Childhood exposure to nonpersistent endocrine disrupting chemicals and multi-omic markers in a population-based child cohort

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Outline

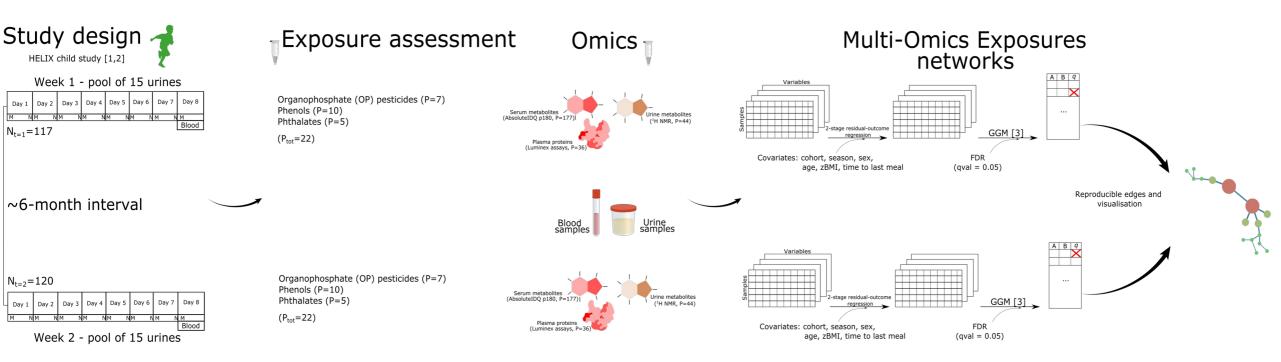
- Background & Objectives
- Methods
- Results
- Conclusions and Future Work

Background & Objectives

- The general population is exposed to a cocktail of chemical exposures
- Non-persistent endocrine disruptors (EDCs) are a class of chemicals that interfere with the endocrine system
- Multi-omic signatures might provide mechanistic insights into the effect of EDC exposure
- We aimed to identify multi-omic signatures associated with non-persistent EDCs using an integrative approach based on

Partial Correlation Networks

- Main idea: move from `single biomarker ~ single exposure` to
 `all biomarkers ~ all exposures` (i.e., integrative approach)
- First attempt: (s)PLS in regression mode
 - Issues: questionable predictive ability, models explained little variation in the Exposome
- Second attempt: regularized partial correlation coefficients and GGMs



- [1] Vrijheid M, et al. "The human early-life exposome (HELIX): project rationale and design." (2014)
- [2] Casas M, et al. "Variability of urinary concentrations of non-persistent chemicals in pregnant women and school-aged children." (2018)
- [3] Schafer J, Strimmer K. "A Shrinkage Approach to Large-Scale Covariance Matrix Estimation and Implications for Functional Genomics." (2005)

Study design 🚽

HELIX child study [1,2]



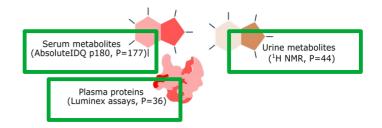
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Γ	Day 1	Day 2	Day 3	Day 4	Day 5	рау б	Day 7	₽ay	8
	M N	M N	M N	M N	M N	M N	M N	М	
	$N_{t=1} =$	117						Blo	od

Exposure assessment

Omics

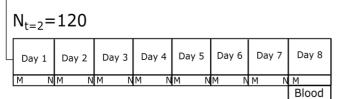
Organophosphate (OP) pesticides (P=7) Phenols (P=10) Phthalates (P=5)

$$(P_{tot}=22)$$



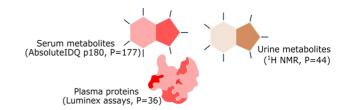


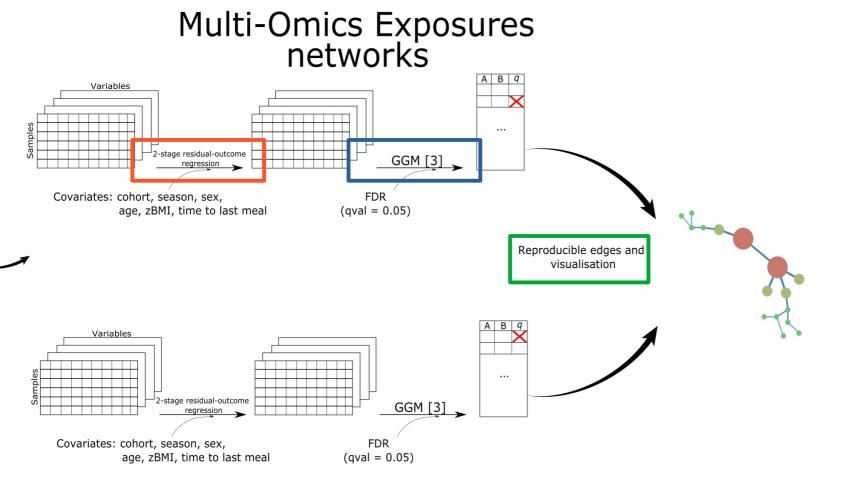
~6-month interval



Week 2 - pool of 15 urines

Organophosphate (OP) pesticides (P=7) Phenols (P=10) Phthalates (P=5) $(P_{tot} = 22)$





Pipeline (for each time point separately):

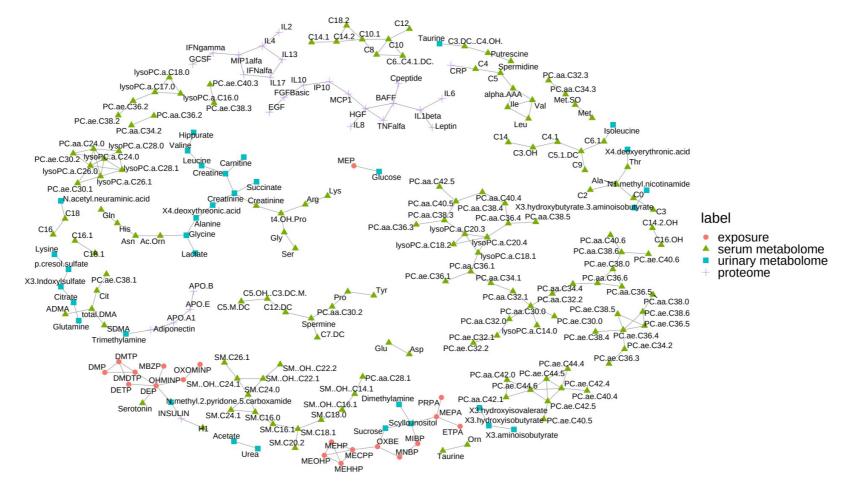
- Adjustment for covariates (-omics) using 2-stage residual-outcome regression (e.g., `residual(biomarkers ~ covariates)`)
- 2) Data transformation: auto-scaling
- 3) Merging exposures and -omics into single matrix
- 4) Computing correlations using `corpcor` R package (`pcor.shrink` function)
- 5) Processing: FDR at 0.05 significance level

Network **merging**:

- 6) Merge by node A, node B and direction (i.e., sign(rho))
- 7) Focus on Ccs with exposures and -omics

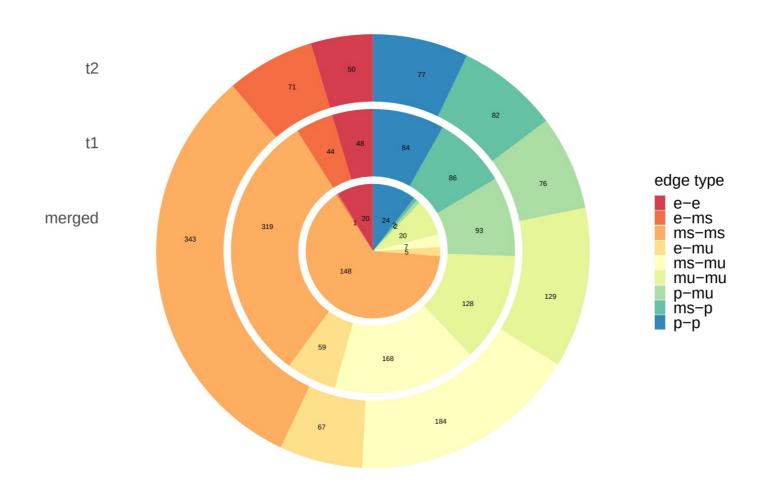
Results

- The time-specific networks (N_{edges} =1,064, N_{edges} =1,109) included associations of comparable strength (ρ =0.09 (-0.09, 0.11)) and statistical significance (q=0.008 (0.001, 0.025), q=0.01 (0.001, 0.027)). The significant edges represented less than 3% of the possible connections
- The merged network consisted of N_{edges}=229



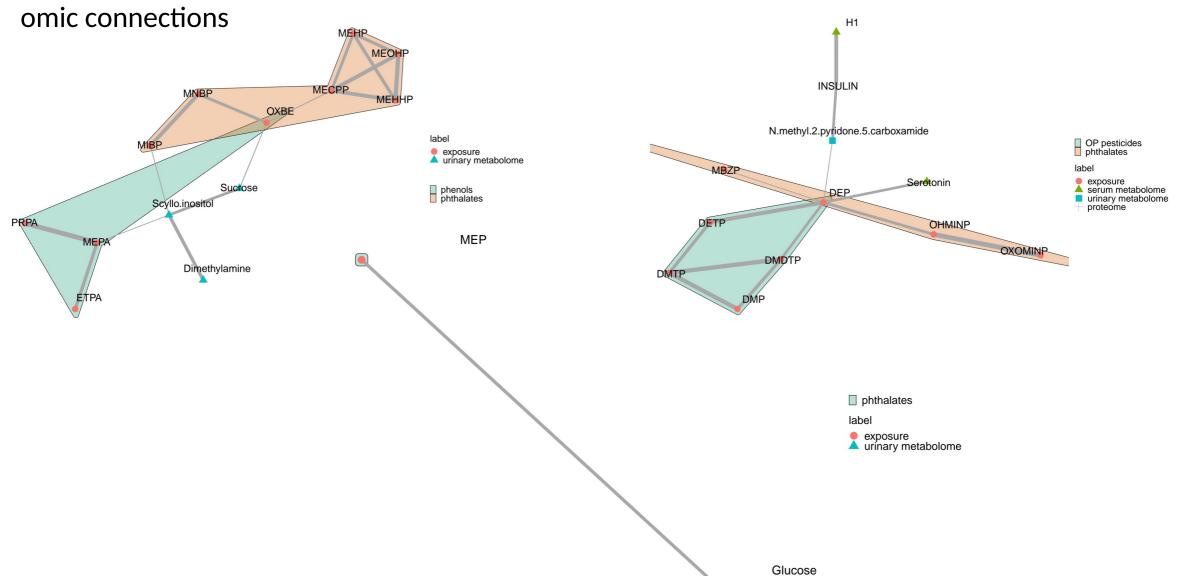
Results

 Graph merging led to the exclusion of the majority of exposure-omic connections. Notably, none of the protein-exposure associations were reproducible



Results

• The merged network consisted of 32 connected components, 3 of which included mixed exposure-



Conclusions

- We integrated Multi-Omic and exposure data from a child cohort using an integrative approach, and we identified associations reproducible across time points
- The association between **DEP** and **Serotonin** (ρ =0.09 for both time points) was reproducible. Exposure to Organophosphate pesticides has been linked to a variety of brain disorders [4], potentially through the serotonergic system

Conclusions

- In future work we plan to include methylation data
 - Large number of variables (also compared to dimension of other -omic layers)
 - Filtering CpG sites using agnostic EWAS: `beta_i ~ exposure_j + covariates` for all i's and j's (computationally expensive)
 - Controlling for multiple testing
 - Select top features
 - Perform analysis (i.e., GGMs) again
 - Interpretation of results