Online supporting information for

Analyzing individual variation in predator hunting mode and the effect of predator and prey behavior on hunting success using an online multiplayer videogame

Supporting Information: Materials and methods

Principal component analysis

We computed a principal components analysis (PCA) using packages "FactoMineR" (Lê et al. 2008) and "factoextra" (Kassambara and Mundt 2020) in the R software version 4.0.4 (R Core Team, 2021), under a Windows 10 computer OS. The "PCA()" function in "FactoMineR" uses singular value decomposition. Before running the PCA, we divided each variable (except travel speed) by the match duration to account for differences in duration among matches. All variables were then standardized to mean and unit variance (Z scores) before running the PCA. We ranked variables based on their contribution (in %) to a given principal component axis. To do so, for each variable, we used the ratio between their cos2 multiplied by 100 and the cos2 of the principal component. The PCA was computed on a sample of 70 831 matches from 2 171 players.

Parametrization of the bayesian multivariate mixed-model

We used a weakly informative LKJ prior with a shape parameter (n) set to 2 for the random effects variance-covariance matrixes, and a gaussian prior with mean 0 and standard deviation of 5 for the fixed effects (i.e. prey travel speed x_1 and rate of space covered x_2) of all the submodels (i.e. for each response variable). We ran four chains using 43 000 iterations, and sampled every 40 intervals (thinning). We used the first 3000 iterations for warmup. We visually inspected trace plots, effective sample sizes, and residuals to assess convergence and stability. We also evaluated the model's prediction accuracy using posterior predictive checks. We computed a variance-covariance matrix (Ω_k) for each random effect (k). We extracted the among-environment, avatar, individual, and within- individual behavioural correlations using the function "posterior_samples()" in the "brms" package. We could thus compute the mean of the correlation sample values, and the HDP intervals to obtain the 95% credible intervals for each correlation. The variance-covariance matrixes were parametrized as :

$$\begin{bmatrix} en_{0y1,g} \\ en_{0y2,g} \\ en_{0y3,g} \\ en_{0y4,g} \end{bmatrix} = MVN(0, \Omega_{en}) : \text{where } \Omega_{en} = \begin{bmatrix} V_{en_{0y1}} & & & \\ Cov_{en_{0y1}en_{0y2}} & V_{en_{0y2}} & & \\ Cov_{en_{0y1}en_{0y3}} & Cov_{en_{0y1}en_{0y4}} & V_{en_{0y3}} & \\ Cov_{en_{0y2}en_{0y3}} & Cov_{en_{0y2}en_{0y4}} & Cov_{en_{0y3}en_{0y4}} & V_{en_{0y4}} \end{bmatrix} \tag{S1}$$

$$\begin{bmatrix} av_{0y1,h} \\ av_{0y2,h} \\ av_{0y3,h} \\ av_{0y4,h} \end{bmatrix} = MVN(0, \Omega_{av}) : \text{where } \Omega_{av} = \begin{bmatrix} V_{av_{0y1}} & & & \\ Cov_{av_{0y1}av_{0y2}} & V_{av_{0y2}} & & \\ Cov_{av_{0y1}av_{0y3}} & Cov_{av_{0y1}av_{0y4}} & V_{av_{0y3}} & \\ Cov_{av_{0y2}av_{0y3}} & Cov_{av_{0y2}av_{0y4}} & Cov_{av_{0y3}av_{0y4}} & V_{av_{0y4}} \end{bmatrix} \tag{S2}$$

$$\begin{bmatrix} id_{0y1,i} \\ id_{0y2,i} \\ id_{0y3,i} \\ id_{0y4,i} \end{bmatrix} = MVN(0, \Omega_{id}) : \text{where } \Omega_{id} = \begin{bmatrix} V_{id_{0y1}} & & & \\ Cov_{id_{0y1}id_{0y2}} & V_{id_{0y2}} & & \\ Cov_{id_{0y1}id_{0y3}} & Cov_{id_{0y1}id_{0y4}} & V_{id_{0y3}} & \\ Cov_{id_{0y2}id_{0y3}} & Cov_{id_{0y2}id_{0y4}} & Cov_{id_{0y3}id_{0y4}} & V_{id_{0y4}} \end{bmatrix} \tag{S3}$$

$$\begin{bmatrix} \varepsilon_{0y1,ghij} \\ \varepsilon_{0y2,ghij} \\ \varepsilon_{0y3,ghij} \\ \varepsilon_{0y4,ghij} \end{bmatrix} = MVN(0, \Omega_{\varepsilon}) : \text{where } \Omega_{\varepsilon} = \begin{bmatrix} V_{\varepsilon_{0y1}} & & & \\ Cov_{\varepsilon_{0y1}\varepsilon_{0y2}} & V_{\varepsilon_{0y2}} & & \\ Cov_{\varepsilon_{0y1}\varepsilon_{0y3}} & Cov_{\varepsilon_{0y1}\varepsilon_{0y4}} & V_{\varepsilon_{0y3}} & \\ Cov_{\varepsilon_{0y2}\varepsilon_{0y3}} & Cov_{\varepsilon_{0y2}\varepsilon_{0y4}} & Cov_{\varepsilon_{0y3}\varepsilon_{0y4}} & V_{\varepsilon_{0y4}} \end{bmatrix} \tag{S4}$$

where the diagonals represent the random effect (k) variance ($V_{k_{0y_n}}$) for each hunting trait (y_n), and the lower off-diagonals the covariance between the random effect intercepts for each combination of hunting traits (travel speed ($y1$), the rate of space covered ($y2$), the proportion of time spent ambushing ($y3$), and the time before first capture ($y4$)).

We ran two additional multivariate mixed-models after observing that the game environments did not explain a high percentage of variation in predator behavior (see the "discussion" in the main text). For the second model, we tested the hypothesis that prey might instead respond to the environment, which may then indirectly affect predator behavior. We thus computed the same multivariate model, and excluded prey travel speed and rate of space covered as the linear fixed effects. For the third model, we investigated if the game environment surface area explained an important portion of the observed variation in space covered when prey were exluded as fixed effects (see results section below). We thus kept prey behavior in this model and included the game environment surface area as a fixed effect.

Parametrization of the Bayesian mixed-models for hunting success

We computed 4 different models to investigate the relationship between predator and prey behavior and predator hunting success. We used a Gaussian prior with mean of 0 and standard deviation of 5 for all the models' fixed effects. We visually inspected trace plots, effective sample sizes, and residuals to assess convergence and stability. We also evaluated the models' prediction accuracies using posterior predictive checks. We calculated the ICC_k estimate for each random effect (k) using the function posterior_samples() in the "brms" package, by dividing each random effect variance sample value by the total variance. We could then compute the mean of the samples to obtain the ICC value for each random effect, and HDP intervals to obtain their corresponding 95% credible intervals.

For the first model, we aimed at investigating the relationship between hunting success and predator behaviour exclusively. For this model, we ran four chains using 103 000 iterations by sampling every 100 intervals (thinning), and used the first 3000 iterations for warmup. The model was parametrized as :

$$
\begin{aligned}
logit(P_{hij}) = (&\beta_0 + env_{0,h} + id_{0,i} + \varepsilon_{0,hij}) \\
&+ \ \beta_{1,pred} speed_{hi} \\
&+ \ \beta_{2,pred} space_{hi} \\
&+ \ \beta_{3,pred} ambush\ time_{hi} \\
&+ \ \beta_{4,pred} time\ 1^{st} capture_{hi}
\end{aligned}
\tag{S5}
$$

We included prey behaviour in the second model and kept the same structure as equation S5. For this model, we ran four chains using 153 000 iterations by sampling every 100 intervals (thinning), and used the first 3000 iterations for warmup. The model was parametrized as :

$$
\begin{aligned}
logit(P_{hij}) = (\beta_0 + env_{0h} + id_{0i} + \varepsilon_{0,hij}) \\
+ \ \beta_{1,pred}\textit{speed}_{hi} \\
+ \ \beta_{2,pred}\textit{space}_{hi} \\
+ \ \beta_{3,pred}\textit{ambush time}_{hi} \\
+ \ \beta_{4,pred}\textit{time 1}^{st}\textit{capture}_{hi} \\
+ \ \beta_{5,prey}\textit{speed}^{'}_{hi} \\
+ \ \beta_{6,prey}\textit{space}^{'}_{hi}
\end{aligned}
\tag{S6}
$$

In the third model, we were interested in investigating nonlinear relationships between hunting success and predator behaviour exlusively. We thus added quadratic effects for each hunting trait. We also investigated how predator behaviours interact to affect huntin success. The model was run for 103 000 iterations by sampling every 100 intervals and using the first 3000 iterations as warmups. This model was computed as :

$$
\begin{aligned}
logit(P_{hij}) = (&\beta_0 + env_{0h} + id_{0i} + \varepsilon_{0,hij}) \\
&+ \beta_{1,pred}\textit{speed}_{hi} + \beta_{2,pred}\textit{space}_{hi} \\
&+ \beta_{3,pred}\textit{ambush time}_{hi} + \beta_{4,pred}\textit{time 1}^{st}\textit{capture}_{hi} \\
&+ \frac{1}{2}\gamma_{1,pred}\textit{speed}^2_{hi} + \frac{1}{2}\gamma_{2,pred}\textit{space}^2_{hi} \\
&+ \frac{1}{2}\gamma_{3,pred}\textit{ambush time}^2_{hi} + \frac{1}{2}\gamma_{4,pred}\textit{time 1}^{st}\textit{capture}^2_{hi} \\
&+ \gamma_{1,pred}\textit{speed}_{hi} \times \textit{space}_{hi} \\
&+ \gamma_{2,pred}\textit{speed}_{hi} \times \textit{ambush time}_{hi} \\
&+ \gamma_{3,pred}\textit{speed}_{hi} \times \textit{time 1}^{st}\textit{capture}_{hi} \\
&+ \gamma_{4,pred}\textit{space}_{hi} \times \textit{ambush time}_{hi} \\
&+ \gamma_{5,pred}\textit{space}_{hi} \times \textit{time 1}^{st}\textit{capture}_{hi} \\
&+ \gamma_{6,pred}\textit{ambush time}_{hi} \times \textit{time 1}^{st}\textit{capture}_{hi}
\end{aligned} \tag{S7}
$$

The fourth and final model included prey behaviours with their quadratic effects. We also included interactions between predator and prey behaviours to investigate how they jointly affect hunting success. The model was run for 103 000 iterations by sampling every 100 intervals and using the first 3000 iterations as warmups. The model is described as :

$$
\begin{aligned}
logit(P_{hij}) = (&\beta_0 + env_{0h} + id_{0i} + \varepsilon_{0,hij}) \\
&+ \beta_{1,pred}\textit{speed}_{hi} + \beta_{2,pred}\textit{space}_{hi} \\
&+ \beta_{3,pred}\textit{ambush time}_{hi} + \beta_{4,pred}\textit{time 1}^{st}\textit{capture}_{hi} \\
&+ \beta_{5,prey}\textit{speed}'_{hi} + \beta_{6,prey}\textit{space}'_{hi} \\
&+ \frac{1}{2}\gamma_{1,pred}\textit{speed}^2_{hi} + \frac{1}{2}\gamma_{2,pred}\textit{space}^2_{hi} \\
&+ \frac{1}{2}\gamma_{3,pred}\textit{ambush time}^2_{hi} + \frac{1}{2}\gamma_{4,pred}\textit{time 1}^{st}\textit{capture}^2_{hi} \\
&+ \frac{1}{2}\gamma_{5,prey}\textit{speed}'^2_{hi} + \frac{1}{2}\gamma_{6,prey}\textit{space}'^2_{hi} \\
&+ \gamma_{1,pred}\textit{speed}_{hi} \times \textit{space}_{hi} \\
&+ \gamma_{2,pred}\textit{speed}_{hi} \times \textit{ambush time}_{hi} \\
&+ \gamma_{3,pred}\textit{speed}_{hi} \times \textit{time 1}^{st}\textit{capture}_{hi} \\
&+ \gamma_{4,pred}\textit{space}_{hi} \times \textit{ambush time}_{hi} \\
&+ \gamma_{5,pred}\textit{space}_{hi} \times \textit{time 1}^{st}\textit{capture}_{hi} \\
&+ \gamma_{6,pred}\textit{ambush time}_{hi} \times \textit{time 1}^{st}\textit{capture}_{hi} \\
&+ \gamma_{7,\textit{pred prey}}\textit{speed}_{hi} \times \textit{speed}'_{hi} \\
&+ \gamma_{8,\textit{pred prey}}\textit{speed}_{hi} \times \textit{space}'_{hi} \\
&+ \gamma_{9,\textit{pred prey}}\textit{space}_{hi} \times \textit{speed}'_{hi} \\
&+ \gamma_{10,\textit{pred prey}}\textit{space}_{hi} \times \textit{space}'_{hi} \\
&+ \gamma_{11,\textit{pred prey}}\textit{ambush time}_{hi} \times \textit{speed}'_{hi} \\
&+ \gamma_{12,\textit{pred prey}}\textit{ambush time}_{hi} \times \textit{space}'_{hi} \\
&+ \gamma_{13,\textit{pred prey}}\textit{time 1}^{st}\textit{capture}_{hi} \times \textit{speed}'_{hi} \\
&+ \gamma_{14,\textit{pred prey}}\textit{time 1}^{st}\textit{capture}_{hi} \times \textit{space}'_{hi}
\end{aligned}
\tag{S8}
$$

Supporting Information: Results

Principal component analysis

The first principal component (PC1) explained 20% of the total variation, and the second principal component (PC2) explained 15.3% of the total variation (figure S1). We found that travel speed and time spent ambushing had the highest contribution (23.19% and 29.38% respectively) to the first principal component (table S1), while the rate of space covered and the time before first capture had the highest contribution (48.12% and 35.55%) to the second principal component (table S1). The time spent ambushing is negatively correlated with travel speed (figure S1), which may indicate the presence of structured tactics where individuals that are fast do not ambush, and individuals who ambush prey are slower travelers.

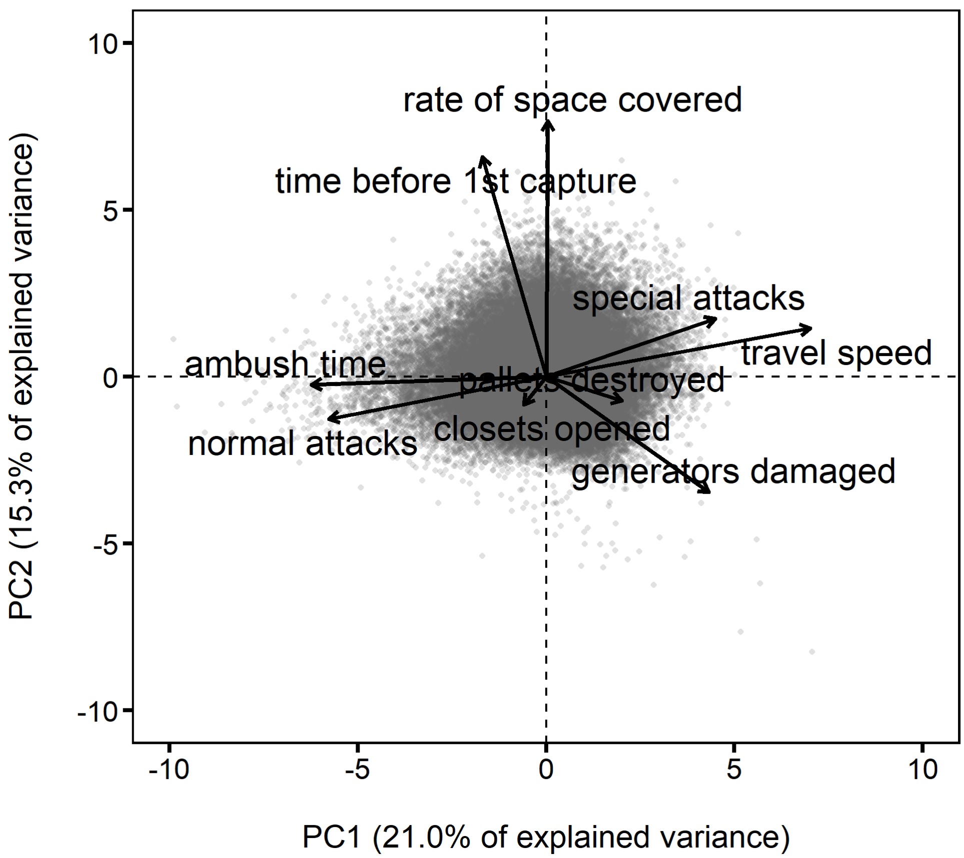

Figure S 1: Biplot of the principal component analysis on predator hunting variables. We extracted correlations and the percentages of explained variance on the first and second PC axes to select variables for the subsequent analyses.

Table S1: Principal component loadings for all the predator behavioural traits.

	PC1 (% variance = 21.0)		PC2 (% variance = 15.3)	
	Correlation	% variance	Correlation	% variance
ambush time	-0.66	23.19	-0.03	0.05
travel speed	0.75	29.38	0.15	1.73
rate of space covered	0.00	0.00	0.82	48.12
closets opened	-0.06	0.21	-0.09	0.56
pallets destroyed	0.21	2.42	-0.08	0.43
generators damaged	0.46	11.17	-0.37	9.79
normal attacks	-0.61	19.89	-0.13	1.31
special attacks	0.48	12.02	0.18	2.47
time before 1st capture	-0.18	1.72	0.70	35.55

Intra-class correlation coefficients of predator behavior without the effect of prey and with the effect of the game environment surface area

After removing prey behavior as linear fixed effects (model 2), the percentage of explained variance by the game environments remained almost the same compared to the first model for predator travel speed, the proportion of time spent ambushing, and the proportion of time required to capture the first prey (table S2). Thus, variation in these three behaviors was not explained by differences among game environments. However, there was considerable variation among game environments in the rate of space covered (table S2). The surface area (model 3) of the game environment did not seem to explain a high portion of the variation in space coverage nor in any of the other measured behaviors (table S2).

Table S2: ICC estimates of the additional multivariate mixed-models. The second model excludes prey behavior, and the third model includes the game environment surface area.

Behavior	Random effect	ICC (95% CI) - Model 2	ICC (95% CI) - Model 3
travel speed	player ID	0.29 (0.26, 0.31)	0.28 (0.25, 0.30)
	game environment	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
	avatar	0.10 (0.04, 0.16)	0.09 (0.04, 0.15)
	residuals	0.62 (0.57, 0.66)	0.63 (0.58, 0.67)
space covered	player ID	0.04 (0.03, 0.05)	0.05 (0.04, 0.06)
	game environment	0.28 (0.17, 0.40)	0.06 (0.04, 0.10)
	avatar	0.01 (0.01, 0.03)	0.02 (0.01, 0.04)
	residuals	0.67 (0.56, 0.77)	0.86 (0.83, 0.89)
ambush time	player ID	0.32 (0.30, 0.35)	0.32 (0.30, 0.34)
	game environment	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
	avatar	0.04 (0.01, 0.07)	0.03 (0.01, 0.07)
	residuals	0.64 (0.61, 0.66)	0.64 (0.62, 0.67)
time 1st capture	player ID	0.13 (0.12, 0.14)	0.10 (0.09, 0.11)
	game environment	0.00 (0.00, 0.00)	0.05 (0.03, 0.08)
	avatar	0.02 (0.01, 0.04)	0.02 (0.01, 0.04)
	residuals	0.85 (0.83, 0.86)	0.82 (0.79, 0.85)

Literature Cited

Kassambara, A., and F. Mundt. 2020. Factoextra: Extract and Visualize the Results of Multivariate Data Analyses. Comprehensive R Archive Network (CRAN).

Lê, S., J. Josse, and F. Husson. 2008. FactoMineR: An R Package for Multivariate Analysis. Journal of Statistical Software 25:1–18.