Supporting information

Cognitive performance of wild Eastern grey squirrels (*Sciurus carolinensis*) in rural and urban, native and non-native environments.

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Note S1. Individual identification

We used mark-recaptured method using video footage to identify individuals. All video footage were analysed by an observer (PKYC) at least three times. Individuals were first 'marked' or 'captured' with their unique characteristics (e.g., particular colour patterns on face, limbs, body, ears and tail). This lasted for about two-months of intensive training with frame-by-frame analysis using Adobe Premiere Pro CS6. Descriptive details about the individual characteristics were noted. The second identification was conducted around a month later to verify the first identification. For this study, the third identification was conducted a year later. For the second and third identifications, the observer re-analysed the video but hiding previous information to ensure each identification was done independently. We conducted intra-rater reliability using an Intra-class reliability test to assess internal consistency of individual identification (ICC = 0.99).

Note S2. The role of social interference and social learning in individual performance

To understand whether social interference may be a confounding variable for individual performance, we recorded whether there was another conspecific present on an apparatus when a squirrel was attempting to solve a problem. As well as this, we also recorded whether there were aggressive behaviours (e.g., chasing) toward the squirrel that was solving the problem. Throughout the experimental period, less than 1% of attempts were emitted in the presence of a conspecific on the task across sites. This indicates that the use of Chow et al. (2018)'s protocol helped to minimise social interference on individuals' problem-solving performance.

Another potential confounding variable that may affect individual problem-solving performance would be social learning. Hypothetically, later comers may have observed early comers solving the task, which could affect their performance (e.g., more likely to success or lower solving latency). If this is the case, then later comers may be more performant than the early comers. Accordingly, we analysed the role of social learning by examining the order of arrival on the first trial in relation to each individual solving outcome ('success' or failure') when it first encountered each task. For solving outcome, we used GLM binomial log link distribution, setting 'the order of arrival on the first trial' as fixed effect whereas solving outcome ('success' or 'failure') of each individual as response variable ('site' or 'individual identity' could be not included as random variable as it either led to singular fit or convergence issues). The result suggest that social learning did not significantly affect individuals' solving outcome (Easy problem (N = 37): $\chi^2_1 = 2.21$, $P = 0.137$; Difficult problem (N = 27): $\chi^2_1 = 0.10$, $P = 0.756$). We also used GLM gamma log link distribution (because data were highly skewed toward (but not on) 0) to model the time spent interaction with each problem, we found that social learning did not have a significant effect on the time spent on interacting with each problem (Easy problem (N = 37): $\chi^2_1 < 0.001$, $P = 0.978$; Difficult problem: $\chi^2_1 = 0.05$, $P = 0.816$). Accordingly, the results do not support the role of social learning in relation to individual's solving performance.

Note S3. Persistence and motivation in innovators and non-innovators.

For the difficult problem, a significant difference was shown in the success rate on the first visit between the native urban and the non-native urban group. Accordingly, we further conducted three between-group analyses to examine whether persistence and motivation (i.e., showing goal-oriented behaviour to retrieve the food reward regardless of the underlying reasons such as hunger level or pressure of hoarding food) may explain the difference in problem-solving success on the first visit. For each individual, we recorded persistence as the time spent on interacting with the difficult problem on the first visit whereas motivation as the number of attempts made (regardless the time spent on interacting with the problem) on the first visit. Both measurements were recorded from when a squirrel started using any part of its body to touch a lever to when it stopped doing so. By using these two measurements, we additionally calculated the attempt rate to reflect whether a squirrel made few attempts with each lasted a longer bout of time (low attempt rate) or multiple attempts within a shorter-bout of time (high attempt rate) when interacting with the problem. Because the inclusion of individual identity or site as random effect led to singular fit or convergence issue, we used GLM for model testing. The time spent on interacting with the box and attempt rate were modelled by gamma log link distribution whereas the number of attempts was modelled by Poisson log link distribution. In all models, we included group (native rural, native urban, non-native rural, and non-native urban), type of solvers on the first visit (an individual was categorised as either 'innovator' who successfully solved the problem or 'non-innovator' who failed to solve the problem), and their interaction.

In the first model, where the response variable was the time spending on interacting with the problems, we found none of the variables were significant (group: $\chi^2_1 = 2.12$, $P = 0.145$; type of solvers: $\chi^2_1 = 1.60$, $P = 0.206$; group*type of solvers: $\chi^2_1 = 2.98$, $P = 0.085$). The second model included the number of attempts as the response variable, and we found that only the type of solvers was significant (group: $\chi^2_1 = 3.35$, $P = 0.067$; type of solvers: $\chi^2_1 = 11.75$, $P < 0.001$; group*type of solvers: $\chi^2_1 = 2.95$, $P = 0.086$); more attempts on the first visit were made by innovators than non-innovators. However, post-hoc analysis using Turkey's Honest Significant Difference test for within-group contrast showed that this was the case for the native urban group (P = 0.001), but not the non-native urban group (P = 0.378). These results suggested that innovators in the native urban group were more motivated than their non-innovators counterparts.

Finally, the third model included attempt rate as the response variable, and we found that group and the interaction of group and the type of solvers were significant (group: $\chi^2_1 = 5.13$, $P = 0.024$; type of solvers: $\chi^2_1 = 2.24$, $P = 0.134$; group*type of solvers: $\chi^2_1 = 10.70$, $P = 0.001$). Compared with non-native urban group, native urban group showed higher attempt rate (using multiple attempts within a short-bout of time). However, post-hoc contrasts at between-group levels showed that higher attempt rate was only shown in the non-innovators of the native urban group than the non-native urban group (P = 0.027), and indeed the innovators of the native urban group showed lower attempt rate than the non-native urban group (P = 0.026). The within-group contrast further showed that significantly higher attempt rate was shown in the innovators than the non-innovators of the non-native urban group (P = 0.004), but no difference was seen between the innovators and the non-innovators of the native urban group (P = 0.145). These results together suggested that the variation of attempt rate in the non-native urban group was wider than the native urban group.

Table S1-S4 additional analyses

The inclusion of both site and individual identity led to single fit or convergence issues in model testing using GLMM. Accordingly, we simplified each model but including either site or individual identity as a random effect. We also conducted additional analyses that included 'site' as a random variable for each task.

Table S1. GLMM gaussian distribution with log link was used to model the performance in the easy problem. Fixed effect included groups (native rural, native urban, non-native rural, and non-native urban) whereas response variables was solving latency across 4 blocks of 5 successes. In all these models, the random variable was site.

Task	Fixed variable			Frequentist approach			
				Estimate	S.E.	Z ratio	P
Easy problem	Group	Native Rural	Native Urban	0.87	0.18	-0.66	0.913
		Native Rural	Non-native Rural	1.01	0.22	0.35	0.985
		Native Rural	Non-native Urban	0.91	0.21	0.42	0.976
		Native Urban	Non-Native Rural	1.23	0.25	1.04	0.729
		Native Urban	Non-native Urban	1.04	0.21	0.20	0.997
		Non-Native Rural	Non-native Urban	0.85	0.19	-0.75	0.876
	Group*Block	Native Rural	Native Urban	0.25	0.12	2.11	0.151
		Native Rural	Non-native Rural	0.30	0.13	2.29	0.101
		Native Rural	Non-native Urban	0.16	0.12	1.33	0.543
		Native Urban	Non-Native Rural	0.05	0.10	0.53	0.953
		Native Urban	Non-native Urban	-0.09	0.08	-1.06	0.711
		Non-Native Rural	Non-native Urban	-0.14	0.10	-1.39	0.508

Table S2. GLMM gaussian distribution with log link was used to model the performance in the difficult problem. Fixed effect included groups (native rural, native urban, non-native rural, and non-native urban) whereas response variables was solving latency across 7 blocks of 5 successes. In all these models, the random variable was site.

‘	Fixed variable			Frequentist approach			
				Estimate	S.E.	Z ratio	P
Difficult problem	Group	Native Rural	Native Urban	-0.51	0.25	-2.04	0.172
		Native Rural	Non-native Rural	-0.37	0.27	-1.37	0.517
		Native Rural	Non-native Urban	-0.59	0.26	-2.31	0.096
		Native Urban	Non-Native Rural	0.14	0.25	0.54	0.949
		Native Urban	Non-native Urban	-0.08	0.22	-0.39	0.980
		Non-Native Rural	Non-native Urban	-0.22	0.26	-0.86	0.824
	Group*Block	Native Rural	Native Urban	0.01	0.09	0.15	0.999
		Native Rural	Non-native Rural	0.02	0.10	0.19	0.998
		Native Rural	Non-native Urban	-0.07	0.11	-0.64	0.920
		Native Urban	Non-Native Rural	<0.01	0.07	0.07	1
		Native Urban	Non-native Urban	-0.08	0.08	-1.01	0.746
		Non-Native Rural	Non-native Urban	-0.09	0.09	-0.98	0.763

Table S3. GLMM gaussian distribution with log link was used to model the performance in the recall test for the difficult problem. We included all individuals that had participated in the difficult problem and returned to the recall test. Fixed effect included groups (native rural, native urban, non-native rural, and non-native urban) whereas response variables was solving latency across blocks of 5 successes. In all these models, the random variable was site. We additionally controlled the number of successful experience that the innovators had in the difficult problem as an offset term in the GLMM model.

Task		Fixed variable		Frequentist approach			
				Estimate	S.E.	Z ratio	P
Recall test	Last–first block (within group) (N = 20)	Native rural	Native rural	0.12	0.73	0.16	1
		Native urban	Native urban	0.12	0.45	0.27	1
		Non-native rural	Non-native rural	0.37	0.57	0.65	0.998
		Non-native urban	Non-native urban	<0.01	0.57	0.01	1
	First block (between groups) (N = 18)	Native Rural	Native Urban	-0.87	0.84	-1.04	0.969
		Native Rural	Non-native Rural	1.01	0.62	1.62	0.739
		Native Rural	Non-native Urban	0.45	0.88	0.52	1
		Native Urban	Non-Native Rural	1.88	0.66	2.83	0.087
		Native Urban	Non-native Urban	1.33	0.66	2.01	0.478
		Non-Native Rural	Non-native Urban	-0.56	0.72	-0.77	0.994
	First–second block (within group) N = 18	Native rural	Native rural	0.38	0.65	0.83	1
		Native urban	Native urban	0.77	0.46	1.69	0.694
		Non-native rural	Non-native rural	-0.16	0.50	-0.32	1
		Non-native urban	Non-native urban	0.03	0.56	0.06	1
	Second block (between groups) (N = 18)	Native Rural	Native Urban	-0.48	0.82	-0.59	0.999
		Native Rural	Non-native Rural	0.47	0.62	0.77	0.995
		Native Rural	Non-native Urban	0.11	0.85	0.13	1
		Native Urban	Non-Native Rural	0.95	0.66	1.45	0.832
		Native Urban	Non-native Urban	0.59	0.67	0.89	0.987
		Non-Native Rural	Non-native Urban	-0.36	0.71	-0.52	1

Table S4. Spatial-learning task. GLMM models for the performance in spatial learning task. Fixed effect included groups (native rural, native urban, non-native rural, and non-native urban) whereas response variables were the total of first openings to reach the criterion in one model, the number of first opening on unrewarded wells before reaching the criterion in another model, and the number of first opening on rewarded (correct) wells before reaching the criterion in a final model. In all these models, the random variable was site. Poisson distribution with log link was used in all these models.

Task	Fixed variable			Frequentist approach			
				Estimate	S.E.	Z ratio	P
Spatial learning task	Total first openings	Native Rural	Native Urban	-0.178	0.40	-0.44	0.971
		Native Rural	Non-native Rural	-0.28	0.35	-0.64	0.918
		Native Rural	Non-native Urban	-0.30	0.37	-0.81	0.848
		Native Urban	Non-Native Rural	-0.05	0.35	-0.14	0.999
		Native Urban	Non-native Urban	-0.12	0.37	-0.34	0.987
		Non-Native Rural	Non-native Urban	-0.07	0.18	-0.41	0.977
	Error first openings	Native Rural	Native Urban	-0.39	0.38	-1.05	0.722
		Native Rural	Non-native Rural	-0.49	0.34	-1.42	0.486
		Native Rural	Non-native Urban	-0.56	0.37	-1.52	0.426
		Native Urban	Non-Native Rural	-0.09	0.34	-0.27	0.993
		Native Urban	Non-native Urban	-0.16	0.36	-0.45	0.969
		Non-Native Rural	Non-native Urban	-0.07	0.23	-0.31	0.990
	Correct first openings	Native Rural	Native Urban	-0.03	0.43	-0.08	1
		Native Rural	Non-native Rural	-0.04	0.39	-0.12	1
		Native Rural	Non-native Urban	-0.05	0.42	-0.11	1
		Native Urban	Non-Native Rural	-0.01	0.38	-0.03	1
		Native Urban	Non-native Urban	-0.01	0.42	-0.03	1
		Non-Native Rural	Non-native Urban	<-0.01	0.26	-0.01	1