

Using BOxCrete to Optimize Concrete Mixtures with AI: From Open-Source Models to Data-Center Deployment

American Concrete Institute Spring Convention 2026 (Chicago, IL)

See: [Using AI to make lower-carbon, faster-curing concrete](#)

Presented by:

Julius Kusuma Meta Platforms, Inc

Nishant Garg University of Illinois Urbana-Champaign

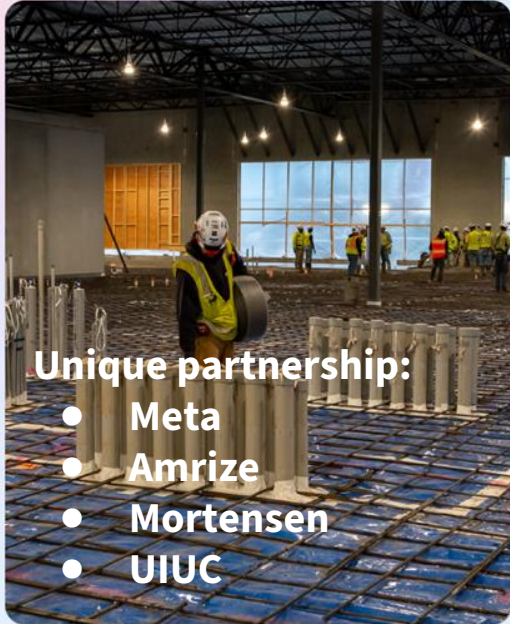
Mark Bintzler Amrize



We demonstrated the end-to-end application of AI in a slab section of Meta's data center



Critical slab-on-grade application



Unique partnership:

- Meta
- Amrize
- Mortensen
- UIUC

Building a greener future.



Met all critical use-case requirements

- **Faster: 43%**
- **Stronger: 37%**
- **Lower carbon: 40%** below regional benchmark (v3.2)
- **Similar cost**
- **Standard materials**

Outline

- Why this partnership
 - Data centers and concrete
 - AI opportunities
- AI development
 - Foundational data
 - Lab tests
 - AI performance
- At-scale deployment
- Scaling the use of AI



Nishant Garg



Julius Kusuma



Mark Bintzler



Data centers and concrete

Concrete is an important element in data center construction



World's concrete production

- **\$440B** annual global spend; **30B tons** of concrete
([Mar 2020 GCCA](#), [Sep 2021 Nature](#))
- **Major CO2** emissions

US cement & concrete

- Cement imports in 2024: **23%**
([Concrete Financial Insights](#))
- New materials need to be incorporated into supply chain

Data Centers & concrete

- **Slab-on-Grade (SOG)**
- **\$3T** total data center investment by 2030
([Jan 2026 DCD](#), [JLL estimate](#))



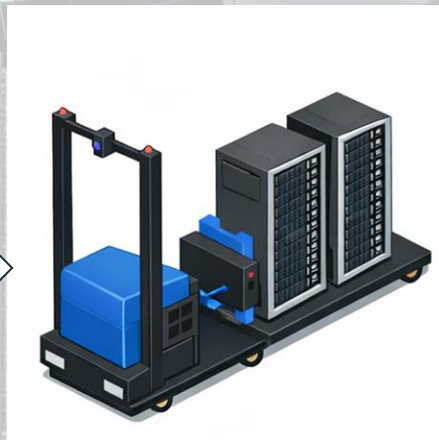
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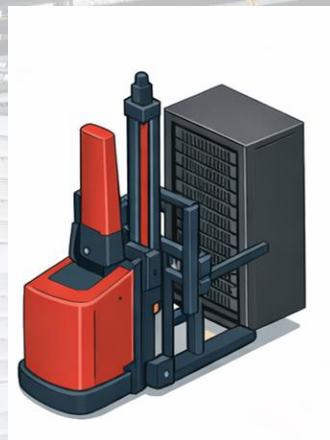
Manual

Max Concrete point load
7.2 MPa (1038 PSI)



Auto Delivery

Max Concrete point load
8.1MPa (1170 PSI)



Auto Pick/Deliver/Drop

Max Concrete point load
7.9 MPa (1146 PSI)



Bigger Rack Automation

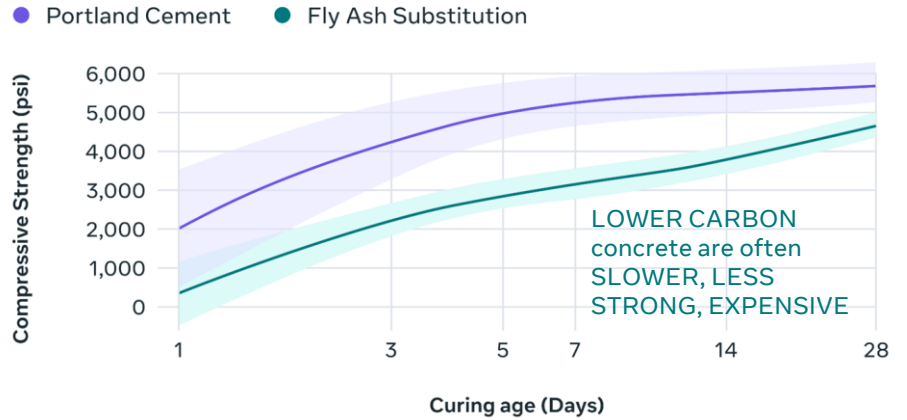
Max Concrete point load
10.38 MPa (1506 PSI)

We need Faster, Stronger, Greener concrete that meet critical Data Center use-case requirements – and AI is a key enabler

Low-carbon concrete

Relative proportion of ingredients by weight

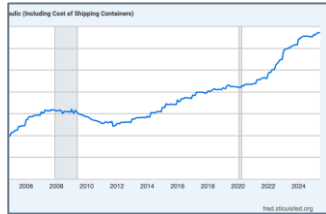
- Cement 8.4%
- Fly Ash 1.5%
- Slag 1.97%
- Water 5.22%
- Fine Agg. 35.9%
- Coarse Agg. 46.9%



STRENGTH



COST



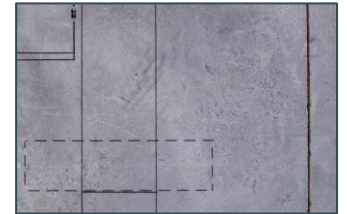
SPEED



SUSTAINABILITY



QUALITY



AI development

Adaptive Experimentation

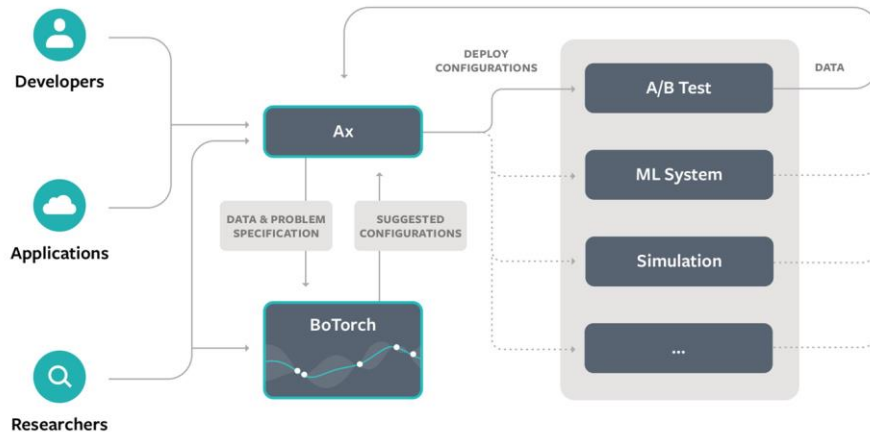
- Meta develops central tools and methods for efficient optimization of ML models, online experiments, and hardware
- Meta's Adaptive Experimentation team maintains two open-source software (OSS) projects
 - Ax: platform for running adaptive experiments
 - BoTorch: framework for Bayesian optimization research
- Team engages with academic research community via publications, OSS, and workshops.



ax.dev

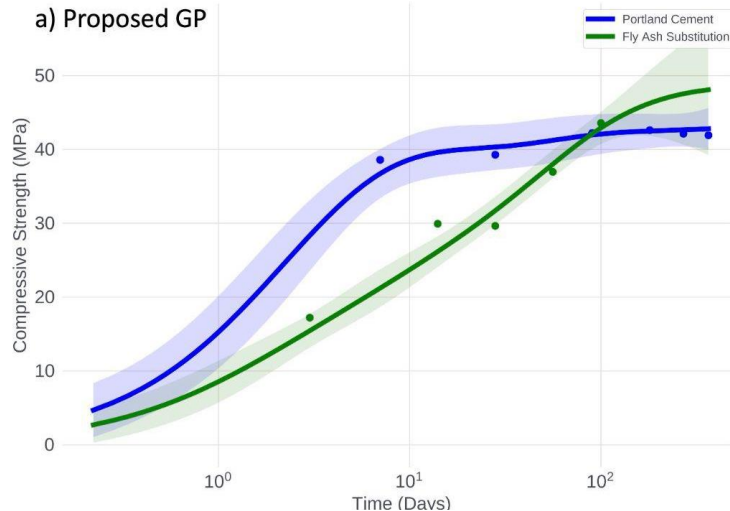
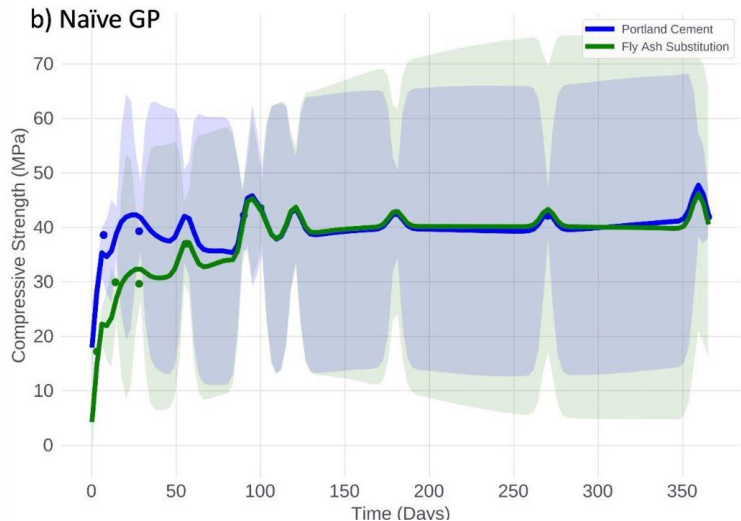


botorch.org



Ax and BoTorch can efficiently learn & solve high-dimensional design problems, and concrete mix design seems promising – what else is needed?

Modeling Compressive Strength Curve



$$k((\mathbf{x}, t), (\mathbf{x}', t')) = \alpha k_{\text{time}}(\log t, \log t') + \beta k_{\text{joint}}((\mathbf{x}, \log t), (\mathbf{x}', \log t'))$$

A problem:

A naïve application of a Gaussian Process (GP) is **inaccurate**, and worse, yields **non-physical** predictions.

The path to a solution:

Incorporate physics-inspired features

- 1) conditioned to have zero strength at day zero zero,
- 2) based on log-transformed time,
- 3) includes an additive time-dependent, composition independent component that learn a representative strength curve, from which we can model composition-dependent deviations.

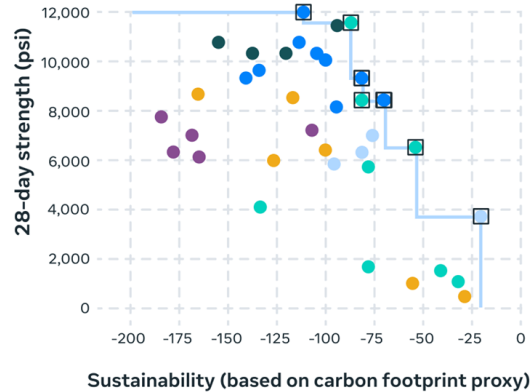
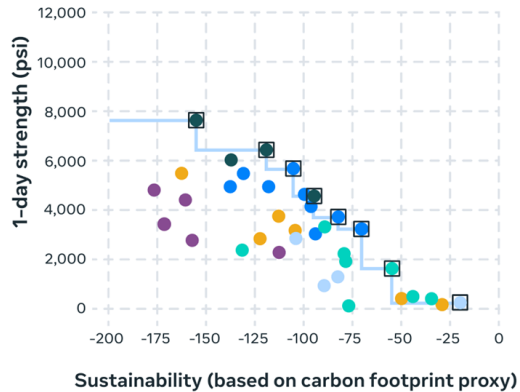
[Sustainable Concrete via Bayesian Optimization, NeurIPS 2023 Workshop on Adaptive Experimental Design and Active Learning in the Real World](#)

AI has arrived

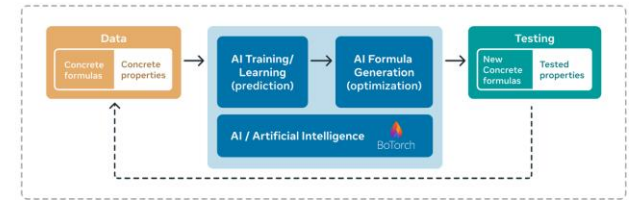
AI can learn, predict, and optimize basic concrete performance with modest training & standard materials

Pareto Frontier of concrete strength and sustainability

□ Pareto ● Batch 2 (AI) ● Batch 4 (AI) ● Batch 6 (AI)
● Batch 1 (Human) ● Batch 3 (AI) ● Batch 5 (AI)



Adaptive experimentation using AI



Meta's AI: [open-sourced in GitHub](#)

- Bayesian optimization for strength, speed, CO2
- Iterative testing with research & industry partners

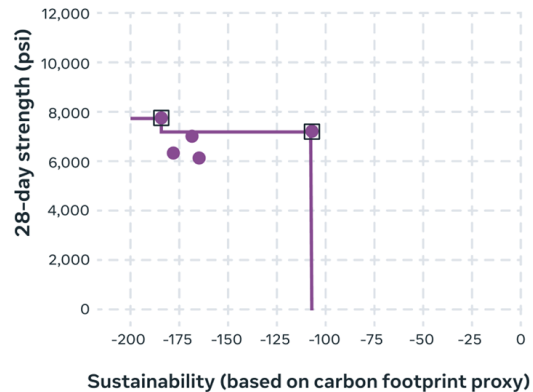
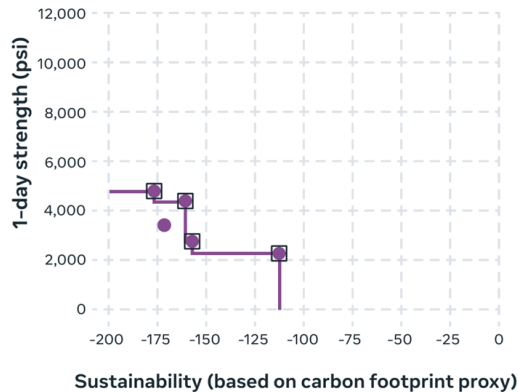
[Meta's Adaptive eXperimentation \(Ax\) AI toolbox](#) optimizes between learning & optimization

AI features available today

<https://github.com/facebookresearch/SustainableConcrete/>

Pareto Frontier of concrete strength and sustainability

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Prediction

- Compressive strength curve
- GWP
- Slump

Optimization & constraints

- x-day strength
- GWP
- Slump
- Other linear functions eg cost
- Constraints:
 - Volumes
 - w/b

Pareto front

See: our [2023 NeurIPS workshop paper](#)

Foundational data: lab tests

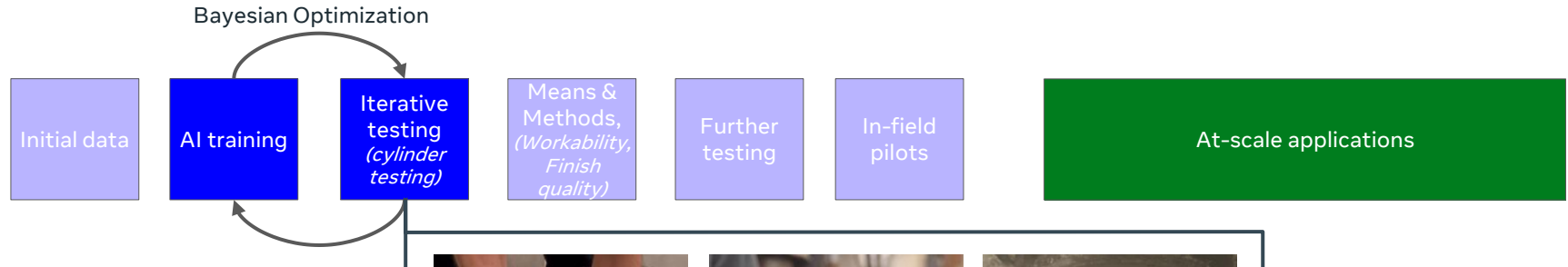


With Bayezid Baten (PhD Candidate) and Ayyan Iqbal (MS Candidate)

News story: [Recipe for Success](#) (U of Illinois, October 2025)

AI for sustainable concrete

Developing new mixes with AI

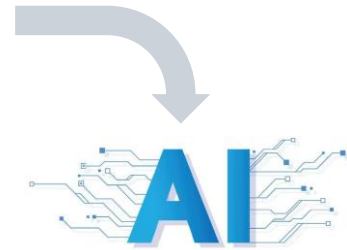
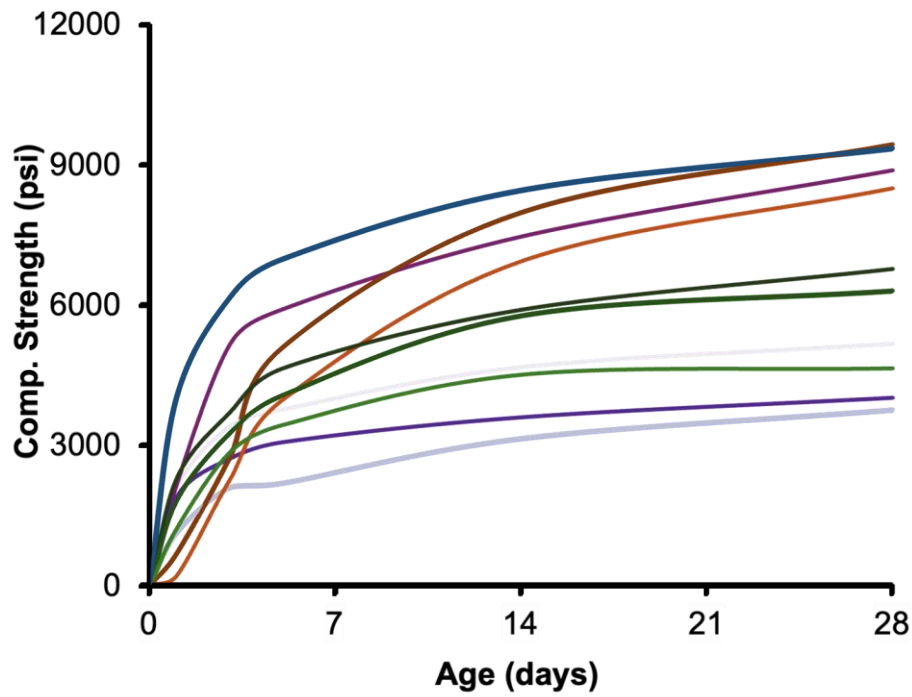
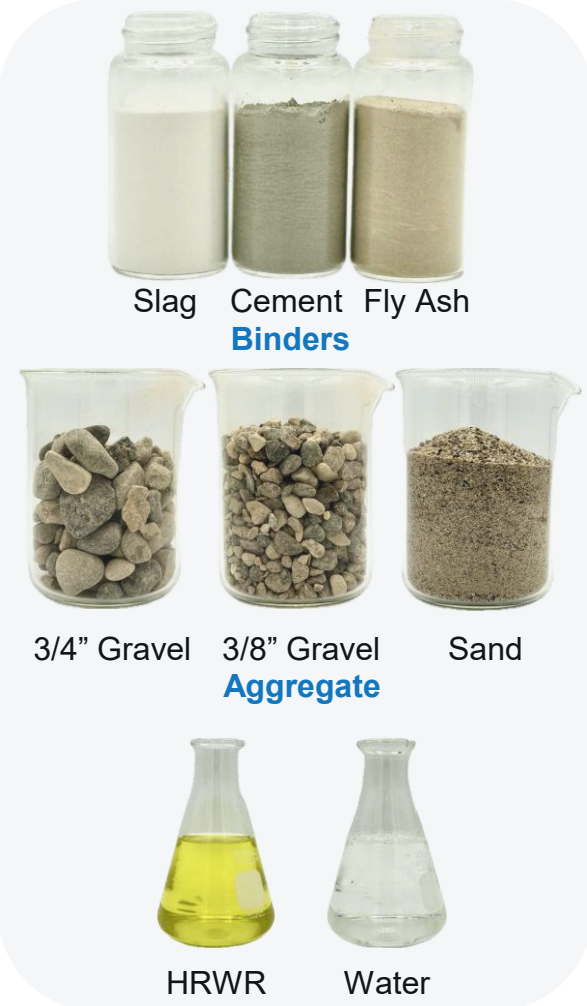


Phase-Wise Mix Development

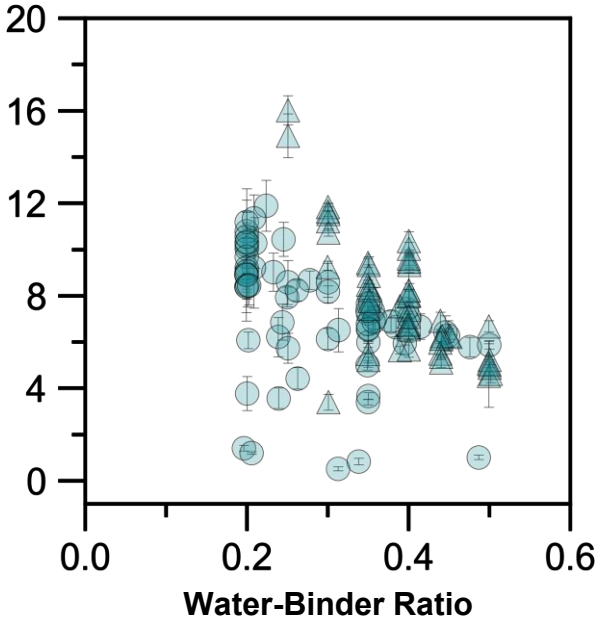
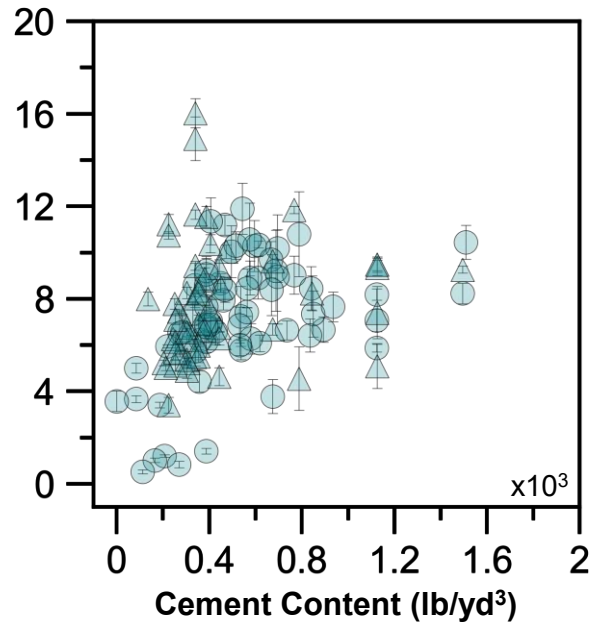
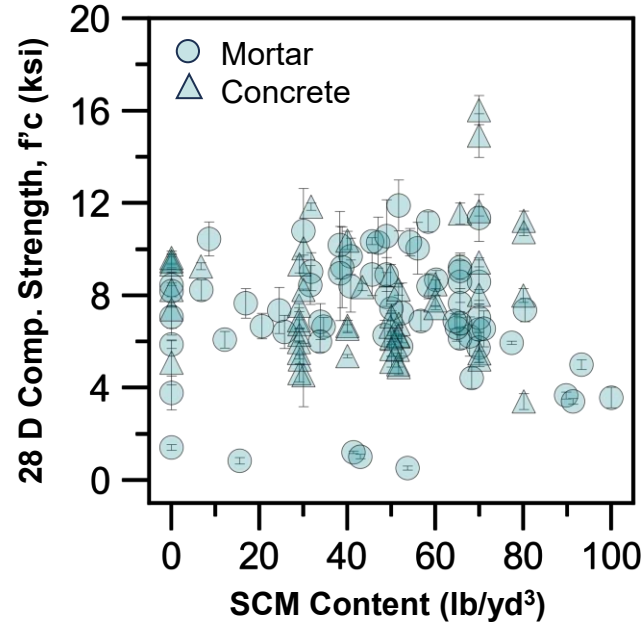
Phase ID	Number of Mixes	Mix Type	Parameters Modified
P I			
P II			
P III			
P IV			
P V			
P VI			

In summary, 500+ diverse strength measurements from a total 123 unique mixes at a single lab (69 mortar + 54 concrete mixes) across five ages (1, 3, 5, 14, and 28 days)

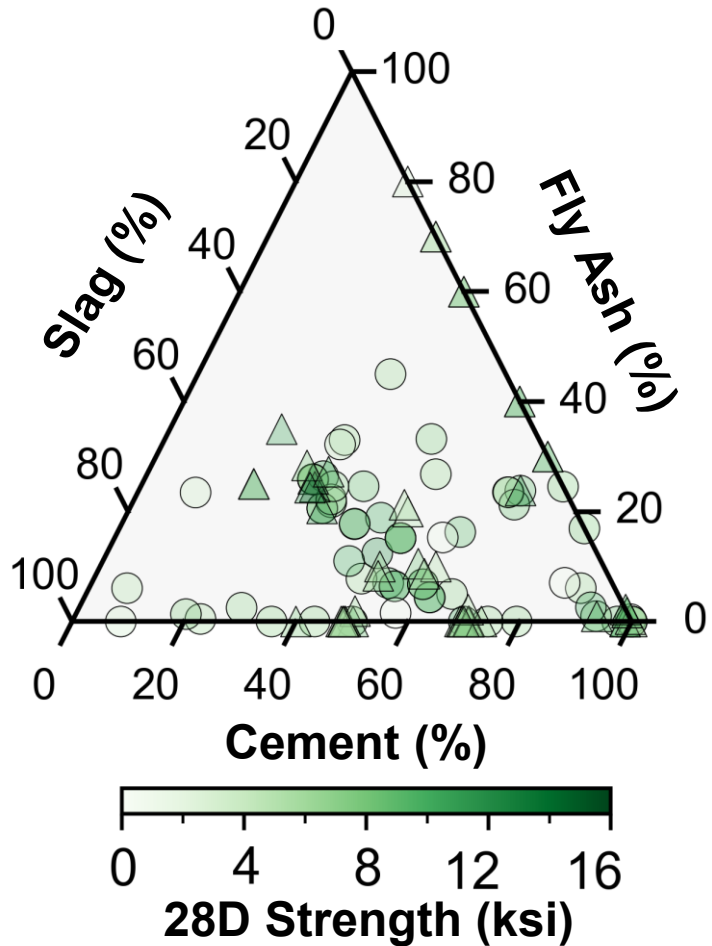
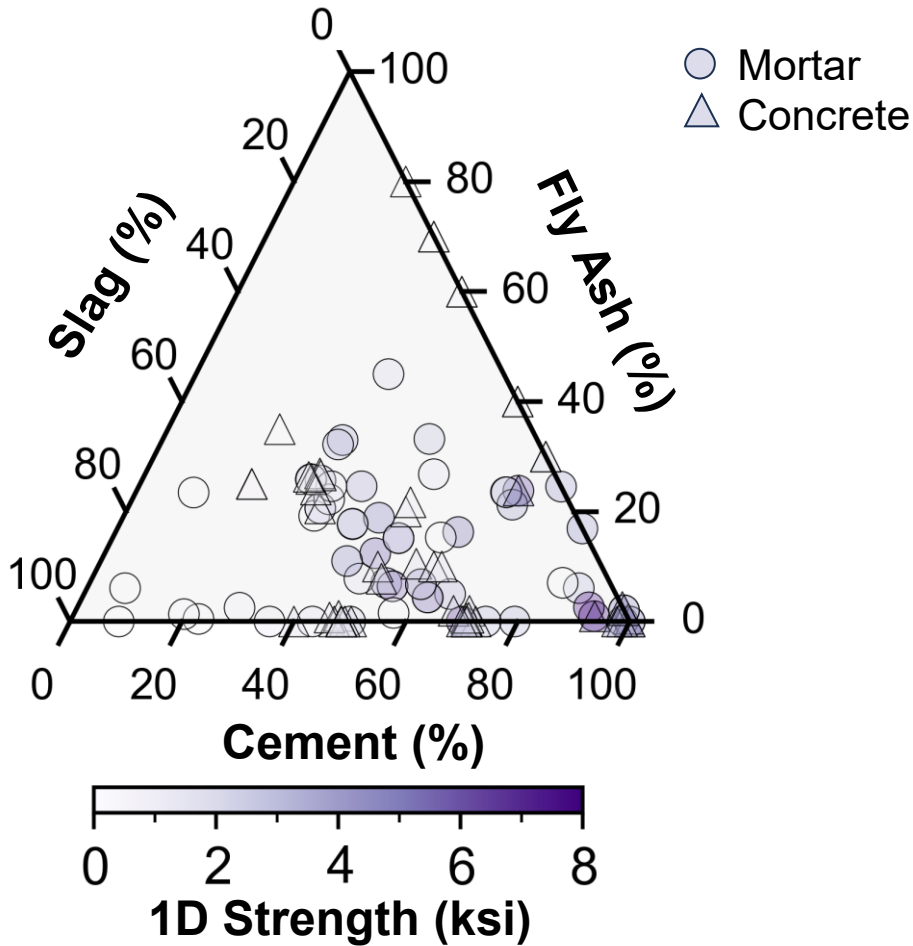
The Perplexity of Strength Prediction



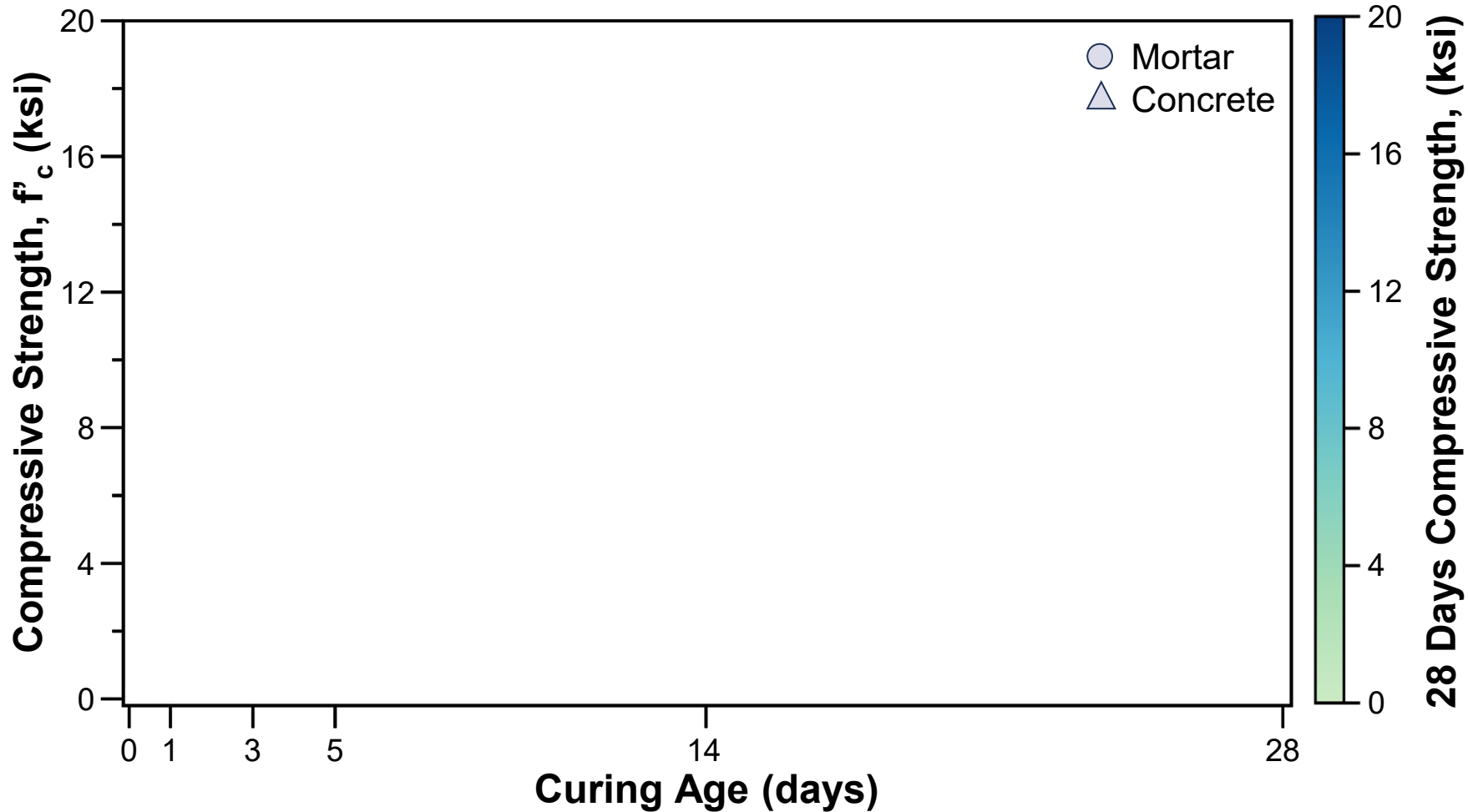
Role of Mix Components on Compressive Strength



The Mix-Design Space

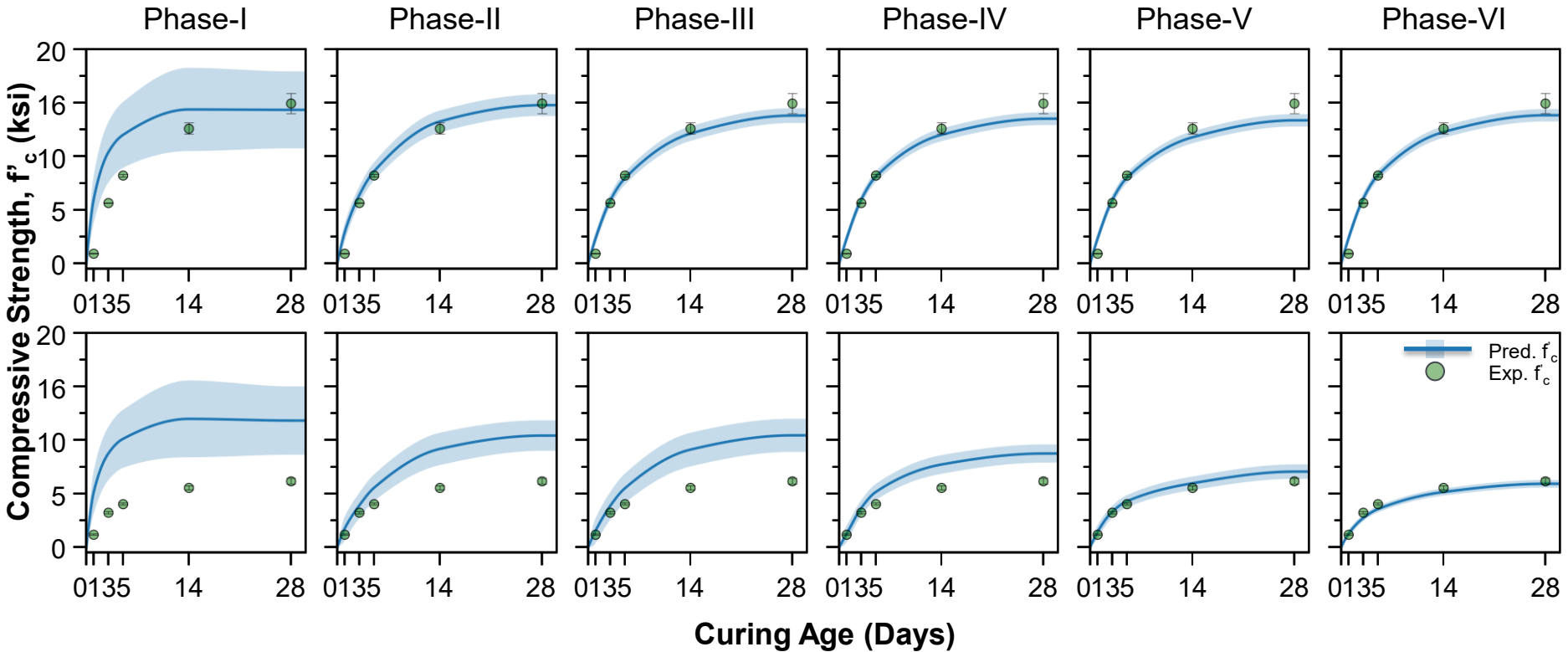


Interplay between Strength and Sustainability

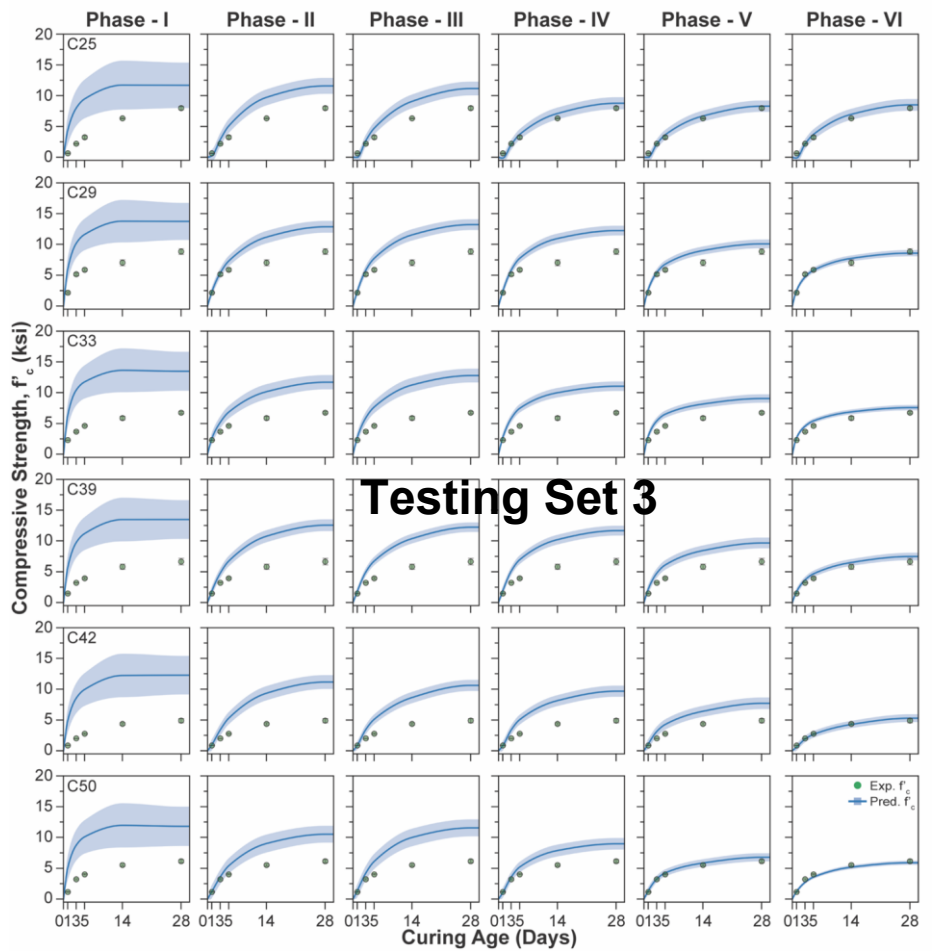
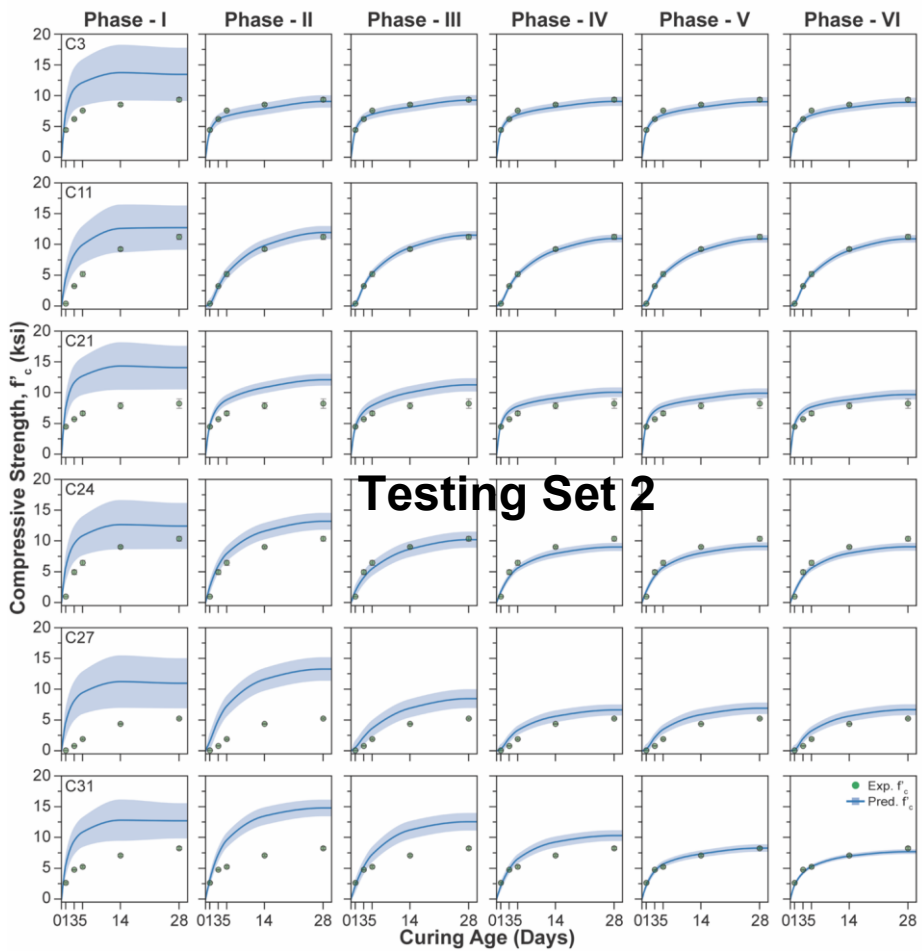


AI performance

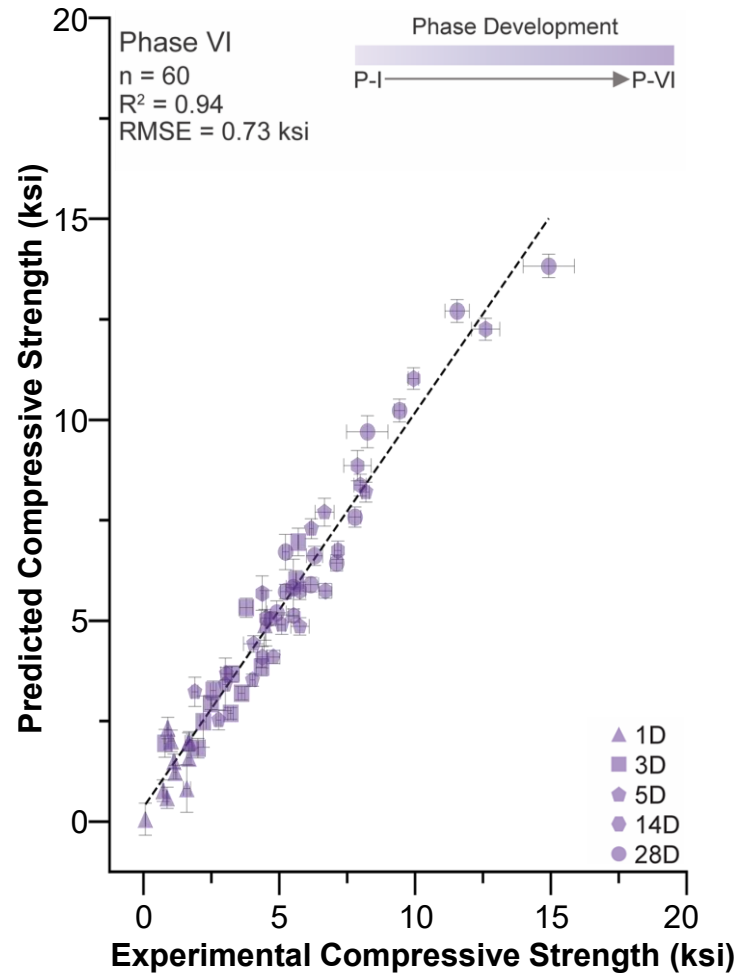
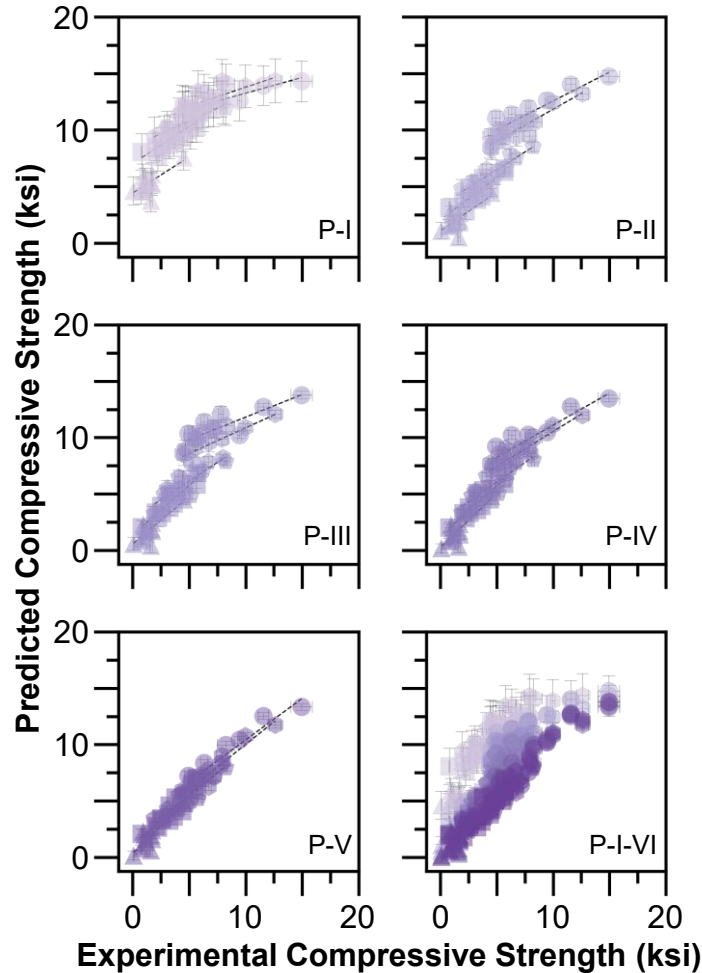
Strength Prediction over Phases



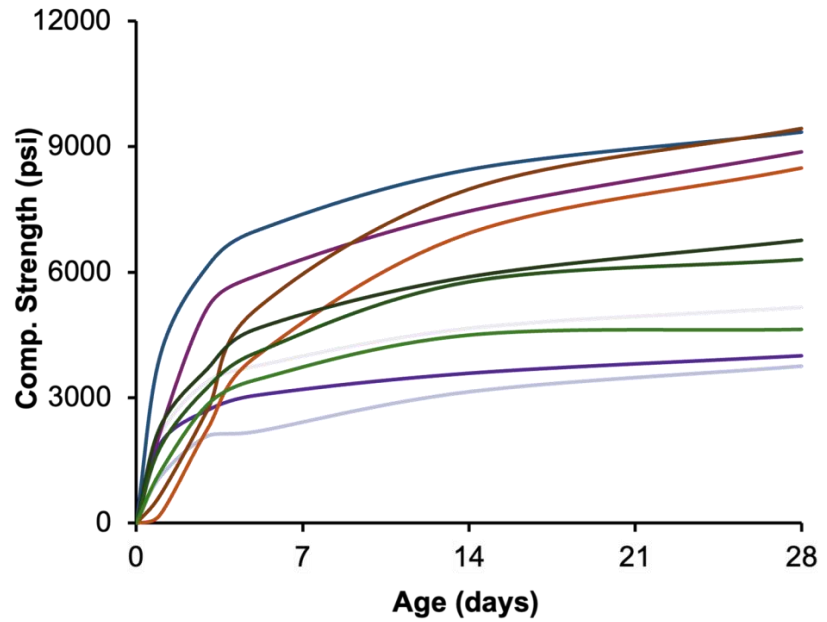
Strength Prediction over Phases



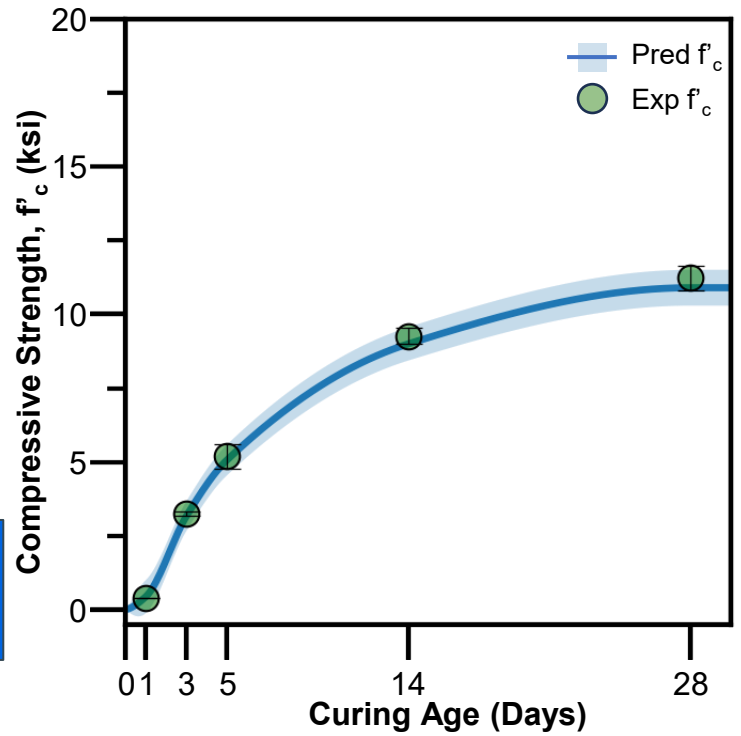
Strength Prediction over Phases



The Perplexity of Strength Prediction – Solved?



AI

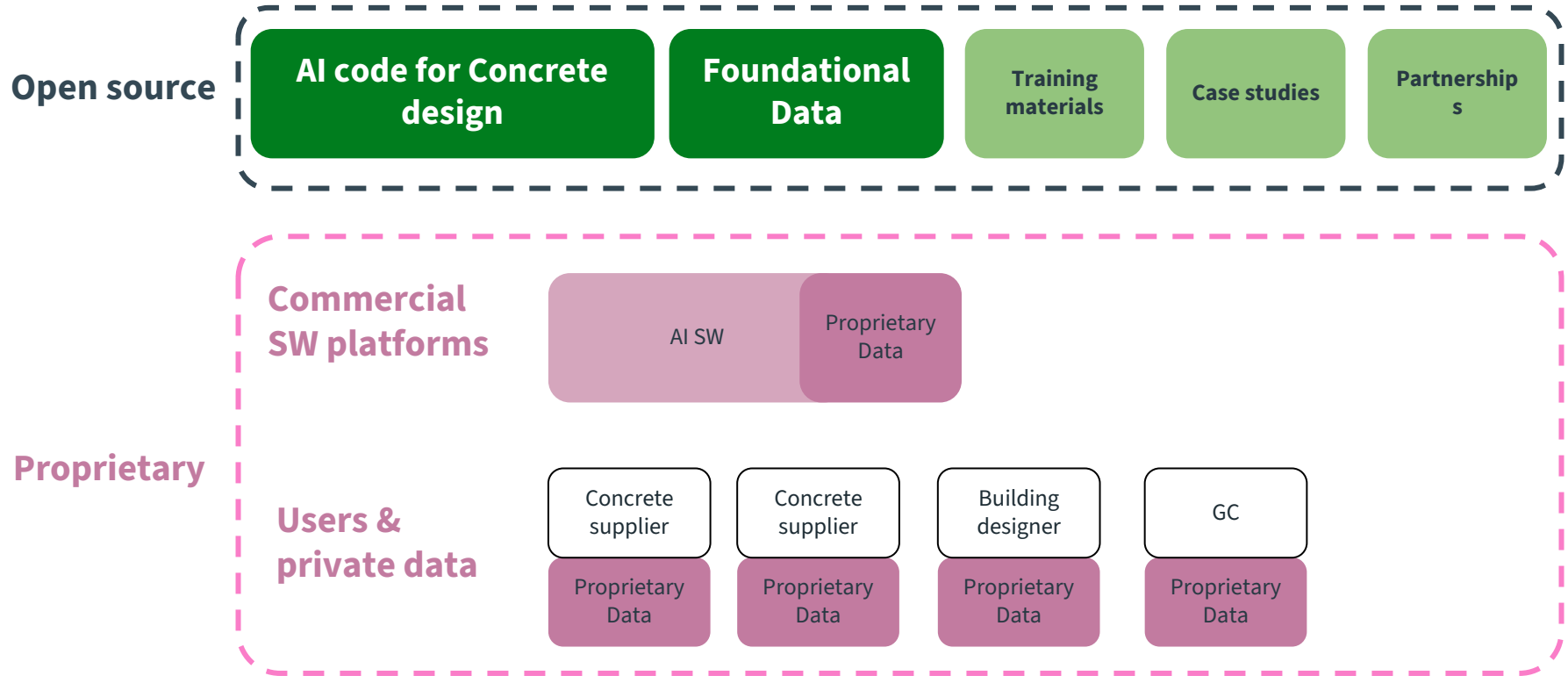


Baten, Iqbal, Ament, Kusuma, and Garg, 2026
(Paper under review, available on [arXiv](#) currently)

Deployment in a Meta data center

Scaling AI for concrete

This is what success looks like



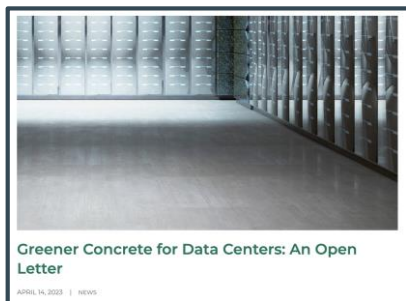
Meta's open-sourced AI model ([GitHub](#)) is provided under MIT license: allows for commercial use with minimum restrictions while benefiting from open-source AI advances and investments

This is what success looks like

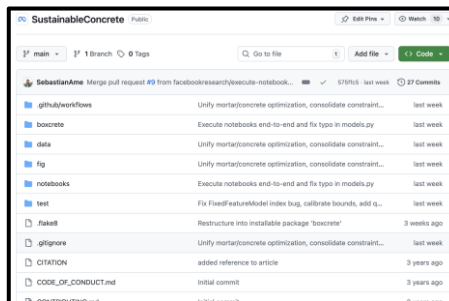
Open source



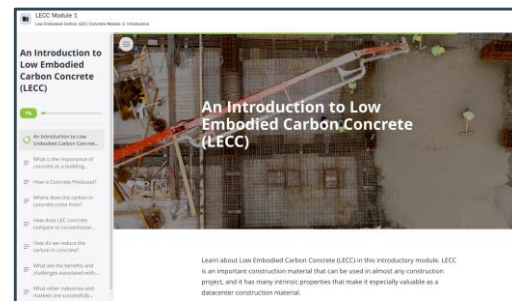
A hyperscalers coalition has started to build elements of this open source ecosystem:



<https://climateaccord.org/news/greener-concrete-for-data-centers-an-open-letter/>



<https://github.com/facebookresearch/SustainableConcrete>



<https://academy.opencompute.org/learn/courses/12/low-embodied-carbon-lec-concrete-module-1-introduction/lessons/95:50/lecc-module-1>

AI use-cases

AI can learn, predict, and optimize basic concrete performance with modest training & standard materials BUT each use-case has its own requirements including AI features, data, pipelines.

Optimize mixes

- Strength
- Speed
- Sustainability
- Cost
- Workability
- Performance limits

Predict field performance

- Placement
- Means & methods
- Performance
- Temperature

**Incorporate
novel
materials**

**Other use
cases**

AI models, pipelines, data

Closing comments

AI has arrived

- Use-cases
- Real-world at-scale examples
- Strong open-source ecosystem in “traditional domains”
- Coalitions of partners
- Opportunities to solve impactful problems

Let's work together

- Scale AI
- Scale foundational data
- Develop the right features and use-cases
- Leverage lessons learned & features built in other domains
- BOxCrete

