

Thank you to our Patrons



We will begin our presentation in a few minutes...



Leadership and Excellence in Environmental Engineering and Science

**When persistence
doesn't pay:
Integrative approaches to
understand and predict the
hazards of poorly studied
per- and polyfluoroalkyl
substances (PFAS).**

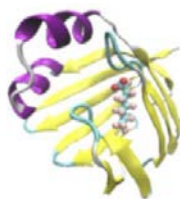
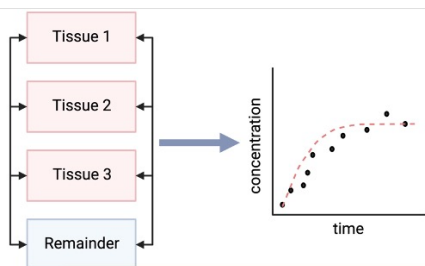


Carla Ng
Department of Civil & Environmental Engineering

AAEES Webinar
Wednesday, January 15, 2025



The Ng Lab at Pitt: Legacy and Emerging Chemicals in Human-Environment Systems



Organisms as Reactors

- Organism models used to predict tissue distribution of chemicals.
- Guide *who and how* to *sample* to protect ecosystems.

Molecular Models

- Understanding toxicity and remediation for degradation of “forever chemicals” (PFAS).

Human Exposure via Food

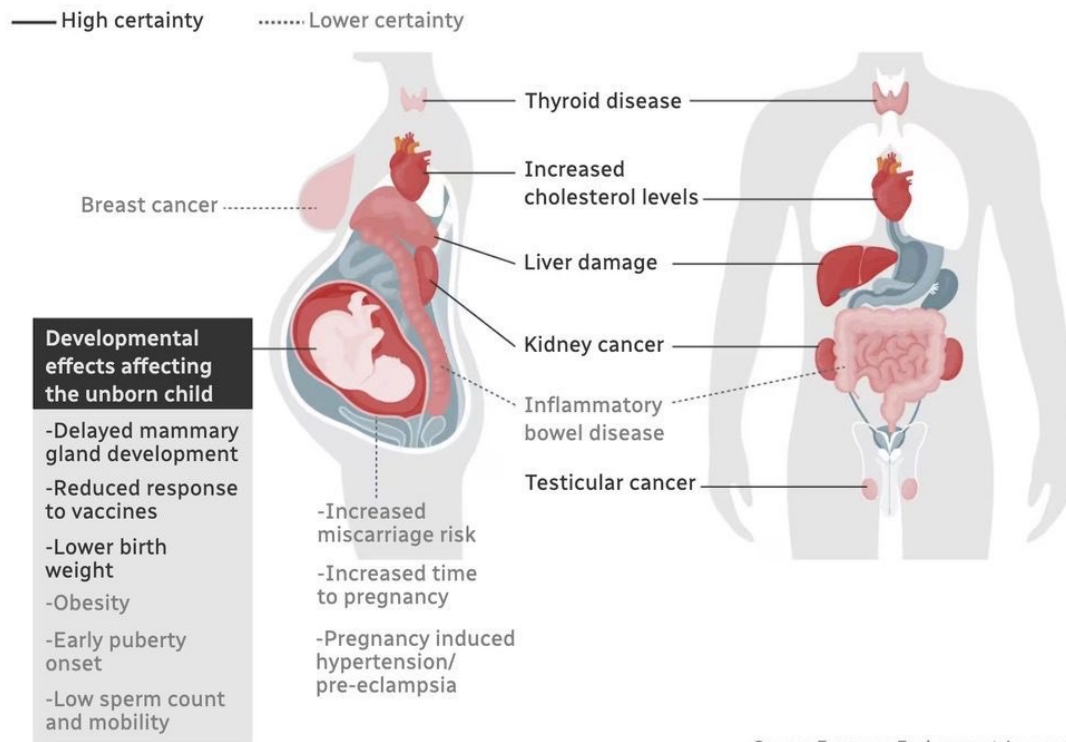
- PFAS in seafood and packaged foods.
- Pesticides, POPs, veterinary drugs in wild and farmed seafood.

Regional Contamination, Near and Far

- Sudden and chronic chemical releases in McKeesport, East Palestine, and Beaver County.
- Collaborative sampling in Ghana and Suriname₃

PFAS: Globally distributed... and global toxicants?

Existing studies on PFAS show effects on a multitude of organ systems.



Source: European Environment Agency (CBC)

PFAS are known to disrupt fetal development, cause liver damage and increase circulating cholesterol.

The IARC recently classified PFOA as carcinogenic to humans, and PFOS as possibly carcinogenic to humans.

Other effects with lower certainty show differing results across studies or between humans and animals.

The compilation of this information has taken decades.

Tissue distribution observations drive theories:

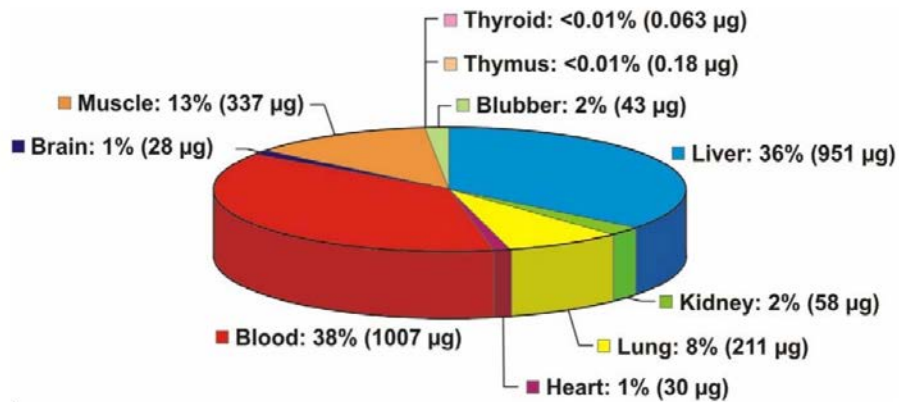
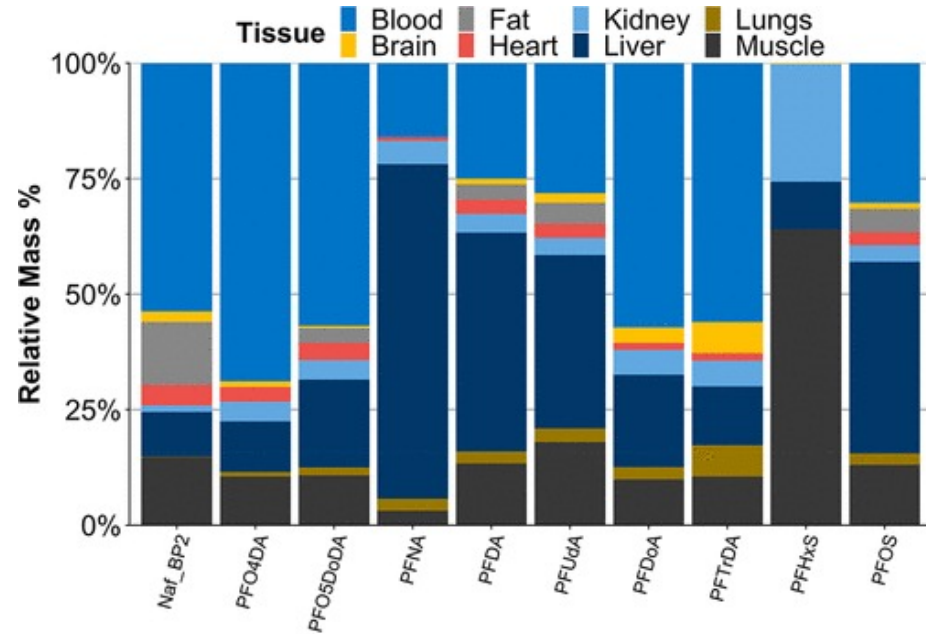


Fig. 1. PFC whole body burden distribution in percent and µg per tissue in brackets for harbor seals (*Phoca vitulina*) from the German Bight.

Ahrens et al. 2009: seals



Robuck et al. 2021: Cape Fear River Estuary birds.

Patterns of PFAS distribution in different species show:

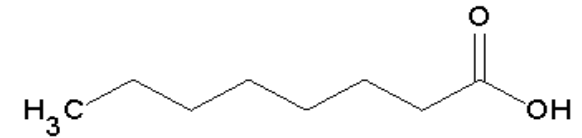
- Specificity (preference for specific tissues/components)
- Selectivity (different patterns for different PFAS).

What can PFAS molecular interactions tell us?

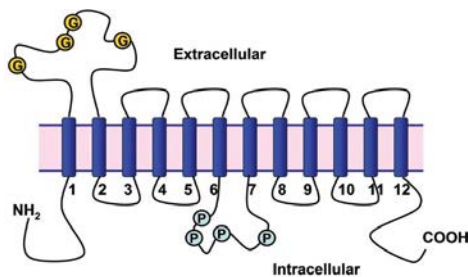
perfluorooctanoic acid (PFOA)



octanoic acid

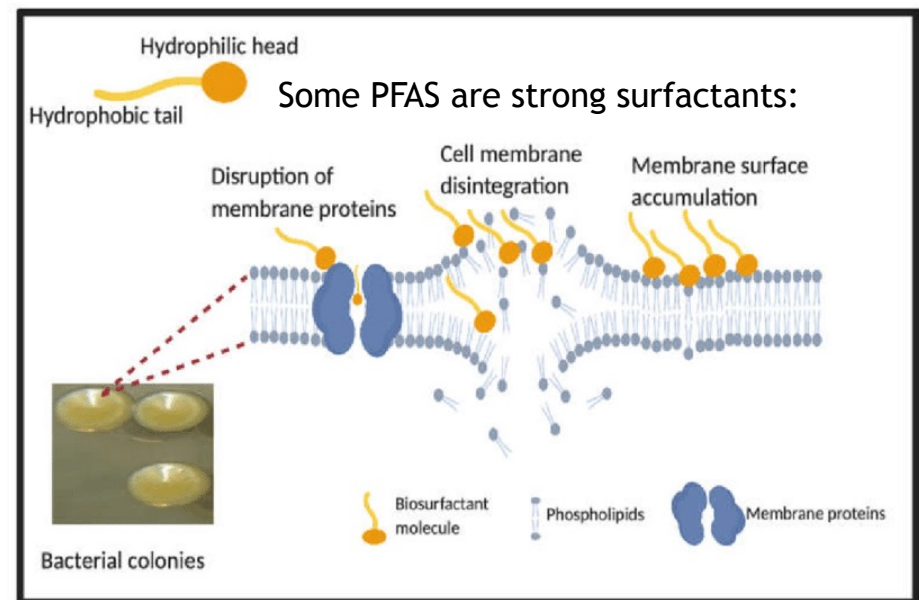


Fatty acid carriers in the body, e.g. serum albumin, liver fatty acid binding protein, bind PFAS.



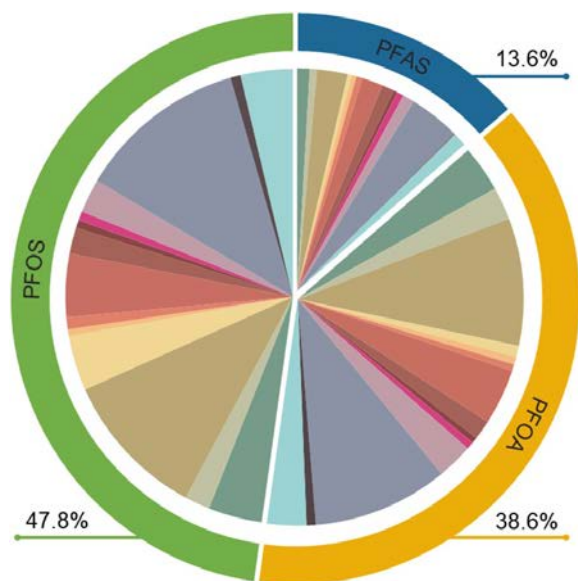
Nigam et al., 2015 Physiol. Rev

Organic anion transport proteins and polypeptides in the liver, kidneys, ... ?, mediate elimination rates.

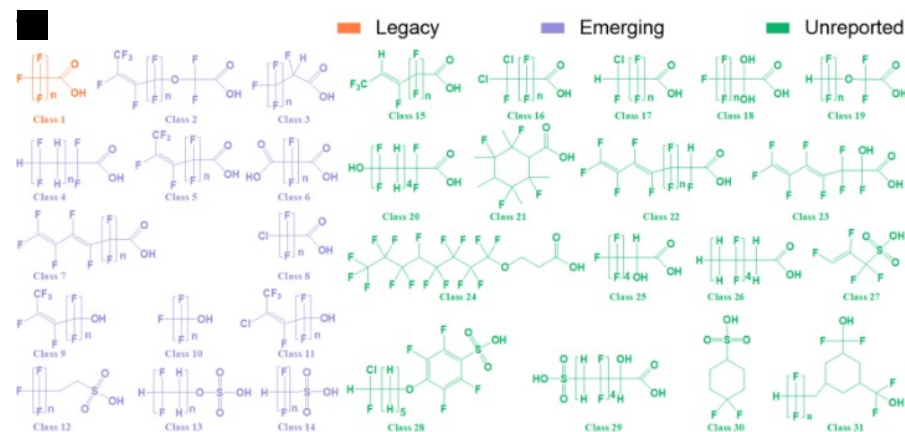


But: still many known and unknown unknowns

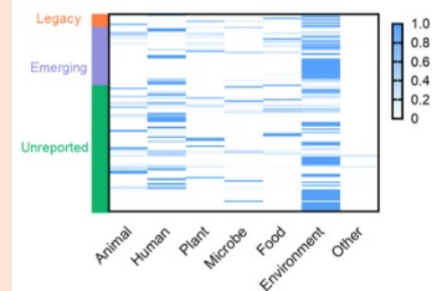
Most (>86%) toxicity studies have focused on only two PFAS: PFOA and PFOS. <15% addressed the thousands of other PFAS. Cell viability, endocrine, reproductive and metabolism effects were the most frequently studied endpoints.



Wee and Aris, *npj Clean Water* 2023

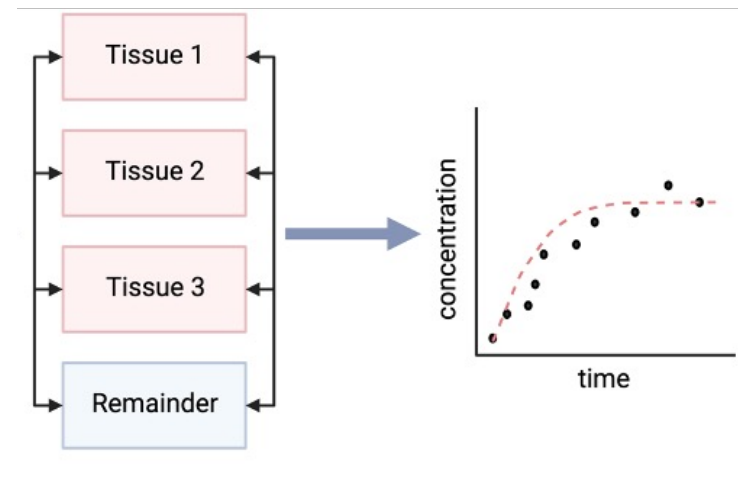
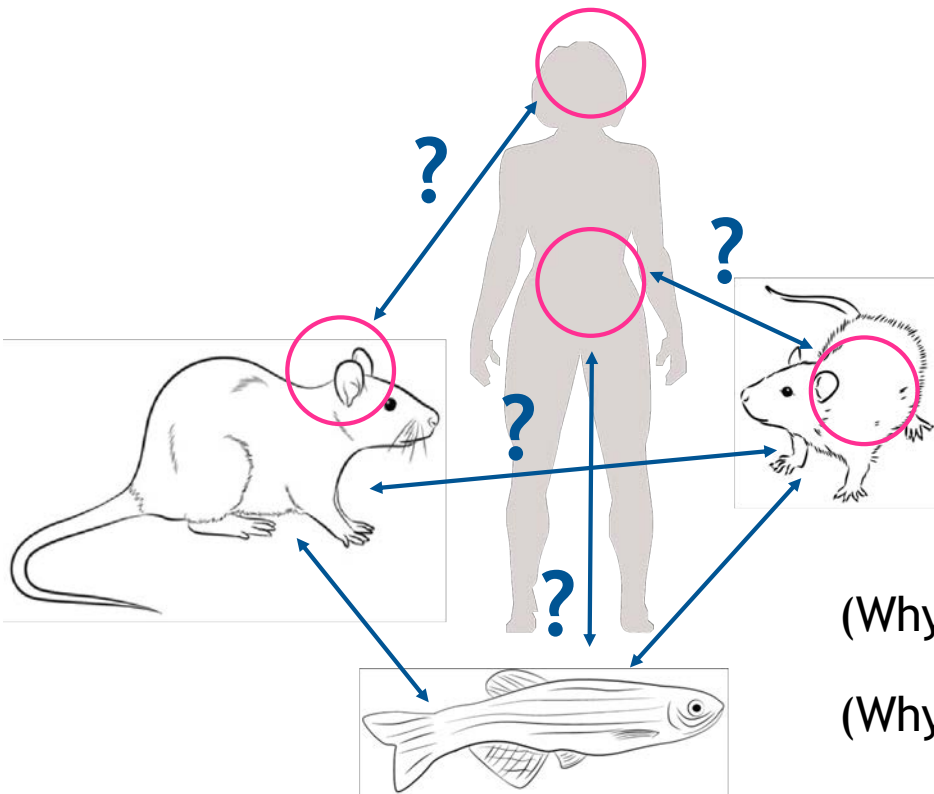


Retrospective analysis illustrates that humans, wildlife and the environment are exposed to many previously unreported PFAS, with no toxicity data and no standards available to enable laboratory testing.



Wang et al., *Science Advances* 2024

Key questions drive our integrative approaches:



(Why) do PFAS bioaccumulate?

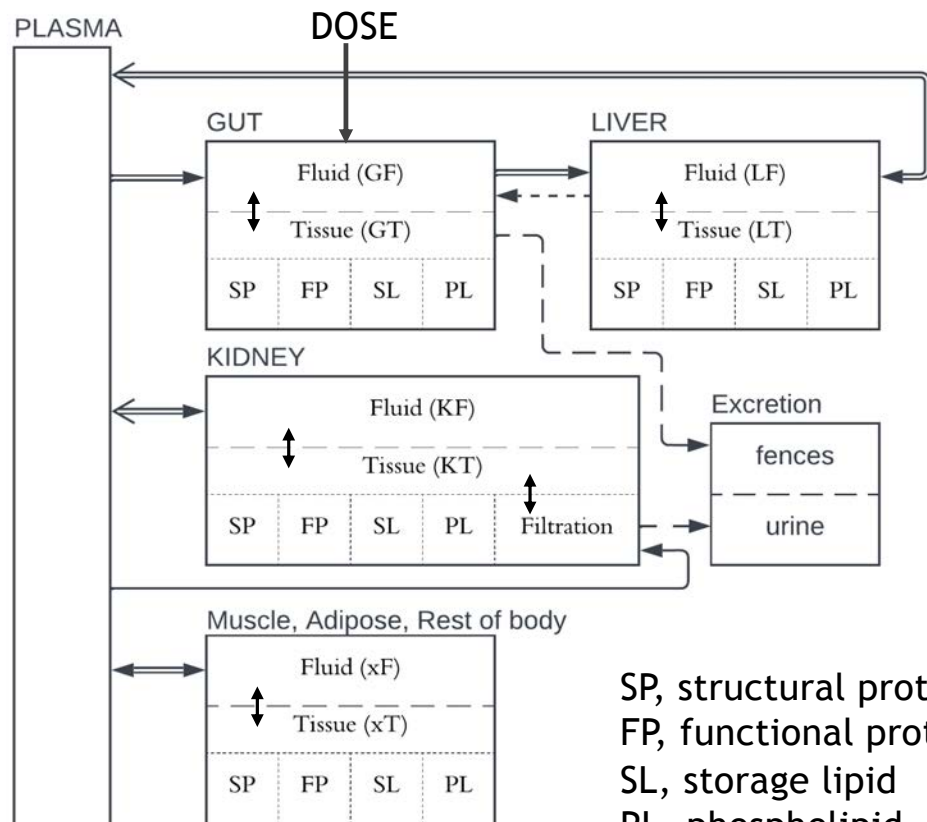
(Why) do they have preferential tissue distribution?

How does this impact toxicity?

Traditional (K_{OW} -based) metrics fall short.

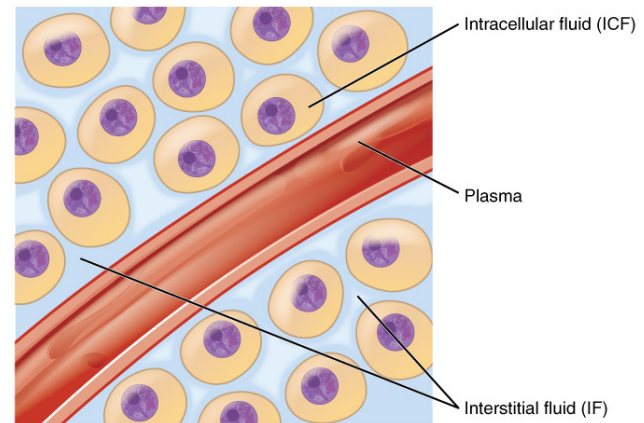


Ruiwen Chen



SP, structural protein
 FP, functional protein
 SL, storage lipid
 PL, phospholipid

Goal: Move from 2-phase partitioning to multi-phase distribution.



https://commons.wikimedia.org/wiki/File:2702_Fluid_Compartments_ICF_ECF.jpg

$$\begin{aligned}
 &K_{Tissue-Fluid} \\
 &= K_{PL}f_{PL} + K_{SL}f_{SL} + K_{SP}f_{SP} \\
 &+ K_{FP}f_{FP}
 \end{aligned}$$

In vitro assays to explore PFAS “partitioning”



Ruiwen Chen

Deriving Membrane–Water and Protein–Water Partition Coefficients from In Vitro Experiments for Per- and Polyfluoroalkyl Substances (PFAS)

Ruiwen Chen, Derek Muensterman, Jennifer Field, and Carla Ng*



Cite This: <https://doi.org/10.1021/acs.est.4c06734>

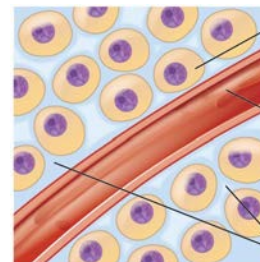
In this work, we investigated the distribution of PFAS to phospholipid membranes and HSA from the aqueous phase via laboratory measurements with 60 PFAS and subsequent modeling. Phospholipid membrane–water partition coefficients (K_{MW}) were measured with SSLM and specific binding to HSA was estimated by equilibrium dialysis. Then, the specific-binding curves from equilibrium dialysis were extrapolated to simulate the PFAS HSA/Water distribution ($D_{HSA/W}$).

Parsing out drivers of tissue distribution

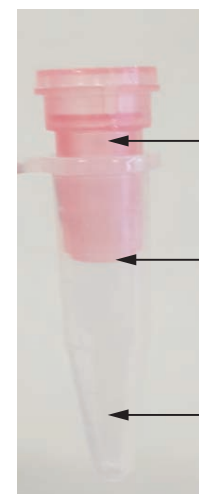
$$K_{tissue-fluid} = K_{PL}f_{PL} + K_{SL}f_{SL} + K_{SP}f_{SP} + K_{FP}f_{FP}$$



Equilibrium dialysis for **protein-PFAS** interactions (HSA) and SSLM assay (Transil assay) for **PFAS-phospholipid** interactions.



SP, structural protein
FP, functional protein
SL, storage lipid
PL, phospholipid



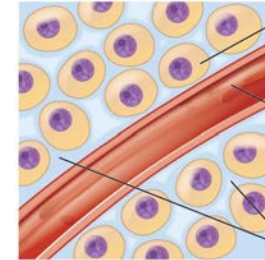
Protein and PFAS in buffer; protein restricted to 100 μ L volume within dialysis cup.

Dialysis membrane with molecular weight cutoff (MWCO) smaller than protein.

PFAS in buffer can diffuse across dialysis membrane to reach equilibrium between bound and unbound fraction.

Parsing out drivers of tissue distribution

$$K_{tissue-fluid} = K_{PL}f_{PL} + K_{SL}f_{SL} + K_{SP}f_{SP} + K_{FP}f_{FP}$$



SP, structural protein
 FP, functional protein
 SL, storage lipid
 PL, phospholipid

Measuring the SSM (PL=phospholipid) part *in vitro*:

$$K_{MW} = \frac{C_{PFAS,M}}{C_{PFAS,W}} = \frac{(C_{spike} - C_{PFAS,W}) \cdot V_W}{C_{PFAS,W} \cdot M_{PL}}$$

Note: for very hydrophobic PFAS, needed to account for sorption to assay surfaces!

Measuring the HSA (FP=functional protein) part *in vitro*:

$$K_A = \frac{[HSA \cdot PFAS]}{[HSA] \cdot [PFAS]} = \frac{1}{K_D} = \frac{k_{on}}{k_{off}}$$

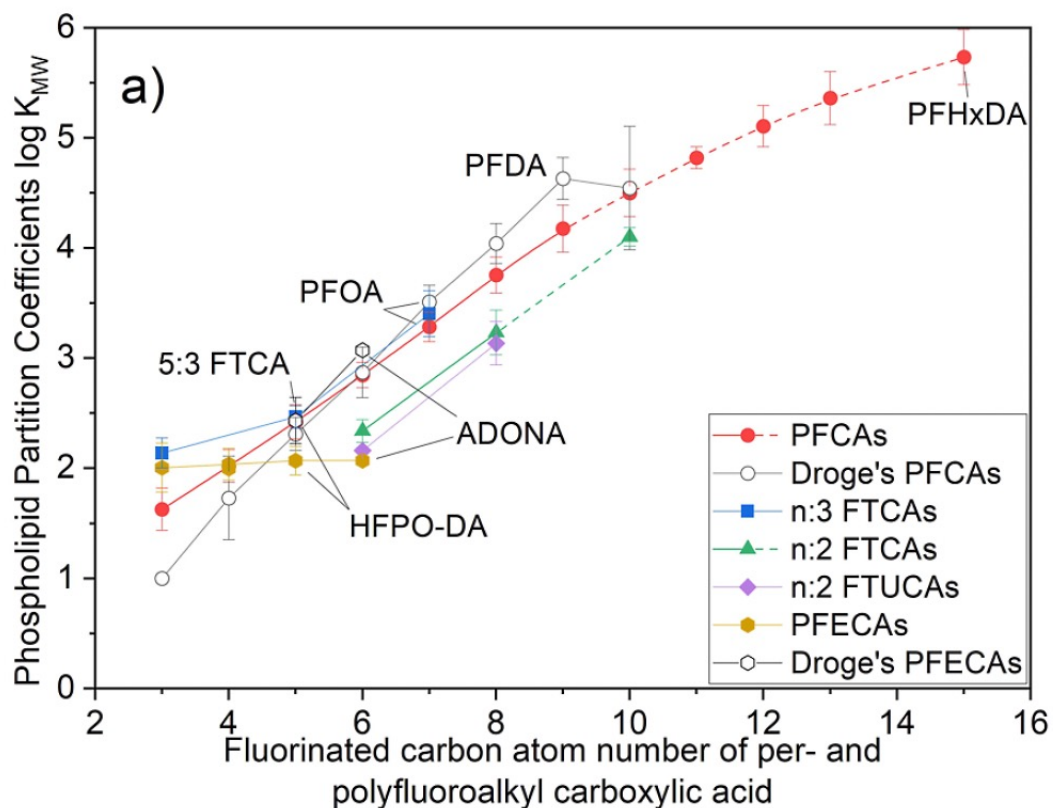
$$\text{total specific binding} = \frac{[HSA \cdot PFAS]}{[\text{total HSA}]} = \frac{[PFAS^*] \cdot B_{max}}{[PFAS^*] + K_D}$$



$$D_{HSA/W} = \frac{B_{max} \cdot \rho_{HSA}}{\left(K_D + \frac{C_{aq}}{MW_{PFAS}} \right) \cdot MW_{HSA}}$$

More complicated!

Results: Some PFAS prefer membranes



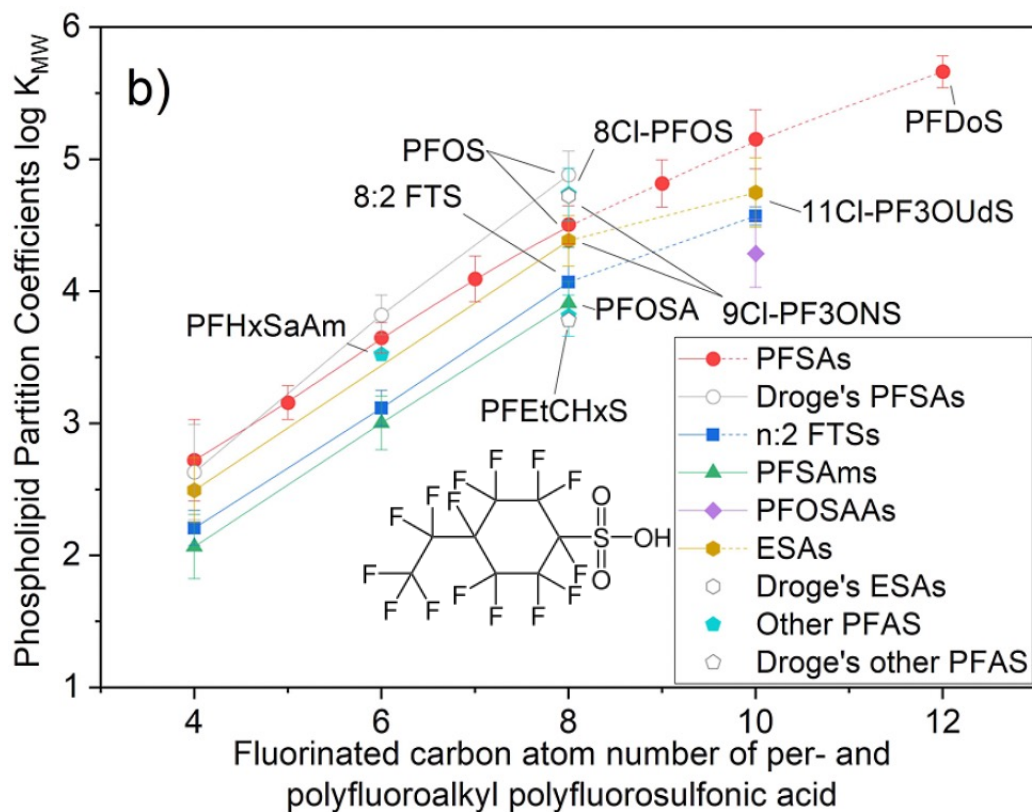
For per- and polyfluoroalkyl carboxylic acids, our results generally agree with and extend the foundational datasets generated by Stephen Droge (<https://pubs.acs.org/doi/10.1021/acs.est.8b05052>, <https://pubs.rsc.org/en/content/articlelanding/2021/em/d1em00327e>).

We found an increase of 0.36 ± 0.01 in K_{MW} per FC.

PFCAs and FTCAs generally increase with chain length, though n:2 FTCAs and FTUCAs are on a different intercept.

No such relationship observed for ether carboxylic acids (PFECAs).

Results: Some PFAS prefer membranes

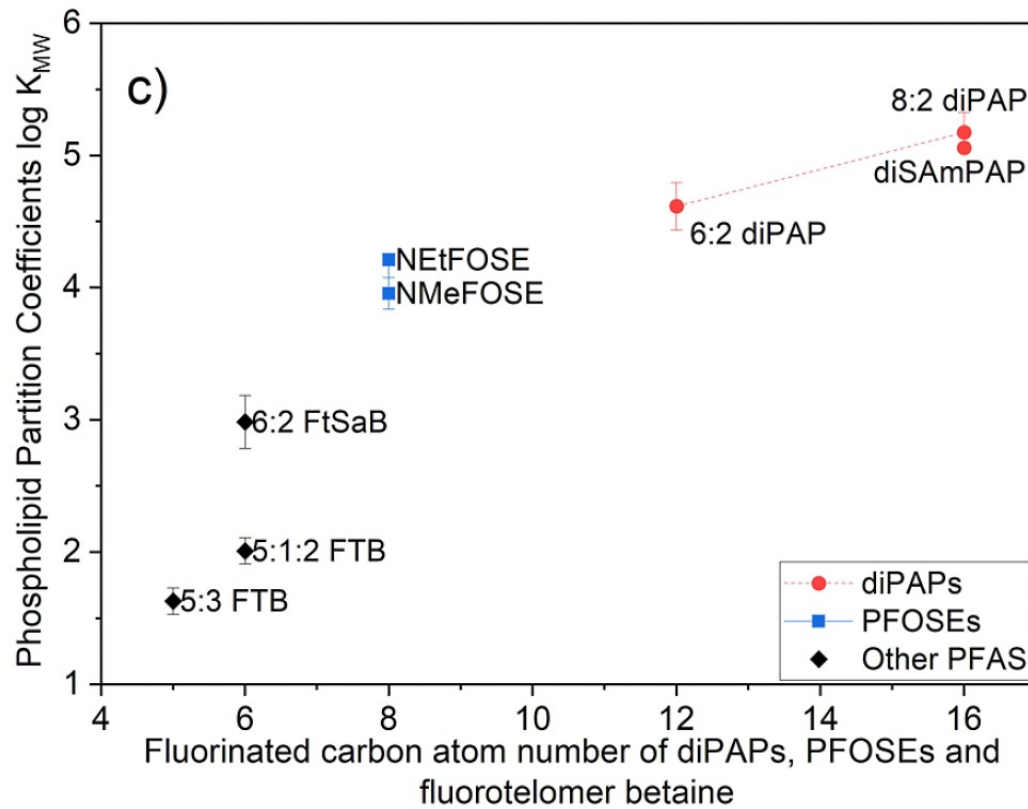


Greater diversity of groups represented within the sulfonates, but slopes are consistent:
We see a 0.37 ± 0.02 log-unit increase per FC.

Sulfonamides and fluorotelomers fall at lower end of intercepts, suggesting effect of lower surface activity on membrane interactions.

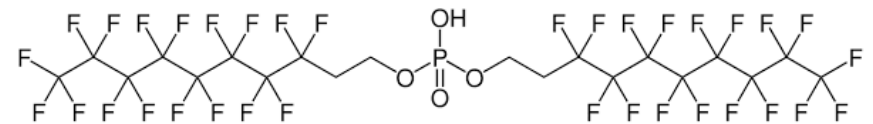
Among C8 sulfonates, PFOS has the highest K_{MW} whereas the cyclic PFETCHxS has the lowest.

Results: Some PFAS prefer membranes



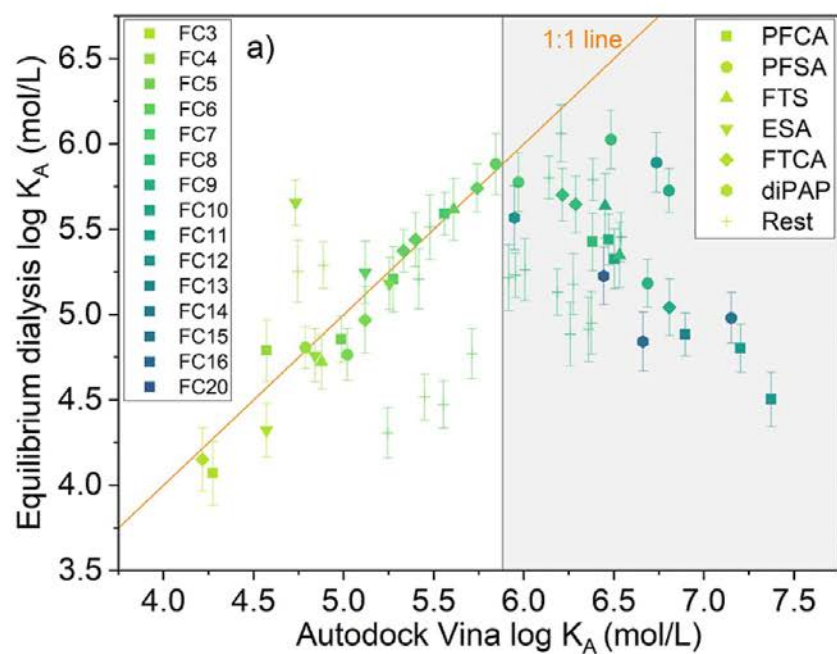
For other groups, too few data points across FCs for clear relationships.

DiPAPs show high K_{MW} due to large number of FC groups.

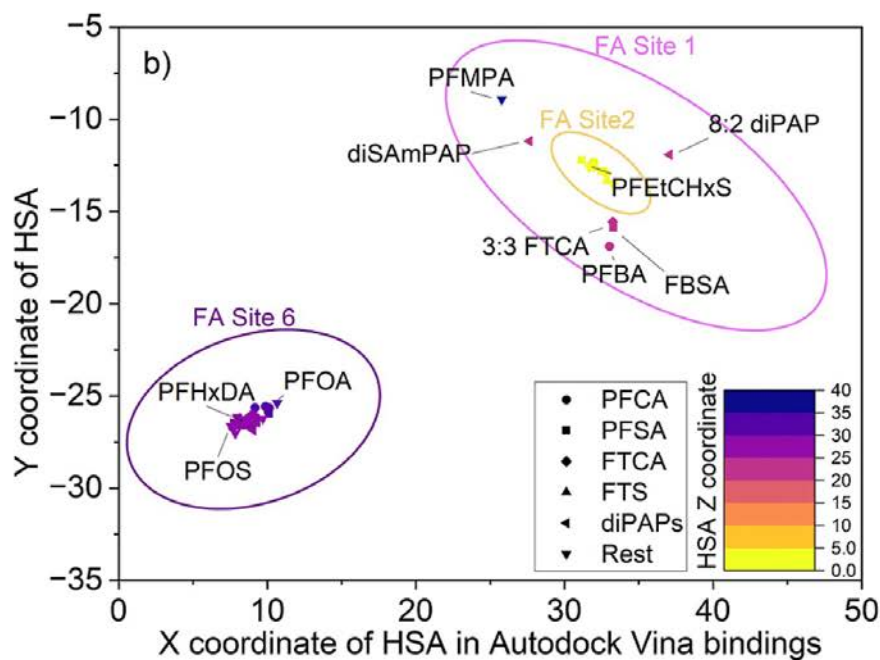


8:2 diPAP

Docking has limitations for long chain lengths:

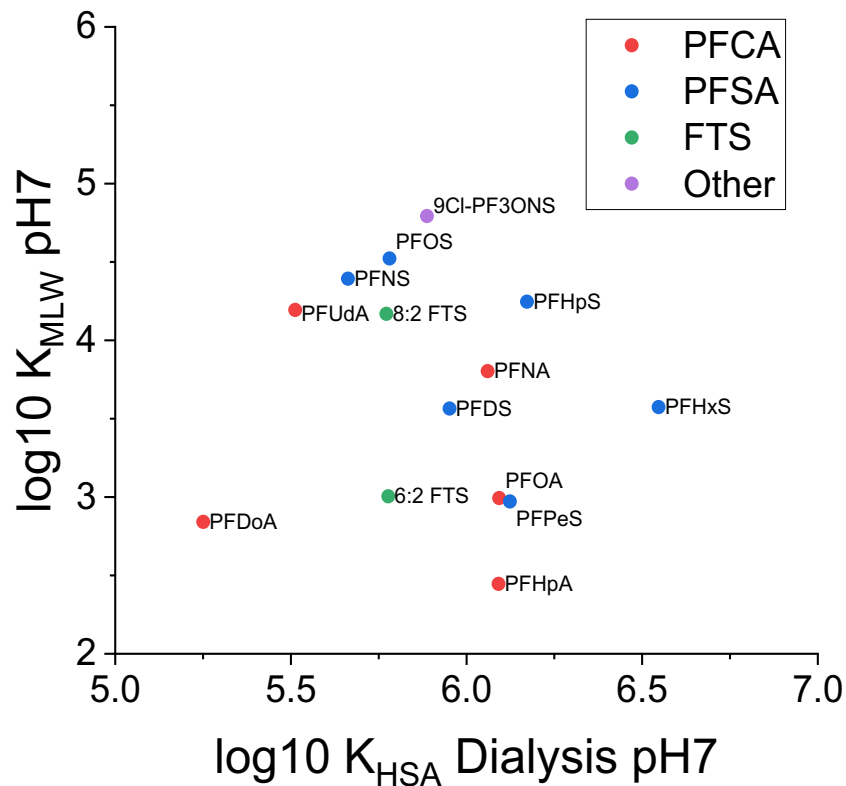


Good agreement for $\log K_A < 6$



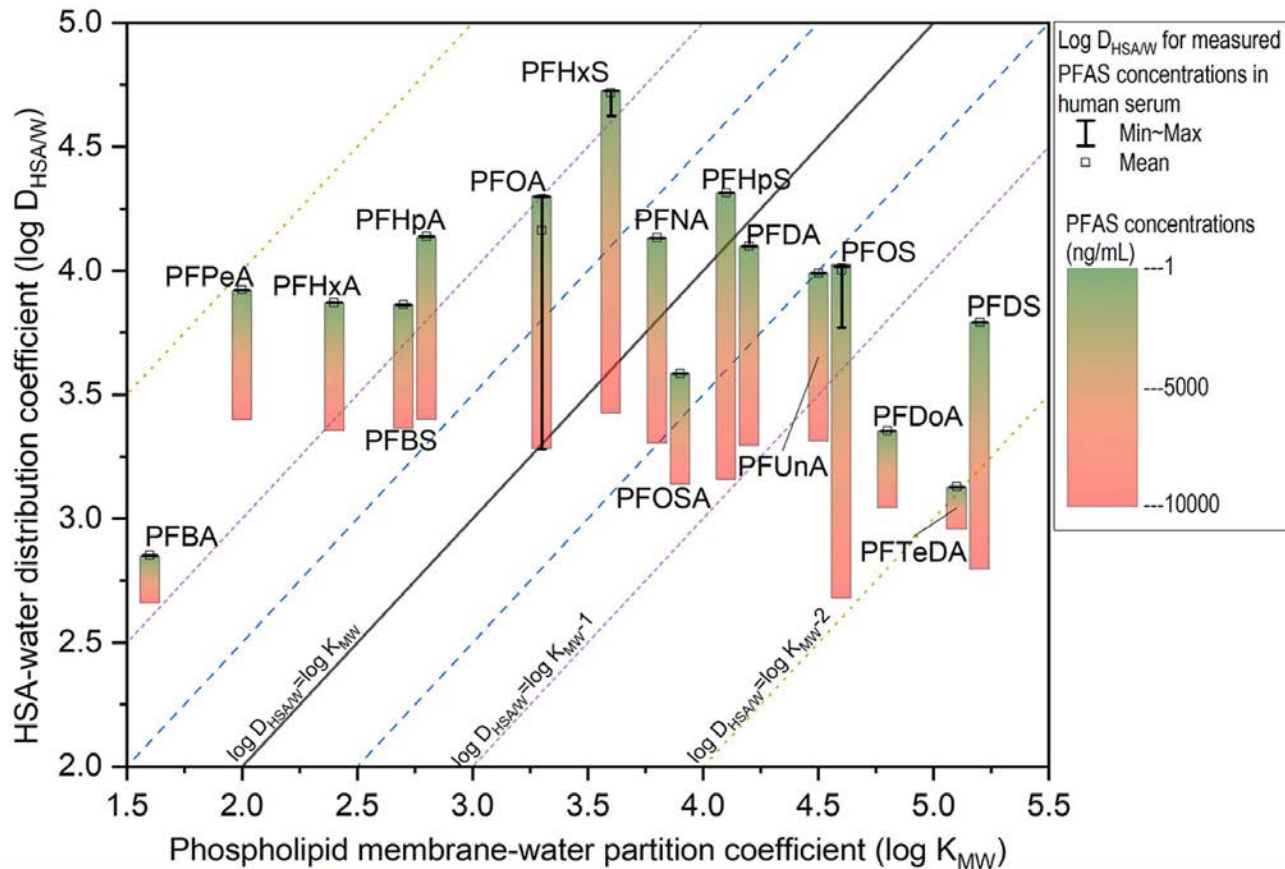
No clear relationship with binding site.

Proteins and phospholipids: complementary data.



- No strong correlation between membrane (K_{MLW}) and protein (K_A for HSA) binding.
- Suggests different mechanisms and influence of chain length/structural features at play.
- **This is good news! These are complementary, not redundant data.**

Non-saturable partitioning meets saturable binding:



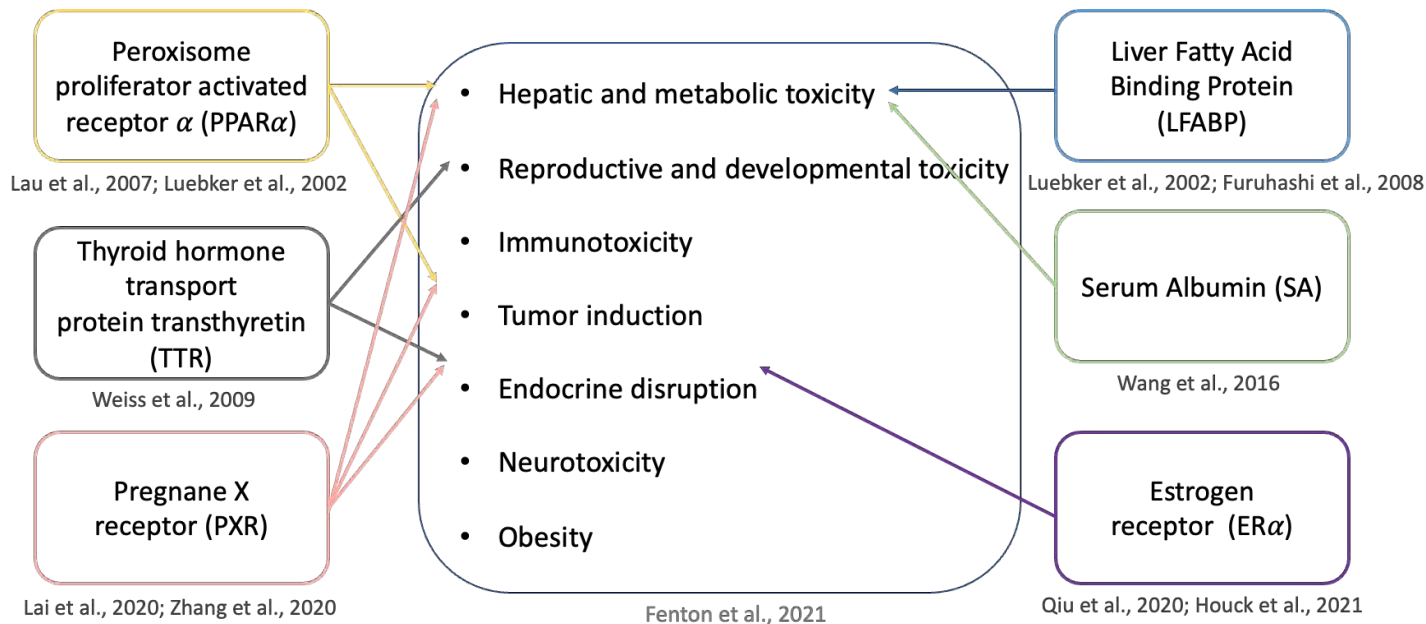
- **Distribution** of PFAS between free and bound phases: larger effect of “exposure concentration” on HSA than membrane binding.
- What are the implications for occupational exposure and typical toxicity experiments?

Take-homes from membrane and HSA assays:

- Consistent relationship between increase in KMW and fluorinated carbons (~ 0.36 log units per additional FC). [slope of curve]
- Intercepts make the difference across functional groups and types (e.g. why sulfonates have higher KMW than carboxylates for the same # of FC).
- HSA is different-- both in terms of chain length relationship and saturability.
- For chain length and functional group, there appears to be a “sweet spot” (i.e. PFOS) for maximum affinity.
- **Need to consider the interplay of membrane and protein interactions and the influence of exposure dose!**
- But what does this mean beyond distribution: what is the *toxic effect*?

Using interactions to categorize hazard: Molecular Screening

Molecular interactions (e.g. MIEs) can inform toxic mechanisms for chemicals.



Problem: We lack data on most PFAS, for many proteins!

Approach: Generate data *in silico* to rank many PFAS.



Case study: PFAS used in photolithography.

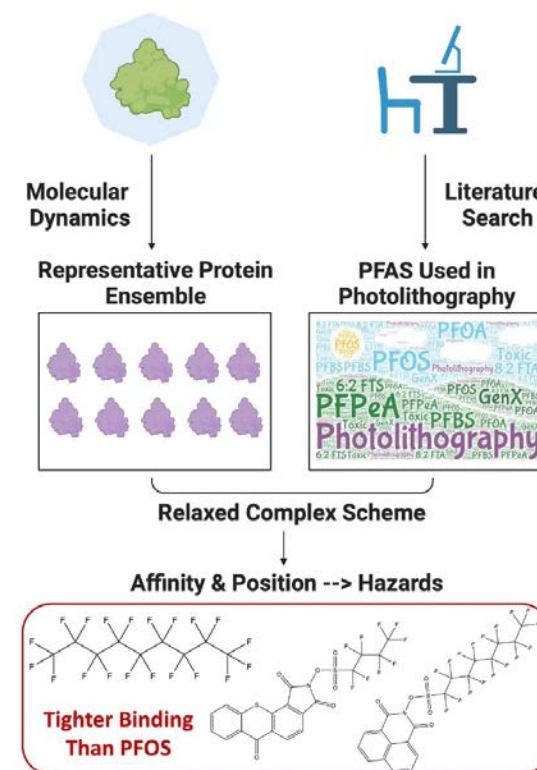


Yuexin Cao

High-throughput Screening of Protein Interactions with Per- and Polyfluoroalkyl Substances (PFAS) Used in Photolithography

Yuexin Cao^a and Carla A. Ng^{a,b*}

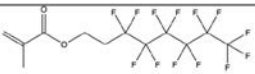
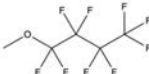

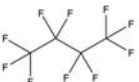
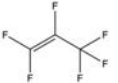
Diverse per- and polyfluoroalkyl substances (PFAS) are widely used in photolithography, and demand for semiconductor manufacturing is growing to support technological and energy transitions. PFAS are persistent in the environment and have been associated with significant health risks, yet remain inadequately studied. Our study, focusing on high-throughput screening of protein interactions with PFAS in photolithography, provides crucial insights into the molecular-level interactions of these substances with proteins. Understanding these interactions is essential for assessing the potential hazards of PFAS, guiding future regulations, and developing safer alternatives, thereby addressing a growing public health concern.



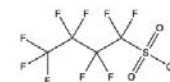
Building the screening dataset

We identified 221 photolithography-relevant PFAS uses in 7 photolithography processes (including 16 specific applications) and 15 PFAS structural types (please see our SI for full list!).

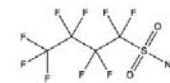
96 PFAS were selected for modeling.

PFAS Type	Definition	Counts	Example Modeled Structure
FTBS	Fluorotelomer-based substances	4	
HFE	Hydrofluoroethers	7	
PASFBS	Perfluoroalkyl carboxylic fluoride (PASF)-based substances	34	
PFAKA	Perfluoroalkanes	6	
PFAKE	Perfluoroalkenes	4	

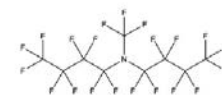
PFSA Perfluoroalkane sulfonic acids 4



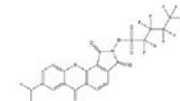
PFSAM Perfluorosulfonamides 4



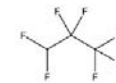
PTA Perfluoroalkyl-*tert*-amines 3



SCFA Side-chain fluorinated aromatics 11



SFA Semifluorinated alkanes 2

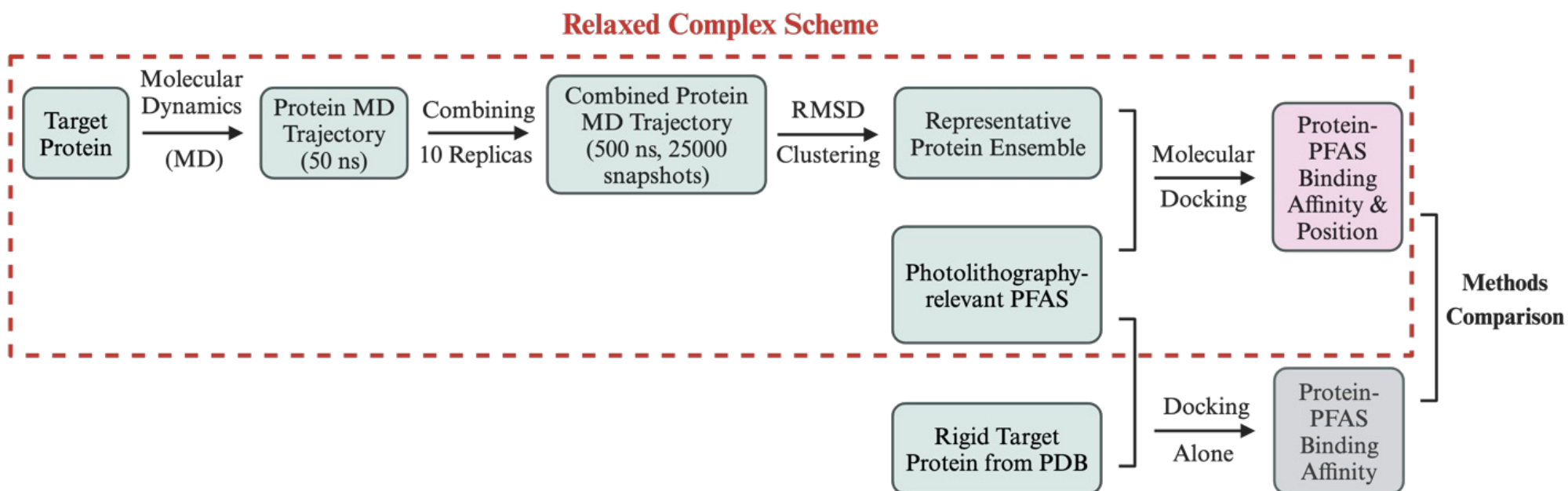


Building the screening dataset

We targeted 5 receptors relevant to bioaccumulation and toxicity of PFAS and modeled them across 4 species to compare model organisms to humans.

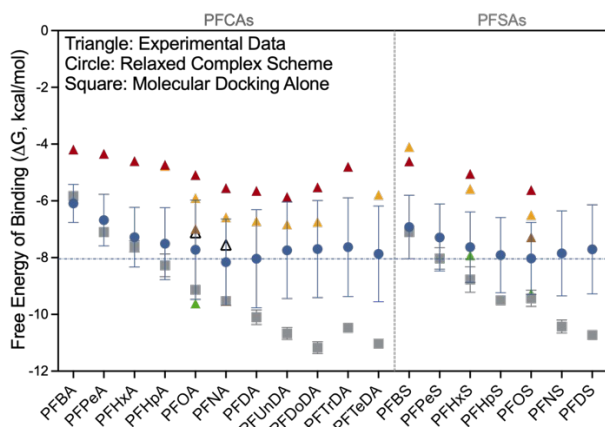
Proteins	ID in Protein Data Bank or entry identifier in UniProt			
	Human (Homo sapiens)	Rat (Rattus norvegicus)	Mouse (Mus musculus)	Zebrafish (Danio rerio)
Liver fatty acid binding protein (LFABP)	3STM	<u>1LFO</u>	P12710*	Q1AMT3**# & 2QO4#
Serum albumin (SA)	4L8U	P02770*	P07724*	-
Peroxisome proliferator activated receptor α (PPAR α)	<u>6LXA</u>	P37230*	P23204*	A6XMH7*
Peroxisome proliferator activated receptor γ (PPAR γ)	<u>6MS7</u>	O88275*	P37238*	A6XMH6*
Transthyretin (TTR)	4KY2^	1KGI	P07309*^	B8JLL8*^

Balancing accuracy and efficiency: *Relaxed Complex Scheme*

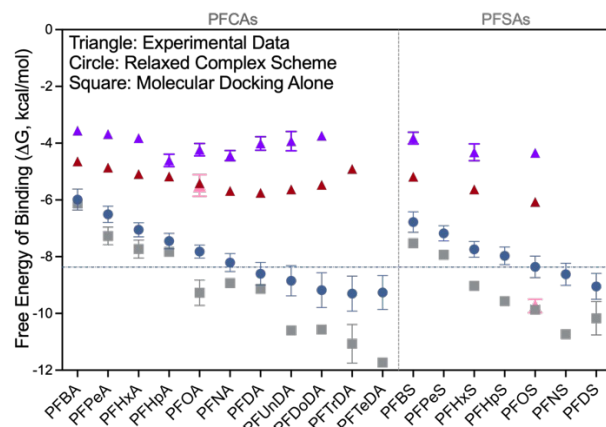


Validation of Relaxed Complex Scheme

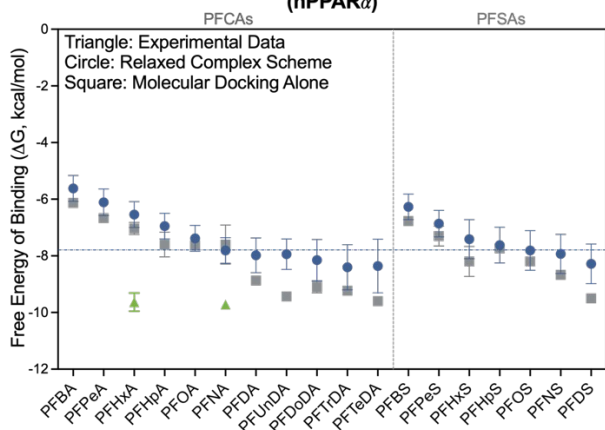
(A) Human liver fatty acid binding protein (hLFABP)



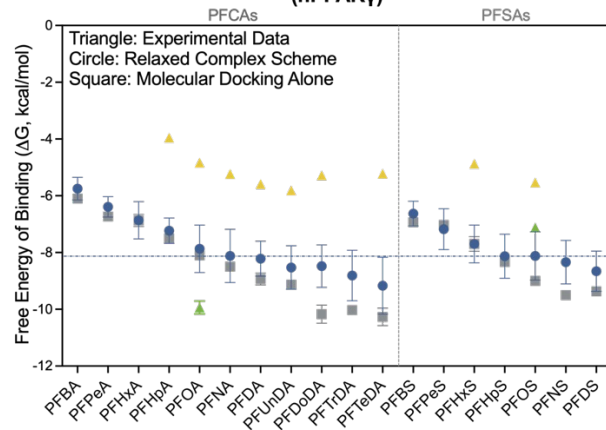
(B) Human serum albumin (hSA)



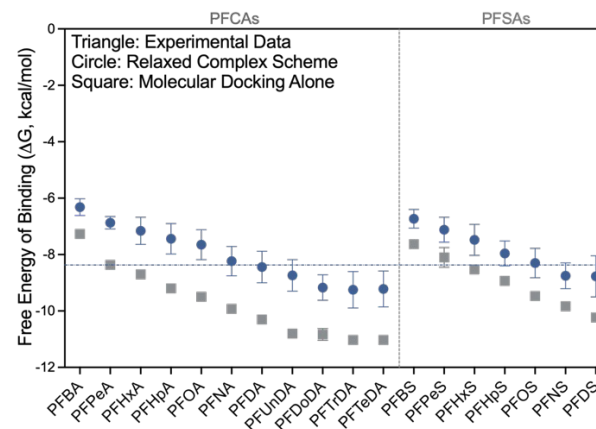
(C) Human peroxisome proliferator activated receptor α (hPPAR α)



(D) Human peroxisome proliferator activated receptor γ (hPPAR γ)



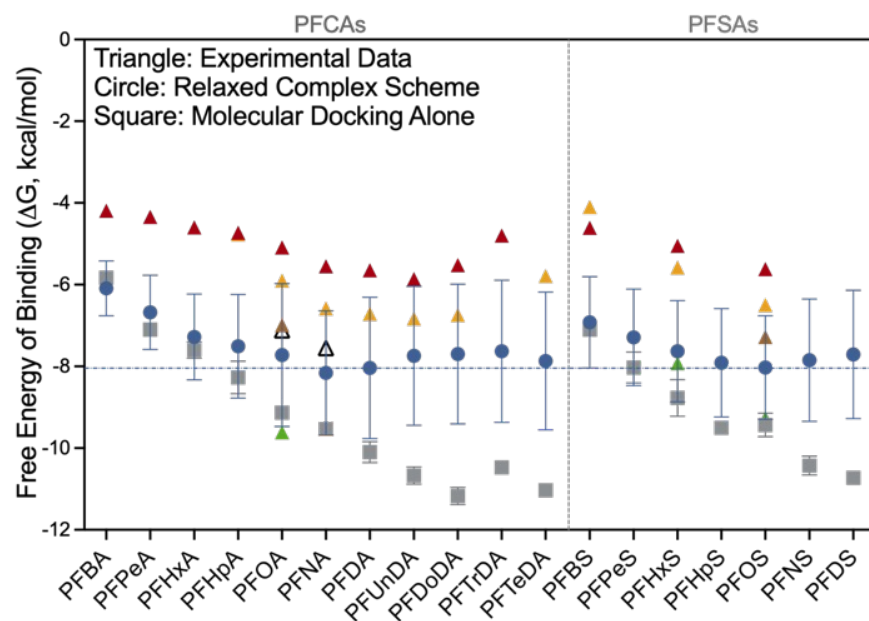
(E) Human transthyretin (hTTR)



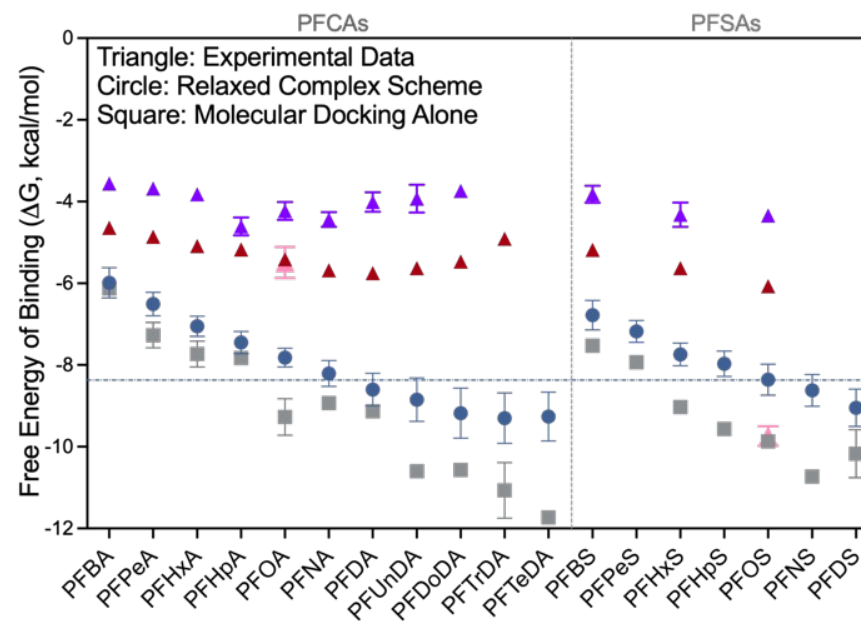
Validation focused on PFAS and receptors with most experimental data available, comparing the RCS with docking alone.

Validation of Relaxed Complex Scheme

(A) Human liver fatty acid binding protein (hLFABP)

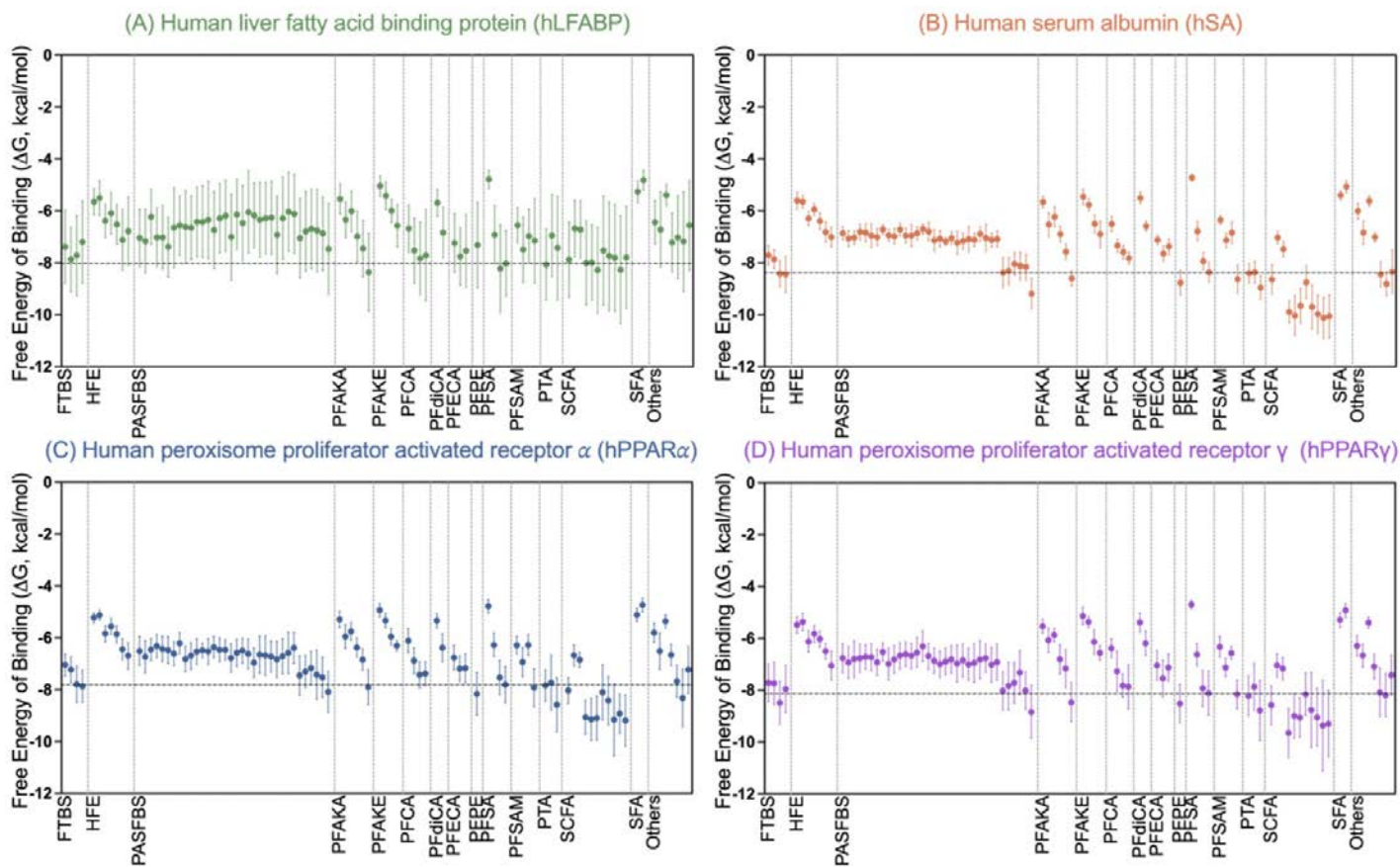


(B) Human serum albumin (hSA)



RCS improves both relative and absolute accuracy of binding affinity predictions, while maintaining reasonable computational efficiency.

Can we use interactions to categorize hazard?

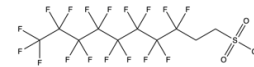
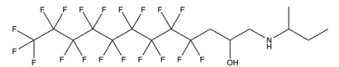
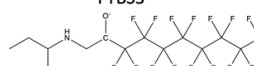

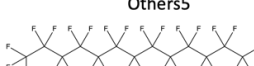
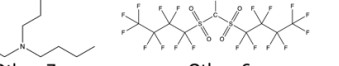
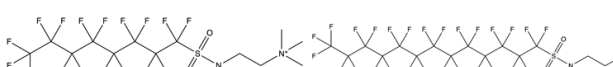

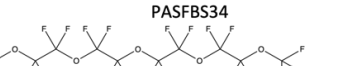
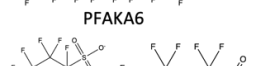
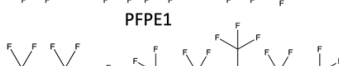
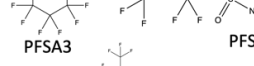
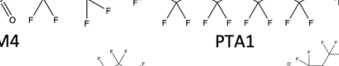

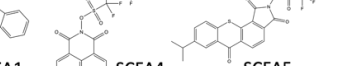
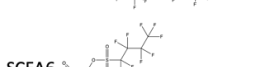
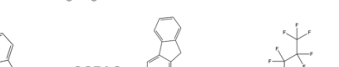
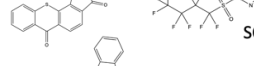
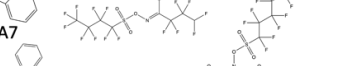
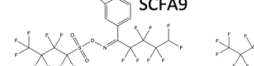




Different groups show different levels of affinity, often related to chain length, which varies across groups.

Note horizontal line is predicted affinity of our benchmark chemical PFOS.

A notable outlier: side-chain fluorinated aromatics (SCFAs).

Can we use interactions to categorize hazard?

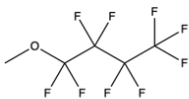
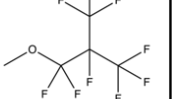
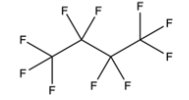
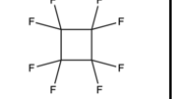
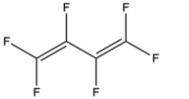
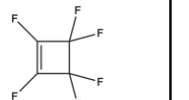

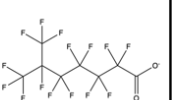

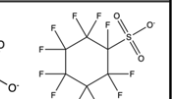
	hLFABP	hSA	hPPAR α	hPPAR γ	hTTR	
FTBS3		0.06		0.37		
FTBS4		0.08	0.06		0.03	
Others5		0.08				
Others6		0.45	0.51	0.08		
Others7					0.16	
PASFB29		0.02				
PASFB34		0.83	0.27	0.72	0.90	
PFAKA6	0.33	0.24	0.09	0.35	0.11	
PFPE1		0.41	0.35	0.40	0.55	
PFSA3	0.19					
PFSAM4		0.27	0.11	0.04		
PTA1	0.04	0.04	0.03	0.11		
PTA3		0.59	0.77	0.67	0.23	
SCFA1		0.28	0.22	0.46	0.32	
SCFA10	0.24	1.76	1.11	1.25	1.54	
SCFA11		1.70	1.38	1.18	1.87	
SCFA4		1.53	1.25	1.53	1.17	
SCFA5		1.68	1.33	0.88	1.03	
SCFA6	0.25	1.30	1.28	0.94	0.81	
SCFA7		0.39	0.29	0.04	0.42	
SCFA8		1.34	0.61	0.65	1.59	
SCFA9		1.62	1.35	0.93	1.83	

High affinity PFAS are dominated by molecules with many CF groups as well as aromatic PFAS and one cyclic PFAS.

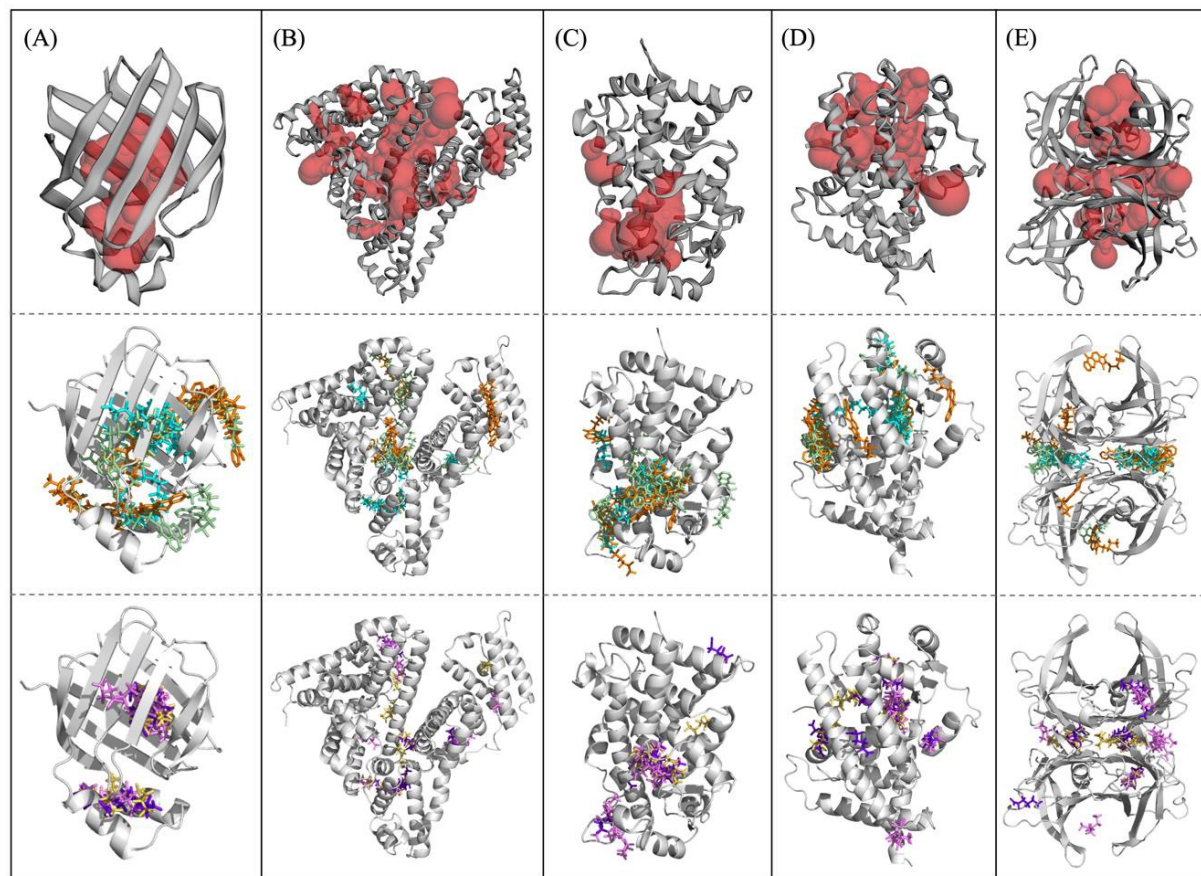
Higher affinity for these PFAS are observed across the modeled human receptors except for LFABP- potential limitation of binding pocket size?

These are largely untested PFAS, most without standards available to carry out experimental assays, but warrant prioritization.

Observations for linear vs. cyclic PFAS within groups

Chain Length	Structural Form	PFAS ID	hLFABP	hSA	hPPAR α	hPPAR γ	hTTR	
4 fluorinated carbons	Linear	HFE3	-6.38	-6.29	-5.84	-6.13	-6.29	
	Branched	HFE4	-6.09	-5.95	-5.56	-5.83	-6.01	
4 fluorinated carbons	Linear	PFAKA2	-6.34	-6.53	-5.95	-6.07	-6.38	
	Cyclic	PFAKA3	-6.01	-6.23	-5.75	-5.87	-6.34	
4 fluorinated carbons	Linear	PFAKE2	-5.42	-5.77	-5.33	-5.37	-5.69	
	Cyclic	PFAKE3	-6	-6.5	-5.95	-6.14	-6.04	
7 fluorinated carbons	Linear	PFCA4	-7.72	-7.82	-7.38	-7.87	-7.65	
	Branched	PFCA3	-7.83	-7.59	-7.43	-7.83	-7.52	
6 fluorinated carbons	Linear	PFHxS	-7.63	-7.74	-7.41	-7.7	-7.48	
	Cyclic	PFSA3	-8.22	-7.94	-7.53	-7.93	-8.27	

Can we use binding sites to categorize hazard?



Top row: active sites of (A) LFABP, (B) HSA, (C) PPAR α , (D) PPAR γ , (E) TTR.

Middle row: Binding positions of strongly-binding PFAS.

Bottom row: Binding positions of weakly-binding PFAS.

What molecular simulations can and can't do:

Predicted protein binding affinities were influenced by PFAS structural features: fluorinated chain length, molecular size, and the presence of aromatic rings

Also affected by the dimensions of the protein binding pockets (e.g. limitations in LFABP).

Notably, 22 PFAS were predicted to bind more strongly than PFOS, suggesting their potential for bioaccumulation and adverse biological effects.

Needs to be further validated with outcomes of protein binding - only one component in a complex cascade!

Some take-home messages for PFAS

- There remain a large number of untested PFAS across many categories of use (and subsequent human exposure).
- Modeling strategies allow us to increase throughput on PFAS evaluation, but are not a panacea.
- Require data for training, validation, and evaluation.
- Combining insights from in vitro and in silico approaches can help to fill these gaps and prioritize chemicals for further study while avoiding animal use.
- In the meantime, treatment and destruction technologies are urgently needed, both inside and outside the box.

Acknowledgments

- Dr. Jennifer Field (OSU) - SERDP/Concawe collaboration on protein and membrane interactions.
- SRC industrial liaisons: Brooke Tvermoes (IBM), Sarah Wallace (TI), David E. Speed (GLOBALFOUNDRIES), Mansour Moinpour (EMD Electronics), Ralph Dammel (EMD Electronics), Kai Williams (TI), Robert E. Leet (Intel), Kevin W. Wolfe (Intel) and Tim S. Yeakley (TI)
- Funding from Concawe, NSF, SERDP and SRC.
- Resources from the University of Pittsburgh Center for Research Computing (CRC).



Questions?

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