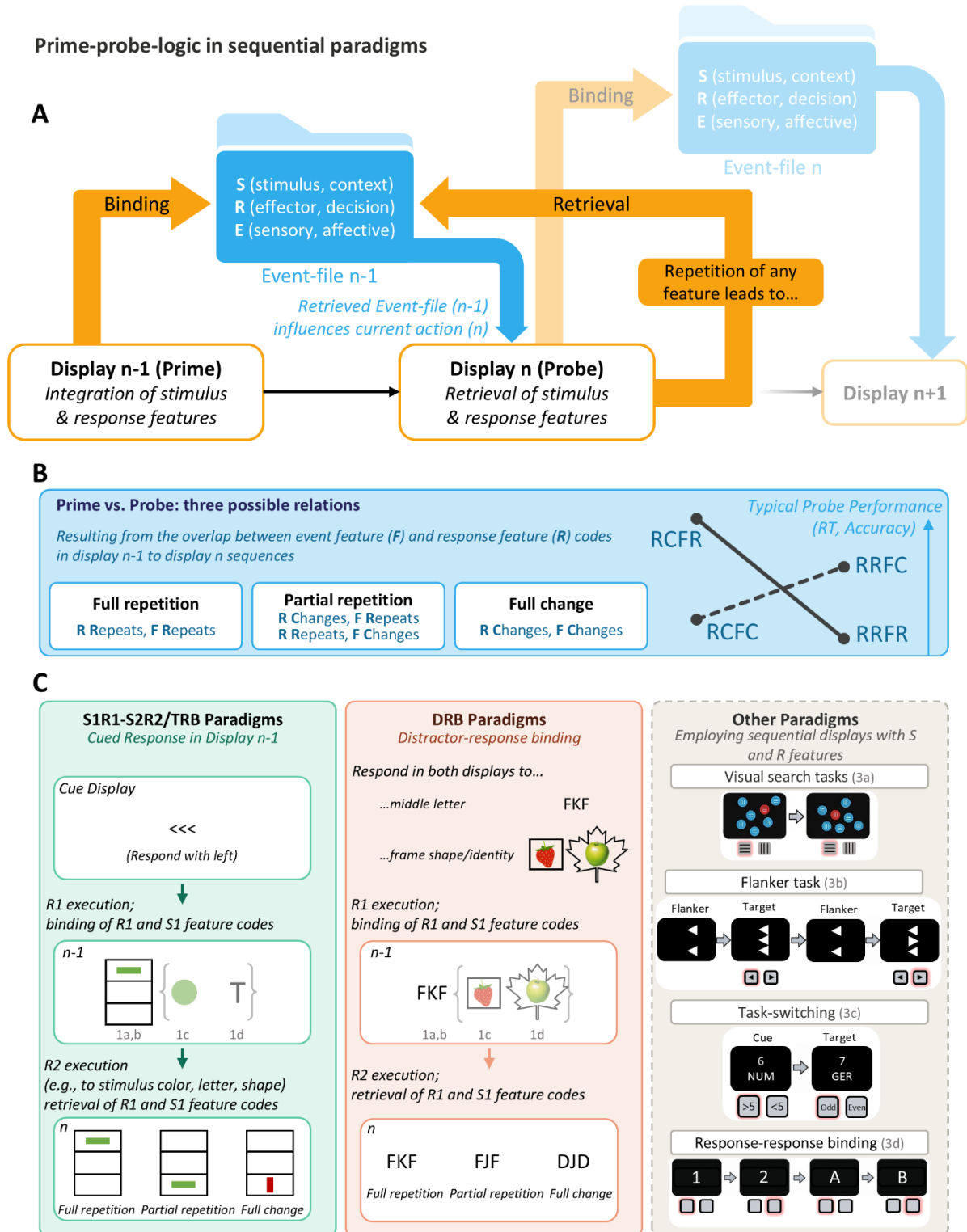
Binding effects are inferred from the interaction between stimulus feature relation and response relation from display_{n-1} to display_n, reflecting the integration of stimulus and response features into event-files and their retrieval when features reoccur. Specifically, this is evident in impaired performance in display_n when some, but not all, features of an event-file repeat (so-called *partial repetition costs*) compared with either full repetitions or full changes.

Distractor–response binding (DRB) paradigms examine the integration of task-irrelevant distractor features with responses. In the prime display_{n-1}, participants respond to a target while ignoring accompanying distractors. In the subsequent probe display_n, they again respond to the target while ignoring distractors. Distractor relation and response relation are orthogonally manipulated. Responses may follow either a 1:1 mapping (one target per response) or a 2:1 mapping (two targets per response). Targets can be separate stimuli (e.g., central letters in a flanker task or frame color, shape or identity surrounding a distractor picture) or features of an object (e.g., object shape, word type), while other object features (e.g., object color, word identity) serve as distractors. Note that, in action-control research, the term *distractor* often refers to a stimulus or feature that is presented alongside the target but is never task-relevant.

S1R1–S2R2 paradigms are sequential prime–probe tasks in which the response to the prime display_{n-1} (R1) is determined by a preceding cue and is integrated into an event-file together with simultaneously presented stimuli (S1). In the subsequent probe display_n, participants execute a second response (R2) based on a target stimulus. This design allows the independent manipulation of stimulus and response repetitions. In the simplest version of the paradigm, a single stimulus feature is presented in both prime and probe displays, with the cue enabling independent manipulation of stimulus and response relations. More complex variants include multiple stimulus features that can independently repeat or change across episodes (e.g., shape, color, and position of the stimulus), allowing to investigate how the degree of feature overlap influences performance in display_n. In contrast to DRB paradigms, in which task-irrelevant distractors are bound to the response, S1R1–S2R2-type paradigms are often also classified as TRB (target-response binding).

Figure 2

Sequential tasks from the perspective of event-file-based action control.



Note. Panel A shows subsequent task displays as a sequence of events that cause both the integration of current and the retrieval of former event-files. Panel B shows how the different prime(n-1)-probe(n) relations of responses and stimuli relate to typical behavioral performance in the probe(n) display. Panel C schematically depicts the subgroups of paradigms that were analyzed in the present study.

Task Descriptions and Participants

S1R1-S2R2/TRB paradigms

1a: Full S1R1-S2R2, figurative^a: Participants completed a classic S1R1-S2R2 task (cf. [6], with slightly adapted stimulus material). Each trial began with a directional cue (left-/right-pointing arrow, 1500 ms) presented centrally among three vertically aligned boxes, followed by a 1000-ms blank interval and two consecutive stimuli (S1, S2: horizontal or vertical lines, red or green, appearing in the upper or lower box; 500-ms S1 presentation, 2000-ms blank interval, S2 until response or 2000 ms). S1 and S2 could therefore differ in orientation, color, and position, with the degree of feature overlap varying randomly across trials (full repetition, partial repetition on one or two features, or full alternation). Participants executed two consecutive responses: R1 indicated cue direction (withheld until S1 onset, independent of S1 features; trials with incorrect R1 were repeated), and R2 classified S2 orientation (left Ctrl key = horizontal, right Ctrl key = vertical), irrespective of color or position; R1 and R2 could repeat or alternate. The task comprised 384 trials (up to 395 including repeats after incorrect R1), separated by 1500–2000-ms inter-trial intervals. Analyses considered response relation (repetition vs. alternation) and stimulus feature overlap (no, one-dimension, two-dimension, or full overlap). The original dataset was recorded at TU Dresden. Data from this task and sample have been used in previous publications[33,34]. For the current analysis, data from N=76 subjects (23.83 ± 2.69 yrs, 43 male) were included.

1b: Reduced S1R1-S2R2, figurative^a: Participants completed a task that was procedurally identical to the Full S1R1–S2R2 paradigm above (same cue, timing, stimulus dimensions, and response buttons), except that only two feature-overlap conditions were included – full overlap (identical S1/S2) and zero overlap (no shared features) – allowing for a shorter task with more trials in the most informative conditions. The task comprised 192 trials across six self-paced blocks. Analyses considered response relation (repetition vs. alternation) and stimulus feature overlap (no vs. full overlap). The original dataset was recorded at TU Dresden. Data from this task and sample have been used in a previous publication[35]. For the current analysis, data from N=33 subjects (23.52 ± 3.05 yrs, 14 male) were included.

1c: TRB, figurative^a: Participants completed a stimulus–response binding task comparable to the reduced S1R1–S2R2 paradigm described above, comprising two successive responses. Each trial began with a fixation display presented for 1000–1500 ms, followed by a centrally presented arrow cue (500 ms) indicating the response to be executed in the prime display. After

a variable interval of 250–750 ms, the prime stimulus (S1; yellow or blue circle) was presented until response. Following a 500-ms response–stimulus interval, the probe stimulus (S2; yellow or blue circle) was presented until response. Participants responded to the probe stimulus by pressing “F” or “J”, depending on the stimulus color. Stimulus relation (repetition vs. change) and response relation (repetition vs. change) were manipulated orthogonally. Participants completed one practice block of 32 trials followed by four experimental blocks of 32 trials each, resulting in 128 experimental trials. Analyses considered response relation (repetition vs. change) and target relation (repetition vs. change). The original dataset was recorded at Trier University. Data from this task and sample have been used in a previous study[36] (see also for further methodological details). For the current analysis, data from N=34 subjects (25.15 ± 4.88 yrs, 9 male) were included. The final sample after DDM-related exclusions consisted of N=26 (24.58 ± 4.96 yrs, 8 male) subjects.

Id: TRB, symbolic^a: Participants completed a prime–probe task comparable to the figurative TRB paradigm described above, comprising two successive responses. In the prime display, participants executed a cued response based on the direction of previously presented arrows. In the probe display, they classified a centrally presented target letter while ignoring two flanking distractor letters. Target letters ("D" or "K"; 42 pt, bold; approximately 1 cm high) were presented between equally sized distractor letters. Arrow cues were presented for 500 ms, followed by the prime display, which remained visible until a response was registered. The probe display appeared after a response–stimulus interval of either 500 or 2000 ms and likewise remained visible until response. Response relation (response repetition vs. change), target relation (repetition vs. change), distractor relation (repetition vs. change), and response–stimulus interval (500 vs. 2000 ms) were manipulated orthogonally. Participants completed 16 practice trials followed by 384 experimental trials while EEG was recorded. Only the target–response binding (TRB) component in the RSI 500 condition of this paradigm was included in the present drift diffusion model analyses. Analyses considered response relation (repetition vs. change) and target relation (repetition vs. change). The original dataset was recorded at Trier University. For the current analysis, data from N=50 subjects (23.22 ± 3.35 yrs, 13 male) were included. The final sample after DDM-related exclusions consisted of N=46 subjects (23.26 ± 3.28 yrs, 11 male).

DRB paradigms

2a: DRB, 1:1 mapping, symbolic^a: Participants completed a standard distractor-response binding task (cf. [31]) comprising a prime and a probe display. In both displays, participants classified a centrally presented target letter while ignoring two flanking distractor letters. Letters (25 px) were presented with the centrally presented target flanked by two distractor letters. Each trial started with a 1000-ms fixation display, followed by a prime display presented for up to 1000 ms (stimulus duration 200 ms, terminated by response), a 1000-ms blank interval, and a probe display with identical timing, followed by a 1500-ms intertrial interval. Response relation (response repetition vs. change) and distractor relation (repetition vs. change) were manipulated orthogonally. Only the low-predictability condition was included in the present analyses. Participants completed 20 practice trials followed by 400 experimental trials. Analyses considered response relation (repetition vs. change) and distractor relation (repetition vs. change). The original dataset was recorded at Trier University. Data from this task and sample have been used in a previous publication[37] (see also for further methodological details). For the current analysis, data from N=76 subjects (22.36 ± 3.40 yrs, 14 male) were included.

2b: DRB, 1:1 mapping, symbolic^b: Participants completed an online version of the standard distractor-response binding task comprising a prime and a probe display. In both displays, participants classified a centrally presented target letter while ignoring two flanking distractor letters. Letters were presented in 25 px font. Each trial began with a 500-ms fixation display, followed by a prime display presented for a maximum of 1500 ms (terminated by response), a 500-ms inter-stimulus interval, and a probe display with identical timing. Trials ended with a 1500-ms blank interval. Response relation (response repetition vs. change), distractor relation (repetition vs. change), and inter-stimulus-interval (ISI 500ms vs. ISI 2000 ms) were manipulated orthogonally. Only the ISI 500ms condition was included in the present analyses. Participants completed five practice trials followed by 256 experimental trials. Analyses considered response relation (repetition vs. change) and distractor relation (repetition vs. change). The original dataset was recorded at Trier University. For the current analysis, data from N=150 subjects (22.18 ± 3.16 yrs, 23 male, 1 other) were included.

2c: DRB, 1:1 mapping, figurative^b: Participants completed an online distractor-response binding task comprising a prime and a probe display. In both displays, participants responded to the shape (circle vs. square; 75×75 px) surrounding a task-irrelevant fruit image (65×65

px). Each trial began with a 1000-ms fixation display, followed by a prime display presented until response (maximum 1000 ms), a 1000-ms blank interval, and a probe display presented until response (maximum 1000 ms), followed by a 1500-ms intertrial interval. Response relation (response repetition vs. change) and distractor relation (repetition vs. change) were manipulated orthogonally. The experiment consisted of five blocks using different fruit pairs, such that distractor repetitions and changes occurred only within each semantic category. Participants completed four practice trials followed by 320 experimental trials. Analyses considered response relation (repetition vs. change) and distractor relation (repetition vs. change). The original dataset was recorded at Trier University. For the current analysis, data from N=116 subjects (21.96 ± 3.68 yrs, 19 male, 1 other) were included.

2d: DRB, 2:1 mapping, figurative^b: Participants completed an online distractor-response binding experiment comprising a prime and a probe display. In all experiments, task-irrelevant images (150×150 px) depicting either fruits (apple vs. pear) or trees (deciduous vs. coniferous) were presented within a frame (175×175 px) that served as target stimulus. Depending on the frame's identity, participants responded with pressing the left or right arrow key (2:1 mapping: spider/scarabaeus: right, maple leaf/sunflower: left). Each trial began with a 1000-ms fixation display, followed by a prime display presented until response, a 500-ms response–stimulus interval, and a probe display presented until response, followed by a 1000-ms intertrial interval. Response relation (response repetition vs. change) and distractor relation (repetition vs. change) were manipulated orthogonally. The experiments differed only in the target task. Participants completed ten practice trials followed by 128 experimental trials in each experiment. Analyses considered response relation (repetition vs. change) and distractor relation (repetition vs. change). The original dataset was recorded at Trier University. For the current analysis, data from N=110 subjects (22.79 ± 3.91 yrs, 29 male) were included.

Further sequential paradigms

3a: Visual search paradigm^a: Participants completed a prime–probe visual-search task comprising two successive responses. In both displays, participants searched for a color singleton target (2×2 cm square) and indicated whether a black dot within the target was located in its upper or lower half while ignoring the remaining stimuli. Target and distractor stimuli were arranged on three concentric circles around fixation. Each trial consisted of a 1000-ms fixation display, a prime display presented until response, a response–stimulus interval of either 500 or 2000 ms, and a probe display presented until response. Response relation

(response repetition vs. change), target-position relation (repetition vs. change), filler-color relation (repetition vs. change), and response–stimulus interval (RSI 500 vs. RSI 2000 ms) were manipulated orthogonally. Participants completed 16 practice trials followed by 384 experimental trials while EEG was recorded. Only the target-response binding effects in the RSI 500 blocks were analyzed in the present study. Analyses considered response relation (repetition vs. change) and target-position relation (repetition vs. change). The original dataset was recorded at Trier University. Data from this task and sample have been used in a previous publication[38] (see also for further methodological details). For the current analysis, data from N=50 subjects (25.02 ± 4.03 yrs, 13 male, 1 other) were included.

3b: Flanker task^a: Participants completed an Eriksen flanker task, responding via left/right key-press (corresponding hand) to the direction of a centrally presented target arrow flanked above and below by congruent (same direction) or incongruent (opposite direction) arrows. Flankers appeared 200 ms before the target; target and flankers were then shown together for 300 ms before a fixation cross followed (trial end: response or 1200 ms elapsed), with a 700–1100-ms response–stimulus interval. The task comprised two blocks of 120 trials (240 total: congruent and incongruent, left and right; congruent trials twice as frequent), with congruency transitions pseudo-randomized across predefined sequences. For the sequential analysis, trial n served as probe and trial $n-1$ as prime (trials directly following a break served only as prime). Response relation and flanker overlap (no vs. full overlap) were the factors analyzed. The original dataset was recorded at TU Dresden. For the current analysis, data from N=33 subjects (23.68 ± 2.69 yrs, 11 male) were included.

3c: Task switching paradigm^a: Participants completed a paradigm comprised cue-based and memory-based task-switching blocks following the procedure of Gajewski et al. (2011); only the cue-based block was analyzed here. Stimuli were the digits 1–9 (excluding 5), presented centrally in white on black, in a small (font 50) or large (font 80) format. Each trial began with a 1300-ms cue indicating one of three task rules (numerical: smaller/larger than 5; parity: odd/even; font-size: small/large), occurring equiprobably, with switches on 50% of trials, followed by the target digit (2500-ms response window), 500-ms visual feedback ("+"/"-"), and a jittered 400–600-ms interval before the next cue (average response–cue interval: 1500 ms). Responses were given via left/right Ctrl key (mapping counterbalanced across participants). For the sequential analysis, trial n served as probe and trial $n-1$ as prime (trials directly following a break served only as prime). Response relation (repetition vs switch) and task

relation (repetition vs switch) were the factors analyzed. Participants completed 198 trials with self-paced breaks every 33 trials. The original dataset was recorded at TU Dresden. Data from this task and included samples have been used in previous publications[39–43]. For the current analysis, data from N=71 subjects (23.90 ± 3.00 yrs, 34 male) were included.

3d: Response–response binding paradigm^a: Participants completed a response–response binding task based on previous work by Moeller and Frings[32] and Moeller et al.[44], comprising four successive responses (prime R1, prime R2, probe R1, and probe R2). In each display, participants responded to centrally presented letters or digits by pressing one of four response keys (D, F, J, or K). Stimuli remained visible until response and were separated by 500-ms intervals. Stimulus identities never repeated between prime and probe, such that response repetitions always occurred with different stimuli. Response relation for R1 (response repetition vs. response change) and response relation for R2 (response repetition vs. response change) were manipulated orthogonally. The original experiment additionally manipulated whether an event boundary (a virtual doorway) occurred before or between the two to-be-integrated responses. For the present drift diffusion model analyses, only the condition in which the event boundary occurred before the to-be-integrated responses (i.e., the standard response–response binding condition) was included. Participants completed 16 practice trials followed by two experimental blocks of 128 trials each. Analyses considered response relation between first responses (repetition vs. change) and response relation between second responses (repetition vs. change). The original dataset was recorded at Trier University. Data from this task and sample have been used in a previous publication[45] (see also for further methodological details). For the current analysis, data from N=76 subjects (23.63 ± 4.37 yrs, 20 male, 1 other) were included.

Drift-Diffusion Modelling

Prior to the drift-diffusion modeling, the behavioral data were curated following theoretical assumptions about binding, leading to the exclusion of trials with a false probe response, and following the recommendations by Voss and colleagues[46] to exclude within-subject outliers in the logarithmic reaction times. Subsequently, probe data were stored trial-wise per participant with the information if the probe was correct (1 = correct, 0 = incorrect), the reaction time in seconds, and the respective condition given the task-specific factor structure.

Afterwards, drift-diffusion modeling was conducted applying the *fast-dm* function of the *fast-dm30* toolbox[46,47]. The maximum-likelihood optimization method was employed at a precision of 4.0. Taking the recommendations of Voss et al.[46], the intertrial variability of the starting point (s_{zr}) and of drift rate (s_v) were fixed to zero, while boundary separation (a), starting point (z_r), drift rate (v), and non-decision time (t_0) were estimated depending on the task-specific conditions (see above).

Participants were excluded from subsequent statistical analyses if the DDM could not be estimated, e.g., due to too few trials per condition, if they had a hit rate below 50%, or if they were reaction time outliers with respect to the sample.

Statistical Analyses

All paradigms shared that the response given by the participants could repeat (response repetition, RR) or change (response change, RC) within the prime-probe structure examined. At the same time, stimulus features of interest could either change between subsequent stimuli in the prime-probe structure examined (feature change, FC) or repeat (feature repetition, FR; for the full S1R1-S2R2 paradigm, we only used the full feature overlap and zero feature overlap conditions in the following analyses). Alpha-levels for all statistical analyses were set to 0.05.

To examine the influence of the task-specific conditions on the estimated DDM parameters, repeated-measures ANOVAs were conducted following the task-specific factor structure (see above) for each parameter. A binding effect was established when the interaction between *Response Relation* and *Feature Relation* was significant.

In addition to the interaction effect between response relation and stimulus relation (or, in the response–response binding dataset, the interaction between the two response-relation factors), post-hoc one-sample *t*-tests were performed to compare the direction of the binding effects. Binding scores were calculated following the formula

$$binding\ score = (RRFC - RRFR) - (RCFC - RCFR) \quad (1)$$

for all direct behavioral measures and the estimated DDM parameters.

To further examine the relationship between the different DDM parameters, a Pearson correlational analysis was computed between parameters a , v , and z_r based on the pattern of binding score results (see *Results*). To verify that the correlations did not arise solely from mathematical dependencies among the parameters, the complete set of condition-specific values for each parameter was independently permuted across participants, while keeping the within-participant grouping of values within each parameter. This preserved the structure regarding the average magnitude of the binding effects while eliminating the existing

correlations among them. After permutation, correlations between the binding effects were allowed to have a p -value of $\geq .5$; otherwise, the permutation was repeated. Subsequently, reaction times and response accuracies were computed from the composite parameter sets using the *construct-samples* function of the *fast-dm30* toolbox[46,47]. DDM parameters and their correlations were then estimated from these constructed data using the same procedure as for the empirical data. The correlations in the constructed data and the empirical data were subsequently compared using the Fisher's z -test.

Results

To characterize the sub-processes underlying the observed behavioral binding effects, separate ANOVAs were conducted for the individual DDM parameters a , z_r , v , and t_0 (see **Appendix A** for full ANOVA outputs). Here, we report the relevant interaction between response relation and feature relation (or, in the response–response binding dataset, the interaction between the two response-relation factors; see **Figures 3B, 4B and 5B**). To take a look at the strength and direction of the described interaction effects, we also performed one-sample t -tests, testing the respective binding effect scores against zero.

Table 1

Interactions between response relation and feature relation and corresponding binding scores.

Dataset	n	Parameter	M	SD	F	η_p^2	t	p	Cohen's d
S1R1-S2R2, full, figurative ^a	76	a	-0.31	0.57	23.32	0.24	-4.83	<.001	-0.55
		v	-2.46	3.51	37.22	0.33	-6.10	<.001	-0.70
		z_r	-0.28	0.40	39.16	0.34	-6.26	<.001	-0.72
		t_0	-0.00	0.07	0.01	0.00	-0.12	0.907	-0.01
S1R1-S2R2, reduced, figurative ^a	33	a	-0.84	0.97	24.66	0.44	-4.97	<.001	-0.86
		v	-1.86	2.88	13.72	0.30	-3.70	0.001	-0.65
		z_r	-0.41	0.32	52.57	0.62	-7.25	<.001	-1.26
		t_0	-0.01	0.08	0.42	0.01	-0.65	0.519	-0.11
TRB, figurative ^a	26	a	-0.39	1.17	3.64	0.13	-1.77	0.088	-0.34
		v	0.04	3.57	0.34	0.01	0.07	0.948	0.01
		z_r	-0.55	0.38	61.66	0.71	-7.56	<.001	-1.43
		t_0	-0.07	0.15	4.35	0.15	-2.38	0.025	-0.45
TRB, symbolic ^a	46	a	-0.34	0.84	7.43	0.14	-2.73	0.009	-0.40
		v	-0.70	3.76	1.61	0.03	-1.27	0.212	-0.19
		z_r	-0.25	0.41	17.82	0.28	-4.22	<.001	-0.62
		t_0	-0.02	0.10	2.65	0.06	-1.63	0.110	-0.24
DRB, 1:1 Mapping, symbolic ^a	76	a	-0.22	0.78	5.75	0.07	-2.40	0.019	-0.28
		v	-1.23	2.41	19.85	0.21	-4.46	<.001	-0.51
		z_r	-0.09	0.27	8.32	0.10	-2.88	0.005	-0.33
		t_0	0.00	0.07	0.06	0.00	0.25	0.804	0.03
DRB, 1:1 Mapping, symbolic ^b	150	a	0.12	1.30	1.27	0.01	1.13	0.262	0.09
		v	0.30	2.66	1.97	0.01	1.40	0.163	0.11
		z_r	-0.07	0.33	6.67	0.04	-2.58	0.011	-0.21
		t_0	-0.02	0.15	2.57	0.02	-1.60	0.111	-0.13
	116	a	-0.28	0.83	23.68	0.17	-3.59	0.001	-0.34

DRB, 1:1 Mapping, figurative ^b		v	-0.19	2.59	19.34	0.14	-0.76	0.447	-0.07
		z_r	-0.13	0.28	26.37	0.19	-4.82	<.001	-0.46
		t_0	-0.01	0.09	0.34	0.00	-0.57	0.570	-0.05
DRB, 2:1 Mapping, figurative ^b	110	a	-0.34	0.75	12.91	0.11	-4.87	<.001	-0.45
		v	-1.02	2.49	0.58	0.01	-4.40	<.001	-0.41
		z_r	-0.13	0.27	23.24	0.18	-5.14	<.001	-0.48
		t_0	0.00	0.08	0.32	0.00	0.59	0.559	0.05
Visual Search ^a	50	a	-0.57	1.27	10.17	0.17	-3.19	0.003	-0.45
		v	0.48	2.95	1.30	0.03	1.14	0.259	0.16
		z_r	-0.51	0.40	81.55	0.62	-9.03	<.001	-1.28
		t_0	-0.01	0.11	0.56	0.01	-0.75	0.458	-0.11
Flanker task ^a	33	a	0.27	1.59	0.93	0.03	0.97	0.341	0.17
		v	1.28	7.81	0.88	0.03	0.94	0.354	0.16
		z_r	-0.26	0.42	12.68	0.28	-3.56	0.001	-0.62
		t_0	0.03	0.08	5.03	0.14	2.24	0.032	0.39
Task-switching ^a	71	a	0.16	0.90	2.36	0.03	1.54	0.129	0.18
		v	-0.10	1.12	0.54	0.01	-0.74	0.465	-0.09
		z_r	-0.05	0.24	3.24	0.04	-1.80	0.076	-0.21
		t_0	-0.05	0.14	11.03	0.14	-3.32	0.001	-0.39
Response-response binding ^a	76	a	0.03	1.52	0.03	0.00	0.18	0.856	0.02
		v	0.40	4.67	0.56	0.01	0.75	0.458	0.09
		z_r	-0.08	0.39	3.04	0.04	-1.74	0.085	-0.20
		t_0	-0.00	0.13	0.07	0.00	-0.26	0.795	-0.03

Note. M and SD refer to the binding-effect score $[(RRFC - RRFR) - (RCFC - RCFR)]$, tested against zero with one-sample t -tests ($df = n - 1$); Cohen's d is the corresponding effect size. F and η^2_p stem from the separate repeated-measures ANOVA interaction term (response relation $\times$ feature relation; for response–response binding: response relation 1 $\times$ response relation 2). “a” marks experiments conducted in the lab, “b” marks data collected online.

Table 1 reports, for each dataset, the ANOVA interaction results (F , η^2_p) alongside the corresponding one-sample t -tests on the binding-effect scores for each DDM parameter. Across the S1R1–S2R2/TRB and DRB datasets, our analyses showed robust interaction effects for boundary separation (a) and starting-point bias (z_r) in almost every dataset, whereas the drift rate parameter (v) reached significance only inconsistently. Critically, the corresponding binding-effect scores were consistently negative wherever significant for both a and z_r . Because higher values of a index greater response caution and higher values of z_r index a stronger bias toward the currently required response, a negative binding effect indicates that *both* boundary separation and starting-point bias were reduced during partial-repetition trials relative to full repetitions and full changes: participants required less accumulated evidence to commit to a response (lower a), and their initial response tendency was simultaneously biased away from the required response (lower z_r).

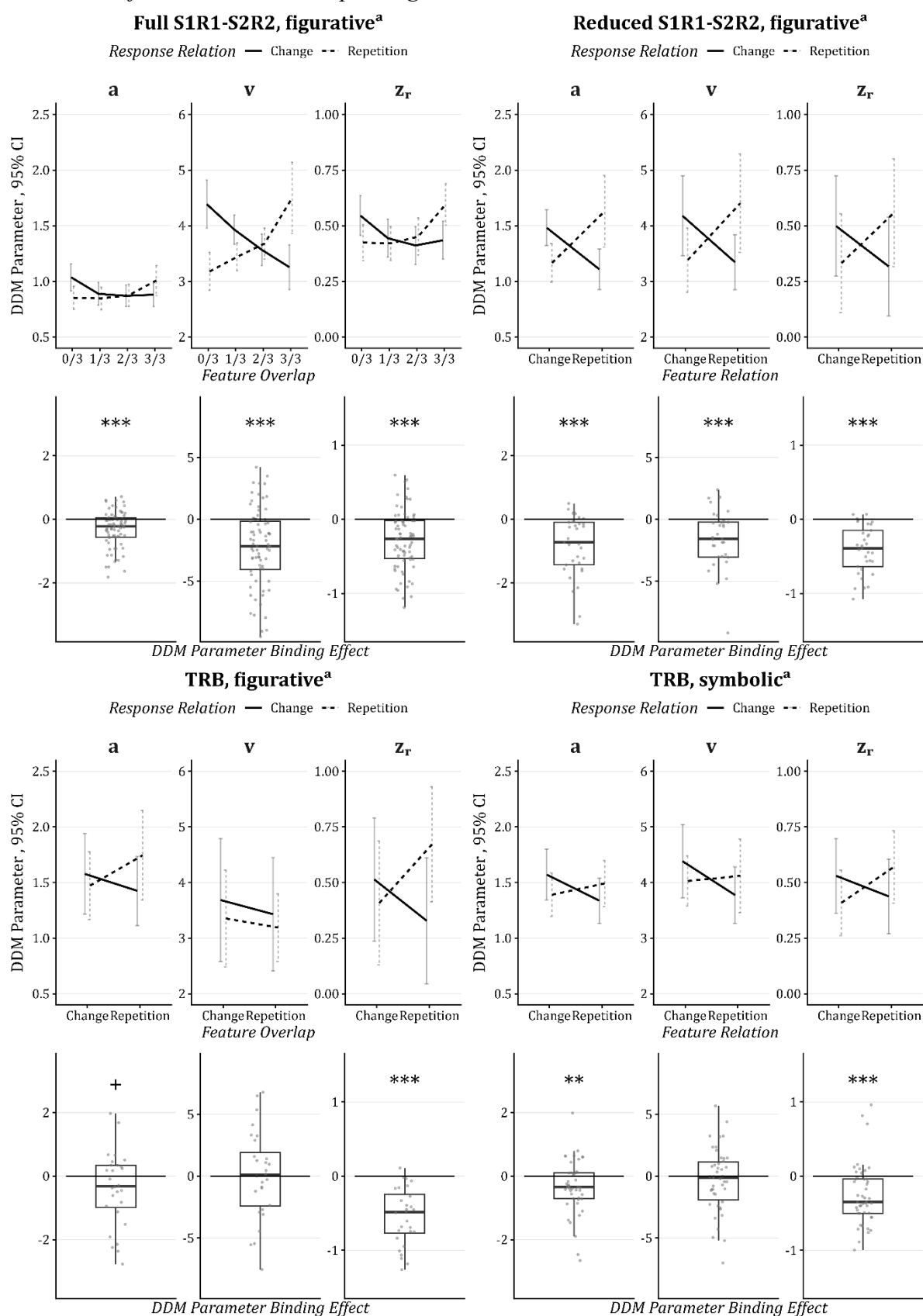
For the other paradigms, this pattern was less pronounced – here, especially z_r showed interaction effects (in the visual search task, here also a , and the flanker task). The task-switching and response–response binding datasets showed, at most, a marginally significant interaction effect for z_r .

Since t_0 did not show systematic interactions between response relation and feature relation, we dismissed it from further analyses. Consequently, the following correlational analyses were performed only on the a , v , and z_r binding effects (see **Figures 3B, 4B and 5B**).

Across most datasets, correlational analyses of the binding scores revealed a consistent pattern: binding scores in z_r and v correlated negatively, and binding scores in a and v correlated positively (see **Appendix B**). By contrast, binding effects in a and z_r were essentially uncorrelated, with observed correlations close to zero and inconsistent in sign across datasets (range $r = -.223$ to $.150$). To evaluate whether this apparent independence between a and z_r could nonetheless reflect a parameter trade-off during model estimation rather than genuine dissociation, we additionally compared the observed a – z_r correlations against the correlations expected under the parameter-recovery model, using Fisher's z -tests (see **Appendix B**). In several datasets, the observed correlation was significantly weaker than the correlation expected under a trade-off account (e.g., DRB, 1:1 mapping, symbolic^a: $z = -2.67$, $p = .008$; S1R1-S2R2, reduced: $z = -2.562$, $p = .010$; DRB, 1:1 mapping, figurative^b: $z = -4.951$, $p < .001$; task-switching: $z = -3.036$, $p = .002$), while in no dataset was the observed correlation significantly stronger than expected. This pattern suggests that the independence between the a and z_r binding effects is not merely a failure to detect a trade-off-induced correlation due to insufficient power; rather, the real data show even less coupling between the two parameters than an estimation-trade-off account would predict.

In contrast to the near-independence of a and z_r , the observed correlations between z_r and v , as well as between a and v , were in most datasets significantly stronger than expected under the parameter-recovery model (11 of 12 datasets for each pairing; cf. **Appendix B**) – indicating that this coupling, too, reflects more than a mere estimation trade-off. Rather than showing an independent binding effect of its own, drift rate therefore appears to be systematically coupled to the starting-point and boundary-separation presets established by retrieval.

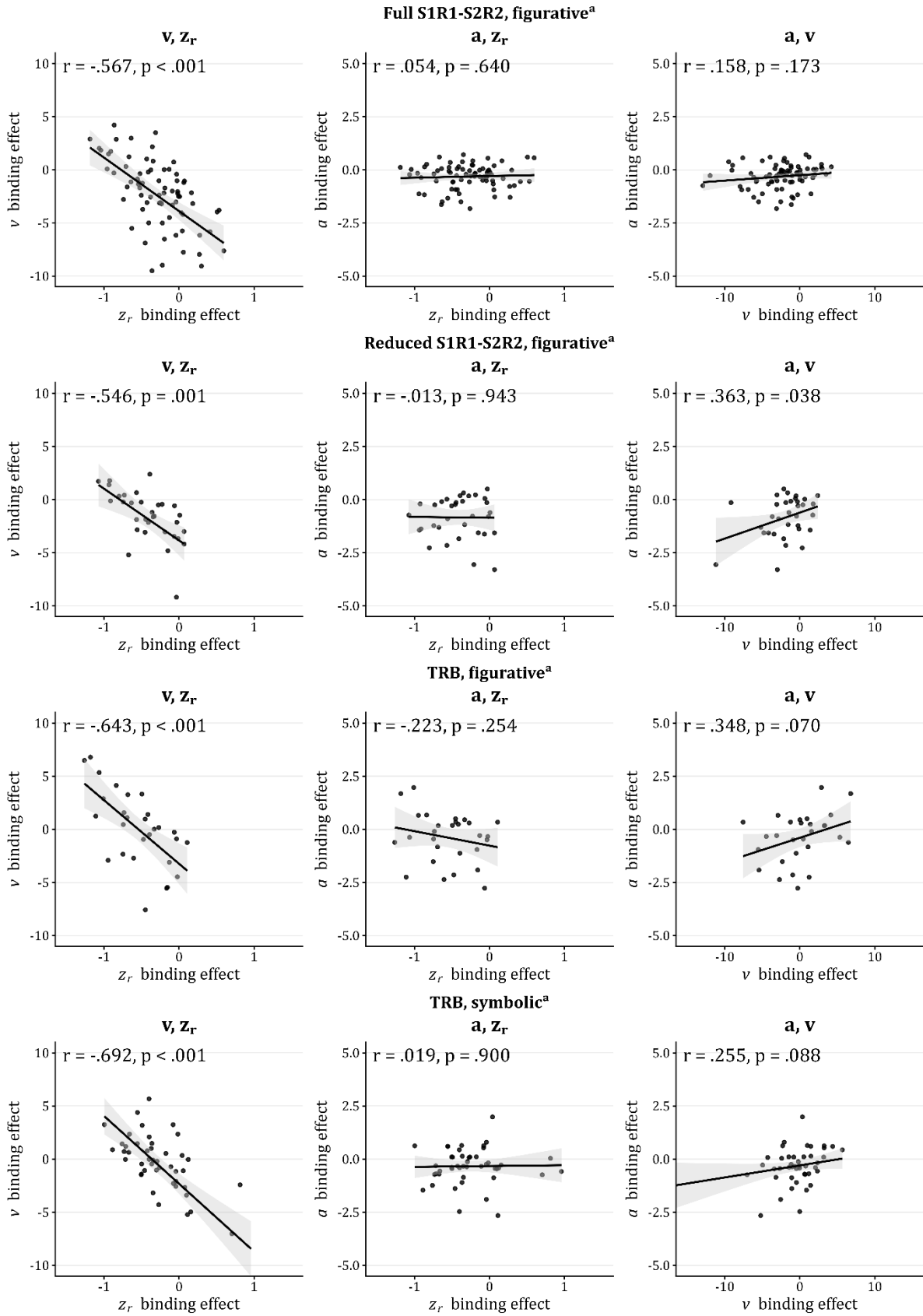
DDM results for S1R1–S2R2/TRB paradigms.



Note. Shown are values for a , v , and z_r for each trial type (upper section) and corresponding binding scores (lower section; *** = $p < .001$, ** = $p < .010$, * = $p < .050$, + = $p < .100$).

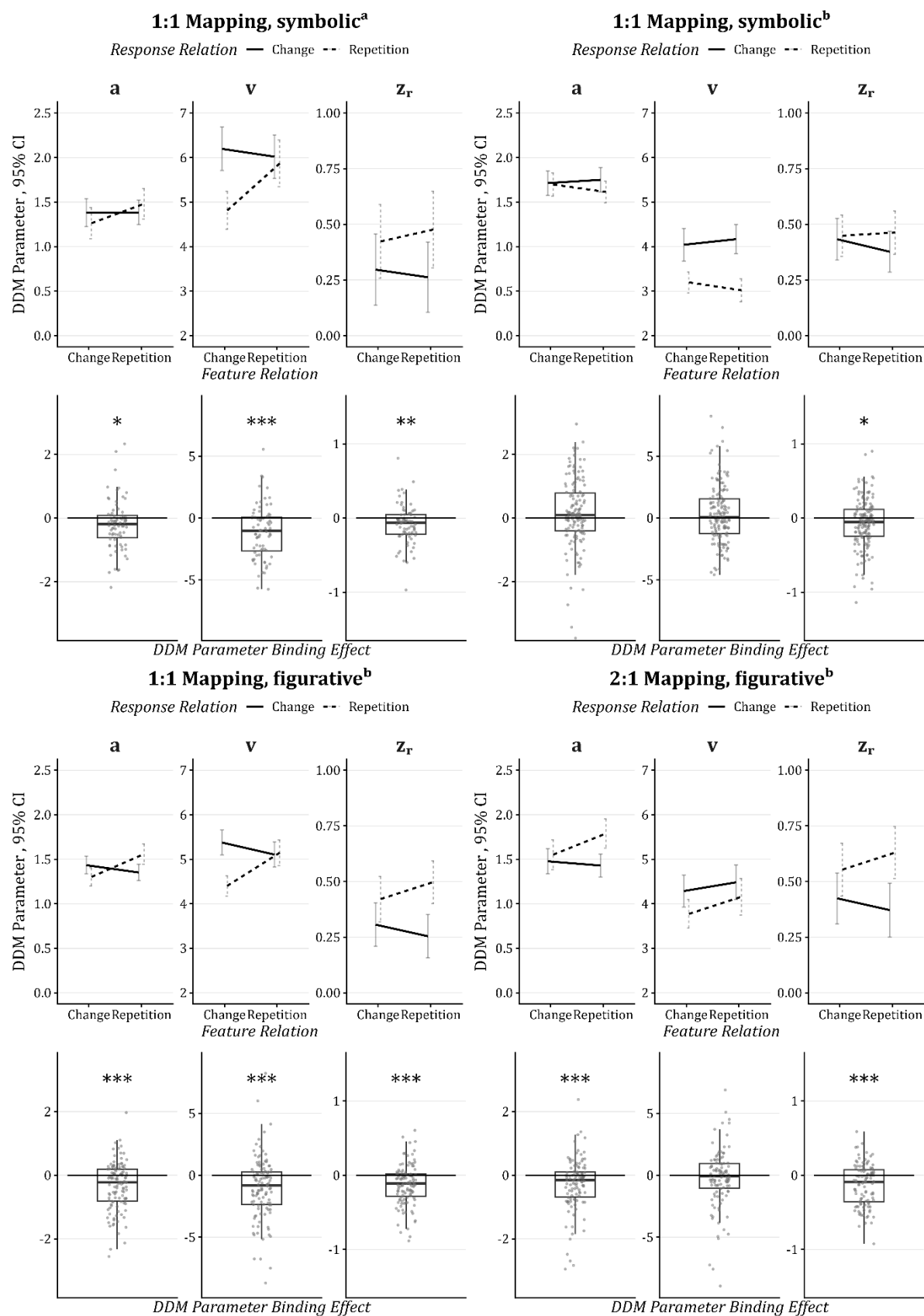
Figure 3B

Correlation results for S1R1–S2R2/TRB paradigms.



Note. Shown are the correlations between the binding scores of v and z_r , a and z_r , and a and v .

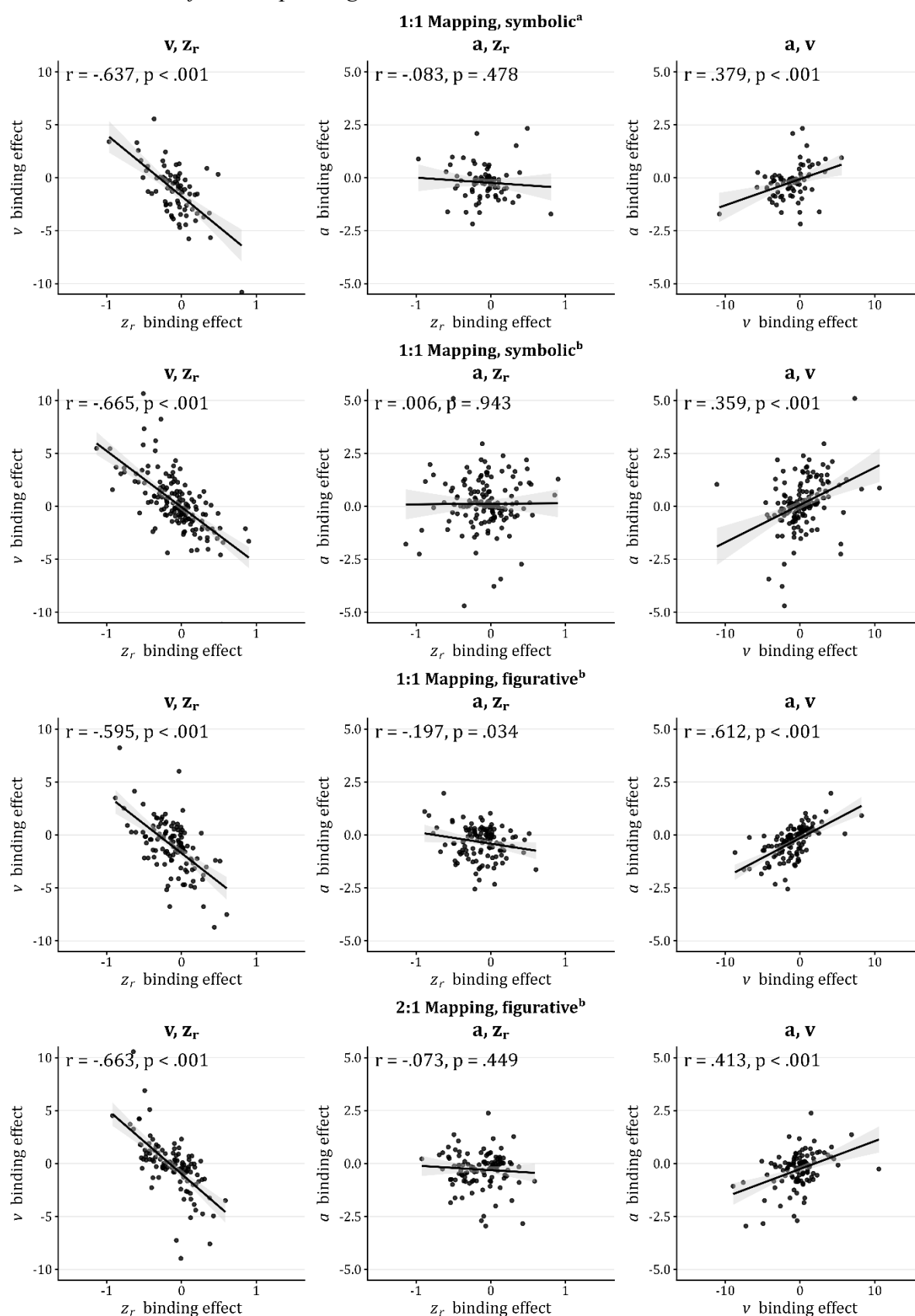
Figure 4A
DDM results for DRB paradigms.



Note. Shown are values for a , v , and z_r for each trial type (upper section) and corresponding binding scores (lower section; *** = $p < .001$, ** = $p < .010$, * = $p < .050$, + = $p < .100$).

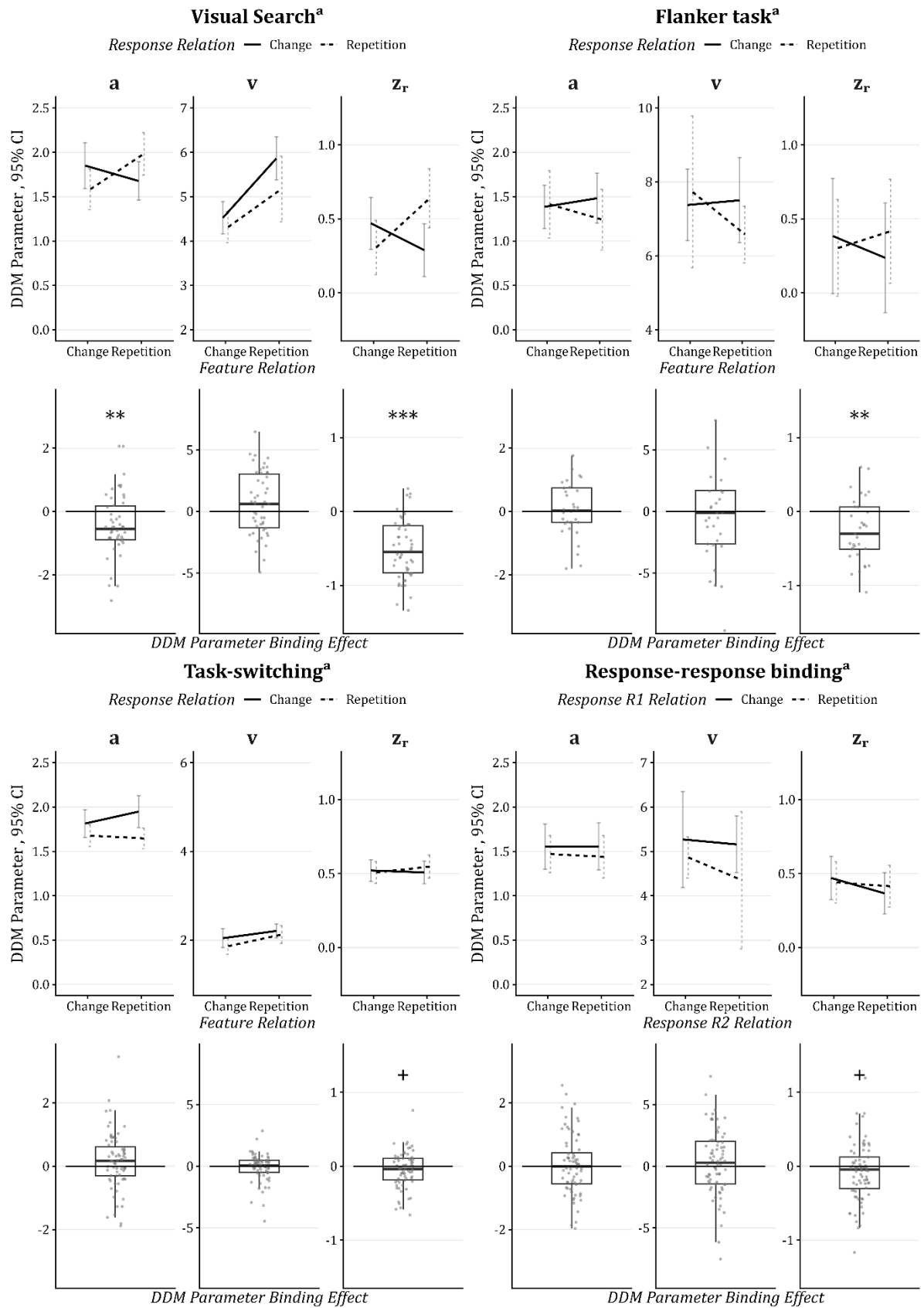
Figure 4B

Correlation results for DRB paradigms.



Note. Shown are the correlations between the binding scores of v and z_r , a and z_r , and a and v .

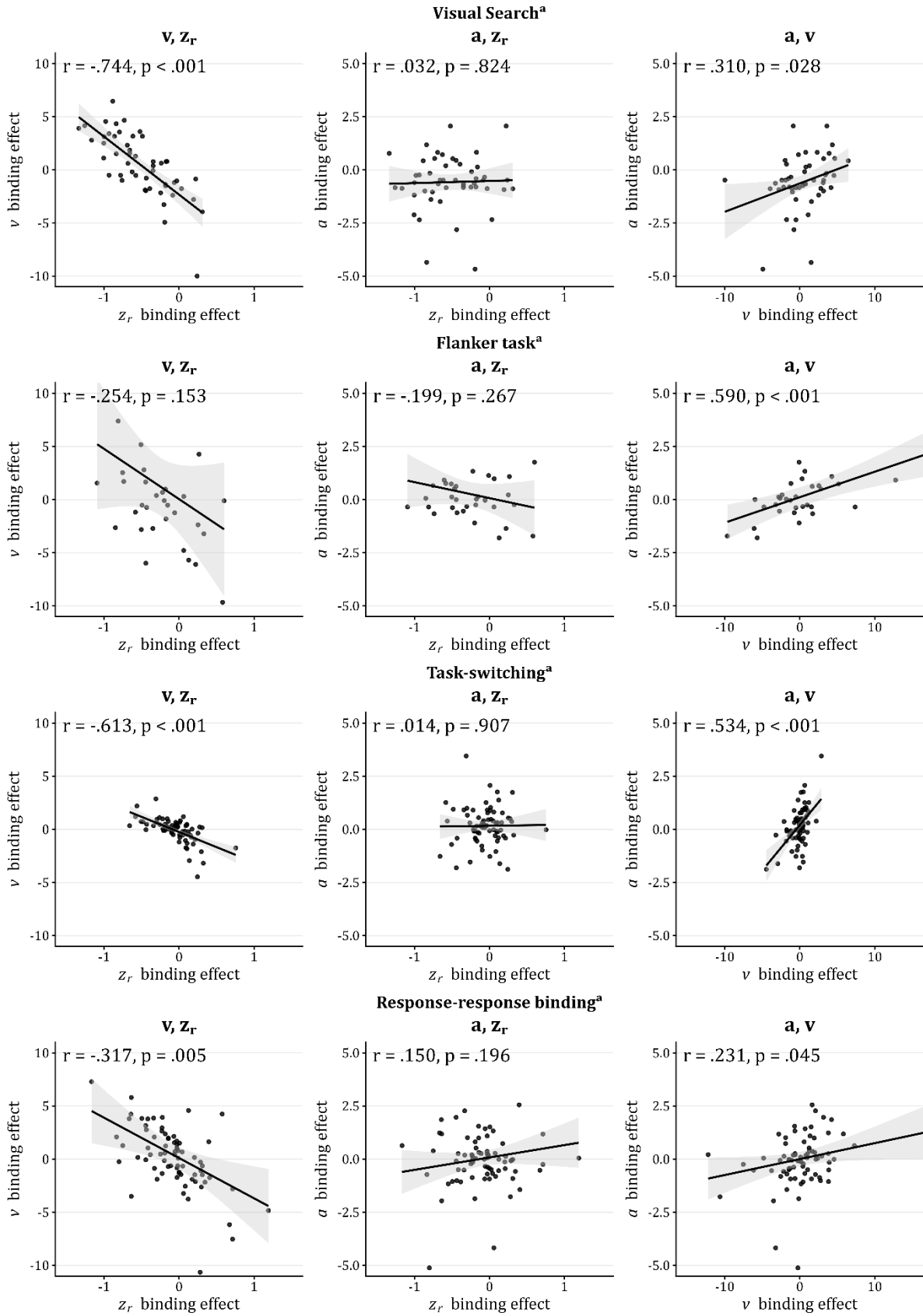
Figure 5A
DDM results for further sequential paradigms.



Note. Shown are values for a , v , and z_r for each trial type (upper section) and corresponding binding scores (lower section; *** = $p < .001$, ** = $p < .010$, * = $p < .050$, + = $p < .100$).

Figure 5B

Correlation results for further sequential paradigms.



Note. Shown are the correlations between the binding scores of v and z_r , a and z_r , and a and v .

Discussion

The present study sought to specify how sequential stimulus–response relations shape the decision process underlying current action selection. Event-file theories propose that repetitions of stimulus or response features trigger retrieval of previously integrated feature bindings[3,4], but comparatively little is known about how the consequences of such retrieval are expressed within the unfolding decision process. To address this question, we applied drift-diffusion modelling[24,26] to twelve datasets spanning classical event-file paradigms – including distractor–response binding[31] and S1R1–S2R2 tasks[6] – as well as visual search, flanker, task-switching, and response–response binding paradigms[32]. Across the core event-file paradigms, a consistent picture emerged. Partial-repetition costs were particularly reflected in changes to the starting-point bias and boundary separation, suggesting that sequential information configures the conditions under which the current decision begins rather than primarily altering evidence accumulation itself.

DDM parameters as retrieval signatures of event files

The clearest effect concerned the starting-point parameter (z_r), which captures an a-priori bias toward one response alternative before evidence accumulation proceeds. Experimental manipulations of response bias have previously been shown to map particularly strongly onto this parameter[28]. In the present datasets, partial repetitions systematically shifted the starting point away from the currently required response, whereas full repetitions favored that response. This pattern corresponds closely to the classical event-file account in that repetition of an event feature retrieves previously associated response information, which facilitates performance when the retrieved response remains appropriate but biases action selection toward the wrong response when current requirements have changed[4,7]. Thus, the starting-point effect provides a computational specification of a central assumption of event-file theories – information carried over from the preceding action episode already biases the state from which current response selection proceeds.

Note, however, this starting-point shift is not uniquely diagnostic of event-file retrieval. The *signaling account* provides an alternative, and potentially complementary, explanation for partial-repetition costs. According to this account, relations between successive stimulus features can themselves serve as response signals in that feature repetitions signal that the previous response should be repeated, whereas feature changes signal that the response should change[48,49]; see also [50]. Such signaling should naturally manifest itself as a starting-point bias in a diffusion model. The present z_r effects therefore identify where in the decision process

sequential information biases response selection, but they do not by themselves determine whether this bias originates from retrieval of a bound response code, relational signaling, or a combination of both.

A second prominent finding was that partial repetitions were associated with reduced boundary separation (a). This direction is noteworthy because it is opposite to what a straightforward conflict-monitoring interpretation might suggest: if retrieval conflict primarily triggered increased response caution, greater rather than smaller boundary separation would be expected [25,51,52]; see also [53]. Instead, participants required less accumulated evidence before committing to a response precisely when sequential information favored a response that conflicted with current demands. We interpret this pattern as a transient relaxation of the decision criterion under partial mismatch. This interpretation should not imply that criterion relaxation is necessarily a strategic adjustment. Rather, retrieval conflict may temporarily compromise the maintenance of the usual decision criterion, allowing comparatively rapid and error-prone responses to escape before sufficient evidence has accumulated. Related ideas have been proposed in accounts in which automatically activated responses can produce premature responses when suppression is incomplete or delayed [54,55], as well as in urgency-gating or collapsing-boundary models in which the effective amount of evidence required for commitment decreases over time [56,57]. The present static-boundary model cannot distinguish a generally reduced criterion from a dynamic within-trial collapse, but it clearly indicates that partial mismatch is associated with less, rather than more, evidence required for response commitment.

An important question is whether the boundary-separation effect could simply arise as an estimation consequence of the concurrent shift in starting point. The correlational and parameter-recovery analyses argue against such a simple interpretation. Binding effects in a and z_r were essentially unrelated across participants, and in several datasets the observed relationship was even weaker than the relationship generated by parameter-estimation dependencies. Thus, the two effects appear to represent dissociable signatures of sequential processing rather than a single effect leaking into two fitted parameters. This does not establish that they constitute cognitively independent mechanisms, but it supports distinguishing a content-specific response bias from a mismatch-related change in the amount of evidence required for commitment. We therefore propose that partial repetitions can alter the initial configuration of the decision process in at least two separable ways, namely (i) by biasing response readiness and (ii) by relaxing the decision criterion when sequentially activated information conflicts with current requirements.

This distinction may also be informative for understanding neurophysiological correlates of event-file processing. Theta-band activity following stimulus onset has been associated both with retrieval of previous event representations and with conflict arising from feature mismatch[18,35,58–61]. The present findings suggest that these signals may reflect more than one functional consequence of sequential processing. One component may carry response-specific information that biases the emerging decision, whereas another may reflect mismatch or conflict and be associated with a transient change in decision criterion. Joint EEG–DDM analyses could test whether these components can be dissociated temporally or neurally. It also remains possible that criterion relaxation does not require complete episodic retrieval but can be triggered by a faster feature-mismatch signal, potentially linking the present findings to accounts emphasizing conflict-triggered arousal[52] or competing inhibition and disinhibition dynamics[62].

In contrast to starting-point bias and boundary separation, drift rate (v) showed considerably less consistent binding effects across paradigms. When present, these effects generally indicated slower accumulation under partial repetitions. This pattern provides little support for a simple account in which the primary consequence of sequential mismatch is a stable impairment of evidence accumulation (but see [36]). This is noteworthy because models developed for conflict tasks such as the flanker paradigm have located effects of automatically activated competing responses within the accumulation process itself, for example through time-varying influences on drift[63]. At the same time, the present results should not be taken to exclude such dynamic accumulation processes. The standard DDM employed here estimates a mean drift rate and therefore cannot capture all forms of time-varying conflict. More informative are the robust relationships of v with the other decision parameters. Stronger starting-point biases towards the incorrect action were associated with relatively more favorable drift-rate effects, a pattern consistent with evidence accumulation partly counteracting an initially inappropriate response tendency. Such a process could correspond to the reconfiguration or updating of retrieved event representations that has repeatedly been invoked to explain how partial mismatches are resolved[6,19,21]. From this perspective, retrieval or signaling may configure an initially biased decision state, while subsequent processing increasingly favors the currently appropriate response.

Similarly, the positive association between boundary-separation and drift-rate binding effects suggests a systematic relationship as well. Participants showing stronger criterion relaxation also tended to show stronger slowing of evidence accumulation, slowing down the overall evidence accumulation process while making it more likely that the appropriate

response is carried out. One possibility is that both effects reflect consequences of the same mismatch-related disruption; the process that reduces the effective decision criterion may simultaneously interfere with efficient evidence uptake. Alternatively, the drift-rate effect could reflect the additional processing demands associated with reconfiguration. These interpretations remain tentative, but the correlational pattern indicates that changes in drift rate are systematically related to the decision settings established under partial mismatch rather than constituting an entirely separate, uniform consequence of sequential retrieval.

Non-decision time (t_0) showed no systematic binding effect. Because t_0 encompasses processes outside evidence accumulation, including perceptual encoding and response execution, this finding suggests that partial-repetition costs do not primarily arise from systematic differences in these non-decisional stages. This conclusion is compatible with the view that the critical consequences of sequential feature relations emerge mainly during response selection itself. The absence of a consistent t_0 effect is also difficult to reconcile with a pure residual-activation account in which sequential effects would arise exclusively from lingering activation outside the decision process[64,65], although the present analyses cannot exclude residual activation as one contributor to the observed effects.

Response bias and criterion-relaxation beyond binding tasks

Finally, the breadth of the datasets allows an initial assessment of generality. The response-bias signature was particularly robust across the classical S1R1–S2R2 and distractor–response binding paradigms and was also evident in visual search and the flanker task. The complete pattern was less pronounced in task switching and response–response binding, where evidence for starting-point effects was weaker and systematic boundary-separation effects were largely absent. Thus, the present data establish the response-bias and criterion-relaxation pattern most clearly for paradigms explicitly organized around sequential stimulus–response relations, while providing more tentative evidence that components of this pattern extend to sequential action control more broadly. The task-switching findings are particularly instructive in this regard. Previous diffusion-model analyses have located classical switch costs primarily in non-decision time and drift rate rather than in starting point or boundary separation[66], suggesting that task-set reconfiguration and the sequential feature effects examined here can constitute distinct processes that nevertheless occur within the same task. Similarly, inter-trial priming effects in visual search have long been established[67], but the present results begin to specify the decision-level processes through which such sequential information can influence action.

Conclusion

Taken together, the present findings suggest that sequential stimulus–response relations do not simply add interference to an otherwise unchanged decision process. Rather, they alter the state from which the current decision proceeds. These findings connect memory-based action control with decision-making theory by showing how preceding episodes shape the configuration of current decisions. Across the core binding tasks, partial mismatch combined an initial bias away from the required response with a reduced threshold for commitment. These largely dissociable effects suggest that difficulties in adapting to changed demands can arise from how a decision is configured, without requiring a uniform impairment of evidence accumulation. Their expression varied across task families, identifying an important boundary condition. This computational perspective helps explain how memory supports continuity in behavior while sometimes compromising the flexibility needed for change. Thereby, it provides a computational extension of event-file approaches while identifying response bias, criterion relaxation, and subsequent reconfiguration as distinguishable components through which past actions shape present decisions.

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Data availability statement

The data that support the findings of this study are openly available in Zenodo.org at <https://doi.org/10.5281/zenodo.22704683> upon publication.

Conflict of interest disclosure

The authors declare no conflict of interest.

Author Contributions

NDM: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – Original Draft. *CF*: Conceptualization, Funding Acquisition, Project administration, Resources, Supervision, Writing – review & editing. *CB*: Resources, Funding Acquisition, Supervision, Project administration, Writing – review & editing. *AP*: Conceptualization, Data curation, Formal analysis, Methodology, Software, Supervision, Validation, Writing – Original Draft.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used OpenAI's ChatGPT (GPT-5.6 Sol) for language editing, including improvements to grammar, clarity, readability, and graphics. The tool was not used to generate scientific content, conduct analyses, or interpret results. All AI-assisted edits were reviewed and approved by the authors, who take full responsibility for the final content of the manuscript.

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Appendix A

ANOVA outputs

S1R1-S2R2 paradigms

Full S1R1-S2R2, figurative^a

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η_p^2
a	(Intercept)	1	75	714.93	< .001***	0.91
	Response Relation	1	75	0.55	.460	0.01
	Feature Relation	1	75	0.00	.994	0.00
	Response Relation x Feature Relation	1	75	23.32	< .001***	0.24
t_0	(Intercept)	1	75	3,913.70	< .001***	0.98
	Response Relation	1	75	2.87	.095	0.04
	Feature Relation	1	75	11.15	.001**	0.13
	Response Relation x Feature Relation	1	75	0.01	.907	0.00
v	(Intercept)	1	75	421.06	< .001***	0.85
	Response Relation	1	75	0.01	.931	0.00
	Feature Relation	1	75	0.22	.637	0.00
	Response Relation x Feature Relation	1	75	37.22	< .001***	0.33
z_t	(Intercept)	1	75	3,213.65	< .001***	0.98
	Response Relation	1	75	1.36	.248	0.02
	Feature Relation	1	75	3.60	.062	0.05
	Response Relation x Feature Relation	1	75	39.16	< .001***	0.34

Reduced S1R1-S2R2, figurative^a

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η_p^2
a	(Intercept)	1	32	255.36	< .001***	0.89
	Response Relation	1	32	1.59	.216	0.05
	Feature Relation	1	32	0.41	.525	0.01
	Response Relation x Feature Relation	1	32	24.66	< .001***	0.44
t_0	(Intercept)	1	32	1,541.32	< .001***	0.98
	Response Relation	1	32	0.22	.639	0.01
	Feature Relation	1	32	8.47	.007**	0.21
	Response Relation x Feature Relation	1	32	0.42	.519	0.01
v	(Intercept)	1	32	134.30	< .001***	0.81
	Response Relation	1	32	0.27	.607	0.01
	Feature Relation	1	32	0.15	.698	0.00
	Response Relation x Feature Relation	1	32	13.72	.001***	0.30
z_t	(Intercept)	1	32	336.04	< .001***	0.91
	Response Relation	1	32	1.33	.258	0.04
	Feature Relation	1	32	0.48	.493	0.01
	Response Relation x Feature Relation	1	32	52.57	< .001***	0.62

TRB, figurative^a

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η_p^2
a	(Intercept)	1	25	130.56	< .001***	0.84
	Response Relation	1	25	4.32	.048*	0.15
	Feature Relation	1	25	2.29	.142	0.08
	Response Relation x Feature Relation	1	25	3.64	.068	0.13
t_0	(Intercept)	1	25	743.75	< .001***	0.97
	Response Relation	1	25	2.63	.117	0.10
	Feature Relation	1	25	0.04	.850	0.00
	Response Relation x Feature Relation	1	25	4.35	.047*	0.15
v	(Intercept)	1	25	80.96	< .001***	0.76
	Response Relation	1	25	0.64	.432	0.02

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
z_t	Feature Relation	1	25	0.08	.777	0.00
	Response Relation x Feature Relation	1	25	0.34	.562	0.01
	(Intercept)	1	25	487.75	< .001***	0.95
	Response Relation	1	25	3.20	.086	0.11
	Feature Relation	1	25	0.63	.434	0.02
	Response Relation x Feature Relation	1	25	61.66	< .001***	0.71

TRB, symbolic^a

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
a	(Intercept)	1	45	267.64	< .001***	0.86
	Response Relation	1	45	0.04	.840	0.00
	Feature Relation	1	45	1.16	.288	0.03
	Response Relation x Feature Relation	1	45	7.43	.009**	0.14
t_0	(Intercept)	1	45	1,332.59	< .001***	0.97
	Response Relation	1	45	1.84	.182	0.04
	Feature Relation	1	45	0.10	.753	0.00
	Response Relation x Feature Relation	1	45	2.65	.110	0.06
v	(Intercept)	1	45	277.46	< .001***	0.86
	Response Relation	1	45	0.00	.981	0.00
	Feature Relation	1	45	1.45	.236	0.03
	Response Relation x Feature Relation	1	45	1.61	.212	0.03
z_t	(Intercept)	1	45	566.30	< .001***	0.93
	Response Relation	1	45	0.04	.835	0.00
	Feature Relation	1	45	1.98	.167	0.04
	Response Relation x Feature Relation	1	45	17.82	< .001***	0.28

DRB paradigms

1:1 Mapping, symbolic^a

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
a	(Intercept)	1	75	611.57	< .001***	0.89
	Response Relation	1	75	0.04	.851	0.00
	Feature Relation	1	75	5.75	.019*	0.07
	Response Relation x Feature Relation	1	75	5.75	.019*	0.07
t_0	(Intercept)	1	75	5,383.70	< .001***	0.99
	Response Relation	1	75	0.03	.870	0.00
	Feature Relation	1	75	1.56	.216	0.02
	Response Relation x Feature Relation	1	75	0.06	.804	0.00
v	(Intercept)	1	75	477.66	< .001***	0.86
	Response Relation	1	75	18.30	< .001***	0.20
	Feature Relation	1	75	12.25	.001***	0.14
	Response Relation x Feature Relation	1	75	19.85	< .001***	0.21
z_t	(Intercept)	1	75	506.46	< .001***	0.87
	Response Relation	1	75	61.89	< .001***	0.45
	Feature Relation	1	75	0.43	.516	0.01
	Response Relation x Feature Relation	1	75	8.32	.005**	0.10

1:1 Mapping, symbolic^b

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
a	(Intercept)	1	149	914.53	< .001***	0.86
	Response Relation	1	149	1.37	.243	0.01
	Feature Relation	1	149	0.18	.668	0.00
	Response Relation x Feature Relation	1	149	1.27	.262	0.01
t_0	(Intercept)	1	149	4,800.55	< .001***	0.97
	Response Relation	1	149	30.36	< .001***	0.17

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
v	Feature Relation	1	149	1.50	.222	0.01
	Response Relation x Feature Relation	1	149	2.57	.111	0.02
	(Intercept)	1	149	865.55	< .001***	0.85
	Response Relation	1	149	38.10	< .001***	0.20
z _r	Feature Relation	1	149	0.04	.846	0.00
	Response Relation x Feature Relation	1	149	1.97	.163	0.01
	(Intercept)	1	149	1,124.69	< .001***	0.88
	Response Relation	1	149	7.06	.009**	0.05
	Feature Relation	1	149	1.84	.177	0.01
	Response Relation x Feature Relation	1	149	6.67	.011*	0.04

1:1 Mapping, figurative^b

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
a	(Intercept)	1	115	731.09	< .001***	0.86
	Response Relation	1	115	0.54	.464	0.00
	Feature Relation	1	115	4.74	.032*	0.04
	Response Relation x Feature Relation	1	115	23.68	< .001***	0.17
t ₀	(Intercept)	1	115	5,282.08	< .001***	0.98
	Response Relation	1	115	0.04	.835	0.00
	Feature Relation	1	115	3.32	.071	0.03
	Response Relation x Feature Relation	1	115	0.34	.559	0.00
v	(Intercept)	1	115	1,581.82	< .001***	0.93
	Response Relation	1	115	13.60	< .001***	0.11
	Feature Relation	1	115	6.43	.013*	0.05
	Response Relation x Feature Relation	1	115	19.34	< .001***	0.14
z _r	(Intercept)	1	115	945.33	< .001***	0.89
	Response Relation	1	115	131.43	< .001***	0.53
	Feature Relation	1	115	1.26	.265	0.01
	Response Relation x Feature Relation	1	115	26.37	< .001***	0.19

2:1 Mapping, figurative^b

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
a	(Intercept)	1	109	824.77	< .001***	0.88
	Response Relation	1	109	12.64	.001***	0.10
	Feature Relation	1	109	6.00	.016*	0.05
	Response Relation x Feature Relation	1	109	12.91	< .001***	0.11
t ₀	(Intercept)	1	109	3,660.12	< .001***	0.97
	Response Relation	1	109	43.92	< .001***	0.29
	Feature Relation	1	109	0.02	.888	0.00
	Response Relation x Feature Relation	1	109	0.32	.570	0.00
v	(Intercept)	1	109	486.56	< .001***	0.82
	Response Relation	1	109	10.89	.001**	0.09
	Feature Relation	1	109	5.20	.024*	0.05
	Response Relation x Feature Relation	1	109	0.58	.447	0.01
z _r	(Intercept)	1	109	1,237.33	< .001***	0.92
	Response Relation	1	109	135.75	< .001***	0.55
	Feature Relation	1	109	0.69	.407	0.01
	Response Relation x Feature Relation	1	109	23.24	< .001***	0.18

Further paradigms

Visual Search^a

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
a	(Intercept)	1	49	206.75	< .001***	0.81
	Response Relation	1	49	0.04	.842	0.00

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
t_0	Feature Relation	1	49	1.44	.237	0.03
	Response Relation x Feature Relation	1	49	10.17	.002**	0.17
	(Intercept)	1	49	3,416.73	< .001***	0.99
	Response Relation	1	49	2.08	.156	0.04
v	Feature Relation	1	49	2.06	.157	0.04
	Response Relation x Feature Relation	1	49	0.56	.458	0.01
	(Intercept)	1	49	494.31	< .001***	0.91
	Response Relation	1	49	4.13	.048*	0.08
z_r	Feature Relation	1	49	23.88	< .001***	0.33
	Response Relation x Feature Relation	1	49	1.30	.259	0.03
	(Intercept)	1	49	419.12	< .001***	0.90
	Response Relation	1	49	13.29	.001***	0.21
	Feature Relation	1	49	10.86	.002**	0.18
	Response Relation x Feature Relation	1	49	81.55	< .001***	0.62

Flanker task^a

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
a	(Intercept)	1	32	91.82	< .001***	0.74
	Response Relation	1	32	1.08	.306	0.03
	Feature Relation	1	32	0.12	.731	0.00
	Response Relation x Feature Relation	1	32	0.93	.341	0.03
t_0	(Intercept)	1	32	575.48	< .001***	0.95
	Response Relation	1	32	17.46	< .001***	0.35
	Feature Relation	1	32	1.61	.214	0.05
	Response Relation x Feature Relation	1	32	5.03	.032*	0.14
v	(Intercept)	1	32	178.96	< .001***	0.85
	Response Relation	1	32	0.27	.608	0.01
	Feature Relation	1	32	1.13	.295	0.03
	Response Relation x Feature Relation	1	32	0.88	.354	0.03
z_r	(Intercept)	1	32	177.20	< .001***	0.85
	Response Relation	1	32	1.33	.257	0.04
	Feature Relation	1	32	0.34	.567	0.01
	Response Relation x Feature Relation	1	32	12.68	.001**	0.28

Task-switching^a

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
a	(Intercept)	1	70	707.99	< .001***	0.91
	Response Relation	1	70	20.18	< .001***	0.22
	Feature Relation	1	70	1.07	.305	0.02
	Response Relation x Feature Relation	1	70	2.36	.129	0.03
t_0	(Intercept)	1	70	1,525.07	< .001***	0.96
	Response Relation	1	70	9.57	.003**	0.12
	Feature Relation	1	70	0.20	.653	0.00
	Response Relation x Feature Relation	1	70	11.03	.001**	0.14
v	(Intercept)	1	70	495.06	< .001***	0.88
	Response Relation	1	70	3.55	.064	0.05
	Feature Relation	1	70	13.99	< .001***	0.17
	Response Relation x Feature Relation	1	70	0.54	.465	0.01
z_r	(Intercept)	1	70	1,717.14	< .001***	0.96
	Response Relation	1	70	0.90	.345	0.01
	Feature Relation	1	70	0.89	.349	0.01
	Response Relation x Feature Relation	1	70	3.24	.076	0.04

Response-response binding^a

DDM parameter	Predictor	df_{num}	df_{den}	F	p	η^2_p
a	(Intercept)	1	75	232.08	< .001***	0.76
	Response Relation1	1	75	1.03	.314	0.01
	Response Relation2	1	75	0.03	.872	0.00
	Response Relation1 x Response Relation2	1	75	0.03	.856	0.00
t_0	(Intercept)	1	75	981.38	< .001***	0.93
	Response Relation1	1	75	2.21	.142	0.03
	Response Relation2	1	75	0.50	.480	0.01
	Response Relation1 x Response Relation2	1	75	0.07	.795	0.00
v	(Intercept)	1	75	599.17	< .001***	0.89
	Response Relation1	1	75	0.62	.434	0.01
	Response Relation2	1	75	0.42	.518	0.01
	Response Relation1 x Response Relation2	1	75	0.56	.458	0.01
z_t	(Intercept)	1	75	412.90	< .001***	0.85
	Response Relation1	1	75	0.16	.690	0.00
	Response Relation2	1	75	8.31	.005**	0.10
	Response Relation1 x Response Relation2	1	75	3.04	.085	0.04

Appendix B

Fisher's z-tests Concerning Difference of Correlations.

Experiment	Expected r	Observed r	Fisher's z	p	Cohen's q	Correlation
S1R1-S2R2, full, figurative ^a	-.098	-.567	-4.52	< .001	-0.544	v, z _r
	.053	.054	0.005	.996	0.001	a, z _r
	.128	.158	0.247	.805	0.03	a, v
S1R1-S2R2, reduced, figurative ^a	.168	-.546	-3.848	< .001	-0.786	v, z _r
	.463	-.013	-2.562	.010	-0.523	a, z _r
	-.084	.363	2.284	.022	0.466	a, v
TRB, figurative ^a	-.298	-.643	-3.331	.001	-0.453	v, z _r
	.002	-.223	-1.682	.093	-0.229	a, z _r
	.033	.348	2.424	.015	0.33	a, v
TRB, symbolic ^a	-.091	-.692	-4.981	< .001	-0.76	v, z _r
	-.01	.019	0.191	.849	0.029	a, z _r
	-.264	.255	3.502	< .001	0.534	a, v
DRB, 1:1 Mapping, symbolic ^a	-.141	-.637	-5.214	< .001	-0.61	v, z _r
	.224	-.083	-2.67	.008	-0.313	a, z _r
	-.045	.379	3.795	< .001	0.444	a, v
DRB, 1:1 Mapping, symbolic ^b	-.036	-.665	-9.282	< .001	-0.766	v, z _r
	-.011	.006	0.207	.836	0.017	a, z _r
	.159	.359	2.605	.009	0.215	a, v
DRB, 1:1 Mapping, figurative ^b	.024	-.595	-7.542	< .001	-0.709	v, z _r
	.259	-.197	-4.951	< .001	-0.466	a, z _r
	-.124	.612	8.901	< .001	0.837	a, v
DRB, 2:1 Mapping, figurative ^b	-.094	-.663	-7.276	< .001	-0.703	v, z _r
	.047	-.073	-1.245	.213	-0.12	a, z _r
	-.043	.413	4.99	< .001	0.482	a, v
Visual Search ^a	-.115	-.744	-5.777	< .001	-0.843	v, z _r
	.099	.032	-0.468	.640	-0.068	a, z _r
	-.124	.31	3.061	.002	0.446	a, v
Flanker task ^a	.052	-.254	-1.434	.152	-0.313	v, z _r
	-.205	-.199	0.049	.961	0.011	a, z _r
	.125	.59	2.517	.012	0.549	a, v
Task-switching ^a	-.088	-.613	-5.076	< .001	-0.625	v, z _r
	.367	.014	-3.036	.002	-0.374	a, z _r
	.004	.534	4.807	< .001	0.592	a, v
Response-response binding ^a	.031	-.317	-3.072	.002	-0.36	v, z _r
	.206	.15	-0.506	.613	-0.059	a, z _r
	-.095	.231	2.829	.005	0.331	a, v