- Article Title: Impacts on Atlantic killifish from neurotoxicants: genes, behavior, and population relevant outcomes
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- 63 pages
- 6 Figures
- 26 Tables

Supplemental

Behavior Assay Methods

 After exposure, 7dpf embryos were rinsed in fresh seawater and transferred into 50-ml conical centrifuge tubes full of fresh seawater (< 50 embryos per tube) and shipped overnight to UWM, where they were placed in 12-well plates and maintained at 23°C (1-2 embryos per well with 1ml artificial seawater; Falcon® Corning, NY 12 well plate 85 x 128 mm, 22 mm diameter well). At 10 dpf, embryos were phenotyped microscopically when abnormalities in 33 developmental stage and features were noted^{1,2}. At 14 dpf, plates were rocked gently $\left(\sim 120$ rpm) and seawater added to each well to initiate hatching. Individual larvae were maintained in single wells for all assessments containing 3 mL seawater, incubated at 23° C, fed 24-h hatched *Artemia* ad lib daily, and renewed with seawater on alternate days. Individuals were assessed daily for survival until 23-24 dpf.

 During larvae development, multiple behavior assays were conducted to determine if chemical exposure altered important behavioral milestones. Logistical constraints required two separate batches of fish to be produced (fertilized on August-8-2017 from parents on diets for 103 days and August-21-2017 from parents on diets for 115 days) and for some fish to be included in multiple assays. KF were exposed to MeHg as embryos via parental transfer or were exposed through aqueous solution of PCB126 1-7 dpf. Embryos hatched at 14 dpf, assessed with 44 the Visual Motor Response (VMR) assay at 16 dpf $(n=144)$, a random subset contributed brain samples using lethal methods for gene expression at 17 dpf (n=69, 36 of whom had been through the VMR assay), assessed with Locomotion Behavior assay at 17 dpf (n=256, 108 of whom had been through the VMR assay), and feeding abilities were assessed at 23 or 24 dpf (n=192, 84 of

 whom had been through the VMR and Locomotion assay and 192 had been through the Locomotion assay; see Table S1 for the total number of fish in each assay and treatment).

VMR Assay

 Visual Motor Response (VMR) assays are a common test of fish neurological system 53 function by startling the fish and evaluating their response³. VMRs were conducted using the same methodology as Mora-Zamorano et al. (2017), where 16 dpf larvae were tested in a special behavior chamber while in the transparent 12-well microliter plates. The testing chamber 56 isolated the larvae from light and sound, as described in three previous studies^{4–6} and provided adequate light and video surveillance to view all individual movement. VMR assays were 58 conducted between the hours of 1200 and 1800 to minimize within day variability⁷. KF larvae were positioned in a dark behavior chamber and acclimated in the dark for 10 minutes (did not use data during this period), after which they underwent two cycles of alternating 10 min light and dark periods for a total of 50 min. This resulted in larvae used in the VMR analysis experiencing two startles each from dark to light and from light to dark and 4-10 minute periods differing light conditions: two dark and two light. Light levels during the light periods were set to 69 lx based on the work by MacPhail et al. (2009; Fisher Scientific Traceable Dual-Range Light Meter, Pittsburgh, PA).

 Spontaneous movement of larvae was constantly recorded at a rate of 30 frames per sec and tracked using DanioVision© system version 8.0 (Noldus Information Technology, Leesburg, VA). Settings for tracking did not include smoothing of track. The minimal distance before movement was recorded was set to 0.2 mm, at which time the direct distance between the two points was calculated. Tracking errors were corrected by plotting all x, y coordinates and

 locating and correcting occurrences where the track indicated movement but the fish did not move or track was outside the boundary of the dish. Occasionally when Ethovision lost a fish for 1 to 3 frames (4-SCO-MeHg, 3-NBH-Ctrl, 3-NBH-PCB), the equidistant point/s between the previous and next location were calculated and used as locations.

 Similar to Albers et al. (2022), this study used the censored fish locations to define individual larvae activity at each frame within each period. Speed at each frame was calculated as mm per sec and distance traveled in mm. Swimming was defined as larval movement that was at least 6 mm/sec or 0.2 mm per frame (i.e. magnitude of velocity at larvae center) and lasted longer than 5 frames (0.166 sec). Whereas the resting behavior occurred during frames where movement was less than 1 mm/sec or if greater than 1 mm/sec, lasted less than 5 frames. Where resting behavior was defined, speed and distance for those frames were changed to zero. In addition, the turning angle associated with each frame of swimming was calculated using the difference between the four-quadrant inverse tangent of the two trajectories. Where the first trajectory was constructed from the first two locations in the sequence, and the second trajectory from the second two locations in the sequence. This results in a turning angle that ranges from - 3.14 to 3.14, where zero is straight ahead movement, negative values indicate right turns and positive values indicate left turns. Swimming bout characteristics (i.e. time between rest periods) were summarized using multiple metrics: number of bouts per second; the mean duration, speed, and turning angle (See Table S3 for definitions). The overall larval behavior during each period in the assay was also summarized using multiple overall summary metrics: total distance traveled, total time swimming, overall average step length and variation, overall turning angle and variation.

 The fish larvae responded to the visual startle from the light change as is typical of previous 94 startle responses³. Consequently, two behavior endpoints were calculated specifically to determine how larvae responding to the visual startle of the light turning off and on. To determine the magnitude of the response to the visual startle, we determined the frame where the maximum speed was traveled within 5 seconds after the startle. Then the difference between this maximum speed and the speed at the time of the startle was calculated to define the magnitude of the startle response. Startle response time was calculated as the difference in time between the startle and the frame where the maximum speed was traveled.

Locomotion Assay

103 Typically, KF larvae initiate swimming soon after hatching⁹. The focus of this study was to assess larvae behavior at the point that larvae were independent and actively swimming. 105 Consequently, the locomotion assay was conducted when KF larvae were 17 dpf (3 dph, $6.8 \pm$ 0.67 mm in length, n=180), where each 12-well plate was transferred to the behavior testing chamber. Since previous locomotion assays indicated some neurotoxicants impact larvae only 108 during light periods⁴, light levels were constant during the entire assay and set to 69 lx⁷. Assays were conducted during the afternoon between 1200 and 1730 hrs. After an acclimation period of 5 min, spontaneous movement of larvae were tracked every 30th of a second using DanioVision© software 8.0 with the same settings described for the VMR assay. Additionally, DanioVision© lost track of one fish for more than 300 frames, so this fish was not included in the analysis (treatment SCO-PCB). Using the censored fish locations, the same activity endpoints used the VMR assay were

calculated: average swimming bout speed, duration, frequency, turning angle (Table S3).

 Additional behavior metrics that summarized other behaviors over the entire assay were also calculated: total distance traveled and swimming time, average step length and turning angle with their respective variations.

 Using the same methods as Albers et al. (2022), a Hidden Markov Chain Model (HMM) was constructed for each fish in the locomotion assay (all fish swam at least once) to describe the different behavioral states and used them as additional behavior endpoints to determine effects from chemical exposure. A brief description of the method follows. For each larva and video frame, the step length and turning angle during the assay were used to construct multiple larval 124 specific HMMs using the R package moveHMM^{10,11}. Multiple behavior state models were examined that contained three possible swimming states: slow, medium, and fast swimming states where s1 HMMs contained only one behavior state, s2 HMMs contained any two behavior states, and s3 HMMs contained all three behavior states. The best fit HMM for each larvae was determined from a suite of ten potential HMM models, differing in the number of behavior states and initial starting values for each state (see Albers et al. 2022 Table S2 for model description and initial values).

 Once all 10 of the possible HMMs were completed, a hierarchical selection for the best fitting model was conducted, essentially using successfully converged models with the lowest AIC. Even though the initial state values were set up in increasing step length means, the resulting best fit HMM state parameter estimates did not always have increasing step length for each additional behavior. This is probably due to the final HMM behavior state being defined by not only the step length but also turning angle characteristics. To make sure the behavior state comparisons were comparing similar states with the same name, the states were reordered and renamed in order to compare between larvae. First, states were reordered using the mean step

 length to describe them as slow, medium and faster swimming behavior states (i.e. changed the state name). Next a Linear Discriminant Model was constructed using the lda function in the 141 MASS package¹² and cross validation to compare between models using the s3 models as a reference. LDA prediction accuracy for all models (s1, s2, and s3) was measured using cross validation where a random draw of 80% of the data was used to construct a model and then calculated prediction accuracy of the remaining 20% of the data. This was done 50 times for 145 each treatment group of data to determine overall accuracy $(98 \pm 0.02 \%)$ and within state 146 accuracy (slow state = 99 ± 0.01 %, medium state = 99 ± 0.01 %, and fast state = 95 ± 0.05 %; Table S4).

 When treatment level tests were conducted on slow, medium and fast states, this comparison was only conducted with fish that performed those states making the number of larvae used for the model (see Treatment Testing section below) different for each comparison (Table S1).

Feeding Assay

153 Typically, KF larvae initiate feeding at 17 dpf¹³. This study focused on assessing larvae behavior at the point that larvae were independent and feeding. Consequently, feeding ability in 155 KF was assessed when they were 23 or 24 dpf (9 or 10 dph; 10.6 ± 0.82 mm). Larva were transferred from the 22 mm diameter wells to 54 mm diameter petri dishes at 22 dpf (60 mm petri dish). Feeding of *Artemia* continued morning and evening until ~24hr prior to the assay, so fish would be in a hungry state for the test. Similar to locomotion assays, feeding assays were conducted over a two-day period between 1300 and 1920 hrs at a light level of 69 lx. Feeding assays were conducted in the same behavior chamber as the locomotion assay, when after 5

 minutes of acclimation, recording started and ~15 (range 13-19) live *Artemia* were added to the dish. The test ended when 5 minutes had elapsed from when the *Artemia* were added to the dish. Feeding bouts consisted of multiple presentations; the characteristic curved body posture, continuously swimming straight or at rest by just opening their mouths. For each of these presentations, the distance between the middle of the larva's mouth and *Artemia* was measured at the time the larva orientated toward the *Artemia*, with their either eyes or body. This distance was termed predator reactive distance and was measured using ImageJ (version 1.51j8). For each capture attempt toward an *Artemia*, we recorded whether the larva successfully captured the *Artemia* and the time it took the larva to handle and consume the *Artemia*. Typically after a catching an *Artemia*, the larva sat or drifted momentarily and did not swim while it was consuming the prey. Handling time was defined as the time between prey capture and when the larva resumed normal swimming activity. Additionally, three consumption metrics were calculated: capture proportion defined as the number of captures divided by the total number of *Artemia* added to the dish, miss proportion defined as the number of feeding capture attempts that missed the *Artemia* divided by the total number of successful and unsuccessful capture attempts, and capture attempt ratio defined as the total number of feeding capture attempts (successful and unsuccessful) divided by the total number of *Artemia* added to the dish. When two *Artemia* were consumed during one feeding capture attempt, the consumption of both *Artemia* were assigned the same measurements.

Bayesian Model Analysis

 For each behavioral endpoint (Table S3), we conducted a series of preliminary and final tests to determine whether there were differences between chemical dose treatments. The three different behavior assays and the number of behavior responses we measured were Feeding-5, Visual Motor Response (VMR) - 58, Locomotion - 30. Behavior responses that were not already normally distributed, we attempted to normalize using the boxcox function in the R MASS 188 package¹² (Table S5). Using a basic model containing only the treatment factor, behavior endpoints were transformed using the maximum lambda parameter for the exponential transformation suggested by the boxcox function in the R MASS package. Below we describe the five different models that were used on the 93 behavior responses to determine differences between treatments, (see Table S5 for final transformation and model used for each behavior endpoint). Fitting multiple model types was necessary due to the various behavior endpoints having distinctively different distributions such as a proportional, normal, or a skewed response that even Box Cox transformations were not successful in normalizing.

Model Description

 The Bayesian models used in locomotion and VMR behavior response models consisted of one main effect (treatment with 5 levels), covariate variable time of assay and a random batch effect because assays were ran in batches of 24-well dishes. The Bayesian model used for a locomotion and VMR behavior responses was

Locomotion or VMR Behavior Endpoint_{iikl}

$$
= \alpha + \beta_j * treatment_j + \delta_k * assay time_{k(i)} + \omega_l * batch_{l(i)} + \varepsilon_{ijkl}
$$

225 normal prior assuming a normal distribution with a mean of 0 and standard deviation of at least 226 1.0 x 10⁴ (i.e. precision of 1.0 x 10⁻⁴). Lastly, the residual error followed a normal distribution 227 $\varepsilon \sim Normal(0,\sigma_{\varepsilon}^2)$ with variance $\frac{1}{\sigma_{\varepsilon}^2}$ $\frac{1}{\sigma_{\epsilon}^2} = \tau_j \sim I - \text{Gamma}(0.0001, 0.0001)$. OpenBUGS code is 228 presented in Table S10. 229 2) Binomial response model 230 $Feeding Behavior\ End point_{ijkl} \sim Binomial(p_{ijkl}, N_{ijkl})$ 231 $logit(p_{ijkl}) = \beta_i * treatment_{i(i)} + \delta * assay time_{k(i)} + \omega * dpf_{l(i)} + \epsilon_{ijkl}$ 232 233 where Feeding Behavior Endpoint_{ijkl} is the prey capture probability or prey miss 234 proportion (Table S8) on the *i*th individual, *j*th treatment, *k*th assay time and *l*th dpf and N_{ijkl} is the 235 number of trials and p_{ijkl} is the probability of success distributed on a logit scale. The priors for 236 β_i , δ and ω where described before. Lastly, the residual error followed a normal distribution

237 $\varepsilon \sim Normal(0,\sigma_{\varepsilon}^2)$ with variance $\frac{1}{\sigma_{\varepsilon}^2}$ $\frac{1}{\sigma_{\epsilon}^2} = \tau_j \sim I - \text{Gamma}(0.01, 0.01)$. OpenBUGS code is 238 presented in Table S11.

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240 *Model Fitting and Convergence Diagnostics*

 Bayesian models were constructed using OpenBUGS version 3.2.3 rev 1012 ¹⁴, R 242 version $3.6.0¹¹$ and packages R2OpenBUGS version $3.2¹⁵$ and coda version 0.19-2 ¹⁶. We fit the basic model using three chains, each with a minimum of 10000 iterations, 1000 burn in, and 1 thin, and monitored a subsample of parameters for convergence: treatment effects, overall 245 mean, residuals, variance(s), precision parameter(s), and degree of freedom parameter(s). Then we performed preliminary multiple MCMC chain convergence diagnostics using Trace plots. If model did not converge, we increased either the number of iterations, burn in, or thin. Once the preliminary model trace plots were not showing any obvious convergence problems, further MCMC diagnostics were applied using a suite of tools to determine adequate MCMC chain length, model convergence and fit. 1) Autocorrelation plots indicated the level of thinning required to remove any autocorrelation. 2) Gelman-Rubin-Brooks shrink factor plots indicated the adequate number of iterations needed for burn in. 3) Raftery and Lewis's diagnostic tables were used to determine the number of additional iterations needed for accurate parameter 254 estimation (default values of $q = 0.025$, $r = \pm 0.005$ and $s = 0.95$). 4) Finally, model goodness- of-fit was evaluated using residual diagnostics. When alternative models were to be compared, the model with the best posterior predictive distributions of residuals and replicated observations was retained.

 Once a best-fitted model had been determined, we re-fit the model with the appropriate settings and monitored a slightly different suite of parameters: overall mean; population level treatment effects; variance and precision parameters; tail area probabilities of observing a difference; degrees of freedom; individual level predicted means, etc. With the model output and iteration levels we also determined effective sample size (effectiveSize function in coda R package), posterior distributions of parameters, and calculated a one-sided tail area probabilities (Bayesian P-values) from the two sided difference of parameter distributions. The summary output of this last model fit is presented in the results section of the paper and all relevant parameter posterior distributions can be found in Table S13.

Behavior Treatment Testing

 All behavioral endpoints were examined for treatment differences using Bayesian statistical methods (see Supplemental section for additional details). Bayesian models for locomotion behavior responses consisted of one main effect (treatment with 5 levels), covariate variable (time of test and/or dpf) and a random batch effect since assays were ran in batches of 12-well dishes. Bayesian models for feeding behavior were the same except no random batch was included since each assay was conducted with one larva. Response variables and residuals were examined for normality using density distributions and Box Cox transformation were applied where needed in all non-negative response variables using the boxcox function in the MASS 277 package (Table S_2^{212}). All responses that were normally distributed either with or without a transformation were predicted using a normal distribution model, responses that were severely right skewed were predicted using a t distribution model where degrees of freedom (df) was estimated with dunif (3, 30), and responses that were proportional were fit with a logistic distribution model (Tables S6, S7, S8 and S9, S10, respectively). Priors were set to be non- informative and all models were ran with three chains (see supplemental material for detailed methods; Table S6). To facilitate future use of parameter estimates, this study generated both overall population and individual level parameter estimates (Table S12). Lastly, a Chi-Square 285 test from the R stats package¹¹ was used to determine whether the proportion of s1, s2 and s3 HMMs selected were different between treatments.

Brain Gene Expression

Brain collection

 Brain collection was performed essentially as described by Vargas et al. (2011) on 17 dpf MeHg and PCB126 exposed larvae. A random subset of larvae were removed after the VMR

Brain Gene Analysis

 Genomic analysis was conducted at Mississippi State University, Institute for Genomics, Biocomputing and Biotechnology. Total RNA was isolated from 6 embryos' brains per treatment from individual 17 dpf embryos using the Qiagen RNeasy® Micro Kit (Germantown, MD, USA) following the Purification of Total RNA from Animal and Human Tissues protocol in the RNeasy® Micro Handbook with slight modifications. The modification included homogenization of brain tissue in 350 µL of RLT buffer using a pellet pestle and elution of Total 310 RNA using 15 µL of RNase-free water. RNA quality was assayed using the Agilent High Sensitivity RNA ScreenTape System (Waldbronn, Germany) for the Agilent 2200 TapeStation (Palo Alto, CA, USA), and RNA was quantified using the NanoDrop 2000 (ThermoFisher Scientific, Waltham, MA).

Individual Based Model

 The model used in this study is described in Ivan et al. (In Review) with a few changes. First, the calibration in this study was unique to KF and did not include any other species. Second, the model in this study did not contain uncertainty as described in Ivan et al. (In Review). Lastly, this study added an additional time period of summer since KF have an extended spawning season and we wanted to investigate the possibility that seasonal changes in predation may occur.

 The IBM tracked 2500 individual larvae (based on wild densities) from hatch to juvenile 337 transition, defined at 24 mm ²³ or until 100 days, whichever occurred first (Figure S2). Daily, individuals forage, grow and experience mortality. Killifish forage on two types of prey. Foraging consists of prey encounters, handling time, capture success and consumption of nauplii and/or copepods. Swimming speed, handling time, larvae reactive distance and capture success 341 all determine how many prey an individual KF larval consumes. KF then grow $(G_{i,d} \text{ in } g/d)$ as

342
$$
G_{j,d} = C_{j,d} - R_{j,d} - F_{j,d} - U_{j,d} - S D A_{j,d}
$$

343 where $C_{i,d}$ (g/d) is the consumption of prey by larval fish j, $R_{i,d}$ is respiration (g/d), $F_{i,d}$ is egestion 344 (g/d), $U_{i,d}$ is the excretion (g/d) and $SDA_{i,d}$ (g/d) is the specific dynamic action. Consumption is 345 determined via the foraging but capped at $Cmax_{i,d} (g/d)$ as determined from the Wisconsin Bioenergetic equations²⁴. Finally, KF are monitored for starvation and predation mortality. 347 Predators of KF are adult KF and their predation rates are temperature dependent²⁴. Fish that die are removed from the daily loop, as are fish that reach 24mm. Output variables of interest are 1) the number of survivors (fry that reach the exit length within the 100 days) and 2) the mean growth rate (mm/d) of survivors.

 Sublethal effects of MeHg and PCB126 were incorporated into the model via multipliers derived from the Bayesian individual level predicted treatment posterior distributions (Table S13). The individual level posterior distributions were used to create 10,000 random values from a truncated normal distribution. If the posterior distribution was from a transformed behavior endpoint, then these random values were back transformed. From these random values, the multiplier distributions were generated (S12). Multipliers were placed on larval swimming speed from the locomotion assay; larval capture success of zooplankton, larval handling time of zooplankton, and larval reactive distance to zooplankton from the feeding assay. At the start of

 each simulation (replication), each model individual *j* was assigned a multiplier for each of the above four variables. For each simulated KF (*j*), a swimming speed multiplier (*SMj*) was generated as

$$
SM_j = TD_j / MD
$$

 where *TD^j* is the average speed (mm/s) by fish *j* and *MD* is the treatment mean average speed 364 (mm/s). Multipliers for handling time ($HM_i = TH_i/MH$), capture success ($CM_i = TC_i/MC$) 365 and reactive distance $(RM_i = TR_i/MR)$ were calculated for each experimental fish *j* as using the same procedure. Finally, the amount of time a fish was active was determined by the proportion of time fish were active in the locomotion assay. Proportions were derived from the posterior distributions for each scenario. If necessary, back-transformations were performed prior to the multiplier calculation. Lastly, the proportion of time a KF was actively searching for food or encountering a predator was scaled to the percent of time active larvae were in the locomotion assay by randomly assigning a time scaler to each fish at the beginning of the simulation (i.e. multiply 12 hours by percent of time active in assay).

 The model was calibrated using SCO KF such that growth rates were set to be approximately 0.3mm/d (unpublished). To determine if differences occurred between which season the adult fish spawn, we ran simulations for spring and summer runs. For spring runs beginning on Julian day 110, the first fish reached 24mm around day 53 with several individuals still growing but under the size of 24mm at the end of the model run (Figure S4). For the summer runs (Julian day 230), the first fish to reach 24mm at the end of the model run was on day 48 with few fish remaining in the simulation at the end of the model run (Figure S4).

Results

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Figure S1. Behavior assays used in this study to collect data on Atlantic killifish larvae for assessment of chemical responses and for inputs into the Individual Based Model.

Figure S2. Model flow chart showing daily processes included in the generalized individual-based model to assess contaminant effects on Atlantic killifish larval cohorts.

Figure S4. An example of the length (mm) verses simulation day for individual Scorton Creek control fish that were alive at the end of one run of a spring and summer scenario.

Figure S5. Significant mercury response patterns shared by gene expression and behavior endpoints in Scorton Creek (SCO) Atlantic killifish found in this study. Both the original and opposite behavior endpoint trends are listed. (HMM = Hidden Markov Chain model endpoint, TP = Transition Probability).

Figure S6. Significant PCB126 treatment patterns shared by gene expression and behavior endpoints in the New Bedford Harbor (NBH) Atlantic killifish found in this study. Both the original and opposite behavior endpoint trends are listed. (HMM = Hidden Markov Chain model endpoint, TP = Transition Probability).

Adverse Outcome Pathway

of the humour of uppured under running Kinhingh harvae (I minimum never occurring) upour in this brute							
Groups	SCO-Ctrl	$SCO-Hg$	SCO-PCB	NBH-Ctrl	NBH-PCB		
VMRs							
Number of Assays-Larvae	30	29	28	29	28		
Locomotion Assays							
Number of Assays-Larvae	56	68	31	66	35		
HMMs							
Number of Larvae Attempted and Fitted a							
Model	56	68	31	66	35		
Feeding Assays							
Number of Assays-Larvae	47	44	23	50	28		
Total Length (mm \pm SD)	10.78(0.77)	10.63(0.60)	9.80(0.98)	10.81(0.77)	10.35(0.80)		
Number of Larvae that did not consume							
Artemia	θ		θ	θ	0		

Table S1. Summary of the number of assays and Atlantic killifish larvae (*Fundulus heteroclitus*) used in this study

Table S2. Embryo treatment groups used in larval behavioral assays, where Atlantic killifish larvae originated from adults from Scorton Creek, MA (SCO) or New Bedford Harbor, MA (NBH). Larvae were fed low mercury (i.e. control) or high mercury (Hg) diets and exposed directly to PCB126 at nominal concentrations of 40 ng/L (Low PCB) or 400 ng/L (High PCB). Endpoints reported include hatching, survival and ratings for phenotypic abnormalities, including those specific to the heart. Lethal treatment groups (PCB126 400) were not used in larval behavior studies (DND = Did not determine, NA = not applicable).

a Estimated using previous experiments (Nacci et al. 1999)

 $\rm b$ Also exposed to \sim 300 ng tHg/g dw/day through salmon-based diet

Table S3. Description of behavior endpoints examined in this study.

THOIC SO. Description of centered endpoints extending in this state, Behavior Endpoint	Definition
Feeding Assay	
Prey Capture Probability	The number of artemia captures divided by the total number of artemia added to the assay
Prey Handling Time (sec)	The number of seconds between the prey capture attempt and resuming normal activity, averaged over all feeding capture attempts during the 5 min assay
Capture Attempt Ratio	The total number of prey capture attempts divided by the total number of artemia added to the assay.
Prey Miss Proportion	The number of prey capture attempts that missed the artemia divided by the total number of prey capture attempts during the assay.
Reaction Distance (proportion of body length)	The distance (mm) between the artemia and larva when the larvae first orientates (notices) the artemia divided by the larva total length (mm), averaged over all the feeding capture attempts during the 5 minute assay.
Visual Motor Response Assay	
Startle Magnitude (mm)	Per frame maximum speed within 5 seconds after the startle minus the speed at the time of the startle.
Startle Response time (sec)	Difference in time between the startle and the maximum speed traveled within 5 seconds after the startle
Locomotion and VMR Assay	
Swimming Bouts (per sec)	The number of active swimming bouts per second. Swimming was defined as movement at least 1 mm/s for more than 5 frames (0.166 sec).
Swimming Bout Duration (sec)	Duration of all swimming bouts averaged over the 5 minute period.
Swimming Bout Speed (mm/s)	Per frame swimming speed averaged during a swimming bout; average bout speed averaged over the 5 minute period.
Swimming Bout Turning Angle	Per frame turning angle averaged during a swimming bout; individual average bout turning angle averaged over the 5 minute period. Ranges from -3.14 to 3.14, where negative values indicate right turns and positive values indicate left turns.
Total Distance Traveled (mm)	Total distanced traveled during swimming bouts for the entire 5 minute assay.
Total Time Swimming (sec) Overall Step Length (mm)	Total time larvae were swimming during 5 minute test. Per frame distance traveled during a 0.033 second period (one frame to the next) averaged over the entire 5 minute test [i.e. includes zeros when fish moved less than 1 mm/s for more than 5 frames (0.166 sec)].
Overall Step Length Variation	Standard deviation of distance traveled during 0.033 second period (one frame to the next).
Overall Turning Angle	Per frame turning angle averaged over frames when fish were swimming. Ranges from -3.14 to 3.14, where negative values indicate right turns and positive values indicate left turns.
Overall Turning Angle	Standard deviation of per frame turning angle during 0.033 second period
Variation	(one frame to the next).
HMM Model Parameters	
Step Length (mm)	Per frame distance traveled during a 0.033 sec period (one frame to the next) while the larvae was in each behavior state.

Table S4. LDA cross validation results for different HMM behavioral states. $N = 50$ iterations. SD = standard deviation

Table S5. Model summary for each behavioral endpoint.

Table S6. Distributions and priors for parameters in models used to determine differences in treatments for locomotion behavior responses.

Model				
Table	Residual	Residual Variance	Batch Effect	Batch Effect Variance
S ₆	$\varepsilon \sim Normal(0,\sigma_{\varepsilon}^2)$	$\frac{1}{\sigma_{\varepsilon}^2} = \tau_j \sim I - \text{Gamma}(0.0001, 0.0001)$	$\varepsilon \sim Normal(0,\sigma_{\varepsilon}^2)$	$\frac{1}{\sigma_{\rm s}^2} = \tau_j \sim I - \text{Gamma}(0.01, 0.01)$
S7	$\varepsilon \sim Normal(0,\sigma_{\varepsilon}^2)$	$\sqrt{\sigma_{\varepsilon}^2} = \sigma_{\varepsilon} \sim U(0.01, 1000)$	$\varepsilon \sim Normal(0,\sigma_{\varepsilon}^2)$	$\sqrt{\sigma_{\varepsilon}^2} = \sigma_{\varepsilon} \sim U(0.01, 1000)$
S ₈	ε ~Student's $T(0,\sigma_{\varepsilon}^2, df)$	$\frac{1}{2} = \tau_i \sim I - \text{Gamma}(0.0001, 0.0001)$	ε ~Student's T $(0,\sigma_{\varepsilon}^2,df)$	$\frac{1}{-2} = \tau_j \sim I - \text{Gamma}(0.01, 0.01)$

Table S7. Normal distribution OpenBUGS model containing treatment and time of assay effects and a random batch effect used to analyze locomotion behavior endpoints.

```
#inits<-function(){
# list(batch.eff=runif(N2,-1000,1000),tau=runif(1,0,10),tau.a=runif(1,0,10))}
\#inits()model;
{
       for(i in 1:N)\{y[i]~dnorm(mu[i],tau)
       mu[i]<-mean+trt.eff[trt[i]]+time[i]*betta_mfn+batch.eff[batchid[i]]
       }
       mean~dnorm(0,1.0E-6)#make covariate effect priors
       #time
       betta mfn~dnorm(0,0.0001)#make fixed main effect priors
       trt.eff[1] < -0for (i in 2:5)\{trt.eff[i]~dnorm(0,1.0E-6)}
#make random effect of batch priors
       for (i in 1:N2)\{batch.eff[i]~dnorm(0,tau.a)
        }
#predict estimates
#cell means models
       for(j in 1:5)\{Trt.mean[j]<-mean+trt.eff[j]
       }
#initial values
       var<-1/tau
       var.a<-1/tau.a
       tau~dgamma(0.0001,0.0001)
       tau.a~dgamma(0.01,0.01)
#difference calculations
       trt1<-Trt.mean[1]#sco salmon-fed ctl
       trt2<-Trt.mean[2]#sco tuna/hg fed
       trt3<-Trt.mean[3]#sco salmon-fed pcb40
       trt4<-Trt.mean[4]#nbh salmon-fed ctl
       trt5<-Trt.mean[5]#nbh salmon-fed pcb40
       diftrt2 1 <- trt2-trt1pvaltrt21 <-step(diftrt21)
       diftrt3_1<-trt3-trt1
       pvaltrt3 1 \le-step(diftrt3 1)
       diftrt3_2<-trt3-trt2
       pvaltrt3_2<-step(diftrt3_2)
       diftrt4_1<-trt4-trt1
       pvaltrt4 1 < -step(diftrt4 1)
```

```
diftrt5_4<-trt5-trt4
       pvaltrt54 <-step(diftrt54)
       diftrt3_5<-trt3-trt5
       pvaltrt3_5<-step(diftrt3_5)
#ratio calculations
       ratiotrt2_1<-trt2/trt1
       ratiotrt3_1<-trt3/trt1
       ratiotrt3_2<-trt3/trt2
       ratiotrt4_1<-trt4/trt1
       ratiotrt5_4<-trt5/trt4
       ratiotrt3_5<-trt3/trt5
#posterior model checking, generate new obs based on model params mu, tau. assume normal dist
  for( i in 1 : N ) {
   ypred[i] ~ dnorm(mu[i], tau) }
#generate individual level predictions
   ypred 1 \sim dnorm(trt1,tau)#approximation of the individual observation, using average for other factors in
the model. 
   ypred 2 \sim dnorm(trt2,tau)#randomly selected individual
   ypred 3 \sim dnorm(trt3,tau)
   ypred 4 \sim \text{dnorm}(\text{tr}t4, \text{tau})ypred 5 \sim dnorm(trt5,tau)
#compute residuals using the kurtosis formula for both orig data (e) and rep data
  for( i in 1 : N ) {
   e[i] < -y[i]-mu[i] }
  SSE<-inprod(e[],e[])#sum of squares which is e squared
 ku < -sum(e[]) #sum up all values, there is one for each data point
  kpred<-sum(ypred[])
difs<-kpred-ku #find difference
difpval<-step(difs) #count how many times the rep data is larger than orig data
}
```
Table S8. Normal distribution OpenBUGS model containing treatment and time of assay effects and a random batch effect using uniform tau prior used to analyze locomotion behavior endpoints.

```
\#inits <-function() {
# list(batch.eff=runif(N2,-1000,1000),sdev=runif(1,0.01,1000),sdev.a=runif(1,0.01,1000))}
\#inits()model;
{
       for(i in 1:N)\{y[i]~dnorm(mu[i],tau)
       mu[i]<-mean+trt.eff[trt[i]]+time[i]*betta_mfn+batch.eff[batchid[i]]
       }
       mean~dnorm(0,1.0E-6)#make covariate effect priors
       #time
       betta mfn~dnorm(0,0.0001)#make fixed main effect priors
       trt.eff[1] < -0for (i in 2:5)\{trt.eff[i]~dnorm(0,1.0E-6)}
#make random effect of batch priors
       for (i in 1:N2}{
       batch.eff[i]~dnorm(0,tau.a)
        }
#predict estimates
#cell means models
       for(j in 1:5)\{Trt.mean[j]<-mean+trt.eff[j]
       }
#initial values
       sdev~dunif(0.01,1000)
       sdev.a~dunif(0.01,1000)
       var<-pow(sdev,2)
       var.a<-pow(sdev.a,2)
       tau-pow(sdev,-2)
       tau.a<-pow(sdev.a,-2)
#difference calculations
       trt1<-Trt.mean[1]#sco salmon-fed ctl
       trt2<-Trt.mean[2]#sco tuna/hg fed
       trt3<-Trt.mean[3]#sco salmon-fed pcb40
       trt4<-Trt.mean[4]#nbh salmon-fed ctl
       trt5<-Trt.mean[5]#nbh salmon-fed pcb40
       diftrt2 1 <-trt2-trt1pvaltrt21 <-step(diftrt21)
       diftrt3_1<-trt3-trt1
       pvaltrt3 1 \le-step(diftrt3 1)
       diftrt3_2<-trt3-trt2
       pvaltrt3 \, 2 \le-step(diftrt3 \, 2)
       diftrt4_1<-trt4-trt1
```

```
pvaltrt4 1 < -step(diftrt4 1)
       diftrt5_4<-trt5-trt4
       pvaltrt5_4<-step(diftrt5_4)
       diftrt3_5<-trt3-trt5
       pvaltrt3_5<-step(diftrt3_5)
#ratio calculations
       ratiotrt2_1<-trt2/trt1
       ratiotrt3_1<-trt3/trt1
       ratiotrt3_2<-trt3/trt2
       ratiotrt4_1<-trt4/trt1
       ratiotrt5_4<-trt5/trt4
       ratiotrt3_5<-trt3/trt5
#posterior model checking, generate new obs based on model params mu, tau. assume normal dist
  for( i in 1 : N) {
   ypred[i] ~ dnorm(mu[i], tau) }
#generate individual level predictions
   ypred 1 \sim dnorm(trt1,tau)#approximation of the individual observation
   ypred 2 \sim dnorm(trt2,tau)#randomly selected individual
   ypred 3 \sim dnorm(trt3,tau)
   ypred 4 \sim \text{dnorm}(\text{tr}t4, \text{tau})ypred 5 ~-dnorm(trt5,tau)
#compute residuals using the kurtosis formula for both orig data (e) and rep data
  for( i in 1 : N ) {
   e[i] < -y[i]-mu[i] }
  SSE<-inprod(e[],e[])#sum of squares which is e squared
 ku \leq sum(e[1]) #sum up all values, there is one for each data point
  kpred<-sum(ypred[])
difs<-kpred-ku #find difference
difpval<-step(difs) #count how many times the rep data is larger than orig data
}
```
Table S9. Student's t distribution OpenBUGS model containing treatment and time of assay main effects and a random batch effect used to analyze locomotion behavior endpoints.

```
#inits<-function(){
# list(batch.eff=runif(N2,-
1000,1000),df=runif(1,3,30),df.a=runif(1,3,30),tau=runif(1,0,10),tau.a=runif(1,0,10))}
\#inits()model;
{
       for(i in 1:N)\{y[i]~dt(mu[i],tau,df)
       mu[i]<-mean+trt.eff[trt[i]]+time[i]*betta_mfn+batch.eff[batchid[i]]
       }
       mean~dnorm(0,1.0E-6)#make covariate effect priors
       #time
       betta mfn~dnorm(0,0.0001)#make fixed main effect priors
       trt.eff[1] < -0for (i in 2:5)trt.eff[i]~dnorm(0,1.0E-6)}
#make random effect of batch priors
       for (i in 1:N2}{
       batch.eff[i]~dt(0,tau.a,df.a)
        }
#predict estimates
#cell means models
       for(i in 1:5)\{Trt.mean[j]<-mean+trt.eff[j]
       }
#initial values
       df~dunif(3,30)
       df.a \sim \frac{dunif(3,30)}{2}var<-1/tau
       var.a<-1/tau.a
       tau~dgamma(0.0001,0.0001)
       tau.a~dgamma(0.01,0.01)
#difference calculations
       trt1<-Trt.mean[1]#sco salmon-fed ctl
       trt2<-Trt.mean[2]#sco tuna/hg fed
       trt3<-Trt.mean[3]#sco salmon-fed pcb40
       trt4<-Trt.mean[4]#nbh salmon-fed ctl
       trt5<-Trt.mean[5]#nbh salmon-fed pcb40
       diftrt2_1<-trt2-trt1
       pvaltrt21 <-step(diftrt21)
       diftrt3_1<-trt3-trt1
       pvaltrt3 1 \le-step(diftrt3 1)
       diftrt3_2<-trt3-trt2
```

```
pvaltrt3 \, 2 \le-step(diftrt3 \, 2)
        diftrt4_1<-trt4-trt1
        pvaltrt4_1<-step(diftrt4_1)
        diftrt5_4<-trt5-trt4
        pvaltrt5_4<-step(diftrt5_4)
        diftrt3_5<-trt3-trt5
        pvaltrt3_5<-step(diftrt3_5)
#ratio calculations
        ratiotrt2_1<-trt2/trt1
        ratiotrt3_1<-trt3/trt1
        ratiotrt3_2<-trt3/trt2
        ratiotrt4_1<-trt4/trt1
        ratiotrt5_4<-trt5/trt4
        ratiotrt3_5<-trt3/trt5
#posterior model checking, generate new obs based on model params mu, tau. assume normal dist
  for( i in 1 : N) {
   ypred[i] \sim dt(mu[i],tau,df) }
#generate individual level predictions
   ypred 1 ~-dt(trt1,tau,df)#approximation of the individual observation, using average for other factors in the
model. 
   ypred 2 ~ d(trt2,tau,df)#randomly selected individual
   ypred 3 \sim dt (trt3, tau, df)ypred 4 \sim dt (trt4, tau, df)ypred 5 ~ \text{d}t(\text{tr}t5, \text{tau}, \text{d}t)#compute residuals using the kurtosis formula for both orig data (e) and rep data
  for( i in 1 : N ) {
   e[i] < -y[i]-mu[i] }
  SSE<-inprod(e[],e[])#sum of squares which is e squared
 ku \leq sum(e[1]) #sum up all values, there is one for each data point
  kpred<-sum(ypred[])
difs<-kpred-ku #find difference
difpval<-step(difs) #count how many times the rep data is larger than orig data
}
```
Table S10. Normal distribution OpenBUGS model containing treatment, time of assay and days post hatch (dpf) effects used to analyze feeding behavior endpoints.

```
#inits<-function(){
# list(tau=runif(1,0,10))
#}
model;
{
       for(i in 1:N)\{y[i]~dnorm(mu[i],tau)
       mu[i]<-mean+trt.eff[trt[i]]+time[i]*betta_mfn+dpf[i]*betta_dpf
       }
       mean~dnorm(0,1.0E-6)#make covariate effect priors
       #time
       betta mfn~dnorm(0,0.0001)#dpf
       #independent gaussian priors for the linear covariate
       betta dpf~dnorm(0,0.0001)#make fixed main effect priors
       trt.eff[1]<-0
       for (i in 2:5)\{trt.eff[i]~dnorm(0,1.0E-6)}
#back transform the outputs
#cell means models
       for(j in 1:5)\{Trt.mean[j]<-mean+trt.eff[j]
       }
#initial values
       tau~dgamma(0.0001,0.0001)
       var<-1/tau
       trt1<-Trt.mean[1]#sco salmon-fed ctl
       trt2<-Trt.mean[2]#sco tuna/hg fed
       trt3<-Trt.mean[3]#sco salmon-fed pcb40
       trt4<-Trt.mean[4]#nbh salmon-fed ctl
       trt5<-Trt.mean[5]#nbh salmon-fed pcb40
       diftrt2 1 <-trt2-trt1pvaltrt21 <-step(diftrt21)
       diftrt3_1<-trt3-trt1
       pvaltrt3 1 <-step(diftrt3 1)
       diftrt3_2<-trt3-trt2
       pvaltrt3 \, 2 \le-step(diftrt3 \, 2)
       diftrt4_1<-trt4-trt1
       pvaltrt4 1 <-step(diftrt4 1)
       diftrt5_4<-trt5-trt4
       pvaltrt54 < -step(diftrt54)
       #diftrt6_4<-trt6-trt4
       #pvaltrt6 4 < -step(diftrt6 4)
```

```
#diftrt6 5 \le-trt6-trt5#pvaltrt6 5 \le-step(diftrt6 5)
       diftrt3_5<-trt3-trt5
       pvaltrt3 \le-step(diftrt3 \le)
#ratio calculations
       ratiotrt2_1<-trt2/trt1
       ratiotrt3_1<-trt3/trt1
       ratiotrt3_2<-trt3/trt2
       ratiotrt4_1<-trt4/trt1
       ratiotrt5_4<-trt5/trt4
       #ratiotrt6_4<-trt6/trt4
       #ratiotrt6_5<-trt6/trt5
       ratiotrt3_5<-trt3/trt5
#posterior model checking, generate new obs based on model params mu, tau. assume normal dist
 for(i in 1 : N) {
   ypred[i] ~ dnorm(mu[i],tau)
   }
#generate individual level predictions
   ypred 1 \sim dnorm(trt1,tau)#approximation of the individual observation, using average for other factors in
the model. 
   ypred 2 \sim dnorm(trt2,tau)#randomly selected individual
   ypred 3 \sim dnorm(trt3,tau)
   ypred 4 \sim dnorm(trt4,tau)
   ypred 5 \sim dnorm(trt5,tau)
   #ypred 6 \sim dnorm(trt6,tau)
#compute residuals using the kurtosis formula for both orig data (e) and rep data
  for( i in 1 : N ) {
   e[i] < -y[i]-mu[i] }
  SSE<-inprod(e[],e[])#sum of squares which is e squared
 ku \leq sum(e[1]) #sum up all values, there is one for each data point
  kpred<-sum(ypred[])
difs<-kpred-ku #find difference
difpval<-step(difs) #count how many times the rep data is larger than orig data
}
```
Table S11. Binomial distribution OpenBUGS model containing treatment, time of assay and days post hatch (dpf) effects used to analyze feeding endpoints.

```
\#inits <- function () {
# list(betta mfn=runif(1,0,5),Trt.mean=runif(5,0,5),tau=runif#(1,0,10),betta dpf=runif(1,0,5))
#}
\#inits()model
{
       for( i in 1 : N ) {
       y[i] \sim \text{dbin}(p[i], bs[i])e[i]~dnorm(0, \text{tau})logit(p[i]) < -time[i]*betta_mfn+dpf[i]*betta dpf+Trt.mean[trt[i]]+e[i]}
#set priors
       tau ~ dgamma(0.01, 0.01)var<-1/tau
#make covariate effect priors
       #time
       betta mfn~dnorm(0,0.0001)#dpf
       #independent gaussian priors for the linear covariate
       betta dpf~dnorm(0,0.0001)#make fixed main effect priors
       for (i in 1:5}{
       Trt.mean[i] \sim \text{dnorm}(0, 1.0E-6)}
#back transform the outputs
#cell means models
       for(i in 1:5)\{trt.eff[j]<-Trt.mean[j]-Trt.mean[1]
       }
#other values
       trt1<-1/(1+exp(-Trt.mean[1]))#sco salmon-fed ctl, back transformed trt mean, in the scale of the 
binomial prob. the probability of being attacked by the average population. do not back transformed
       trt2<-1/(1+exp(-Trt.mean[2]))#sco tuna/hg fed
       trt3<-1/(1+exp(-Trt.mean[3]))#sco salmon-fed pcb40
       trt4<-1/(1+exp(-Trt.mean[4]))#nbh salmon-fed ctl
       trt5<-1/(1+exp(-Trt.mean[5]))#nbh salmon-fed pcb40
       diftrt2 1<-Trt.mean[2]-Trt.mean[1]#compare on linear scale logit
       pvaltrt21 <-step(diftrt21)
       diftrt3 1<-Trt.mean[3]-Trt.mean[1]
       pvaltrt3 1 \le-step(diftrt3 1)
       diftrt3 2<-Trt.mean[3]-Trt.mean[2]
       pvaltrt3 \, 2 \le-step(diftrt3 \, 2)
       diftrt4_1<-Trt.mean[4]-Trt.mean[1]
       pvaltrt4 1 < -step(diftrt4 1)
       diftrt5 4<-Trt.mean[5]-Trt.mean[4]
       pvaltrt5 4 < -step(diftrt5 4)
```

```
diftrt3 5 <-Trt.mean[3]-Trt.mean[5]
        pvaltrt3\le-step(diftrt3\le)
#ratio calculations
        ratiotrt2 1 <-trt2/trt1 #use the back transformed scale
        ratiotrt3_1<-trt3/trt1
        ratiotrt3_2<-trt3/trt2
        ratiotrt4_1<-trt4/trt1
        ratiotrt5_4<-trt5/trt4
        ratiotrt3_5<-trt3/trt5
#posterior model checking, generate new obs based on model params 
        for( i in 1 : N ) {
                ypred[i] \sim dbin(p[i], bs[i]) }
#generate individual level predictions
        #need to estimate error for each group
        for(j in 1:5)\{ee[i]~dnorm(0, \text{tau})}
        ypred 1 < -1/(1+\exp(-(Trtmean[1]+\text{ee}[1])) #probability of bs capture by a random individual in trt1
        ypred 2 < -1/(1+\exp(-(Trt) \cdot \text{mean}[2]+\text{ee}[2]))ypred 3 < -1/(1+\exp(-(Trt) \cdot \text{mean}[3]+\text{ee}[3]))ypred 4 < -1/(1+\exp(-(Trt) \cdot \text{mean}[4]+\text{ee}[4]))ypred 5 < - 1/(1 + exp(-(Trt)mean[5] + ee[5]))
```
}

Table S13. A list of all behavior parameter distributions and resulting multipliers used to assess treatment impacts in the individual based model. Posterior distributions are from the individual level predicted responses and multipliers were generated from back transformed values. N indicates this behavior was significantly lower than the control, P indicates this behavior was significantly higher than the control.

Table S14. Posterior distributions for all model parameters and each behavioral endpoint.

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Table S15. Significant results of the treatment effects on Atlantic killifish larvae behavior after exposure to sublethal levels of MeHg and PCB126. Presented for each behavior endpoint and treatment is the mean (original or back-transformed), transformed mean, P-value in parentheses, and pattern of significant trends. Trends are based on original mean trends. P-values and trends are reported in the following order: SCO-Ctrl vs SCO-Hg, SCO-Ctrl vs SCO-PCB, SCO-Ctrl vs NBH-Ctrl, SCO-PCB vs NBH-PCB, NBH-Ctrl vs NBH-PCB (Neg = significant negative trend, Pos = significant positive trend, \square = no significant trend, HMM = Hidden Markov Chain model endpoint).

Table S16. Significantly differentially expressed genes (alpha = 0.05) found in the brains of Atlantic killifish *Fundulus heteroclitus* in this study. Significant trends and FDR value are reported (Ctrl = Control treatment, $Neg =$ significant negative trend, $Pos =$ significant positive trend, $SCO =$ Scorton Creek larvae, NBH = New Bedford Harbor larvae, Hg = methylmercury). Blanks indicate comparison was tested but did not result in a significant difference.

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Table S17. Significantly altered gene pathways (alpha = 0.05) found in the brains of Atlantic killifish *Fundulus heteroclitus* in this study. Significant trends and q-value are reported (Ctrl = Control treatment, Neg = significant negative trend, Pos = significant positive trend, SCO = Scorton Creek larvae, NBH = New Bedford Harbor larvae, Hg = methylmercury). Blanks indicate comparison was tested but did not result in a significant difference.

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Table S18. Significant MeHg treatment patterns shared by differentially expressed genes and behavior endpoints in Atlantic killifish *Fundulus heteroclitus* found in this study. Both the original and opposite behavior endpoint trends are listed (Neg = significant negative trend, Pos = significant positive trend, - = no significant trend, HMM = Hidden Markov Chain model endpoint).

Table S19. Significant PCB126 (PCB) treatment patterns shared by differentially expressed genes and behavior endpoints in Atlantic killifish *Fundulus heteroclitus* found in this study. Both the original and opposite behavior endpoint trends are listed (Ctrl = Control treatment, Neg = significant negative trend, Pos = significant positive trend, $NS =$ no significant trend, $HMM = Hidden Markov Chain model endpoint, TP =$ Transition Probability).

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Table S20. Significant PCB126 (PCB) treatment patterns shared by gene pathways and behavior endpoints in Scorton Creek (SCO) Atlantic killifish found in this study. Both the original and opposite behavior endpoint trends are listed (Ctrl = Control treatment, Neg = significant negative trend, Pos = significant positive trend, NS = no significant trend, HMM = Hidden Markov Chain model endpoint, TP = Transition Probability).

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Table S21. Summary of PCB126 (PCB) significant treatment patterns found in Atlantic killifish behavior endpoints (Ctrl = control treatment, Tan = significant negative trend compared to control, Blue = significant positive trend compared to control, Black = no significant trend compared to control, $HMM =$ Hidden Markov Chain model endpoint, $TP =$ Transition Probability).

Table S22. Summary of mercury (Hg) significant treatment patterns found in Atlantic killifish behavior endpoints (Ctrl = control treatment, Tan = significant negative trend compared to control, Blue = significant positive trend compared to control, Black = no significant trend compared to control, HMM = Hidden Markov Chain model endpoint, $TP =$ Transition Probability).

Table S23. Summary of mercury (Hg) and PCB126 significant treatment patterns found in Scorton Creek (SCO) and PCB126 (PCB) effects on New Bedford Harbor (NBH) Atlantic killifish behavior endpoints $(Ctr1 = control treatment, Tan = significant negative trend compared to control, Blue = significant positive$ trend compared to control, Black = no significant trend compared to control, HMM = Hidden Markov Chain model endpoint).

Table S24. Significant PCB126 (PCB) treatment patterns shared by gene expression and behavior endpoints in the endpoints in Scorton Creek (SCO) and New Bedford Harbor (NBH) Atlantic killifish found in this study. Genes with unknown names and functions are reported in Table S19. Both the original and opposite behavior endpoint trends are listed (Ctrl = control treatment, Tan = significant negative trend compared to control, Blue $=$ significant positive trend compared to control, Black $=$ no significant trend compared to control, HMM = Hidden Markov Chain model endpoint).

Neural: grna, fam53b, psma6a, nusap1, scinla, pmm2, ckma **Nucleic:** nrm, anapc15, olig4, tead3b, msx1a, nsmce2, emx2, heyl, nt5c2l1, foxn4, rad51ap1, her12, pane1, cpsf3, pagr1, spi1b, ascl1b **Signaling:** myl1, adh5, si:dkey-148a17.6, fcer1g, mylz3, pvalb3, hvcn1, sparc **Metabolic:** naga, lcat, gch2, rgs18, rac2 **Development:** acta1b, tnnt3a, vegfd, dla **Sensory:** vps28, lhfpl4b, bco1 Stress: slc25a39, cpn1 **Circulatory:** hcls1, ckmb, mb **Transport:** scamp4, cahz **Cellular:** nmrk1, mlc1, egln3, mibp, hs2st1b, vsir, rdh8a, tmem45a, si:dkey-9i23.16 **Imunity:** ctss2.1, tnfaip8l2b **Protein Binding and Synthesis:** sumf1 **Miscellaneous:** si:dkey-225f5.4, si:ch211-236d3.4, fam89b

Neural: atcaya, ubap1, hectd1, rnf41, tulp4a, lrrc4.1, neurl1aa, desi1a, lnx1, sema3ab, zdhhc17, cntnap2a, usp24 **Nucleic:** fam98a, seta, senp3b, bhlhe41, rerea, rc3h1b, rprd2a, grid2ipa, evx2, khdc4, tent4a, kdm3b, arid2, fut9a, znf346, rfx1b, elk4, qkia, foxj3, srfb, zfr2, klf6a, larp4ab, pdik1l, ssbp4 **Signaling:** erbin, spred2a, crk, map3k9, ppp3ccb, nlk1, araf, gramd4a, ndrg3a, zmym2, bmp2k, slit1b, ppp2r5ca, iqsec2b, gpr63, pdpk1b, dusp8a, gnb1b **Metabolic:** tbc1d22b, gal3st3, arfgap1, casd1, atp8a2, cdk17, pitpnab, pdk3a, ralaa, ptdss1a, nudt3b **Development:** tmem65 Stress: rlim, kmt2e **Circulatory:** mybpc2b **Transport:** atp1a3a, ptpn23a, scamp1, slc6a17, ap2b1 **Cellular:** ano8b, zgc:114120, tmem86a, asphd2, si:dkeyp-27e10.3, shank1, enah, ubap2a, kiaa1549la, tm9sf3, syt14a, zdhhc20b, clip3, tspan7b, klc2, ubap2l, dmtn **Digestive:** mtor **Protein Binding and Synthesis:**

Overall Turning Angle Period 2

Swimming Bout Duration Period 3 (sec), Total Distance Traveled (mm)

Total Time Swimming (sec) Ratio

Capture Attempt

Table S25. Individual based model results showing treatment means for individual larva survival and growth of Atlantic killifish *Fundulus heteroclitus* found in this study.

