Supplementary materials

1. Posterior Predictive Checks: summary statistics

1.1. Experiment 1

Supplementary Table 1. Summary statistics of the posterior predictive checks in Experiment 1. The first and second columns represent the observed and simulated mean values for each measure indicated by the row name. The upper boundary represents correct responses while the lower boundary represents incorrect responses. STD is a measure of how much variation is produced in the summary statistics. The rest of the columns are various measures of the extent of deviation between the simulated and the observed data (SEM is the standard error from the mean, MSE is the mean-squared error).

	Observed	Simulated	STD	SEM	MSE	within 95% credible interval	Mahalanobis distance
mean accuracy	0.94	0.96	0.05	0.001	0.003	TRUE	0.51
mean RT upper boundary	0.53	0.55	0.07	<0.001	0.005	TRUE	0.26
std upper boundary	0.11	0.14	0.05	0.001	0.003	TRUE	0.61
10 quartile upper boundary	0.41	0.42	0.05	<0.001	0.003	TRUE	0.13
30 quartile upper boundary	0.47	0.46	0.06	<0.001	0.003	TRUE	0.07
50 quartile upper boundary	0.52	0.51	0.06	<0.001	0.004	TRUE	0.07
70 quartile upper boundary	0.58	0.59	0.08	<0.001	0.006	TRUE	0.14
90 quartile upper boundary	0.67	0.74	0.12	0.004	0.019	TRUE	0.54
mean RT lower boundary	-0.51	-0.55	0.11	0.001	0.014	TRUE	0.33
std lower boundary	0.14	0.09	0.08	0.002	0.009	TRUE	0.55
10 quartile lower boundary	0.37	0.47	0.11	0.008	0.020	TRUE	0.86
30 quartile lower boundary	0.43	0.50	0.11	0.005	0.016	TRUE	0.64
50 quartile lower boundary	0.48	0.53	0.11	0.002	0.015	TRUE	0.41
70 quartile lower boundary	0.55	0.58	0.13	0.001	0.017	TRUE	0.21
90 quartile lower boundary	0.70	0.65	0.17	0.002	0.032	TRUE	0.27

1.2. Experiment 2

Supplementary Table 2. Summary statistics of the posterior predictive checks in Experiment 2.

	Observed	Simulated	STD	SEM	MSE	within 95% credible interval	Mahalanobis distance
mean accuracy	0.95	0.97	0.04	0.001	0.003	TRUE	0.53
mean RT upper boundary	0.53	0.54	0.07	<0.001	0.006	TRUE	0.14
std upper boundary	0.12	0.15	0.07	0.001	0.005	TRUE	0.42
10 quartile upper boundary	0.41	0.40	0.06	<0.001	0.004	TRUE	0.11
30 quartile upper boundary	0.46	0.45	0.06	<0.001	0.004	TRUE	0.16
50 quartile upper boundary	0.51	0.51	0.07	<0.001	0.005	TRUE	0.09
70 quartile upper boundary	0.57	0.58	0.09	<0.001	0.008	TRUE	0.09
90 quartile upper boundary	0.69	0.73	0.15	0.002	0.024	TRUE	0.33
mean RT lower boundary	-0.47	-0.54	0.14	0.006	0.025	TRUE	0.55
std lower boundary	0.15	0.09	0.11	0.003	0.014	TRUE	0.54
10 quartile lower boundary	0.32	0.46	0.14	0.019	0.037	TRUE	1.00
30 quartile lower boundary	0.39	0.49	0.13	0.010	0.028	TRUE	0.77
50 quartile lower boundary	0.44	0.52	0.14	0.008	0.027	TRUE	0.64
70 quartile lower boundary	0.49	0.57	0.16	0.006	0.030	TRUE	0.49
90 quartile lower boundary	0.66	0.64	0.21	0.000	0.045	TRUE	0.05

2. Results for the non-target categories

In our study, we did not ask participants to do a binary categorical decision (such as bird vs. dog or animal vs. vehicle) but asked them to report the presence or absence of a particular category (bird/non-bird task in Experiment 1 and animal/non-animal task in Experiment 2). Hence, participants would not be looking for attributes of two separate categories but for a particular combination of attributes (e.g. bird in Experiment 1) versus an absence of this combination. In this situation, it is hard to determine what mechanisms are at play when categorising distractor images. The decision could be based on an absence of target attributes or the presence of a different combination of attributes for the distractor category which might vary substantially depending on each participant's strategy (since the distractor category is not stated). We therefore decided not to include the analysis of responses to non-target images in the main text but we report it below.

2.1. Experiment 1

1.1.1. Priming effect

For each participant we computed the median RT for correct rejections and mean ER (false alarms) for non-bird animal and vehicle test images separately. The test image could be presented preceded by a congruent prime (non-bird animal or vehicle preceding a non-bird animal or a vehicle, respectively) or by an incongruent prime (a bird image). The incongruent prime was either related to the target image in the case of a non-bird animal target, or unrelated in the case of a vehicle target image. The priming effect was calculated by taking the difference between congruent and incongruent trials for non-bird animal and vehicle test images separately (Supp. Fig. 1).

Effect of response congruency

To test the effect of response congruency, we pooled trials with related and unrelated incongruent primes. Participants made slightly more errors, around 2.2 percentage points, after an incongruent than a congruent prime at 80 ms SOA ($t(12)=2.00$, $p=0.07$). This effect was stronger at 180 ms SOA. In this condition, participants made 4.5 percentage points more errors while making a "no" response if a bird prime preceded the test image compared to a trial in which a non-bird prime preceded the non-bird test image ($t(12)=4.23$, $p=0.001$).
RT results followed this pattern showing that participants were faster at categorising a distractor (non-bird) image when it was presented after another non-bird image than after a bird image ($t(12)=6.95$, $p<0.001$ and $t(12)=4.60$, $p=0.001$ at 80 ms and 180 ms SOA, respectively). This effect was similar at both SOAs, with congruent primes around 29 ms faster than incongruent primes.

Effect of relatedness

As can be observed in Supplementary Figure 1, ER priming was in general higher for related than for unrelated primes ($F(1,12)=3.90$, $p=0.07$, $_p\eta^2=0.24$) and higher at long than at short SOA ($F(1,12)=4.24$, $p=0.06$, $_p\eta^2=0.26$). There was no interaction between these factors ($F(1,12)=1.31$, $p=0.27$, $_p\eta^2=0.10$).
We did not observe a difference in RT priming depending on relatedness ($F(1,12)=0.68$, $p=0.43$, $_p\eta^2=0.05$) or on SOA ($F(1,12)=0.10$, $p=0.76$, $_p\eta^2=0.01$), and there was also no interaction between these factors ($F(1,12)=1.90$, $p=0.19$, $_p\eta^2=0.14$).

Summary

As already observed for bird test stimuli, the prime image was automatically processed and influenced participants' performance. Participants were faster and more accurate in congruent

than incongruent trials even for the non-target category. The effect of relatedness on ER priming was similar (more errors for related than unrelated primes), although weaker, than the one reported for bird target images.
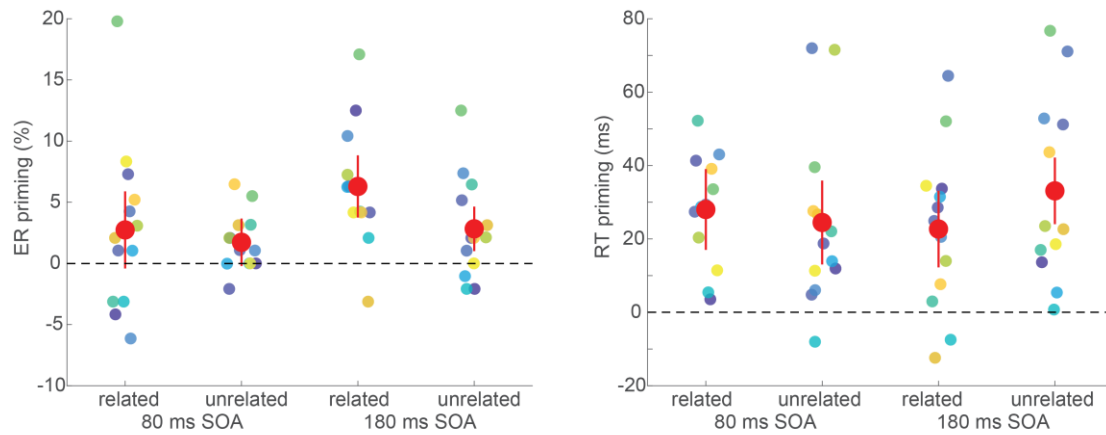
Supplementary Figure 1. Priming effect (ER and RT) for non-bird images in Experiment 1 depending on the prime (related for non-bird animals and unrelated for vehicles) and the SOA condition (80 or 180 ms).

1.1.2. Drift-Diffusion Modelling

The same HDDM modelling procedure as described in the main text was used. Gelman-Rubin $\hat{R}$ values were all less than 1.003 showing excellent convergence of the model. Visual inspection of the chains and posterior predictive checks also confirmed that the data predicted by the model was within 95% credible interval of the observed data (see also Supp. Fig. 2). We used the same Bayesian analysis method based on posterior probabilities (P) to compare our experimental conditions.
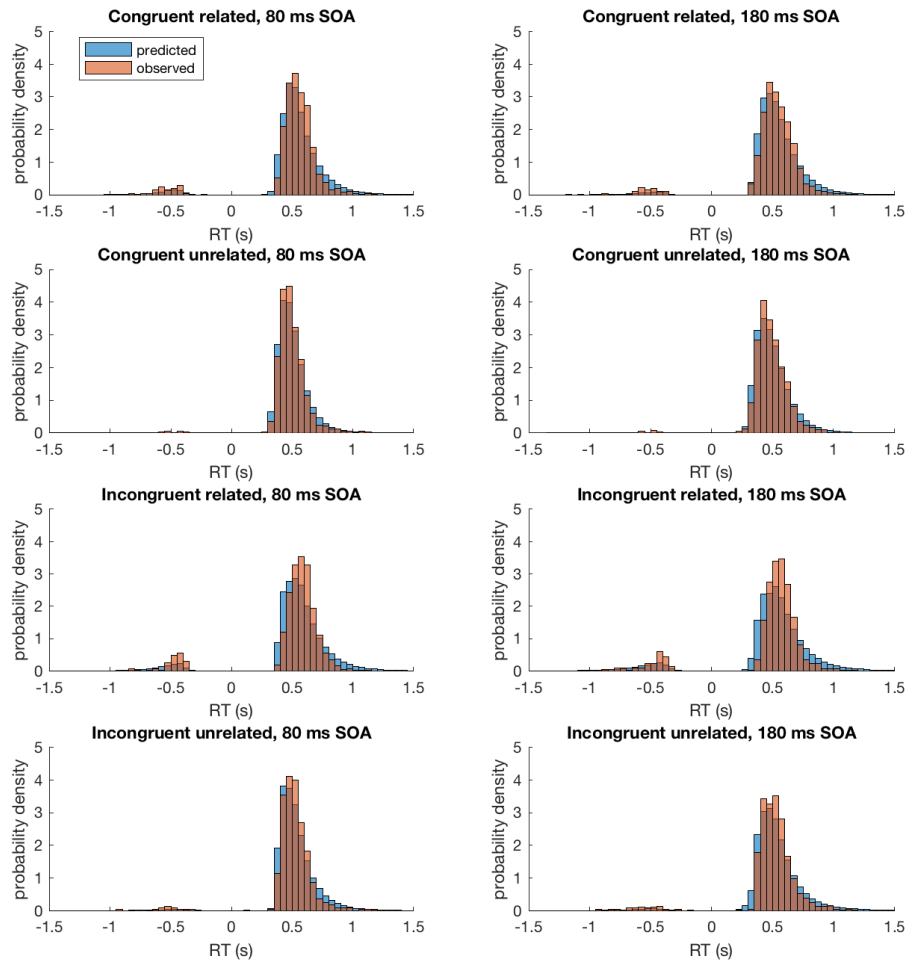
Supplementary Figure 2. Observed (red histograms) and HDDM predicted (blue histograms) RT distributions in Experiment 1 for non-bird responses. Incorrect responses are represented with negative RTs.

The HDDM showed that accumulation of evidence (v) was faster when the test image was a vehicle than a non-bird animal (P<0.001 for all comparisons, Supp. Fig. 3). There was also a tendency for faster v in the congruent than in the incongruent conditions particularly at long SOA (P=0.06 and P=0.07 for non-bird animal and vehicle test images, respectively). Non-decisional processes, t, were in general faster for vehicle test images than for animal test images and this effect increased with longer SOAs (in the congruent conditions, P=0.07 and P=0.002; in the incongruent conditions, P=0.09 and P=0.02; at short and long SOA, respectively).

Better performance for vehicle compared to non-bird animal images was also visible in higher decision boundary, a. Decision threshold was higher for vehicle images at both SOAs in the congruent (P=0.003 and P=0.001) and in the incongruent condition (P=0.05 and P=0.04) compared to non-bird animal images.

In summary, vehicle images were categorised faster than non-bird animal images. This effect was visible at all processing stages (in v, a and t) and increased with long SOA. Compared to the results found for responses on bird images, the congruency effect on t was not very strong. This might be because the stimulus-response mapping is weaker for non-target (non-bird) than for target (bird) images.
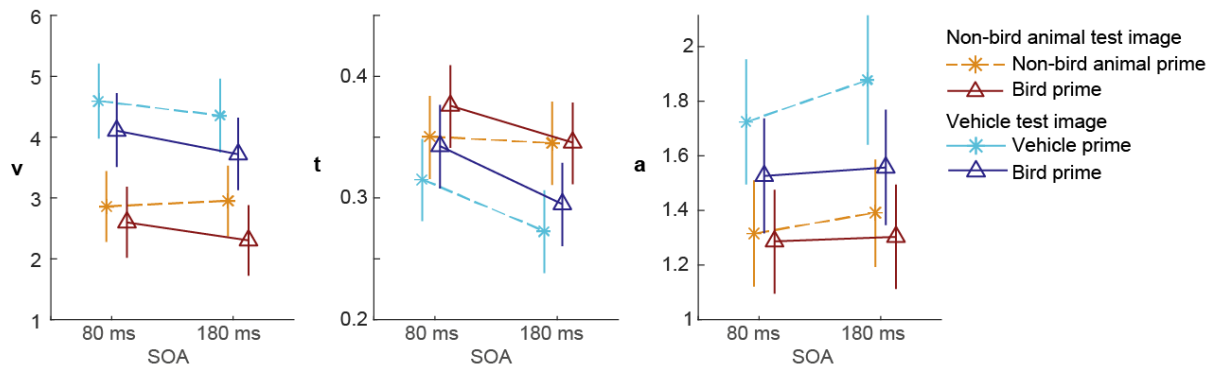
Supplementary Figure 3. Posterior estimates of the accumulation of evidence (*v*), non-decisional processes (*t*) and decision threshold (*a*) in Experiment 1 for responses to non-bird images. Error bars represent 89% credible intervals.

2.2. Experiment 2

1.1.3. Priming effect

For each participant we computed the median RT for correct responses and mean ER for vehicle test images (corresponding to correct rejections and false alarms). These values were then used to calculate the priming effect, that is the difference between incongruent and congruent trials (Supp. Fig. 4).

Effect of response congruency
To test the effect of response congruency, we pooled ER and RT priming for related and unrelated primes.
Participants made more errors after an incongruent than a congruent prime, by around 4 percentage points at short SOA (t(12)=5.38, p<0.001) and 5 percentage points at long SOA (t(12)=2.20, p=0.048).
In addition, participants were on average 49 ms faster to categorise a vehicle image when it was presented after another vehicle image than after an animal image (at both SOAs t(12)>7.40, p<0.001).

Effect of relatedness
ER priming was not affected by SOA (F(1,12)=0.27, p=0.61, $_p\eta^2$=0.02) or the relatedness of the prime to the test image (F(1,12)=0.05, p=0.82, $_p\eta^2$=0.05). We also did not find any interaction between these two factors (F(1,12)=0.75, p=0.40, $_p\eta^2$=0.06).
RT priming was 10 ms more for related than for unrelated prime (50 ms vs. 40 ms at short SOA and 58 ms vs. 48 ms at long SOA; F(1,12)=7.05, p=0.02, $_p\eta^2$=0.37). There was no effect of SOA (F(1,12)=1.97, p=0.19, $_p\eta^2$=0.14) or interaction (F(1,12)=0.001, p=0.98, $_p\eta^2$<0.001).

Summary
Results for vehicle images (distractor category) are similar as the ones observed for animal images (target category). We found an effect of congruency on both ER and RT but the effect of relatedness was weak (10 ms difference on RT priming).
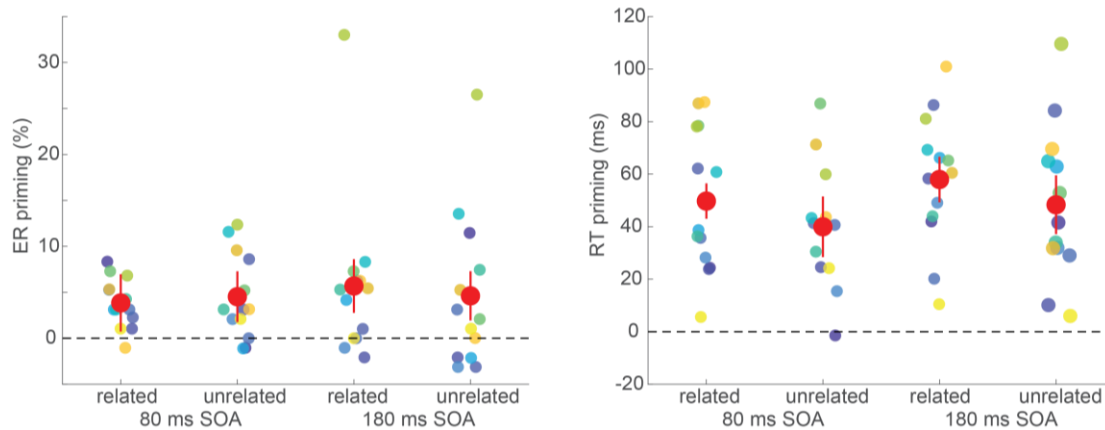
Supplementary Figure 4. ER and RT priming effect in Experiment 2 for responses to non-animal images.

1.1.4. Drift-Diffusion Modelling

Model convergence was confirmed after visual inspection of the chains, Gelman-Rubin diagnosis (all $\hat{R}$ were below 1.005) and posterior predictive checks (predicted data were within 95% credible interval of the observed data; see also Supp. Fig. 5).

The results of the HDDM (Supp. Fig. 6) showed that the congruency effect was visible at short SOA in all parameters, for v (P=0.006, P=0.003 for related and unrelated prime respectively), t (P=0.04, P=0.01) and a (P=0.11, P=0.007). The effect was smaller at long SOA for the related conditions (v: P=0.01, t: P=0.11, a: P=0.05) and started to disappear for the unrelated conditions (v: P=0.12, t: P=0.26, a: P=0.29). We note that the unrelated congruent condition seems to follow a different pattern than the other conditions. The facilitation effect drops with longer SOA for v (P=0.07) and instead of faster t and higher a with longer SOA, there was no effect of SOA. That is, a vehicle prime is not facilitating the categorisation of a vehicle test image at long SOA if the vehicle is unrelated to the test image (e.g. a boat prime followed by a truck target). The congruency effect for responses to vehicle images observed in Experiment 2 can be explained by a strong effect in the drift-rate, and to a lesser extent by the other parameters in the model. We also found that the facilitation in categorising vehicle images after seeing an unrelated vehicle image decreased with longer SOA. In comparison, in the main analysis we found that with longer SOA a related congruent prime facilitated the categorisation of animal images (via parameters t and a). In both cases, the effect of relatedness was more visible at longer SOA.
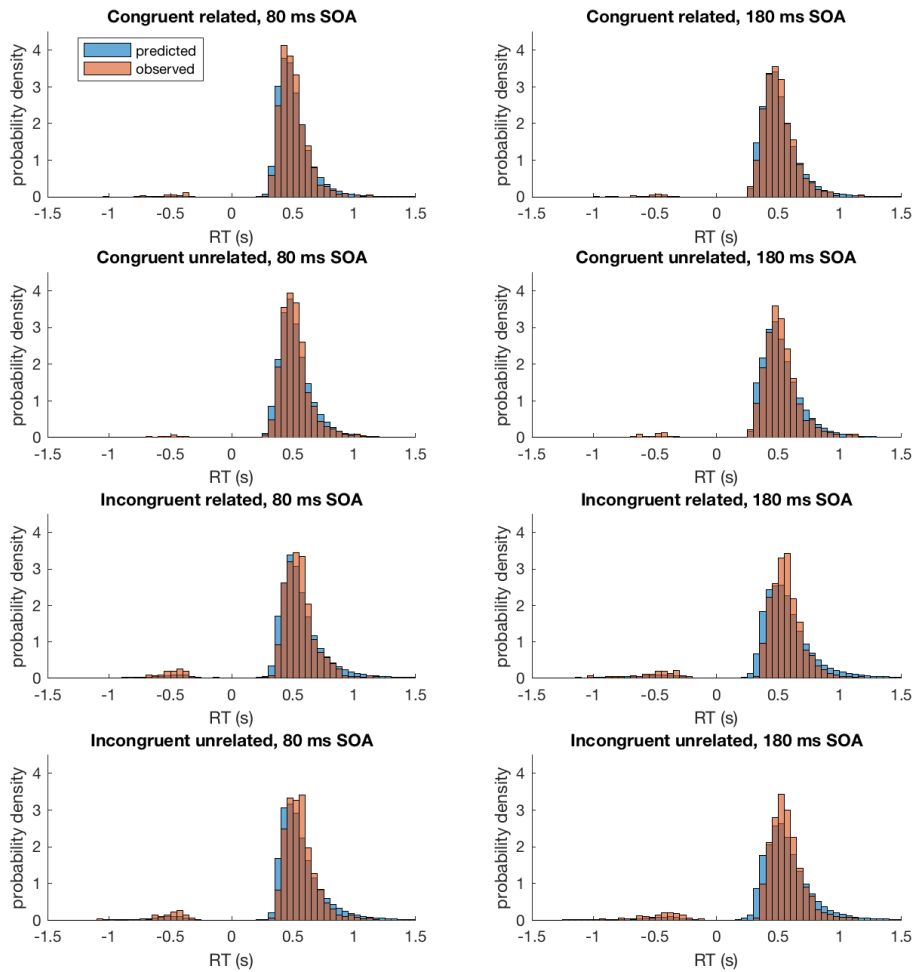
Supplementary Figure 5. Observed (red histograms) and HDDM predicted (blue histograms) RT distributions in Experiment 2 for non-animal responses.
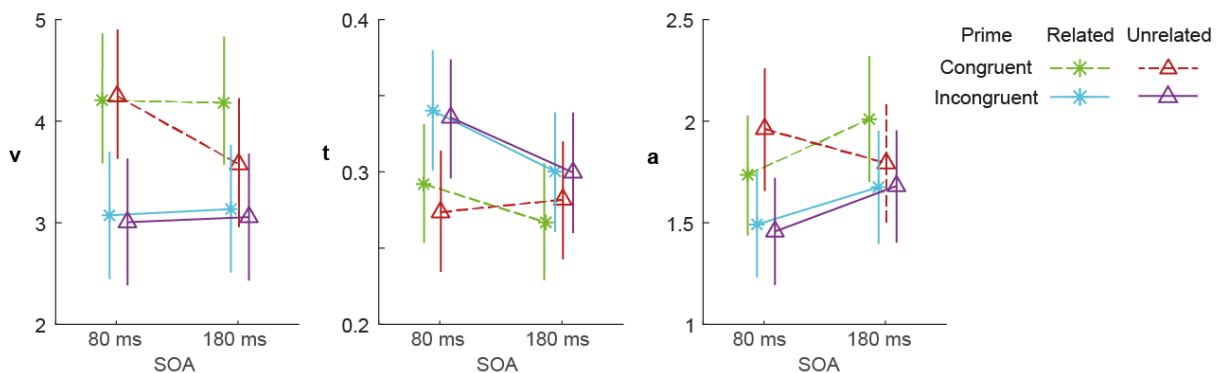
Supplementary Figure 6. Posterior estimates of the HDDM parameters in Experiment 2 for responses to vehicle images. Error bars represent 89% credible intervals.

3. Drift-diffusion modelling with stimulus coding

An alternative explanation to our findings might be that the effects that we observed in *v* could instead be the result of a change in *z*. That is, the prime does not change the *rate* of evidence accumulation but changes its *starting point* (bias, parameter *z*). This possibility can be tested with the HDDM toolbox by implementing a 'stimulus-coding' procedure in which the upper boundary corresponds to the target category (e.g. bird images in Experiment 1) and the lower boundary corresponds to the distractor category (e.g. non-bird images in Experiment 1). This

will allow us to determine if a prime (say bird) biases responses towards one of the boundaries (say the upper one), and if so, would the effect in *v* consequently disappear. However, in such models, the drift-rate (*v*) is assumed to be the same for the upper and the lower boundary, that is, the speed of evidence accumulation is set to be the same for target and distractor images (*v* of the target category = -*v* of the distractor category).

It is unjustified, and probably incorrect, to make this assumption given our paradigm; this is one of the reasons why we chose to only report the accuracy-coding models in the main text. Further, we would not expect participants to have an a-priori bias since all image categories were counterbalanced as prime or target and no reward was associated with one image category. Finally, the interpretation of the parameters can be difficult in a stimulus-coding model since an increase in *v* in one condition means that the accumulation of evidence is faster for both the target and distractor categories. Therefore, we report the results of a stimulus-coding model for Experiments 1 and 2 mainly to test whether the differences in drift-rate could instead be explained by differences in bias.

3.1. Experiment 1

A similar HDDM modelling procedure as described in the main text was used except that instead of an accuracy-coding procedure (upper boundary: correct response, lower boundary: incorrect response), a stimulus-coding procedure was used (upper boundary: bird response, lower boundary: non-bird response). The visual inspection of the model chains illustrated good convergence of the model. This was confirmed with Gelman-Rubin statistics showing that all $\hat{R}$ values were less than 1.002. Posterior predictive checks also confirmed that the data predicted by the model was within 95% credible interval of the observed data. We used the same Bayesian analysis method based on posterior probabilities (P) to compare our experimental conditions.

The results of the three parameters, *v*, *t* and *a* (Supp. Fig. 7) paint a very similar picture to what we observed in the accuracy-coding model (Fig. 5). In trials with non-bird animals, *v* was slower for incongruent than congruent images at short (P=0.05) and long (P=0.003) SOA. On the other hand, in trials with vehicle images, *v* was the same in congruent and incongruent trials (P>0.36 at both SOAs) and faster than in trials with non-bird images (all Ps<0.05). Thus, as found in the main text, non-bird animal images but not vehicle images interfere with the speed of the accumulation of evidence. Further, just as in the main text, *t* decreased in the incongruent unrelated conditions with longer SOA (P=0.02) such that the effect of congruency was smaller at long than at short SOA for trials including vehicle images. The decision threshold was also smaller in incongruent related than unrelated conditions (P=0.06 and P=0.001 at short and long SOA respectively) demonstrating lower accuracy for trials in which non-bird animals were present. Finally, the starting-point *z* showed an effect of relatedness. This parameter can vary between 1 (bias for a bird response) and 0 (bias for a non-bird response), with 0.5 representing a non-biased starting point. Here, the model revealed that conditions with non-bird animal images were biased towards a bird response while conditions with vehicle images were biased towards a non-bird response (all Ps<0.001 between related and unrelated conditions at both SOAs for congruent and incongruent trials). In conclusion, although the stimulus-coding procedure demonstrated a bias in the starting point, the other parameters (*v*, *a*, and *t*) are remarkably similar to those reported in the main text. These results confirm that the accumulation of evidence is affected specifically in conditions with non-bird animal images and not vehicle images.
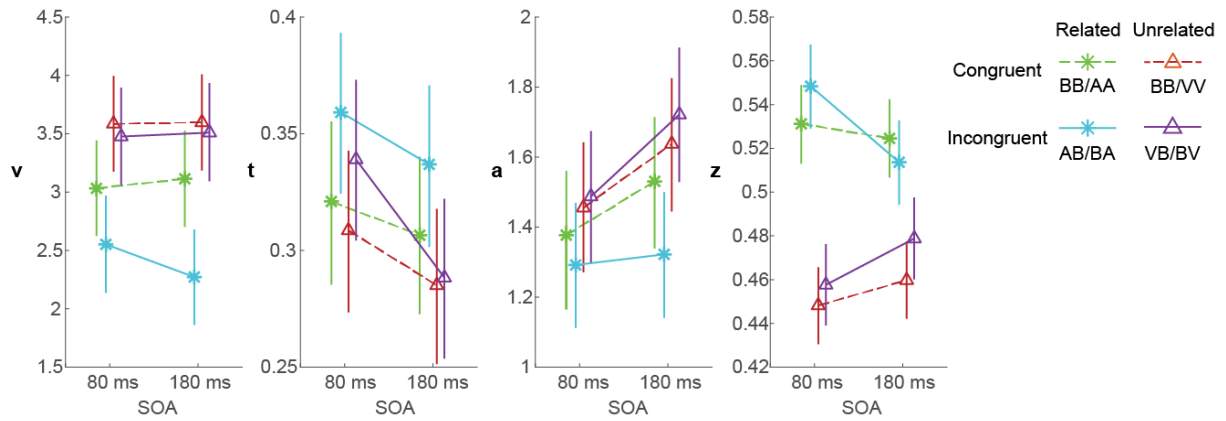
Supplementary Figure 7. Posterior estimates of the HDDM parameters in Experiment 1 using a stimulus-coding procedure in which bird responses are represented as the upper threshold and non-bird responses are represented as the lower threshold. In the congruent conditions bird target images are preceded by a bird prime (BB) for the upper boundary, while the lower boundary conditions are non-bird animal images preceded by non-bird animal primes (AA) or vehicle images preceded by vehicle primes (VV). In the related incongruent condition, the upper boundary contains trials in which a bird is preceded by a non-bird animal (AB) while the lower boundary contains trials in which a non-bird animal is preceded by a bird (BA). Similarly, in the unrelated incongruent condition, the upper boundary includes vehicle bird target trials (VB) and the lower boundary includes bird vehicle target trials (BV). In the legend, the upper boundary condition is followed by the lower boundary condition (e.g. BB/AA). Error bars represent 89% credible intervals.

3.2. Experiment 2

The inspection of the chains and the Gelman-Rubin statistics showed that the HDDM model converged very well (all $\hat{R}$ values were below 1.006). Posterior predictive checks also confirmed that the data predicted by the model was within 95% credible interval of the observed data. The estimates of the model parameters were very similar to what we observed with the accuracy coding procedure (Supp. Fig. 8). The drift-rate was faster for images preceded by congruent than incongruent primes (all Ps<0.03), non-decisional processes became faster and the threshold became higher in the congruent related condition at long SOA (P=0.03 in both conditions). There was no difference in a-priori bias between all conditions (all Ps>0.21). This rules out the possibility that the priming effect was due to a difference in the starting point.
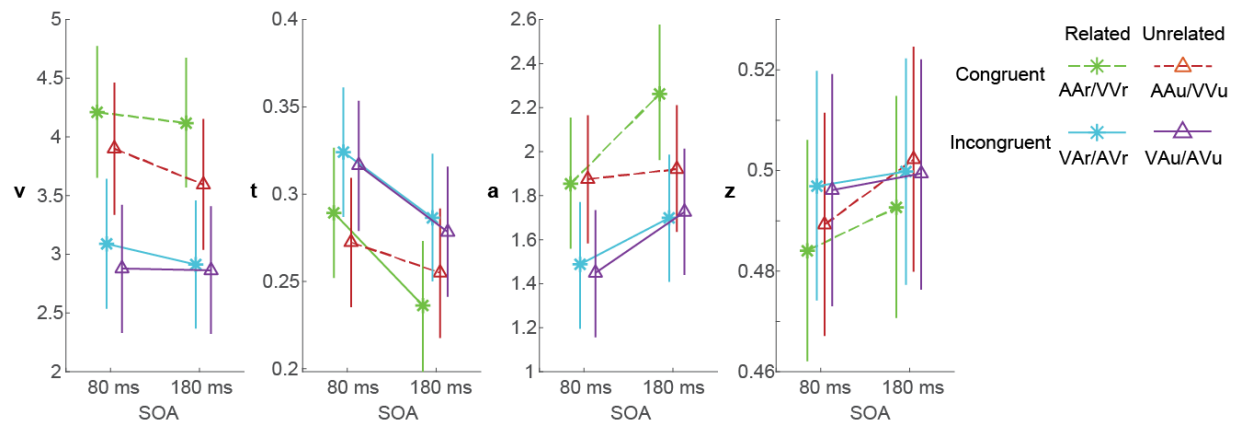
Supplementary Figure 8. Posterior estimates of the HDDM parameters in Experiment 2 using the stimulus coding procedure. In the incongruent related condition animal images were preceded by related vehicle primes for the upper boundary (VAr), vehicle images were preceded by related animal primes for the lower boundary (AVr). In the legend the upper boundary condition is followed by the lower boundary condition (AAr/VVs). Error bars represent 89% credible intervals. (A: animal, V: vehicle, r: related, u: unrelated)