**Supplementary Materials**

**Supplementary Text 1. Excluded data**

From the final sample of *N* = 34 mother-child and stranger-child dyads, functional near-infrared spectroscopy (fNIRS) data were excluded if a participant had more than 25% bad channels in a specific condition and electrocardiography (ECG) data were excluded if the participant had more than 5% missing heart beats. Furthermore, data were excluded of one mother-child dyad in all three conditions (mother-child baseline, mother-child cooperation, mother-child competition) because of a heart condition of the mother and of one stranger-child dyad in all three conditions (stranger-child baseline, stranger-child cooperation, stranger-child competition) because of a technical error. This resulted in unequal sample sizes for the six conditions and for the fNIRS and ECG data, depicted in Table S1.

**Table S1.**

Sample sizes for the ECG and fNIRS measurements in each of the six conditions.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | CoopM | CompM | CoopStr | CompStr | BaseM | BaseStr |
| *n*, ECG | 32 | 32 | 31 | 33 | 32 | 33 |
| *n*, fNIRS  | 32 | 33 | 34 | 34 | 31 | 33 |

*Note.* CoopM = mother-child cooperation, CompM = mother-child competition, CoopStr = stranger-child cooperation, CompStr = stranger-child competition, BaseM = mother-child baseline, BaseStr = stranger-child baseline.

**~~Supplementary Text 2. Procedures and task descriptions~~**

**~~Procedures~~**~~. Prior to the experiment, participants were instructed not to exercise, not to drink alcohol or energy drinks and not to smoke at least one hour before the lab visit, as these factors may influence the autonomic nervous system (ANS) measurements. After arriving in the lab, first, ECG electrodes were attached to the participants’ bodies. This was done in the beginning of the testing session to give participants enough time to habituate to the procedure. Afterwards, the cooperative and competitive tasks were explained and five practice trials were provided for each. fNIRS optodes were placed on the participant’s heads shortly before the start of the measurements to reduce wearing times.~~

**~~Task descriptions.~~** ~~During~~ *~~cooperation~~*~~, the goal was to “catch the ball together” by reacting as simultaneously as possible (Fig. S1). In the beginning of each trial, two dolphins appeared and remained on the screen. After 2 s, a black circle appeared above the dolphins (‘ready’ signal) and was replaced by a colorful ball (‘go’ signal) after a variable time interval (0.6 s - 1.5 s). Dyads were asked to respond as simultaneously as possible after the ‘go’ signal had appeared via pressing a computer key. If the difference in response times was below a predefined threshold, both dolphins jumped to the ball (feedback screen, 1.5 s), caught the ball (result screen, 1.5 s) and earned a point. If the difference between the response times was above the threshold, only the faster dolphin jumped towards the ball (feedback screen), none of the dolphins caught the ball (result screen) and both participants lost a point. The temporal threshold was individually adjusted to the response times of the dyad (set to T = 1/8 [RT1 + RT2], where RT1 and RT2 indicate the response times of the two participants). If one of the players reacted too early, that is before the ‘go’ signal, the trial started again from the beginning and both players lost a point.~~

~~During~~ *~~competition~~*~~, the goal was to “catch and win the ball by oneself” by pressing the response key faster than the other partner after the ‘go’ signal had appeared (Fig. S1). Only the faster dolphin jumped to the ball (feedback screen, 1 s), caught the ball (result screen, 1 s) and earned a point while the slower participant lost a point. If both reacted equally fast with an error margin of 50 ms, both dolphins jumped to the ball (feedback screen), caught the ball (result screen) and gained a point. Again, if one of the players reacted too early, the respective player lost a point and the trial started from the beginning.~~

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**~~Fig. S1.~~**

~~Illustration of the experimental design. During cooperation (A), the task was to react as simultaneously as possible to a signal via button press, while during competition (B), the task was to react faster than the other partner to win. Each cooperative / competitive trial was organized in the following way: (i) wait screen showing the two dolphins for 2 s, (ii) display of ‘ready’ signal (black hollow circle) for a randomly sampled time interval of 0.6 s – 1.5 s, (iii) display of ‘go’ signal (colorful ball), (iv) feedback screen for 1.5 s / 1 s (cooperation / competition), and (v) result screen for 1.5 s / 1 s (cooperation / competition). RT = response time of the slower participant / faster participant (cooperation / competition).~~

**Supplementary Text 2. Task performance results**

Task performance was quantified first by calculating how mean response time (RT) differed between conditions (Table S2). Results showed that overall RTs were slower in the cooperation condition. Mean RTs across all conditions did not correlate with interpersonal neural synchrony (INS).

Behavioral synchrony was quantified as the mean of the absolute differences in response times – DRT (described in more detail in the main text). Results showing the correlations between this measure and the INS and ANS synchrony measures are depicted in Tables S6 - S11.

In addition, we calculated the relative number of joint wins during cooperation and competition, and the relative number of child wins during competition (Table S3). As expected, dyads won more often during cooperation than during competition (μ = -0.29, CI = [-0.33, -0.26]), however no partner differences were found across conditions (μ = -0.01, CI = [-0.04, 0.03]) and no interaction between task and partner (μ = 0.04, CI = [-0.02, 0.10]). In contrast, during competition, the child won more often against the mother than against the stranger (μ = 0.08, CI = [0.04, 0.12]). Taken together, these results indicate that only competitive but not cooperative task performance was influenced by the interaction partner, in so far as children won more often against their mothers than against strangers.

**Table S2.**

Descriptive results for behavioral response times (RT) of child and adult during cooperation and competition

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | **Mean-RT** |  |
|  |  | *Child* | *Adult* |  |
|  | *n* | *M* | *SD* | *M* | *SD* |  |
| **CoopM** | 34 | 0.44 | 0.10 | 0.45 | 0.10 |  |
| **CompM** | 34 | 0.34 | 0.04 | 0.36 | 0.04 |  |
| **CoopStr** | 34 | 0.45 | 0.09 | 0.46 | 0.10 |  |
| **CompStr** | 34 | 0.33 | 0.02 | 0.33 | 0.02 |  |

*Note.* Mean-RT = mean of the response times (in seconds); CompStr = stranger-child competition; CoopStr = stranger-child cooperation; CompM = mother-child competition; CoopM = mother-child cooperation.

**Table S3.**

Descriptive results for behavioral synchrony (operationalized as the mean of the absolute differences in response times-DRT) of actual and shuffled pairs as well as for the percentage of joint wins during cooperation and competition and the percentage of child wins during competition

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  | **Mean-DRT** |  | **Task Performance** |
|  |  | *Actual* | *Shuffled* |  | *Joint wins* | *Child wins* |
|  | *n* | *M* | *SD* | *M* | *SD* |  | *M* | *SD* | *M* | *SD* |
| **CoopM** | 34 | 0.13 | 0.08 | 0.18 | 0.04 |  | 0.59 | 0.15 |  |  |
| **CompM** | 34 | 0.09 | 0.03 | 0.11 | 0.02 |  | 0.32 | 0.14 | 0.42 | 0.12 |
| **CoopStr** | 34 | 0.12 | 0.04 | 0.18 | 0.04 |  | 0.62 | 0.11 |  |  |
| **CompStr** | 34 | 0.07 | 0.02 | 0.08 | 0.01 |  | 0.30 | 0.12 | 0.34 | 0.14 |

*Note.* Mean-DRT = mean of the absolute differences in response times (in seconds); Joint wins = relative number of joint wins; Child wins = relative number of child wins during competition; CompStr = stranger-child competition; CoopStr = stranger-child cooperation; CompM = mother-child competition; CoopM = mother-child cooperation.

**~~Supplementary Text 4. Task performance results – adaptations.~~**

~~We further considered trial-specific changes in performance by examining how performance changed as a result of the feedback screen, which gave information on who had responded more quickly or more slowly (in case of cooperation: only in trials in which the dyad had failed to achieve a win). To do this, we calculated the difference between the mean-DRT of the present trial and its subsequent trial, averaged across all ‘feedback’ trials of each block (Table S4). Thus, positive values indicate that the mean-DRT decreased in the subsequent trial, and participants adapted their response times after seeing the feedback. Results show that dyads adapted their RTs more strongly during cooperation than during competition (task effect: μ = 0.36, CI = [0.32, 0.41]). Further, some evidence was found that mother-child dyads adapted their RTs more strongly than stranger-child dyads (partner effect: μ = 0.04, CI = [-0.00, 0.09], 92.89% > 0). However, having a closer look at the partner effect, differences were only found for competition (CompM vs. CompStr; μ = 0.06, CI = [-0.00, 0.13], 94.18% > 0) but not for cooperation (Table S4). The dyad’s adaptations were not correlated with INS (Tables S9 – S14).~~

**Table S4.**

Descriptive results for the dyad’s adaptations during cooperation and competition

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | ***Adaptations*** |  |
|  | *n* | *M* | *SD* |  |
| **CoopM** | 34 | 0.10 | 0.04 |  |
| **CompM** | 34 | 0.04 | 0.03 |  |
| **CoopStr** | 34 | 0.10 | 0.04 |  |
| **CompStr** | 34 | 0.03 | 0.02 |  |

*Note.* Adaptations = average difference in Mean-DRT of the present and subsequent trial after receiving feedback on who was faster.CompStr = stranger-child competition; CoopStr = stranger-child cooperation; CompM = mother-child competition; CoopM = mother-child cooperation.

**Supplementary Text 3. Implementation of ECG data analysis**

The automatic R-peak detection algorithm of the Vrije Universiteit Data Analysis and Management Software, Version 4.0 (VU-DAMS; Vrije Universiteit Amsterdam, 2015) was used to process the raw ECG signal. The resulting interbeat interval (IBI) time series were then further processed in Matlab (The MathWorks, Inc., Natick, MA). Specifically, we used the Matlab functions ‘fillmissing’ (method: ‘spline’) to interpolate missing values, ‘parcorr’ for the PACFs, ‘armax’ for ARIMA modelling and ‘xcorr’ (with zero time lag) for the calculation of the cross-calculation. To ensure an equal length of the IBI and fNIRS time series, we excluded the first and last four epochs of the resampled IBI signal (8 s each) in the baseline conditions, since these were outside the cone of influence of the wavelet coherence analysis (see Supplementary Text 6).

**~~Supplementary Text 6. Partial autocorrelations of IBI signals~~**

~~To examine the autocorrelative properties of the signals, partial autocorrelation functions (PACF) of the IBI time series after detrending, i.e., on the residuals after polynomial fitting, were plotted (Figs. S2 & S3). The partial autocorrelation measures the signal’s autocorrelation at lag k after removing effects of autocorrelations due to shorter lags. PACF results, averaged across participants, showed a strong autocorrelative component at lag = 1, likewise for adult (stranger / mother) and child and for all experimental conditions. At none of the other lags, the average autocorrelation exceeded the upper or lower confidence bounds. These results indicate that an ARIMA model with a lag = 1 is appropriate to effectively reduce the signals’ autocorrelations.~~

~~One further aspect of these results which is of note is the stronger autocorrelation at lag = 3 for the cooperative / competitive task relative to baseline (child PACF, baseline vs. cooperation: μ = 0.12, CI = [0.08, 0.16], baseline vs. competition: μ = 0.10, CI = [0.05, 0.14]; adult PACF, baseline vs. cooperation: μ = 0.16, CI = [0.11, 0.20], baseline vs. competition: μ = 0.14, CI = [0.10, 0.18]). Since the structure of our task was that, in the cooperation and competition conditions, trials were presented roughly once every six seconds (i.e., every three epochs given that a 2000 ms epoch was used), this likely reflects that both adult and child heart rate became entrained to the task structure.~~

~~Furthermore, for the child’s time series we found some evidence for an interaction between competition and partner, indicating that the child had higher PACF values at lag = 3 when competing against the stranger compared to the mother (μ = -0.06, CI = [-0.13, 0.01]). Similarly, for the adult’s time series, we found an interaction between competition and partner (μ = -0.08, CI = [-0.15, -0.00]) and some evidence for an interaction between cooperation and partner (μ = -0.06, CI = [-0.14, 0.01], 0.07% > 0), indicating that strangers had higher PACF values at lag = 3 during the two task conditions than mothers.~~

**~~~~**

**~~Fig. S2~~**~~.~~

~~PACF averaged across the child’s resampled IBI time series after detrending in the conditions: mother-child competition (CompM), mother-child cooperation (CoopM), stranger-child competition (CompStr), stranger-child cooperation (CoopStr), mother-child baseline (BaseM) and stranger-child baseline (BaseStr). Error bars represent standard errors. Across participants, the following mean lower and upper confidence bounds were found: CompM: ± 0.22; CoopM: ± 0.24; CompStr: ± 0.26; CoopStr: ± 0.24; BaseM: ± 0.21; BaseStr: ± 0.21.~~

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**~~Fig. S3~~**~~.~~

~~PACF averaged across the adult’s resampled IBI time series after detrending in the conditions: mother-child competition (CompM), mother-child cooperation (CoopM), stranger-child competition (CompStr), stranger-child cooperation (CoopStr), mother-child baseline (BaseM) and stranger-child baseline (BaseStr). Error bars represent standard errors. Across participants, the following mean lower and upper confidence bounds were found: CompM: ± 0.22; CoopM: ± 0.24; CompStr: ± 0.26; CoopStr: ± 0.24; BaseM: ± 0.21; BaseStr: ± 0.21.~~

**Supplementary Text 4. Wavelet coherence analysis on the IBI signal**

To validate our findings, we additionally calculated the wavelet coherence on the resampled IBI time series as a measure of ANS synchrony. To keep the analysis as similar as possible to the analysis of the fNIRS signal, the wavelet coherence was calculated on the detrended signal, i.e., on the residuals after polynomial fitting, and before the ARIMA modelling. The epoch length was chosen to be 1000 ms because a higher sampling rate is advantageous for the wavelet coherence analysis in accordance with the Nyquist theorem. Identical to the fNIRS analysis, we calculated the number of salient wavelet coherence values, above a cut-off value (here: 0.70) in a task-related frequency band between a period length of 2.02 s – 12.8 s (see Supplementary Text 6 for more details on the implementation).

BHM results showed an effect of baseline vs. cooperation (μ = 0.10, CI = [0.03, 0.16]), with higher synchrony of the cooperation compared to the baseline condition. Further, an interaction between stranger vs. mother and baseline vs. competition was observed (μ = -0.23, CI = [-0.36, -0.10]). Breaking down this two-way interaction, higher synchrony for competition compared to baseline was found only for stranger-child dyads (μ = 0.25, CI = [0.16, 0.35]) but not for mother-child dyads (μ = 0.02, CI = [-0.07, 0.12]). Further, stranger-child dyads had a higher synchrony than mother-child dyads for competition (μ = 0.16, CI = [0.06, 0.26]) but not for baseline (μ = -0.07, CI = [-0.19, 0.05]).

**Supplementary Text 5. Implementation of fNIRS preprocessing**

Preprocessing of fNIRS signals was conducted using functions of the SPM for fNIRS toolbox (1) and the Homer2 toolbox (2) in Matlab. Please see Table S5 for a detailed description of the functions and their parameters.

**Table S5.**

Description of the employed functions for fNIRS preprocessing and, if applicable, their parametrization.

|  |  |  |  |
| --- | --- | --- | --- |
| Objective | Source  | Function | Parameters |
| Conversion to optical density  | *Homer2* | hmrIntensity2OD | - |
| Motion artifact detection | *Homer2* | hmrMotionArtifactByChannel | SDthresh = 20, AMPthresh = 5, tMotion = 0.5 s, tMask = 0.9 s  |
| Motion artifact correction  | *Homer*2 | hmrMotionCorrectSpline | p = 0.99  |
| Conversion to HbO and HbR | *Homer2* | hmrOD2Conc | - |
| Detrending | *spm for fNIRS*  | spm\_fnirs\_dct | cut-off = 128 |

**Supplementary Text 6. Calculation of wavelet coherence**

For the dyad’s signals, denoted by $x and y,$ the wavelet coherence was calculated. Matlab routines from (3) and (4) were adjusted to enable extensive parametrization, to optimize the runtime and to ensure interoperability with high performance clusters.

To transform each signal into the time and ‘frequency’ space, the continuous wavelet transformation was performed using the generalized Morse wavelet (GMW, parameters: *β* = 3, *γ* = 3, normalization: unit peak energy). The GMW provides a high time-frequency concentration which enables a precise calculation of the coefficient matrices $W\_{x} and W\_{y}$ (5, 6). Subsequently, the modulus of $W\_{x}, W\_{y}$ and the power spectra $W\_{x y} $ were smoothed via Hanning windows in time and scale, here denoted by ‘*S*’. Finally, the wavelet coherence was calculated by (7*)*:

$$ R\_{x y}=\frac{\left|S\left(W\_{x y}\right)\right|}{\left[S\left(\left|W\_{x}\right|^{2}\right) S\left(\left|W\_{y}\right|^{2}\right) \right]^{1/2}}.$$

In accordance with the Nyquist sampling theorem, $R\_{x y}$ was calculated for a frequency range between 5 Hz and 0.016 Hz (period length: 0.2 s – 64 s). Furthermore, we mitigated potential dispersions at the signal’s ends by i) applying periodic padding and 2) considering only wavelet coefficients within the cone-of influence multiplied by two.

$R\_{x y}$ measures the relationship between two signals in time and frequency space, whereby $R\_{x y}=1$ describes a perfect relationship and $R\_{x y}=0$ the absence of any linear relationship between the signals. Yet, even totally unrelated signals tend to have a coherence $R\_{x y}>0.$ Hence, to avoid the influence of spurious coherence and to obtain a reliable estimator, we only considered salient coherence coefficients, higher than a cut-off value.

To calculate the cut-off value, 324 surrogate time series were generated by applying an AR(1) model based bootstrapping technique to each signal (3). Next, for each $R\_{x y}$, corresponding surrogate coherency matrices, $R\_{\hat{x}\_{i} \hat{y}\_{i}} with i= \{1,..,324\}$, were calculated. $R\_{x y}$ coefficients were considered salient if they were higher than 99% of the corresponding $R\_{\hat{x}\_{i} \hat{y}\_{i}}$ coefficients at the same time and scale. For each $R\_{x y}$, the minimum of the salient coefficients was determined and averaged across dyads and experimental conditions. This average, rounded to the second decimal place, constitutes the cut-off value (HbO: 0.65, HbR: 0.64).

Next, the percentage of coefficients of $R\_{x y}$, higher than the cut-off value, was calculated for a task-related frequency between 0.5 Hz and 0.08 Hz (period length: 2.02 s - 12.80 s). The percentage of salient wavelet coherence values was computed separately for each cooperative and competitive task block and the baseline condition.

**Supplementary Text 7. Implementation of the bipartite graph analysis**

The bipartite graph analysis was implemented in Python, using the package ‘NetworkX’(8). The analysis was parallelized via Dask (9).

For the cooperative and competitive task, the timing of the trials and the length of the task blocks differed between subjects due to the variable inter-trial interval and the subjects’ individual response times. To obtain time series of equal length for the shuffled pairs, the longer task block was cut at the end to have the same length as the shorter task block. Afterwards, blocks were reconnected (rest, task1, rest, task2, rest) and the wavelet coherence was calculated for the entire time series of the cooperative / competitive task.

**Supplementary Text 8. Implementation of the NMF**

The matrix decomposition was performed in Python via the machine learning package scikit-learn (10) and parallelized via Dask (9). The visualization was realized using Seaborn (11) and nilearn (12).

Specifically, the loss function of the NMF was minimized using the coordinated decent solver. We used the default reconstruction error (based on Frobenius norm), default tolerance for the stopping condition of the solver (1e-4) and up to 10.000 iterations to ensure reliable results. Moreover, the NMF was performed using nonnegative double singular value decomposition to ensure a sparse and meaningful representation (13).

The rank of the NMF, i.e., the number of components, was estimated based on the reconstruction error. For this purpose, we shuffled the original input matrix *V* in accordance to Frigyesi (14). Next, based on the Frobenius norm, the sum of squared residuals was calculated for the randomized and the original data. This procedure was repeated 100 times for each rank [2-10] to ensure reliable results. We identified the smallest rank that still preserved a larger information gain in the original data compared to the randomized data by determining the inflection point of the reconstruction error differences (see also 14, 15).



**Fig. S1.**

Mapping of NMF components (HbR) to brain regions. Channels and their positions, projected on a 3D glass brain, ~~corresponding MNI coordinates~~ are depicted on the left. The basis matrix is visualized as a heat map, showing the contribution of each fNIRS channel of child (C) and adult partner (P) (x-axis) to the corresponding component (y-axis).

**Supplementary Text 9. BHM implementations and quality checks**

BHM analyses were conducted using the R package ‘brms’ (16), which implements the BHM via the probabilistic programming language Stan (17). Prior to the analyses, missing INS and ANS synchrony values of actual dyads were imputed using multiple imputation with m = 20 in the R package ‘mice’ (18). Afterwards, the multiple imputed data frames were merged into a single data frame by computing the mean of the imputed values using the ‘merge\_imputations’ function of the R package ‘sjmisc’ (19).

For the BHM analyses, we chose the brms default priors, which are weakly informative and thereby have a negligible influence on the results (see 16). Models were fitted with three chains with 5000 samples each, whereby the first 2000 samples are warm-up samples. Joint posterior parameter distributions were approximated using the No U-Turn Sampler (NUTS, 20). To find the most parsimonious and accurate model, different candidate models were compared by their leave-one-out indices (LOO, 21), whereby smaller values indicate a better model fit (using the R package ‘loo’). We started with the maximum model justified by the experimental design, allowing the intercepts and experimental effects to vary by child (see 22 for model formulations), and then iteratively reduced the complexity of the models. Furthermore, for non-Gaussian distributed variables, models with Gaussian and lognormal response functions were compared and the models with the best predictive accuracy were chosen for inference. Of note is that models with a lognormal response distribution had a better fit for nodal and global graph metrics than models with a Gaussian response distribution, supporting the utility of the Bayesian approach to appropriately analyse the data. Since the logarithm is defined only for values > 0, for variables which included zero, a small constant value (0.1) was added to the data prior to the BHM analysis. Finally, convergence of the models was checked using the Gelman-Rubin statistic $\hat{R}$ and effective sample size (ESS) indices (provided in Table S12) as well as by visually inspecting the trace plots for funnels. Furthermore, to examine how well the model reflects the actually observed data, plots were generated which compare the observed outcome variable to the simulated datasets from the posterior predictive distribution (using the ‘pp\_check’ function of the R package ‘bayesplot’).

**Table S6.**

Correlations between synchrony measures in the mother-child competition condition

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
| 1: HbO density |  |  |  |  |  |  |  |
| 2: HbR density | 0.74, *p* < 0.001 |  |  |  |  |  |  |
| 3: IBI cross-correlation | 0.11, *p* = 0.57 | 0.28, *p* = 0.12 |  |  |  |  |  |
| 4: IBI wavelet coherence | 0.07, *p* = 0.72 | 0.11, *p* = 0.57 | 0.37, *p* = 0.036 |  |  |  |  |
| 5: Mean-DRT | 0.22, *p* = 0.22 | -0.05, *p* = 0.79 | -0.13, *p* = 0.46 | -0.05, *p* = 0.81 |  |  |  |
| 6: Adaptations | -0.12, *p* = 0.50 | 0.05, *p* = 0.77 | -0.17, *p* = 0.36 | -0.01, *p* = 0.97 | -0.30, *p* = 0.08 |  |  |
| 7: Joint wins | -0.15, *p* = 0.40 | 0.09, *p* = 0.63 | -0.11, *p* = 0.54 | 0.01, *p* = 0.94 | -0.68, *p* < 0.001 | 0.75, *p* < 0.001 |  |
| 8: Child age  | -0.13, *p* = 0.47 | 0.02, *p* = 0.91 | 0.16, *p* = 0.39 | -0.21, *p* = 0.24 | 0.04, *p* = 0.83 | 0.05, *p* = 0.78 | 0.03, *p* = 0.85 |

*Note.* Non-parametric Spearman correlations are reported. Prior to the correlation analyses, the mean across the two task blocks was calculated. Mean-DRT = mean of the absolute differences in response times; Adaptations = average difference in mean-DRT of the present and subsequent trial after receiving feedback on who was faster. Uncorrected *p*-values are provided.

**Table S7.**

Correlations between synchrony measures in the mother-child cooperation condition

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
| 1: HbO density |  |  |  |  |  |  |  |
| 2: HbR density | 0.39, *p* = 0.030 |  |  |  |  |  |  |
| 3: IBI cross-correlation | 0.07, *p* = 0.71 | 0.02, *p* = 0.93 |  |  |  |  |  |
| 4: IBI wavelet coherence | -0.03, *p* = 0.88 | 0.05, *p* = 0.81 | 0.41, *p* = 0.021 |  |  |  |  |
| 5: Mean-DRT | 0.19, *p* = 0.29 | 0.01, *p* = 0.96 | -0.31, *p* = 0.08 | -0.11, *p* = 0.54 |  |  |  |
| 6: Adaptations | 0.05, *p* = 0.79 | 0.01, *p* = 0.96 | -0.31, *p* = 0.09 | -0.34, *p* = 0.06 | -0.38, *p* = 0.026 |  |  |
| 7: Joint wins | -0.23, *p* = 0.20 | -0.08, *p* = 0.67 | 0.21, *p* = 0.24 | 0.06, *p* = 0.76 | -0.92, *p* < 0.001 | 0.53, *p* < 0.001 |  |
| 8: Child age  | -0.27, *p* = 0.14 | 0.15, *p* = 0.42 | 0.16, *p* = 0.39 | 0.01, *p* = 0.97 | -0.11, *p* = 0.55 | -0.23, *p* = 0.19 | 0.15, *p* = 0.39 |

*Note.* Non-parametric Spearman correlations are reported. Prior to the correlation analyses, the mean across the two task blocks was calculated. Mean-DRT = mean of the absolute differences in response times; Adaptations = average difference in mean-DRT of the present and subsequent trial after receiving feedback on who was faster. Uncorrected *p*-values are provided.

**Table S8.**

Correlations between synchrony measures in the stranger-child competition condition

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
| 1: HbO density |  |  |  |  |  |  |  |
| 2: HbR density | 0.46, *p* = 0.006 |  |  |  |  |  |  |
| 3: IBI cross-correlation | 0.35, *p* = 0.043 | 0.30, *p* = 0.09 |  |  |  |  |  |
| 4: IBI wavelet coherence | 0.21, *p* = 0.25 | 0.04, *p* = 0.82 | 0.37, *p* = 0.04 |  |  |  |  |
| 5: Mean-DRT | 0.24, *p* = 0.17 | 0.04, *p* = 0.82 | -0.07, *p* = 0.69 | 0.03, *p* = 0.89 |  |  |  |
| 6: Adaptations | -0.13, *p* = 0.48 | 0.29, *p* = 0.10 | -0.08, *p* = 0.67 | 0.13, *p* = 0.47 | -0.02, *p* = 0.91 |  |  |
| 7: Joint wins | -0.22, *p* = 0.22 | 0.25, *p* = 0.16 | 0.21, *p* = 0.24 | 0.16, *p* = 0.37 | -0.62, *p* < 0.001 | 0.59, *p* < 0.001 |  |
| 8: Child age  | -0.14, *p* = 0.44 | 0.24, *p* = 0.17 | 0.10, *p* = 0.57 | -0.01, *p* = 0.96 | -0.24, *p* = 0.17 | 0.36, *p* = 0.039 | 0.24, *p* = 0. |

*Note.* Non-parametric Spearman correlations are reported. Prior to the correlation analyses, the mean across the two task blocks was calculated. Mean-DRT = mean of the absolute differences in response times; Adaptations = average difference in mean-DRT of the present and subsequent trial after receiving feedback on who was faster. Uncorrected *p*-values are provided.

**Table S9.**

Correlations between synchrony measures in the stranger-child cooperation condition

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **1** | **2** | **3** | **4** | **5** | **6** |  |
| 1: HbO density |  |  |  |  |  |  |  |
| 2: HbR density | 0.17, *p* = 0.35 |  |  |  |  |  |  |
| 3: IBI cross-correlation | -0.01, *p* = 0.96 | 0.08, *p* = 0.68 |  |  |  |  |  |
| 4: IBI wavelet coherence | 0.38, *p* = 0.031 | -0.01, *p* = 0.97 | 0.23, *p* = 0.21 |  |  |  |  |
| 5: Mean-DRT | -0.06, *p* = 0.72 | -0.07, *p* = 0.70 | -0.07, *p* = 0.70 | 0.02, *p* = 0.92 |  |  |  |
| 6: Adaptations | 0.06, *p* = 0.75 | 0.19, *p* = 0.29 | 0.28, *p* = 0.12 | -0.17, *p* = 0.35 | -0.12, *p* = 0.48 |  |  |
| 7: Joint wins | 0.08, *p* = 0.65 | 0.00, *p* = 0.99 | 0.23, *p* = 0.22 | 0.04, *p* = 0.84 | -0.71, *p* < 0.001 | 0.36, *p* = 0.038 |  |
| 8: Child age  | -0.16, *p* = 0.37 | -0.02, *p* = 0.93 | -0.11, *p* = 0.57 | -0.16, *p* = 0.41 | 0.05, *p* = 0.78 | -0.50, *p* = 0.003 | -0.18, *p* = 0.32 |

*Note.* Non-parametric Spearman correlations are reported. Prior to the correlation analyses, the mean across the two task blocks was calculated. Mean-DRT = mean of the absolute differences in response times; Adaptations = average difference in mean-DRT of the present and subsequent trial after receiving feedback on who was faster. Uncorrected *p*-values are provided.

**Table S10.**

Correlations between synchrony measures in the mother-child baseline condition

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **1** | **2** | **3** | **4** |
| 1: HbO density |  |  |  |  |
| 2: HbR density | 0.43, *p* = 0.016 |  |  |  |
| 3: IBI cross-correlation | 0.12, *p* = 0.53 | 0.16, *p* = 0.40 |  |  |
| 4: IBI wavelet coherence | -0.09, *p* = 0.66 | -0.18, *p* = 0.35 | 0.13, *p* = 0.48 |  |
| 5: Child age (years) | -0.18, *p* = 0.34 | -0.07, *p* = 0.72 | -0.06, *p* = 0.73 | -0.01, *p* = 0.94 |

*Note.* Non-parametric Spearman correlations are reported. Uncorrected *p*-values are provided.

**Table S11.**

Correlations between synchrony measures in the stranger-child baseline condition

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **1** | **2** | **3** | **4** |
| 1: HbO density |  |  |  |  |
| 2: HbR density | 0.48, *p* = 0.004 |  |  |  |
| 3: IBI cross-correlation | -0.19, *p* = 0.30 | -0.00, *p* = 0.99 |  |  |
| 4: IBI wavelet coherence | 0.08, *p* = 0.66 | 0.23, *p* = 0.21 | -0.09., *p* = 0.62 |  |
| 5: Child age (years) | -0.28, *p* = 0.12 | 0.06, *p* = 0.74 | 0.01, *p* = 0.95 | 0.04, *p* = 0.83 |

*Note.* Non-parametric Spearman correlations are reported. Uncorrected *p*-values are provided.

**Supplementary Text 10. HbR results**

**Neural synchrony on the global level.** Compared to shuffled pairs, increased INS was observed for mother-child competition (posterior mean (μ) = 0.12, 90% credible interval (CI) = [0.05, 0.20]) and mother-child cooperation (μ = 0.14, CI = [0.07, 0.21]). In none of the other conditions sufficient evidence was found for an increased INS of actual pairs.

When directly comparing the different conditions, we found strong statistical evidence for a partner effect (μ = 0.15, CI = [0.07, 0.24]) and a competitive task effect (μ = 0.08, CI = [0.00, 0.15]), with higher INS for mother-child dyads compared to stranger-child dyads and higher INS for competition compared to baseline. No sufficient evidence was found for an effect of cooperation or any of the two-way interactions between cooperation / competition and partner (Table S12).

**Neural synchrony on the nodal level.** Confirming the global density results, we found a partner effect in three out of four components (component 1: μ = 0.10, CI = [0.01, 0.18]; component 2: μ = 0.19, CI = [0.08, 0.30]; component 4: μ = 0.15, CI = [0.06, 0.25]) and a competitive task effect in component 3 (μ = 0.14, CI = [0.05, 0.23]). In addition, increased INS was observed for mother-child cooperation in component 3 (partner x cooperation interaction: μ = 0.20, CI = [0.03, 0.37]). For the parameter estimates please see Table S12. The brain regions which contribute most to these components in terms of their nodal densities are shown in Fig. S1.

**Relation to ANS synchrony.**Global density was predicted by the interaction of ANS synchrony with baseline vs. competition (μ = 0.87, CI = [0.28, 1.47]; Table S12). Breaking down this interaction, we found evidence for a positive effect of ANS synchrony on global density in the competition condition (μ = 0.84, CI = [0.51, 1.17]), however no evidence for an effect in the baseline condition. On the nodal level, results showed an interactive effect between ANS synchrony and baseline vs. competition in components 2, 3 and 4 as well as some evidence for an effect in component 1 (Table S12).

**Table S12** (Microsoft Excel format). Excel sheet with the full results of the Bayesian Hierarchical Models.

**Table S13.**

Descriptive results for neural synchrony, as assessed by HbO and HbR global density, of actual and shuffled pairs

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  | *HbO density* |  | *HbR density* |
|  |  | *Actual* | *Shuffled* |  | *Actual* | *Shuffled* |
|  | *n* | *M* | *SD* | *M* | *SD* |  | *M* | *SD* | *M* | *SD* |
| CoopM | 32 | 0.07 | 0.08 | 0.05 | 0.02 |  | 0.09 | 0.09 | 0.05 | 0.02 |
| CompM | 33 | 0.09 | 0.11 | 0.05 | 0.02 |  | 0.09 | 0.10 | 0.05 | 0.02 |
| CoopStr | 34 | 0.06 | 0.06 | 0.05 | 0.02 |  | 0.05 | 0.05 | 0.05 | 0.02 |
| CompStr | 34 | 0.07 | 0.11 | 0.05 | 0.03 |  | 0.06 | 0.07 | 0.05 | 0.02 |
| BaseM | 31 | 0.06 | 0.09 | 0.05 | 0.02 |  | 0.06 | 0.06 | 0.05 | 0.03 |
| BaseStr | 33 | 0.03 | 0.04 | 0.05 | 0.02 |  | 0.04 | 0.04 | 0.05 | 0.02 |

*Note.* CoopM = mother-child cooperation, CompM = mother-child competition, CoopStr = stranger-child cooperation, CompStr = stranger-child competition, BaseM = mother-child baseline, BaseStr = stranger-child baseline.

**Table S14.**

Descriptive results for the mean IBI of child and adult as well as ANS synchrony of actual and shuffled pairs measured by the cross-correlation and the wavelet coherence

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | ***Mean IBI (ms)*** |  | ***Cross-correlation*** |  | ***Wavelet Coherence*** |
|  |  | *IBI Child* | *IBI Adult* |  | *Actual* | *Shuffled* |  | *Actual* | *Shuffled* |
|  | *n* | *M* | *SD* | *M* | *SD* |  | *M* | *SD* | *M* | *SD* |  | *M* | *SD* | *M* | *SD* |
| CoopM | 32 | 794.0 | 116.7 | 840.3 | 109.7 |  | 0.09 | 0.12 | 0.01 | 0.02 |  | 0.06 | 0.05 | 0.04 | 0.01 |
| CompM | 32 | 789.0 | 112.4 | 835.7 | 106.1 |  | 0.12 | 0.11 | 0.01 | 0.01 |  | 0.05 | 0.04 | 0.04 | 0.01 |
| CoopStr | 31 | 794.9 | 107.7 | 787.6 | 108.9 |  | 0.10 | 0.11 | 0.02 | 0.02 |  | 0.05 | 0.05 | 0.05 | 0.01 |
| CompStr | 33 | 784.4 | 108.2 | 776.0 | 106.7 |  | 0.12 | 0.13 | 0.02 | 0.02 |  | 0.08 | 0.07 | 0.04 | 0.01 |
| BaseM | 32 | 798.3 | 123.9 | 856.7 | 115.5 |  | 0.03 | 0.13 | 0.00 | 0.01 |  | 0.05 | 0.06 | 0.04 | 0.01 |
| BaseStr | 33 | 799.8 | 118.2 | 803.1 | 95.8 |  | 0.01 | 0.13 | -0.00 | 0.01 |  | 0.03 | 0.03 | 0.04 | 0.01 |

*Note.* CoopM = mother-child cooperation, CompM = mother-child competition, CoopStr = stranger-child cooperation, CompStr = stranger-child competition, BaseM = mother-child baseline, BaseStr = stranger-child baseline.

**Supplementary Text 11. BHM results predicting ANS synchrony**

Because no direction of effects can be assumed, we additionally calculated models with ANS synchrony as the response variable and INS as predictor. Prior to the analysis, INS values were log transformed to reduce skewness. For both HbO and HbR, there was (some) evidence for an interaction effect of INS and baseline vs. competition on ANS synchrony (HbO: μ = 0.11, CI = [0.02, 0.20]; HbR: μ = 0.09, CI = [-0.02, 0.19], posterior samples above zero: 91.5% > 0). Breaking down this interaction, an effect was found for competition (HbO: μ = 0.05, CI = [0.01, 0.10]; HbR: μ = 0.11, CI = [0.06, 0.16]) but not for baseline (HbO: μ = -0.06, CI = [-0.14, 0.03]; HbR: μ = 0.02, CI = [-0.07, 0.11]). This indicates that only during competition, increased ANS synchrony was associated with increased INS.

**~~Supplementary Text 15. Relation between INS and behavioral synchrony~~**

~~For behavioral synchrony, BHMs were calculated with task (cooperation vs. competition), partner (stranger vs. mother) and behavioral synchrony (Mean-DRT) as well as the two-way interactions between task / partner and behavioral synchrony as predictors. For HbO, the BHM showed an interaction between task and behavioral synchrony on global density (μ = 4.02, CI = [1.87, 6.20]; Table S6). Breaking down this interaction, evidence for an effect of behavioral synchrony on INS was found only for competition: less synchronous responses were associated with higher INS (μ = 4.52, CI = [2.45, 6.58]). However, because no evidence was found for an effect of behavioral synchrony on HbR (Table S6), this finding is not further interpreted. For the effects on nodal density please refer to Table S6.~~

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