Hunting experience shapes individual foraging specialization and predator-prey interactions in an online videogame

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Open research statement : The data and code used to produce the results in this manuscript are freely available on GitHub <https://github.com/quantitative-ecologist/experience-hunting-tactics>

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# ABSTRACT

Many predator-prey systems are driven by reciprocal interactions where one responds to changes in the behaviour of the other. However, the mechanisms driving these individual responses are only beginning to be explored, in part because of the challenges associated with monitoring direct predator-prey interactions. In this study, we used a virtual predator-prey system (the online game *Dead by Daylight*) to test how hunting experience shapes individual foraging specialization and success in predators across repeated interactions with their prey. With increasing experience, predators fine-tuned their tactics to the behaviour of their prey. Individuals that adopted a flexible tactic (i.e. generalists) encountered groups of prey with varying speeds, and those that adopted a cursorial and specialized tactic (i.e. specialists) encountered groups of prey with similar speeds throughout the study period. Our results suggest that experience enables predators to learn how to optimize their tactics to the type of prey that they encounter (i.e. fast or slow), which may act as a stabilizing mechanism promoting behavioural diversification in predator-prey systems.

# INTRODUCTION

Individual variation in predator foraging behaviour is increasingly recognized as a major driver of trophic interactions and community dynamics (Griffen et al. 2012, Michalko and Pekár 2016, Moran et al. 2017, Michalko et al. 2021). Indeed, predator populations often comprise assemblages of individuals specializing in different foraging tactics, with consequences for habitat use, functional responses, prey choice, and foraging rate (Kobler et al. 2009, Toscano and Griffen 2014, Patrick and Weimerskirch 2014a, Matsumura and Miyatake 2022). Despite the clear evidence that individual specialization is important for predator-prey interactions, its underlying mechanisms remain surprisingly unclear. However, it has recently been suggested that reciprocal interactions between predators and prey could drive individual foraging specialization (Araújo et al. 2011, Toscano et al. 2016, De Lisle et al. 2022). For instance, predators often hunt using techniques that are fine-tuned to the type of prey that they encounter (Estes et al. 2003, Woo et al. 2008, Courbin et al. 2018), and their refinement is crucial for young predators to reach adulthood and survive (Phillips et al. 2017, Heithaus et al. 2018). Thus, the capacity of predators to effectively use hunting tactics should be contingent on periods of extensive practice (i.e. experience), which may result in different foraging specializations.

Theory predicts that foraging specialization may emerge via learning and expertise acquisition (Tinker et al. 2009, Dukas 2019). Dukas (2019) defines expertise as the characteristics, skills, and knowledge allowing individuals with extensive experience to outperform novices on complex tasks. It is described as the relationship between success and experience, where extensive practice optimizes success when individuals reach an advanced level of experience. Empirical studies on human and non-human hunters show that experience optimizes foraging efficiency (e.g. search and handling times, return rates) potentially via associative images or reliance on prey and environmental cues (Edwards and Jackson 1994, Morse 2000, MacDonald 2007, Reid et al. 2010, Wilson-Rankin 2015). This body of work suggests that such optimization may thus promote individual foraging specialization (e.g. repeatedly using fast attacks) if the success of a tactic is constant through time. It may also be costly to test different tactics by trial and error when prey are scarce or unpredictable. Alternatively, the costs/risks faced by hunters when switching tactics may be offset through extensive practice, as individuals gain experience and information on their prey, leading to increased individual foraging flexibility (Stephens 1993, Ishii and Shimada 2010, Mery and Burns 2010, Kelley and Magurran 2011, Snell-Rood 2013). To develop proper responses to fluctuating resources, individuals would need to sample their environment broadly during an extensive period of time, leading to greater performance at later stages of development (reviewed in Snell-Rood 2013). However, predators can differ in the challenges that they face during their lifetime, which could result in both processes (i.e. specialization and flexibility) operating at the same time within a predator population. For instance, some individuals may hunt in habitats where prey are faster, which are often proven to be more difficult to hunt (Walker et al. 2005, Kelley and Magurran 2011, Martin et al. 2022). It should thus be essential for predators to learn how to match their tactic to their prey to optimize their success.

There is currently a lack of consensus on the fitness advantages of specialized vs flexible foraging (Phillips et al. 2017). This is reflected in the literature showing contrasting results in the links between specialization and fitness. Some studies report greater benefits when specializing (Patrick and Weimerskirch 2014b, Pintor et al. 2014, van den Bosch et al. 2019), some report that flexible foraging has greater benefits (Paull et al. 2012, Santoro et al. 2019, Manlick et al. 2021), and others find equal benefits depending on timescales (Woo et al. 2008, Potier et al. 2015). This may in part be due to the limited information we have on the ecological contexts favoring specialization over flexibility. However, in predator-prey systems, studies suggest that fluctuations in the predictability of resources throughout a predator’s lifetime may be a key factor shaping foraging specialization (Weimerskirch 2007, Woo et al. 2008, Phillips et al. 2017, Courbin et al. 2018). It is hypothesized that when resources are predictable (or stable), individual specialists should have higher capture rates by reducing the energy and time required to search for and handle prey. In contrast, individual generalists should benefit from adjusting to fluctuating resources by reducing the consequences of uncertainty. While it is clear that predators can match their behaviour and locomotion to their prey (Bro-Jørgensen 2013, McGhee et al. 2013, Chang et al. 2017, Szopa-Comley and Ioannou 2022), the important question remaining is how? Given the dynamic nature of predator-prey interactions, it is unlikely that evolution alone could explain such behavioural adjustments by predators, because complex hunting strategies require practice to be effective (Kelley and Magurran 2011). Thus, uncovering the role of learning during direct predator-prey interactions would help in better predicting the behavioural decisions and the success of predators when they are hunting.

A recurring challenge impeding research on predator-prey behavioural interactions, at the individual level, is the need to collect data simultaneously on both the predator and prey. We recently demonstrated, using an online predator-prey videogame called *Dead by Daylight* (*DBD*), that virtual systems can overcome this challenge (Fraser Franco et al. 2022). In this dynamic virtual system, four prey players need to forage for resources while avoiding a predator player. The prey can contribute to the group’s success by healing or helping others escape the predator, or be selfish and attempt to escape by themselves (Céré et al. 2021). The predators’ hunting tactics and success are driven by the movement of the prey (Fraser Franco et al. 2022). Predators should thus benefit from learning how the prey behave to be successful. Other virtual predator-prey studies show that predation regimes drive individual variation in risk perception (Beauchamp 2020), that familiarity between prey has a positive indirect effect on survival (Céré et al. 2021), and that prey face contrasting natural and social selection regimes (Santostefano et al. in prep). These examples outline how virtual systems could be useful in identifying general ecological patterns, which might in turn help to advance the current gaps in predator-prey research. They also generate large volumes of data on interacting players throughout their lifetime in the game under realistic ecological scenarios. Hence, virtual systems offer the opportunity to tackle fundamental questions about the role of experience on predator-prey interactions.

In this study, we test how hunting experience shapes predator foraging specialization using data from players in the online videogame *Dead by Daylight*. *DBD* simulates a direct predator-prey interaction, where one predator player hunts four prey players in different virtual environments. The data grants a high degree of precision on the behavioural interaction, as the behaviour of both the predator and the four prey along with the predator’s success are monitored simultaneously in each trial. First, we investigate how predators develop their individual hunting expertise. We hypothesize that predators should differ in the development of their expertise, partly because they encounter varying levels of difficulty with the prey that they pursue. For example, a predator may face greater difficulty than other individuals if it more often encountered groups of prey that were elusive. Second, we test the hypothesis that experience will shape foraging specialization. If experience reduces the costs of switching between hunting tactics, we predict that the predator population should become more flexible. Alternatively, if experience enables the refinement of the hunting tactics, then the predator population may instead specialize. Otherwise, if both processes operate at the same time, then we should see no change with experience at the population level, but differences in specialization among individuals should increase. Third, we evaluate how predator foraging specialization emerges from behavioural interactions with the prey. We expect predators that experienced more predictable encounters with their prey to specialize, while predators that experienced unpredictable encounters with their prey should adopt a flexible hunting tactic. If we detect such prey-dependent fine-tuning, then specialist and flexible hunters should attain equal success because both should have learned to optimize their hunting style to their prey.

# MATERIALS AND METHODS

## Study system

*DBD* is a survival asymmetric (i.e. a game where the gameplay mechanics differ between two groups) multiplayer online game developed by Behaviour Interactive Inc, in which players can play either as a predator or a prey. The objective of the predator is to hunt and capture the four prey across a virtual environment. The objective of the four prey is to search for resources while avoiding the predator. The resources are in the form of power generators that, once all activated, will enable the prey to escape through one of two exit doors. The composition of the predator and prey group in a match is determined by a skill-based matchmaking algorithm. A match ends when the predator kills all the prey available (i.e. that have not escaped), or when the last remaining prey escapes the virtual environment. Each player, predator or prey, can choose an avatar with abilities that encourage specific play styles (e.g. bold vs cautious prey, or ambush vs roaming predator). During our study period, the game offered 23 predator avatars. The virtual environments are composed of fixed and procedurally generated habitat components, such as vegetation, mazes, and buildings. Some of these environments are larger than others, with varying structural complexity. However, predators display only minimal changes in behaviour and hunting success across the environments, probably due to a game feature enabling them to have visual cues of the generators (Fraser Franco et al. 2022). There were 35 virtual game environments available for play during the study period.

## Data collection

The videogame company provided data that spanned a period of 6 months of gameplay recorded for every player. The first recorded match was played on 2020-12-01 and the last one on 2021-06-01. We analyzed only matches where players did not know each other (i.e. “Online” mode). We filtered any matches where players were inactive, such as when speed values were equal to, or very close to, zero. Moreover, we used our knowledge of the game to remove any matches where players were potentially hacking, or not playing the game as it is supposed to be played. We then sampled players that played 300 matches or more, and monitored all their matches from the first to a maximum of 500 matches.

Our population consists of 253 predator players with a total record of 100 412 matches. The predator-players’ experience varied between 301 and 500 matches played. These matches lasted between 3 and 70-min (mean = 11-min). The following information is collected and reported for every match : the player’s anonymous ID, its avatar (i.e. the predator character chosen with its specific skill-gameplay mechanics), the game environment, the predator-player’s experience along with its speed, and the average speed of the group of prey it encountered.

We analyzed the predator’s average speed and the average speed of the prey group encountered by the predator. The predator’s average speed is measured as the average distance traveled per second during a match ( = 3.31 ± 0.49 m/s). We measured the preys’ average speed as the average travel speed of the four individual prey within a match ( = 2.40 ± 0.32 m/s). We defined hunting success as the number of prey consumed during the match (min = 0, max = 4). Lastly, we defined the predator’s cumulative experience as the number of matches played prior to the match being monitored. For example, the first match of a player would have a cumulative experience value of 0, while the tenth match would have a value of 9.

We recognize that we could have introduced a bias in our analyses since we sampled individuals who stayed in the game for at least 300 matches. For instance, these players may already be used to play videogames, and thus, could differ in the way they play at early stages of their experience in the game. To ensure that our sample was not biased, we compared a random sample of players that played between 20 and 50 matches, between 51 and 100 matches, and between 101 and 300 matches from the same timeframe with our sampled population. We then took the first 20 matches played by these players, including those from our sampled population, and compared their average behaviour using a Bayesian hierarchical linear model. We found that neither of the four groups differed in their average speed (Appendix 2: Table S1-S2), which gives us confidence that our player population was not biased.

## Statistical analyses

### Software and computer specifications

All our statistical analyses were executed on Cedar (<https://docs.alliancecan.ca/wiki/Cedar>), a computer cluster maintained by the Digital Research Alliance of Canada. The operating system for Cedar is CentOS Linux 7. The models were fitted in R (version 4.1.2) using Markov chain Monte Carlo (MCMC) sampling with the package “brms” version 2.16.3 (Bürkner 2017), an R front-end for the STAN software (Team 2023), and “cmdstanr” version 0.4.0 (Gabry and Češnovar 2021) as the back-end for estimation (cmdstan installation version 2.28.2).

### Effect of experience on hunting success

We tested whether predators varied in the development of their expertise by computing five Bayesian generalized additive mixed models (GAMM) with thin plate regression splines, all of which estimated the relationship between hunting success (i.e. number of prey captured) and the predators’ cumulative experience (i.e. number of matches played before the current match). We parametrized the models following the method of Pedersen et al. (2019). The first model was the simplest, with a common global smoothing function and random intercepts for the predator ID. In this model, we assume that individuals have the same development of expertise, with the model estimating a trend for the average individual (i.e. global smoother). For the second model, we included varying group-level smoothers for the predator ID. In this model, we assume that individuals share a similar relationship between success and experience, but that this relationship can vary (e.g. individual 1 has a steeper curve than individual 2). This enabled us to test whether predators differed in the development of their expertise. In the third model, we kept the group-level smoothers for the predators, but removed the global smoother. This allows each individual to have a unique relationship between success and experience without penalization by the global smoother. This model assumes that predators do not share a common relationship between success and experience. The fourth and fifth models were a reproduction of the second and third models respectively, where we included the prey group’s average speed to assess its effect on the relationship between success and experience. We included match duration as a covariate in all five models.

We computed the five models using a modified version of the beta-binomial distribution implemented in “brms”. Hunting success was estimated as the probability of capturing the four prey (), drawn from a Beta distribution () with mean () and precision () parameters. We used a logit link function to estimate where and is the linear predictor, while the precision parameter () was estimated with an identity link. We used the default number of basis functions (K) in “brms” for the models to estimate the relationship between hunting success and experience. We assumed that the random intercepts for the predator ID () followed a Gaussian distribution with estimated standard deviation (). We used weakly informative Gaussian priors for the intercept () and the global trend of cumulative experience (). Based on previous results (Fraser Franco et al. 2022), we defined a positive Gaussian prior on the precision parameter (), a positive Gaussian prior () on the game duration because longer trials lead to greater success, and a negative Gaussian prior on prey speed () because encountering faster prey is associated with lower success in this system. We employed weakly informative half-Gaussian priors on all the standard deviation parameters (). We compared the models’ predictive accuracies using approximate leave-one-out cross-validation with Pareto-smoothed importance sampling (Piironen and Vehtari 2017, Vehtari et al. 2017, Vehtari et al. 2022).

### Changes in foraging behaviour and predator-prey interactions with experience

We categorized predators by their experience based on the number of matches they played. Since we monitored all predator players throughout their experience, they appeared in all of the three following experience categories. First, we assigned predators the status of “novice” when they had a cumulative experience below 100 matches. For example, a predator player that played 500 matches in total would be labelled as a novice in its first 100 matches. Following this logic, we labelled predators as “intermediate” hunters when they had a cumulative experience between 100 and 299 and matches. Lastly, we defined predators as “advanced” hunters when they had a cumulative experience equal or above 300, with a maximum of 499 cumulated matches.

We tested whether foraging behaviour changed with experience, and compared the success of generalists vs specialists, using a multivariate, double-hierarchical generalized linear model (MDHGLM) (Lee and Nelder 2006, Cleasby et al. 2015, Mitchell et al. 2016). For each level of experience (i.e. novice, intermediate, advanced), the model estimated the mean speed of every individual (which we call the mean part of the model), and the intra-individual standard deviation of speed of every individual (which we call the dispersion part of the model). From the mean part of the model, we could infer on among individual differences in foraging tactics (i.e. along the slow-fast continuum), while in the dispersion part of the model, we could infer on among individual differences in foraging specialization (i.e. intra-individual variability, IIV). We followed the same structure for the preys’ speed. For the mean part, we tested whether individual predators differed in the average speed of the groups of prey encountered across the study. For the dispersion part, we tested whether individual predators differed in how (dis)similar were the groups of prey they encountered across the study (i.e. if resource heterogeneity was higher for some individuals compared to others). We controlled for the square-root of the average rank of the prey group as proxy for prey skills for both the predator and the prey’s speed (mean and dispersion). The ranking system in *DBD* was implemented by the company to pair players in a match based on their skill (<https://deadbydaylight.fandom.com/wiki/Rank>). For hunting success, we quantified among individual differences in mean prey capture and controlled for the square-root of the game duration.

The model estimated the correlation between the individual identity random effect on the mean and on the dispersion within each trait (e.g. ) and among each trait (e.g. ) within a level of experience. In the first case, this allows us to assess, for example, whether predators that are on average slower/faster are more specialized or flexible. In the second case, it enables us to estimate, for example, whether predators that adopted a slower/faster (or more specialized/flexible) tactic encountered prey that were faster/slower, or if slower/faster predators had lower/greater hunting success.

The full model has the following form, with each equation repeated three times (i.e. one for each level of experience):

|  |  |
| --- | --- |
|  | (eqn. 1.1) |
|  | (eqn. 1.2) |
|  | (eqn. 2.1) |
|  | (eqn. 2.2) |
|  | (eqn. 3) |

where , , and are the vectors of random environment, random avatar, and random individual identity effects associated with their incidence matrices , , and . is the vector of fixed effects with its incidence matrix . The and subscripts indicate that an estimate is from the mean or dispersion part of the model, respectively. On the mean part, we assumed that the game environment and avatar random effects followed a Gaussian distribution with estimated standard deviation ( and ). is the identity matrix, with indicating that the random effects are independently and identically distributed. The residuals are assumed to follow a Gaussian distribution (). On the dispersion part, the residuals vary among individuals, allowing us to estimate among individual differences in specialization. The individual identity random effects on both the mean and dispersion parts follow a multivariate Gaussian distribution where is a 15x15 variance-covariance matrix. The parameters , , and , correspond to the among environment, among avatar, and among individual standard deviations, respectively.

We parameterized equations 1.1 to 2.2 with a Gaussian distribution family (predator and prey speed) and used a beta-binomial distribution family for equation 3 (predator hunting success). We used weakly informative Gaussian priors for the prey rank (: eqn. 1.1 to 2.2) and game duration (: eqn. 3). Based on previous results showing that the mean predator speed revolves around 3 m/s (Fraser Franco et al. 2022), we applied a weakly informative Gaussian prior on the intercept for predator and prey speed (: eqn. 1.1 and 2.1). Similarly, we used a weakly informative Gaussian prior on the intercept for the dispersion part (: eqn 1.2 and 2.2). For hunting success, we applied a positive Gaussian prior on the precision parameter (: eqn. 3) and a negative Gaussian prior (: eqn 3) on the intercept because hunting success should be close to 0 at the lowest game duration. For every predicted variable, we applied a weakly informative half-Gaussian prior () on the random effects for the mean part and the dispersion part of the model. We used a regularizing prior on the correlation matrix.

After inspection of the results, we found that key parameter values for our hypotheses were in the direction of our predictions, but they were largely driven by the very slow speed of one predator. Removing this individual reduced the estimates by a significant margin. To remain conservative, we thus present the results of the model without this individual in the main text, and provide the results of the model including it in the Appendix S3.

### Markov Chain Monte Carlo settings

We parametrized both the GAMMs and the MDHMLM to run four MCMC chains with 1000 posterior samples for each parameter. We ran 2500 iterations with a thinning set to eight for the additive model with a global smoother only (see Table 1), and 1500 iterations with a thinning set to four for the other additive models. We set the first 500 iterations in each model as warm ups. We parametrized the MDHGLM to run 2500 iterations with a thinning set to eight, with the first 500 iterations used as warm ups. We assessed the convergence of the MCMC chains using trace plots, R-hat diagnostics with a threshold of <1.01, and effective sample sizes (ESS) with a threshold of >100 (Vehtari et al. 2021). We also performed posterior predictive checks which showed an adequate fit of the models (for details, see <https://github.com/quantitative-ecologist/experience-hunting-tactics>).

# RESULTS

## Effect of experience on hunting success

Out of all five models, the two that best predicted the data, with very similar expected log pointwise densities (elpd), were the models accounting for the prey group’s speed (Table 1). Predators differed substantially in the relationship between hunting success and cumulative experience (i.e. expertise: Figure 1A-B). We found evidence that these differences were in part mediated by prey speed because individuals had distinct patterns after we controlled for the mean speed of the prey groups compared to when we did not (Figure 1A-B). For instance, many individual curves shifted upwards. Precisely, the percentage of individuals that displayed a >0.5 increase in success changed from 28.5% to 53.4% after we accounted for prey speed (Appendix S1: Figure S1A). In this model (i.e. Figure 1B-C), 4.3% of the population showed a >0.5 decrease in success (Appendix S1: Figure S1B), and the remaining 42.3% displayed little to no change (between -0.5 and 0.5) in success across experience (Appendix S1: Figure S1C).

Moreover, all models where we did not account for prey speed had a global trend of predator experience that was nearly flat (results not shown). Yet, we see that there is an increase up to 13% in the probability of capturing all prey with experience in the population when we account for prey speed (Figure 1C).

## Effect of experience on behavioural specialization and hunting success

The mean speed of the predator population did not change with experience (i.e. intercept (mean) of predator speed; Figure 2 and Appendix S1: Table S1). There was also strong evidence that foraging specialization in the population remained stable across experience levels (i.e. intercept (sigma) of predator speed; Figure 2 and Appendix S1: Table S1). We did not find evidence that the predator population had a change in mean success with experience (intercept (mean) of hunting success; Figure 2 and Appendix S1: Table S1). There was, however, a decrease in among individual differences in success at the intermediate stage, which was maintained at the advanced stage (predator ID (mean) of hunting success; Figure 2 and Appendix S1: Table S2).

Individual predators differed slightly in their average movement speed across experience levels (i.e. predator ID (mean); Figure 2 and Appendix S1: Table S2). However, there was strong evidence that they displayed differences in foraging specialization, with a 0.1 unit increase in standard deviation from novice to advanced, indicating that differences increased slightly (i.e. predator ID (sigma) is higher at the advanced level; Figure 2 and Appendix S1: Table S2). Moreover, some individual predators switched from a flexible to a specialized hunting tactic, and vice-versa, as they gained experience (Figure 3). Importantly, 12.6% of the predator population displayed a large change in foraging specialization/flexibility with experience (i.e. >0.2 change in standard deviation), 44.7% displayed lower changes (i.e. >0.05 and <0.2 change in standard deviation), while 42.7% remained relatively stable (i.e. <0.05 change in standard deviation).

Contrary to predictions, there was strong evidence that predators did not differ in the speed of the prey groups that they encountered on average across experience (i.e. predator ID (mean); Figure 2 and Appendix S1: Table S2). However, individuals differed in the heterogeneity of the groups of prey encountered across the study period (i.e. predator ID (sigma); Appendix S1: Table S2). Hence, some predators encountered prey groups with similar average speeds, while others encountered prey groups with varying average speeds throughout the study period. The differences in the prey encountered among predators increased only slightly with experience (i.e. predator ID (sigma); Figure 2).

## Relationship between behavioural specialization and prey behaviour

Predators that were on average faster (mean speed) had a lower intra-individual variability (IIV speed) (Figure 4A-B and Appendix S4: Table S1). Thus, faster predators specialized on fast movement, while slower predators were more flexible in their movement through time. As predators gained experience, these strategies were increasingly defined as there was a 0.16 unit increase in the correlation at the advanced stage (Figure 4C). Predators that were on average faster (mean speed) also encountered groups of prey that were on average faster (mean prey speed) and more similar (IIV prey speed) (Figure 4A-B and Appendix S4: Table S1). There was however only weak to no evidence that these correlations increased with experience (Figure 4C)

There was almost no correlation between mean prey speed and IIV in predator speed when predators were novice (Figure 4A). There was however a 0.17 unit increase in this correlation at the advanced stage, such that advanced hunters that encountered faster prey tended to be more specialized (Figure 4C). The predator IIV in speed and IIV in prey speed were moderately positively correlated (Figure 4A-B and Appendix S4: Table S1). Hence, predators that encountered groups of prey with similar speeds were more specialized in their tactic while those that encountered groups of prey with varying speeds were more flexible. We did not however find evidence that this correlation increased with experience (Figure 4C).

## Hunting success of behavioural specialists vs generalists

The predator’s mean speed and IIV were only weakly negatively correlated with hunting success across experience (Figure 4 and Appendix S4: Table S1), suggesting that slower/flexible and faster/specialist predators were both equally successful. However, there was strong evidence that individuals who encountered groups of prey with faster speeds were less successful (Figure 4A-B and Appendix S4: Table S1). Predators also had greater success across the study when encountering more variable groups of prey (Figure 4A-B and Appendix S4: Table S1). Both relationships remained structurally stable across experience (Figure 4-C)

# DISCUSSION

Hunting experience is predicted to increase predator foraging specialization when resources are predictable (Estes et al. 2003, Tinker et al. 2008, 2009). However, when resources vary, others predict that learning with experience should increase behavioural flexibility (Stephens 1993, Ishii and Shimada 2010, Mery and Burns 2010, Snell-Rood 2013, Wright et al. 2022). Our results show that there was no directional increase in either behavioural specialization or flexibility with experience at the population level. Instead, individual predators developed their own expertise and behavioural trajectory over successive encounters with prey; there was a continuum of hunting styles ranging from a slower and flexible strategy to a highly specialized fast-paced strategy. Specialized cursorial hunters encountered similar groups of prey while slower and flexible hunters encountered varying groups of prey, with both achieving similar success over the study period. With experience, predators increasingly matched their foraging specialization to the speed of the prey that they encountered, but they did not achieve greater success, probably because the prey were also matching their speed to the predator. Our observations suggest that predators in *DBD* learn to adjust foraging specialization to the behaviour of the prey that they encounter throughout their lifetime in the game.

## The development of expertise with hunting experience

Empirical research shows that task proficiency often increases nonlinearly with experience and stabilizes at an expert level (reviewed in Dukas 2019). Our analyses revealed a similar trend, with a 13% population increase in success with experience. However, as we mentioned before, the matchmaking pairs players using a rank-based system, and the increase in expertise could have been even greater if predators were not paired with prey of similar skill. Individual predators in *DBD* also displayed distinct patterns of expertise acquisition. We predicted that this would occur if, by chance, predators differed in the prey that they encountered, because some may be easier and others more difficult to capture. In nature, prey can use a variety of defenses such as physical armaments, toxins, camouflage, or antipredator behaviours to escape predation (Brodie III and Brodie Jr. 1999, Bowen et al. 2002, Brodie and Wilkinson 2010, Carey and Wahl 2011, Nomura et al. 2011). In *DBD* we previously showed that faster movement is an effective strategy used by the prey to avoid predation (Fraser Franco et al. 2022), and other studies have found that as well (Walker et al. 2005, Kelley and Magurran 2011, Martin et al. 2022). Our results confirm that prey speed influenced expertise acquisition at the individual level to some extent. This is not surprising because capturing faster prey requires costly and specialized cognitive abilities and coordination (Kelley and Magurran 2011). However, even if we accounted for prey speed, there were still important differences in expertise acquisition, which suggests that other antipredator tactics may also be involved.

For example, two well known antipredator tactics known to confuse human and non-human predators during the attack sequence are unpredictable escapes and turning angles (Jones et al. 2011, Herbert-Read et al. 2017, Moore et al. 2017, Richardson et al. 2018). Yet, even if predators can adjust to unpredictable prey escapes (Szopa-Comley and Ioannou 2022), it could still be arduous for an individual to learn and optimize its hunting success if it more often encountered prey using these tactics. Alternatively, it is possible that individual variation in learning rates due to time delays between hunting events drove the observed differences in expertise acquisition. For example, in *DBD*, a predator that played 300 matches in the span of six months might forget more critical information (e.g. prey escape patterns or muscle memory) than one that played 300 matches in the span of 6 days. While this has not been formally tested, a greater delay between exposure events is hypothesized to attenuate or even negate the relationship between success and experience (Endler 1991, Wright et al. 2022). Moreover, the predators could have differed in their ability to detect prey. For instance, it is widely demonstrated that predators learn visual cues such as coloration to recognize and avoid unpalatable prey (Skelhorn et al. 2016, Ward-Fear et al. 2020, McLellan et al. 2021), or habitat characteristics to locate food patches (Ehlinger 1989, Hughes et al. 1992, Warburton 2003). Szopa-Comley et al. (2020) also found consistent among individual variation in the capacity to detect cryptic and conspicuous prey in three-spined sticklebacks (*Gasterosteus aculeatus*). Thus, predators could differ in their expertise if they do not learn equally how to exploit the visual cues that facilitate prey detection.

## Changes in individual hunting specialization with experience and consequences for predator-prey interactions

*je suis rendu ici pour la correction*

The predator population displayed an increase in foraging flexibility when reaching the intermediate level of experience. As it reached an advanced level of experience, it returned to a level of flexibility that was similar to novice levels. This is commonly observed in juvenile predators across the animal kingdom, because exploring and learning different tactics at this developmental stage is crucial to become a skillful hunter (Vehanen 2003, Johnson and Wilbrecht 2011, Thiers et al. 2014, de Grissac et al. 2016). Thus, predators in *DBD* were probably exploring and refining different tactics at this stage of experience. Within the population, differences in individual foraging specialization among predators increased with experience, which was related to the degree of variability in prey encounters. Predators that encountered groups of prey with similar speeds across matches specialized in hunting at high speeds, while those that encountered varying groups of prey adopted a slower and flexible strategy. Fast-paced hunting is indeed a highly specialized tactic suited for prey that use rapid escapes (Endler 1991, Bro-Jørgensen 2013, Wilson et al. 2018), while a slower and flexible tactic can be useful to minimize the consequences of uncertainty when hunting prey that use unpredictable escapes (Szopa-Comley and Ioannou 2022). This is further supported by the fact that specialist and flexible hunters both achieved similar success throughout the study period. Interestingly, the behavioural response (i.e. tactic use and specialization) to experience by individual predators differed. For instance, 42.7% of the population did not alter their degree of specialization with experience (i.e. remaining either faster and more specialized, or slower and more flexible), while 57.3% of the population displayed a switch from a specialized to a flexible tactic or vice-versa with experience. Thus, our results provide direct evidence that the mechanism underlying the resource-predictability hypothesis may indeed involve predators learning at varying degrees how to specialize on their prey (Weimerskirch et al. 2005, Weimerskirch 2007, Woo et al. 2008, Phillips et al. 2017).

As predators gained experience, their tactic was increasingly matched to the speed of their prey. One interpretation could be that both predators and prey learned from each other in an arms-race-like reciprocal relationship (Kishida et al. 2006, 2009, Edgell and Rochette 2009, Mougi et al. 2011). For instance, predators that encountered faster prey could have learned to increase their speed to better capture them, resulting in an increase in the speed of the prey to circumvent the predator’s attacks. In this type of system, faster prey should be better at escaping both slower and faster predators (Mougi et al. 2011), which concords with what we previously observed in this sytem (Fraser Franco et al. 2022). Brodie III and Brodie Jr. (1999) argue that when prey express defensive phenotypes (e.g. physical armaments or venom), selection on predators should be strong because the consequences of being injured are greater than missing a meal. If predators improve their exploitative ability, then an arms-race should emerge, and the consequences of hunting dangerous prey should decrease (Brodie III and Brodie Jr. 1999). Similarly, we found that has the predator gained experience, the negative consequences of encountering prey groups with higher speeds were relaxed, and the variation in success among predators decreased. However, in an arms-race, faster predators would have successfully preyed upon faster and slower prey and would have obtained higher success than slower predators (Mougi et al. 2011), which was not the case in the present study. A more likely scenario is that predators and prey in *DBD* were involved in a matching response relationship (Mougi et al. 2011), because faster-specialist and slower-flexible hunters preyed upon different prey, but they both achieved equal success. Thus predators in *DBD* appear to optimize their success by learning to match their tactic to their prey with experience, suggesting that learning through reciprocal interactions may attenuate selection exerted by prey on predators (Anderson 1995, Ancel 1999, Borenstein et al. 2006, Paenke et al. 2007).

## Conclusions

*simplifier la 1ere phrase*

Trait-mediated interactions that affect prey capture are the most important processes driving predator-prey dynamics (Abrams 2000). While most studies assume that predators maximize prey capture by matching their tactic to their prey (Abrams 2000), it has remained largely unknown whether this results from predators learning how to hunt their prey, in part because of the challenges of investigating direct interactions in the wild. By capitalizing on a virtual predator-prey system where interactions were directly monitored, we found that individual predators displayed large differences in the development of their expertise. With experience, half of the predator population changed their behaviour by developping either a specialized or flexible tactic that was matched to the speed of their prey. Overall, both type of hunters achieved equal hunting success. Our results have potential applications for predator-prey models of trait-matching. For instance, simulation studies could incorporate individual variation in experience or learning to better predict under which ecological/evolutionary contexts specialization should be favoured over flexibility. Lastly, virtual systems are increasingly recognized among ecologists as being useful to test hypotheses on consumer-resource interactions (Beauchamp 2020, Barbe et al. 2020, Céré et al. 2021, Fraser Franco et al. 2022), but also in other fields such as citizen science and conservation (Sandbrook et al. 2015, Redpath et al. 2018, Duthie et al. 2021). We therefore hope that our study will inspire more collaborations between scientists and the videogame industry to tackle fundamental questions in ecology.

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# CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest

# REFERENCES

Abrams, P. A. 2000. [The Evolution of Predator-Prey Interactions: Theory and Evidence](https://doi.org/10.1146/annurev.ecolsys.31.1.79). Annual Review of Ecology and Systematics 31:79–105.

Ancel, L. W. 1999. [A Quantitative Model of the Simpson-Baldwin Effect](https://doi.org/10.1006/jtbi.1998.0833). Journal of Theoretical Biology 196:197–209.

Anderson, R. W. 1995. [Learning and Evolution: A Quantitative Genetics Approach](https://doi.org/10.1006/jtbi.1995.0123). Journal of Theoretical Biology 175:89–101.

Araújo, M. S., D. I. Bolnick, and C. A. Layman. 2011. [The Ecological Causes of Individual Specialisation](https://doi.org/10.1111/j.1461-0248.2011.01662.x). Ecology Letters 14:948–958.

Barbe, L., C. Mony, and B. W. Abbott. 2020. [Artificial Intelligence Accidentally Learned Ecology through Video Games](https://doi.org/10.1016/j.tree.2020.04.006). Trends in Ecology & Evolution 35:557–560.

Beauchamp, G. 2020. [Predator Attack Patterns Influence Vigilance in a Virtual Experiment](https://doi.org/10.1007/s00265-020-02833-0). Behavioral Ecology and Sociobiology 74:49.

Borenstein, E., I. Meilijson, and E. Ruppin. 2006. [The Effect Of Phenotypic Plasticity on Evolution in Multipeaked Fitness Landscapes](https://doi.org/10.1111/j.1420-9101.2006.01125.x). Journal of Evolutionary Biology 19:1555–1570.

Bowen, W. D., D. Tully, D. J. Boness, B. M. Bulheier, and G. J. Marshall. 2002. [Prey-Dependent Foraging Tactics and Prey Profitability in a Marine Mammal](https://doi.org/10.3354/meps244235). Marine Ecology Progress Series 244:235–245.

Brodie, E. D., and A. Wilkinson. 2010. [Co-Evolution of Predators and Prey](https://doi.org/10.1016/B978-0-08-045337-8.00301-6). Pages 287–295 *in* M. D. Breed and J. Moore, editors. Encyclopedia of Animal Behavior. Academic Press, Oxford.

Brodie III, E. D., and E. D. Brodie Jr. 1999. [Predator-Prey Arms Races: Asymmetrical Selection on Predators and Prey May Be Reduced When Prey Are Dangerous](https://doi.org/10.2307/1313476). BioScience 49:557–568.

Bro-Jørgensen, J. 2013. [Evolution of Sprint Speed in African Savannah Herbivores in Relation to Predation](https://doi.org/10.1111/evo.12233). Evolution 67:3371–3376.

Bürkner, P.-C. 2017. [Brms: An R Package for Bayesian Multilevel Models Using Stan](https://doi.org/10.18637/jss.v080.i01). Journal of Statistical Software 80:1–28.

Carey, M. P., and D. H. Wahl. 2011. [Foraging Modes of Predators and Behaviors of Prey Determine the Outcome of Multiple Predator Interactions](https://doi.org/10.1080/00028487.2011.603983). Transactions of the American Fisheries Society 140:1015–1022.

Céré, J., P.-O. Montiglio, and C. D. Kelly. 2021. [Indirect Effect of Familiarity on Survival: A Path Analysis on Video Game Data](https://doi.org/10.1016/j.anbehav.2021.06.010). Animal Behaviour 181:105–116.

Chang, C., H. Y. Teo, Y. Norma-Rashid, and D. Li. 2017. [Predator Personality and Prey Behavioural Predictability Jointly Determine Foraging Performance](https://doi.org/10.1038/srep40734). Scientific Reports 7:40734.

Cleasby, I. R., S. Nakagawa, and H. Schielzeth. 2015. [Quantifying the Predictability of Behaviour: Statistical Approaches for the Study of Between-Individual Variation in the Within-Individual Variance](https://doi.org/10.1111/2041-210X.12281). Methods in Ecology and Evolution 6:27–37.

Courbin, N., A. Besnard, C. Péron, C. Saraux, J. Fort, S. Perret, J. Tornos, and D. Grémillet. 2018. [Short-Term Prey Field Lability Constrains Individual Specialisation in Resource Selection and Foraging Site Fidelity in a Marine Predator](https://doi.org/10.1111/ele.12970). Ecology Letters 21:1043–1054.

de Grissac, S., L. Börger, A. Guitteaud, and H. Weimerskirch. 2016. [Contrasting Movement Strategies Among Juvenile Albatrosses and Petrels](https://doi.org/10.1038/srep26103). Scientific Reports 6:26103.

De Lisle, S. P., D. I. Bolnick, E. D. Brodie III, A. J. Moore, and J. W. McGlothlin. 2022. [Interacting phenotypes and the coevolutionary process: Interspecific indirect genetic effects alter coevolutionary dynamics](https://doi.org/10.1111/evo.14427). Evolution 76:429–444.

Dukas, R. 2019. [Animal Expertise: Mechanisms, Ecology and Evolution](https://doi.org/10.1016/j.anbehav.2018.05.010). Animal Behaviour 147:199–210.

Duthie, A. B., J. Minderman, O. S. Rakotonarivo, G. Ochoa, and N. Bunnefeld. 2021. [Online Multiplayer Games as Virtual Laboratories for Collecting Data on Social-Ecological Decision Making](https://doi.org/10.1111/cobi.13633). Conservation Biology 35:1051–1053.

Edgell, T. C., and R. Rochette. 2009. [Prey-Induced Changes to a Predator’s Behaviour and Morphology: Implications for Shell in the Northwest Atlantic](https://doi.org/10.1016/j.jembe.2009.10.004). Journal of Experimental Marine Biology and Ecology 382:1–7.

Edwards, G. B., and R. R. Jackson. 1994. [The Role of Experience in the Development of Predatory Behaviour in Phidippus regius, a Jumping Spider (Araneae, Salticidae) from Florida](https://doi.org/10.1080/03014223.1994.9517994). New Zealand Journal of Zoology 21:269–277.

Ehlinger, T. J. 1989. [Learning and Individual Variation in Bluegill Foraging: Habitat-Specific Techniques](https://doi.org/10.1016/S0003-3472(89)80010-7). Animal Behaviour 38:643–658.

Endler, J. A. 1991. Interactions between predators and prey. Pages 169–196 *in* J. R. Krebs and N. B. Davies, editors. Behavioural Ecology. Third. Blackwell, Oxford.

Estes, J. A., M. L. Riedman, M. M. Staedler, M. T. Tinker, and B. E. Lyon. 2003. [Individual Variation in Prey Selection by Sea Otters: Patterns, Causes and Implications](https://doi.org/10.1046/j.1365-2656.2003.00690.x). Journal of Animal Ecology 72:144–155.

Fraser Franco, M., F. Santostefano, C. D. Kelly, and P.-O. Montiglio. 2022. [Studying Predator Foraging Mode and Hunting Success at the Individual Level with an Online Videogame](https://doi.org/10.1093/beheco/arac063). Behavioral Ecology 33:967–978.

Gabry, J., and R. Češnovar. 2021. Cmdstanr: R Interface to "CmdStan".

Griffen, B. D., B. J. Toscano, and J. Gatto. 2012. [The Role of Individual Behavior Type in Mediating Indirect Interactions](https://doi.org/10.1890/11-2153.1). Ecology 93:1935–1943.

Heithaus, M. R., L. M. Dill, and J. J. Kiszka. 2018. [Feeding Strategies and Tactics](https://doi.org/10.1016/B978-0-12-804327-1.00126-6). Pages 354–363 *in* B. Würsig, J. G. M. Thewissen, and K. M. Kovacs, editors. Encyclopedia of Marine Mammals (Third Edition). Academic Press.

Herbert-Read, J. E., A. J. W. Ward, D. J. T. Sumpter, and R. P. Mann. 2017. [Escape Path Complexity and its Context Dependency in Pacific Blue-Eyes (Pseudomugil signifer)](https://doi.org/10.1242/jeb.154534). Journal of Experimental Biology 220:2076–2081.

Hughes, R. N., M. J. Kaiser, P. A. Mackney, and K. Warburton. 1992. [Optimizing Foraging Behaviour Through Learning](https://doi.org/10.1111/j.1095-8649.1992.tb03870.x). Journal of Fish Biology 41:77–91.

Ishii, Y., and M. Shimada. 2010. [The Effect of Learning and Search Images on Predator-Prey Interactions](https://doi.org/10.1007/s10144-009-0185-x). Population Ecology 52:27–35.

Johnson, C., and L. Wilbrecht. 2011. [Juvenile Mice Show Greater Flexibility in Multiple Choice Reversal Learning than Adults](https://doi.org/10.1016/j.dcn.2011.05.008). Developmental Cognitive Neuroscience 1:540–551.

Jones, K. A., A. L. Jackson, and G. D. Ruxton. 2011. [Prey Jitters; Protean Behaviour in Grouped Prey](https://doi.org/10.1093/beheco/arr062). Behavioral Ecology 22:831–836.

Kelley, J. L., and A. E. Magurran. 2011. [Learned Defences and Counterdefences in Predator-Prey Interactions](https://doi.org/10.1002/9781444342536.ch3). Pages 36–58 Fish Cognition and Behavior. John Wiley & Sons, Ltd.

Kishida, O., Y. Mizuta, and K. Nishimura. 2006. [Reciprocal Phenotypic Plasticity in a Predator-Prey Interaction Between Larval Amphibians](https://doi.org/10.1890/0012-9658(2006)87[1599:RPPIAP]2.0.CO;2). Ecology 87:1599–1604.

Kishida, O., G. C. Trussell, and K. Nishimura. 2009. [Top-Down Effects on Antagonistic Inducible Defense and Offense](https://doi.org/10.1890/08-0238.1). Ecology 90:1217–1226.

Kobler, A., T. Klefoth, T. Mehner, and R. Arlinghaus. 2009. [Coexistence of Behavioural Types in an Aquatic Top Predator: A Response to Resource Limitation?](https://doi.org/10.1007/s00442-009-1415-9) Oecologia 161:837–847.

Lee, Y., and J. A. Nelder. 2006. [Double Hierarchical Generalized Linear Models (With Discussion)](https://doi.org/10.1111/j.1467-9876.2006.00538.x). Journal of the Royal Statistical Society: Series C (Applied Statistics) 55:139–185.

MacDonald, K. 2007. [Cross-Cultural Comparison of Learning in Human Hunting](https://doi.org/10.1007/s12110-007-9019-8). Human Nature 18:386–402.

Manlick, P. J., K. Maldonado, and S. D. Newsome. 2021. [Competition Shapes Individual Foraging and Survival in a Desert Rodent Ensemble](https://doi.org/10.1111/1365-2656.13583). Journal of Animal Ecology 90:2806–2818.

Martin, B. T., M. A. Gil, A. K. Fahimipour, and A. M. Hein. 2022. [Informational Constraints on Predator-Prey Interactions](https://doi.org/10.1111/oik.08143). Oikos 2022:e08143.

Matsumura, K., and T. Miyatake. 2022. [Effects of Individual Differences in the Locomotor Activity of Assassin Bugs on Predator-Prey Interactions](https://doi.org/10.1111/eth.13272). Ethology 128:395–401.

McGhee, K. E., L. M. Pintor, and A. M. Bell. 2013. [Reciprocal Behavioral Plasticity and Behavioral Types during Predator-Prey Interactions.](https://doi.org/10.1086/673526) The American Naturalist 182:704–717.

McLellan, C. F., N. E. Scott-Samuel, and I. C. Cuthill. 2021. [Birds Learn to Avoid Aposematic Prey by Using the Appearance of Host Plants](https://doi.org/10.1016/j.cub.2021.09.048). Current Biology 31:5364–5369.e4.

Mery, F., and J. G. Burns. 2010. [Behavioural Plasticity: An Interaction Between Evolution and Experience](https://doi.org/10.1007/s10682-009-9336-y). Evolutionary Ecology 24:571–583.

Michalko, R., A. T. Gibbons, S. L. Goodacre, and S. Pekár. 2021. [Foraging Aggressiveness Determines Trophic Niche in a Generalist Biological Control Species](https://doi.org/10.1093/beheco/araa123). Behavioral Ecology 32:257–264.

Michalko, R., and S. Pekár. 2016. [Different Hunting Strategies of Generalist Predators Result in Functional Differences](https://doi.org/10.1007/s00442-016-3631-4). Oecologia 181:1187–1197.

Mitchell, D. J., B. G. Fanson, C. Beckmann, and P. A. Biro. 2016. [Towards powerful experimental and statistical approaches to study intraindividual variability in labile traits](https://doi.org/10.1098/rsos.160352). Royal Society Open Science 3:160352.

Moore, T. Y., K. L. Cooper, A. A. Biewener, and R. Vasudevan. 2017. [Unpredictability of Escape Trajectory Explains Predator Evasion Ability and Microhabitat Preference of Desert Rodents](https://doi.org/10.1038/s41467-017-00373-2). Nature Communications 8:440.

Moran, N. P., B. B. M. Wong, and R. M. Thompson. 2017. [Weaving Animal Temperament Into Food Webs: Implications for Biodiversity](https://doi.org/10.1111/oik.03642). Oikos 126:917–930.

Morse, D. H. 2000. [The Effect of Experience on the Hunting Success of Newly Emerged Spiderlings](https://doi.org/10.1006/anbe.2000.1546). Animal Behaviour 60:827–835.

Mougi, A., O. Kishida, and Y. Iwasa. 2011. [Coevolution of Phenotypic Plasticity in Predator and Prey: Why Are Inducible Offenses Rarer Than Inducible Defenses?](https://doi.org/10.1111/j.1558-5646.2010.01187.x) Evolution 65:1079–1087.

Nomura, F., V. H. M. do Prado, F. R. da Silva, R. E. Borges, N. Y. N. Dias, and D. de C. Rossa-Feres. 2011. [Are You Experienced? Predator Type and Predator Experience Trade-Offs in Relation to Tadpole Mortality Rates](https://doi.org/10.1111/j.1469-7998.2011.00791.x). Journal of Zoology 284:144–150.

Paenke, I., B. Sendhoff, and T. J. Kawecki. 2007. [Influence of Plasticity and Learning on Evolution Under Directional Selection.](https://doi.org/10.1086/518952) The American Naturalist 170:E47–58.

Patrick, S. C., and H. Weimerskirch. 2014a. [Personality, Foraging and Fitness Consequences in a Long Lived Seabird](https://doi.org/10.1371/journal.pone.0087269). PLOS ONE 9:e87269.

Patrick, S. C., and H. Weimerskirch. 2014b. [Consistency Pays: Sex Differences and Fitness Consequences of Behavioural Specialization in a Wide-Ranging Seabird](https://doi.org/10.1098/rsbl.2014.0630). Biology Letters 10:20140630.

Paull, J. S., R. A. Martin, and D. W. Pfennig. 2012. [Increased Competition as a Cost of Specialization During the Evolution of Resource Polymorphism](https://doi.org/10.1111/j.1095-8312.2012.01982.x). Biological Journal of the Linnean Society 107:845–853.

Pedersen, E. J., D. L. Miller, G. L. Simpson, and N. Ross. 2019. [Hierarchical Generalized Additive Models in Ecology: An Introduction With mgcv](https://doi.org/10.7717/peerj.6876). PeerJ 7:e6876.

Phillips, R. A., S. Lewis, J. González-Solís, and F. Daunt. 2017. [Causes and Consequences of Individual Variability and Specialization in Foraging and Migration Strategies of Seabirds](https://doi.org/10.3354/meps12217). Marine Ecology Progress Series 578:117–150.

Piironen, J., and A. Vehtari. 2017. [Comparison of Bayesian Predictive Methods for Model Selection](https://doi.org/10.1007/s11222-016-9649-y). Statistics and Computing 27:711–735.

Pintor, L. M., K. E. McGhee, D. P. Roche, and A. M. Bell. 2014. [Individual Variation in Foraging Behavior Reveals a Trade-Off Between Flexibility and Performance of a Top Predator](https://doi.org/10.1007/s00265-014-1779-7). Behavioral Ecology and Sociobiology 68:1711–1722.

Potier, S., A. Carpentier, D. Grémillet, B. Leroy, and A. Lescroël. 2015. [Individual Repeatability of Foraging Behaviour in a Marine Predator, the Great Cormorant, Phalacrocorax carbo](https://doi.org/10.1016/j.anbehav.2015.02.008). Animal Behaviour 103:83–90.

Redpath, S. M., A. Keane, H. Andrén, Z. Baynham-Herd, N. Bunnefeld, A. B. Duthie, J. Frank, C. A. Garcia, J. Månsson, L. Nilsson, C. R. J. Pollard, O. S. Rakotonarivo, C. F. Salk, and H. Travers. 2018. [Games as Tools to Address Conservation Conflicts](https://doi.org/10.1016/j.tree.2018.03.005). Trends in Ecology & Evolution 33:415–426.

Reid, A., F. Seebacher, and A. Ward. 2010. [Learning to Hunt: The Role of Experience in Predator Success](https://doi.org/10.1163/000579509X12512871386137). Behaviour 147:223–233.

Richardson, G., P. Dickinson, O. H. P. Burman, and T. W. Pike. 2018. [Unpredictable Movement as an Anti-Predator Strategy](https://doi.org/10.1098/rspb.2018.1112). Proceedings of the Royal Society B: Biological Sciences 285:20181112.

Sandbrook, C., W. M. Adams, and B. Monteferri. 2015. [Digital Games and Biodiversity Conservation](https://doi.org/10.1111/conl.12113). Conservation Letters 8:118–124.

Santoro, D., S. Hartley, and P. J. Lester. 2019. [Behaviourally Specialized Foragers are Less Efficient and Live Shorter Lives Than Generalists in Wasp Colonies](https://doi.org/10.1038/s41598-019-41791-0). Scientific Reports 9:5366.

Skelhorn, J., C. G. Halpin, and C. Rowe. 2016. [Learning About Aposematic Prey](https://doi.org/10.1093/beheco/arw009). Behavioral Ecology 27:955–964.

Snell-Rood, E. C. 2013. [An Overview of the Evolutionary Causes and Consequences of Behavioural Plasticity](https://doi.org/10.1016/j.anbehav.2012.12.031). Animal Behaviour 85:1004–1011.

Stephens, D. W. 1993. [Learning and Behavioral Ecology: Incomplete Information and Environmental Predictability](https://doi.org/10.1007/978-1-4615-2814-2_8). Pages 195–218 *in* D. R. Papaj and A. C. Lewis, editors. Insect Learning: Ecology and Evolutionary Perspectives. Springer US, Boston, MA.

Szopa-Comley, A. W., W. G. Donald, and C. C. Ioannou. 2020. [Predator Personality and Prey Detection: Inter-Individual Variation in Responses to Cryptic and Conspicuous Prey](https://doi.org/10.1007/s00265-020-02854-9). Behavioral Ecology and Sociobiology 74:70.

Szopa-Comley, A. W., and C. C. Ioannou. 2022. [Responsive Robotic Prey Reveal How Predators Adapt to Predictability in Escape Tactics](https://doi.org/10.1073/pnas.2117858119). Proceedings of the National Academy of Sciences 119:e2117858119.

Team, S. D. 2023. Stan Modeling Language Users Guide and Reference Manual. 2.31 edition.

Thiers, L., K. Delord, C. Barbraud, R. A. Phillips, D. Pinaud, and H. Weimerskirch. 2014. [Foraging Zones of the Two Sibling Species of Giant Petrels in the Indian Ocean Throughout the Annual Cycle: Implication for Their Conservation](https://www.jstor.org/stable/24893563). Marine Ecology Progress Series 499:233–248.

Tinker, M. T., G. Bentall, and J. A. Estes. 2008. [Food Limitation Leads to Behavioral Diversification and Dietary Specialization in Sea Otters](https://doi.org/10.1073/pnas.0709263105). Proceedings of the National Academy of Sciences 105:560–565.

Tinker, M. T., M. Mangel, and J. A. Estes. 2009. Learning to Be Different: Acquired Skills, Social Learning, Frequency Dependence, and Environmental Variation can Cause Behaviourally Mediated Foraging Specializations. Evolutionary Ecology Research 11:841–869.

Toscano, B. J., N. J. Gownaris, S. M. Heerhartz, and C. J. Monaco. 2016. [Personality, Foraging Behavior and Specialization: Integrating Behavioral and Food Web Ecology at the Individual Level](https://doi.org/10.1007/s00442-016-3648-8). Oecologia 182:55–69.

Toscano, B. J., and B. D. Griffen. 2014. [Trait-Mediated Functional Responses: Predator Behavioural Type Mediates Prey Consumption](https://doi.org/10.1111/1365-2656.12236). Journal of Animal Ecology 83:1469–1477.

van den Bosch, M., J. M. Baert, W. Müller, L. Lens, and E. W. M. Stienen. 2019. [Specialization Reduces Foraging Effort and Improves Breeding Performance in a Generalist Bird](https://doi.org/10.1093/beheco/arz016). Behavioral Ecology 30:792–800.

Vehanen, T. 2003. [Adaptive Flexibility in the Behaviour of Juvenile Atlantic Salmon: Short-Term Responses to Food Availability and Threat From Predation](https://doi.org/10.1046/j.1095-8649.2003.00228.x). Journal of Fish Biology 63:1034–1045.

Vehtari, A., A. Gelman, and J. Gabry. 2017. [Practical Bayesian Model Evaluation Using Leave-One-Out Cross-Validation and WAIC](https://doi.org/10.1007/s11222-016-9696-4). Statistics and Computing 27:1413–1432.

Vehtari, A., A. Gelman, D. Simpson, B. Carpenter, and P.-C. Bürkner. 2021. [Rank-Normalization, Folding, and Localization: An Improved $\widehat{}R{}$ for Assessing Convergence of MCMC (with Discussion)](https://doi.org/10.1214/20-BA1221). Bayesian Analysis 16:667–718.

Vehtari, A., D. Simpson, A. Gelman, Y. Yao, and J. Gabry. 2022, August. [Pareto Smoothed Importance Sampling](https://doi.org/10.48550/arXiv.1507.02646). arXiv.

Walker, J. A., C. K. Ghalambor, O. L. Griset, D. McKENNEY, and D. N. Reznick. 2005. [Do Faster Starts Increase the Probability of Evading Predators?](https://doi.org/10.1111/j.1365-2435.2005.01033.x) Functional Ecology 19:808–815.

Warburton, K. 2003. [Learning of Foraging Skills by Fish](https://doi.org/10.1046/j.1467-2979.2003.00125.x). Fish and Fisheries 4:203–215.

Ward-Fear, G., G. P. Brown, and R. Shine. 2020. [Predators Learning to Avoid Toxic Invasive Prey: A Study on Individual Variation Among Free-Ranging Lizards](https://doi.org/10.1163/1568539X-bja10040). Behaviour 157:1153–1172.

Weimerskirch, H. 2007. [Are Seabirds Foraging for Unpredictable Resources?](https://doi.org/10.1016/j.dsr2.2006.11.013) Deep Sea Research Part II: Topical Studies in Oceanography 54:211–223.

Weimerskirch, H., A. Gault, and Y. Cherel. 2005. [Prey Distribution and Patchiness: Factors in Foraging Success and Efficiency of Wandering Albatrosses](https://doi.org/10.1890/04-1866). Ecology 86:2611–2622.

Wilson, A. M., T. Y. Hubel, S. D. Wilshin, J. C. Lowe, M. Lorenc, O. P. Dewhirst, H. L. A. Bartlam-Brooks, R. Diack, E. Bennitt, K. A. Golabek, R. C. Woledge, J. W. McNutt, N. A. Curtin, and T. G. West. 2018. [Biomechanics of Predator-Prey Arms Race in Lion, Zebra, Cheetah and Impala](https://doi.org/10.1038/nature25479). Nature 554:183–188.

Wilson-Rankin, E. E. 2015. [Level of Experience Modulates Individual Foraging Strategies of an Invasive Predatory Wasp](https://doi.org/10.1007/s00265-014-1861-1). Behavioral Ecology and Sociobiology 69:491–499.

Woo, K. J., K. H. Elliott, M. Davidson, A. J. Gaston, and G. K. Davoren. 2008. [Individual Specialization in Diet by a Generalist Marine Predator Reflects Specialization in Foraging Behaviour](https://doi.org/10.1111/j.1365-2656.2008.01429.x). Journal of Animal Ecology 77:1082–1091.

Wright, J., T. R. Haaland, N. J. Dingemanse, and D. F. Westneat. 2022. [A Reaction Norm Framework for the Evolution of Learning: How Cumulative Experience Shapes Phenotypic Plasticity](https://doi.org/10.1111/brv.12879). Biological Reviews 97:1999–2021.

# TABLES

Table 1. Leave-one-out cross-validation table of the five hierarchical GAMMs relating hunting success to player experience.

| model | elpd  difference | sd  difference | elpd loo  value | elpd loo  standard error |
| --- | --- | --- | --- | --- |
| prey speed + group-level smoothers | 0.00 | 0.00 | -138 767.57 | 193.95 |
| predator xp + prey speed + group-level smoothers | -6.93 | 5.60 | -138 774.49 | 193.98 |
| group-level smoothers | -7 572.53 | 121.24 | -146 340.10 | 166.90 |
| predator xp + group-level smoothers | -7 657.56 | 121.28 | -146 425.13 | 167.09 |
| predator xp | -8 411.02 | 127.93 | -147 178.59 | 163.33 |
| a 'elpd' refers to the expected log pointwise density and is the value chosen to select the best model. b 'xp' is an acronym for experience | | | | |

# FIGURE CAPTIONS

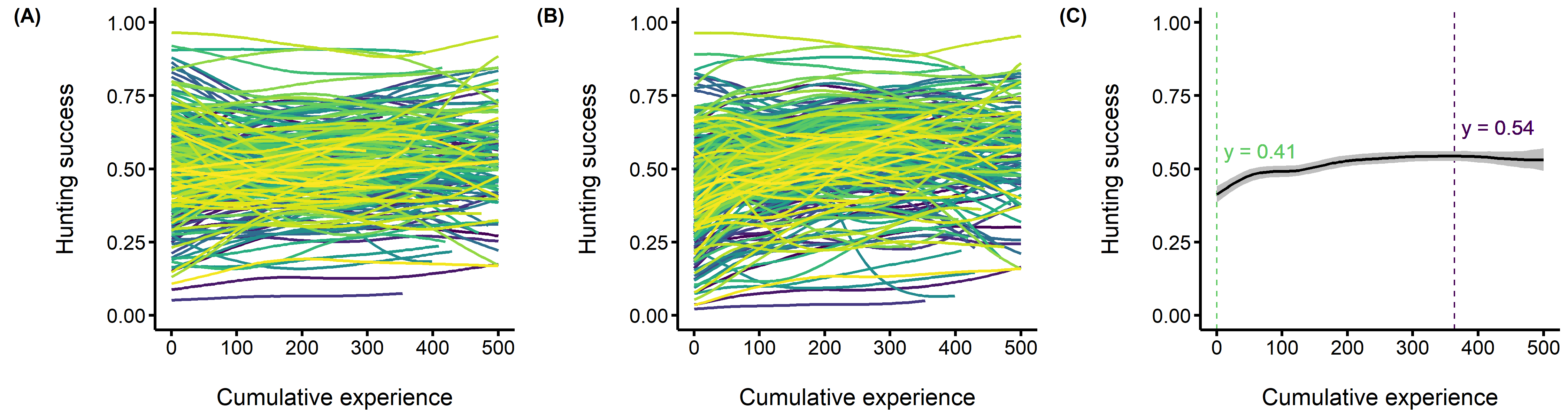
**Figure 1.** Among individual differences in the development of hunting expertise. The predators’ hunting success (i.e. the probability of capturing the four prey) is on the y axis, and the predators’ cumulative experience (i.e. the number of matches played prior to each observation) is on the x axis. Each fitted curve represents an individual predator. (A) A generalized additive mixed model where we do not control for prey speed (B) A generalized additive mixed model where we control for prey speed.

**Figure 2.** Posterior median differences and highest posterior density intervals between each predator experience level’s parameters. Each panel shows the experience levels that are compared. The parameter compared is on the y axis, and the difference of the values predicted by the MDHGLM is on the x axis. The intercepts correspond to mean population speed and specialization. The predator ID on the mean are individual differences in mean speed, mean speed of prey groups encountered, and success. The predator ID on the dispersion (i.e. sigma) are individual differences in specialization, and in the heterogeneity of prey encountered.

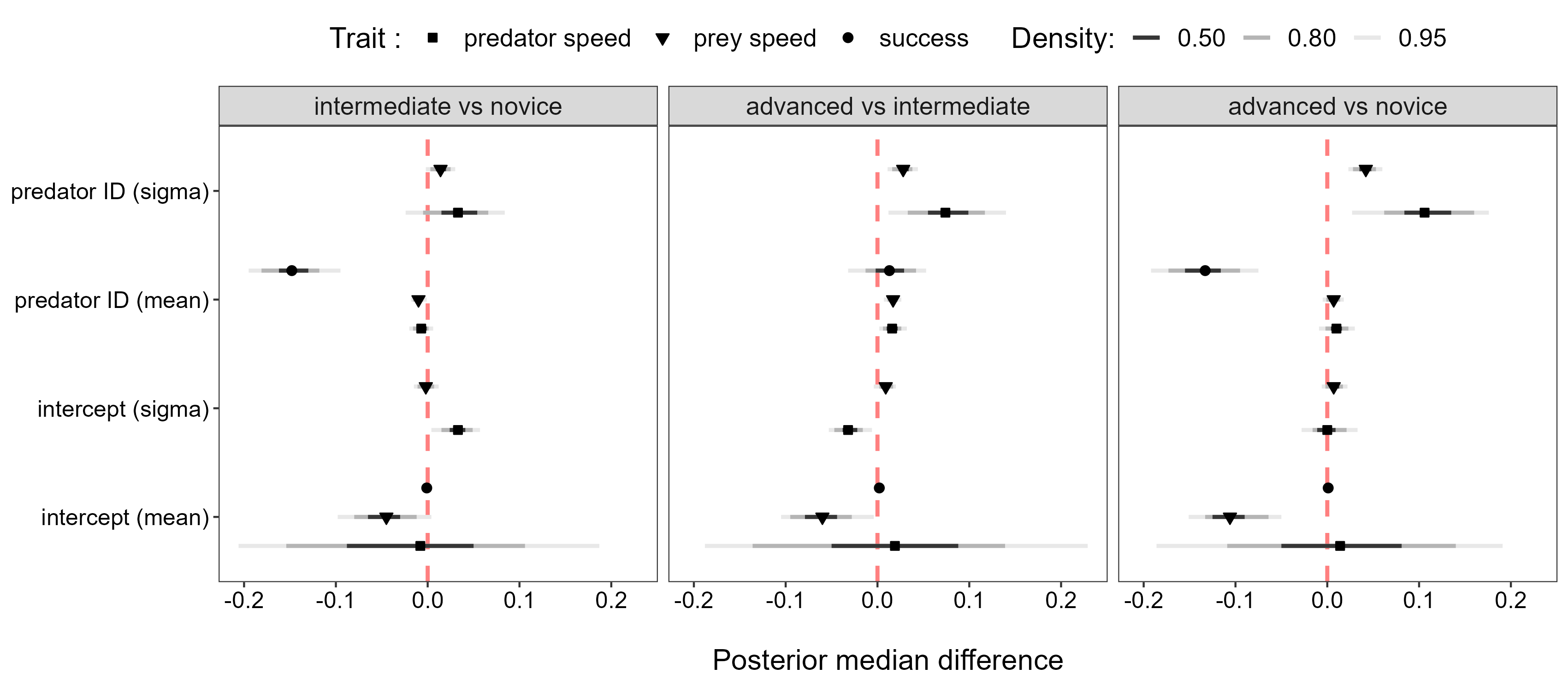
**Figure 3.** Individual behavioural distribution of the predators’ speed drawn from the MDHGLM estimates for individuals that had (A) the greatest increase in specialization and (B) the greatest increase in flexibility. The background (gray) distributions are for when individuals were novice hunters, and the foreground (blue) distributions with solid contour lines are for when they were advanced hunters. Both figure panels are ordered by ascending degree of increase in either specialization or flexibility. We selected the individuals displayed in the figure by first subtracting the estimated standard deviation of all individuals as novices with their standard deviation as advanced hunters, and then selecting those with the greatest difference using the 25% and 75% quantiles. Individuals on panel A have an increase in specialization equal or greater than 0.2 standard deviations, while those on panel B have an increase in flexibility equal or greater than 0.28 standard deviations. *check ici que les pourcentages font du sens*

**Figure 4.** Correlation matrices of the MDHGLM relating the mean and intra individual variability (IIV) in speed of the predators, the mean and IIV in speed of the prey they encountered, and mean hunting success. Larger dark blue circles indicate stronger positive correlations (positive values on the color legend), while larger dark red circles indicate stronger negative correlations (negative values on the color legend). A) Correlations when predators were novice hunters. B) Correlations when predators were advanced hunters. C) Posterior median differences and highest posterior density intervals comparing the correlations between traits when predators were advanced vs novice. The differences were computed on the absolute values of the correlations since the signs did not change with experience, such that positive values indicate an increase in correlation at the advanced stage. The median difference is displayed on the y axis and the trait correlations being compared are displayed on the x axis.

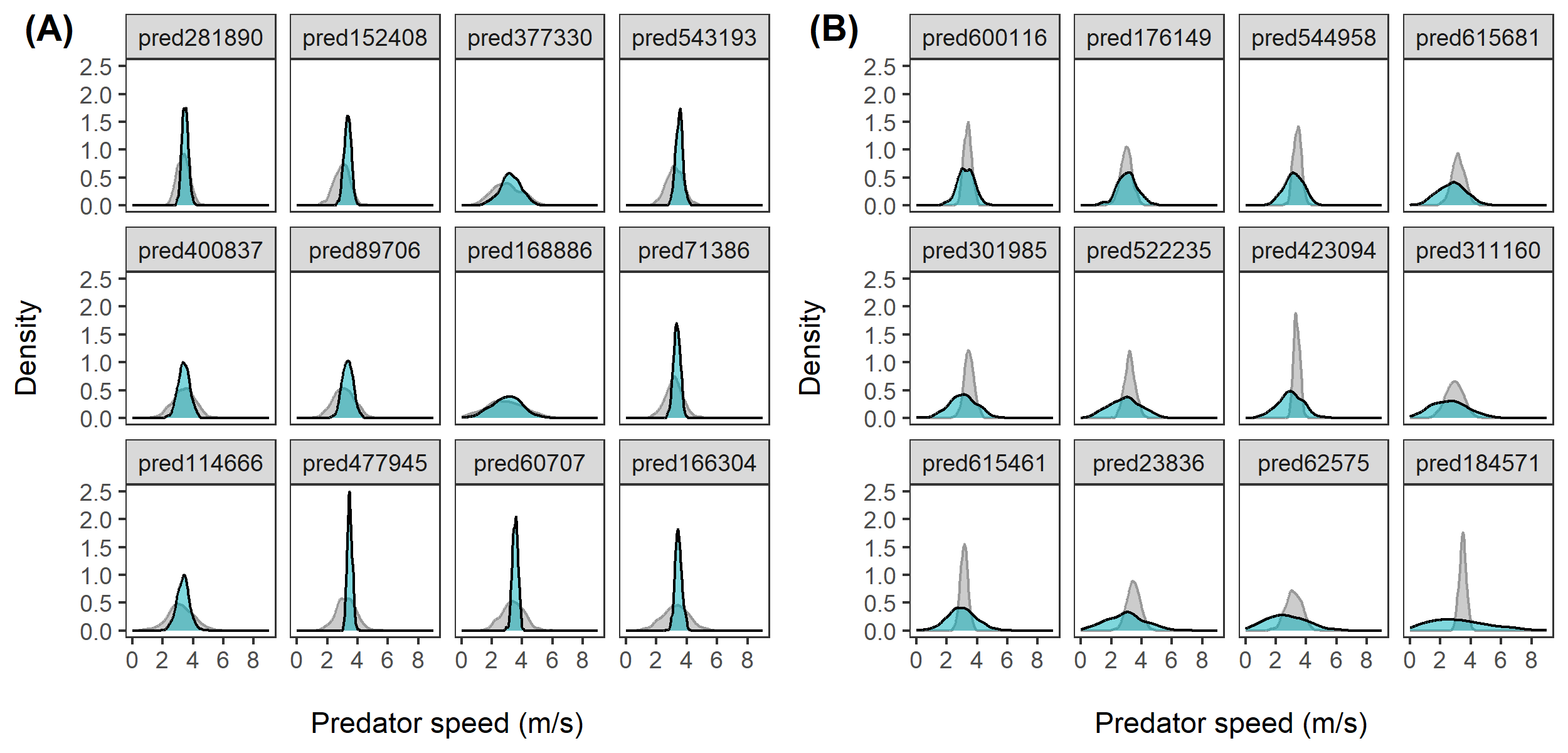
# FIGURES



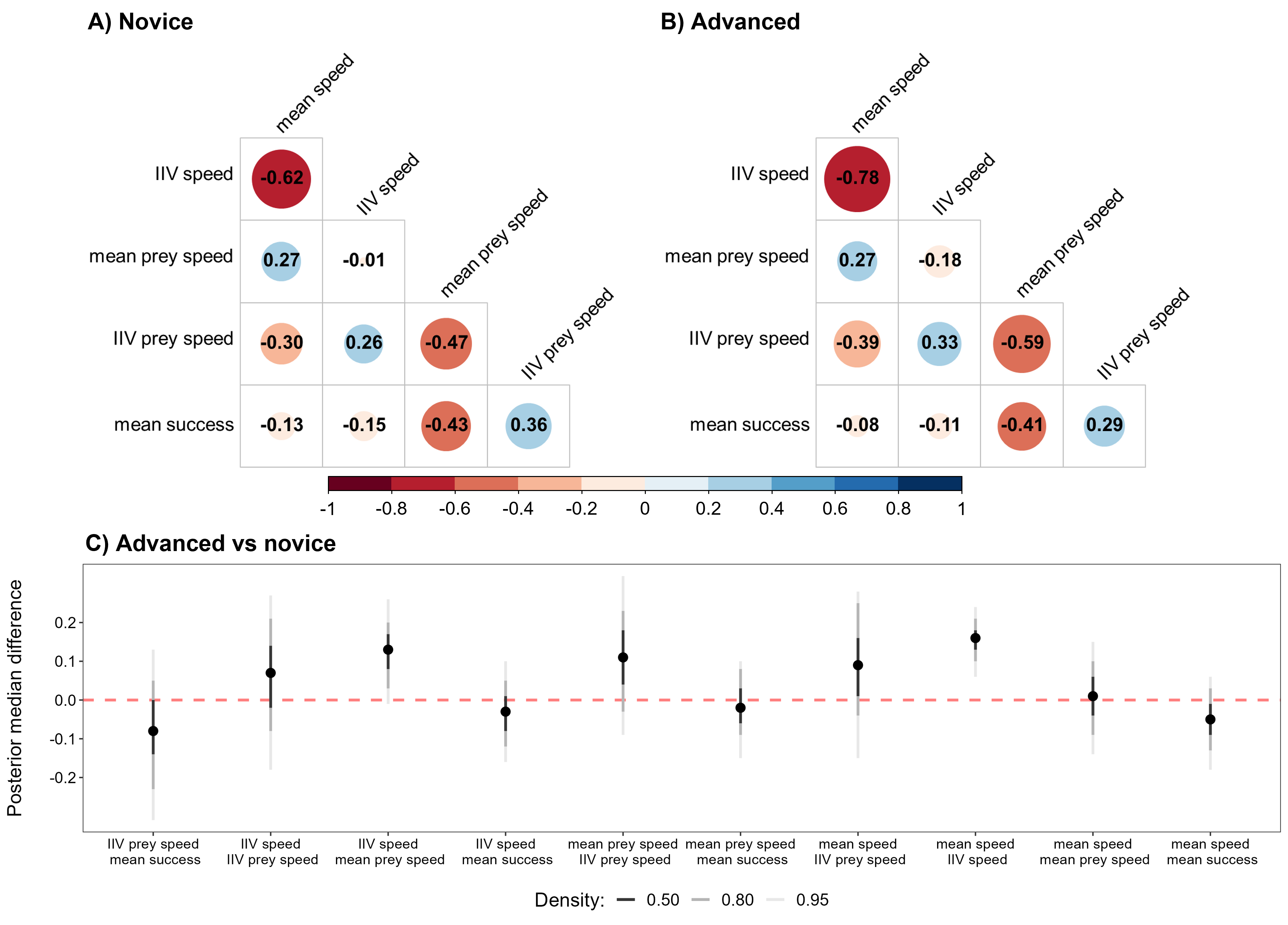
**Figure 1**



**Figure 2**



**Figure 3**



**Figure 4**