

Digital innovation for sustainable, accelerated development in an era of uncertainty

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Advanced clinical
understanding

Patient specificity

(un)Availability of raw
materials

Disease X

Complex supply chains

Sustainability

How hard is it to be prepared?





AstraZeneca's 'Ambition Zero Carbon' strategy to eliminate emissions by 2025 and be carbon negative across the entire value chain by 2030

WHO calls for transformative action towards a greener future in pharmaceutical manufacturing and distribution

23 December 2024 | Departmental

AUGUST 21, 2024

Sustainability: A key differentiator as biopharma faces momentum challenges, global survey by Cytiva reports

By Cytiva Communications

Classification: Official



Manufacturing Transport Storage Transport Administration

Delivering a 'Net Zero' National Health Service

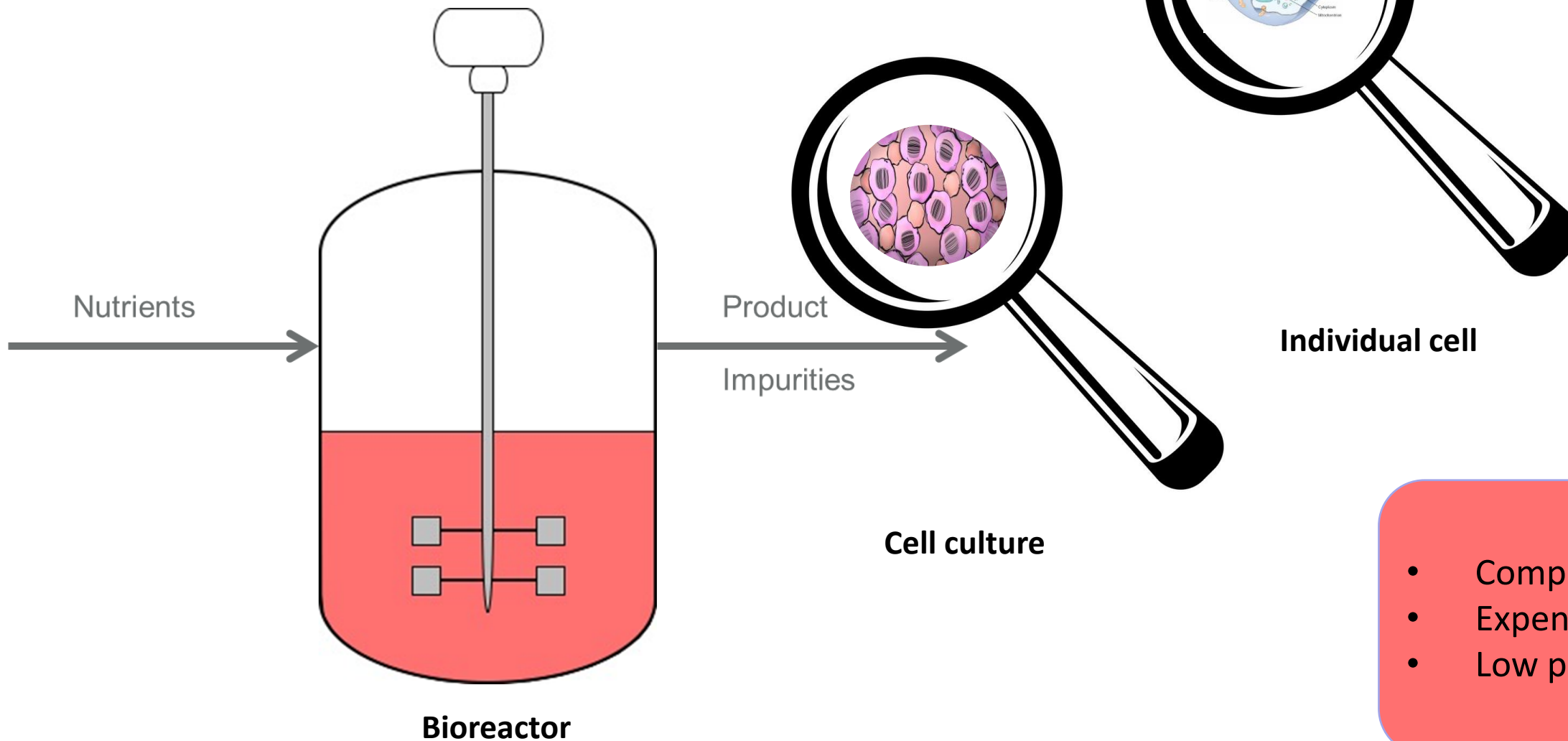


New UKRI funding aims to enhance UK sustainable biomanufacturing



Our pathway to reach **net zero** carbon by 2030

COP26: Biopharmaceutical Industry Actions to Tackle Climate Change



- Complex
- Expensive
- Low productivity

Challenge #1: Scal(in)ability

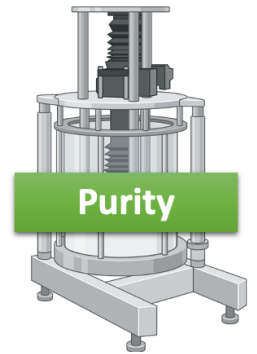
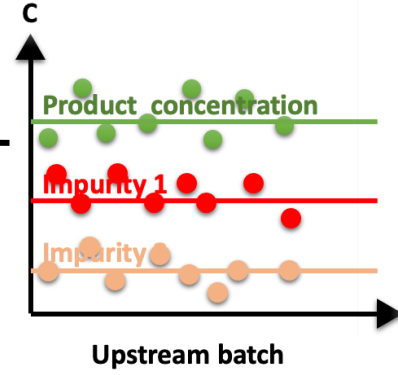
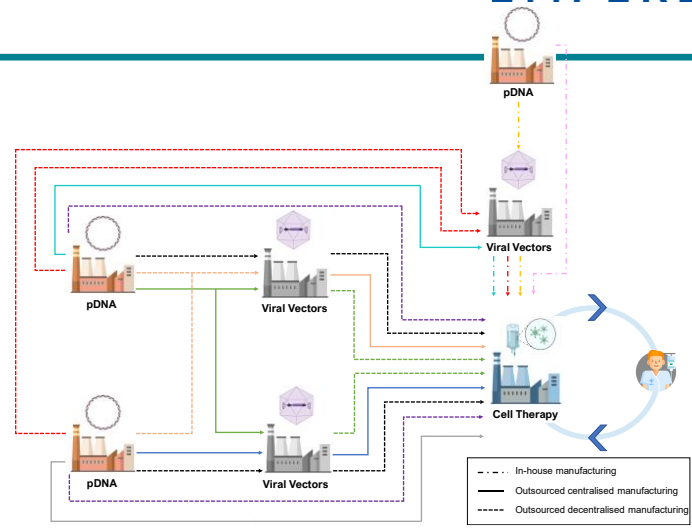
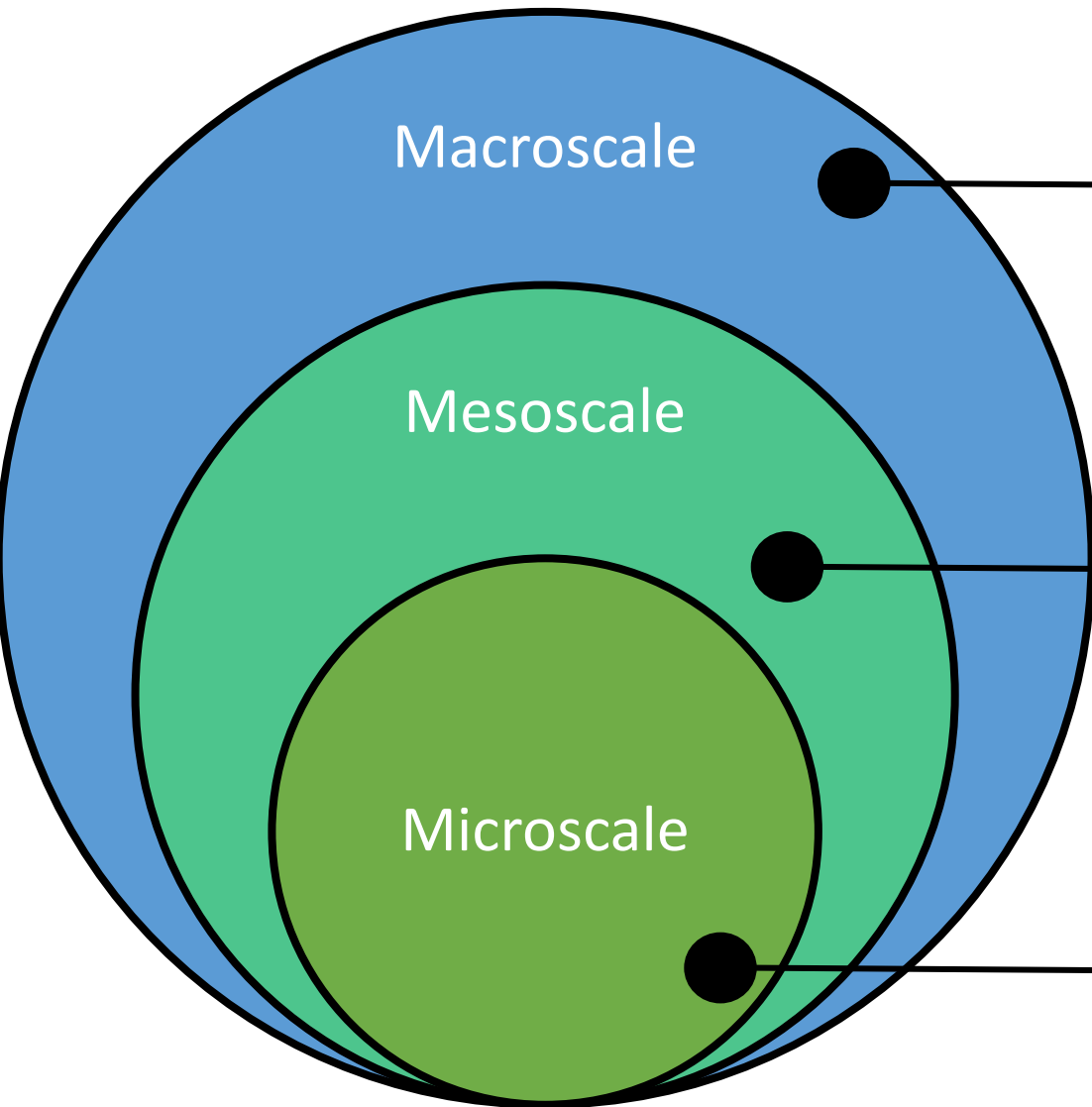
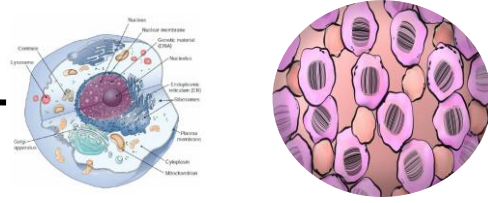


Figure created with BioRender.com





To help get ahead of disease and deliver real human health impact we need to look broadly and deeply at the interconnections of climate, nature and health.

We're committed to a net zero, nature positive, healthier planet, with ambitious goals set for 2030 and 2045.

AbbVie's science-based targets to lower emissions



- By 2030
- Reducing absolute scope 1 and 2 CO2 emissions by 42% from a 2021 base year
 - Reaching 100% sourcing of electricity from renewable sources

To build a more sustainable future, we've set ambitious emissions reduction targets that are in line with the Paris Climate Agreement. Our targets, which have been validated by the Science Based Targets initiative (SBTi), include:

Amgen 2027 Environmental Sustainability Goals

- Achieve Carbon Neutrality
- Reduce water consumed by 40%*
- Reduce waste by 75%*

*Compared to the 2019 baseline

Amgen Breda

- Adhere to Dutch and European regulations
- Contribute to Amgen 2027 ES Goals
- 'Go Beyond' projects in selected areas
- Engagement of staff and community

AMGEN

Amgen Breda's Environmental Sustainability Successes

- Energy label A++++ for security building and energy label C for our offices
- Increased electrical vehicles in fleet. (Amgen is our parking lot we have a spot (electrical) table also)
- Segregated waste. More than 85% of our waste stream is already segregated at this moment
- Intelligent LED technology in lighting as our standard
- Reusable bottles and cups for all our employees
- Product packaging. Amgen Breda (Product) Paper and carton components, PVC-free packaging, electronic heater (also)
- Green energy usage only, solar and wind as our standard
- Community involvement, donation of refurbished toys, clean up activities in our community
- Smart domestic water usage and no pollution of ground water as our products are biodegradable

3 Ensure healthy lives and promote well-being for all at all ages

9 Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation

12 Ensure sustainable consumption and production patterns





Responsiveness and Preparedness



Patient centric approach



In-time, at-point manufacturing



**Can we revolutionise the way
we design product lifecycle?**



**Capacity
Planning**

→ **Sufficient capacity** to meet demand forecasts

**Systematic
methods**

**Process
uncertainty**

→ **Prediction of lot sizes** and costs at scales

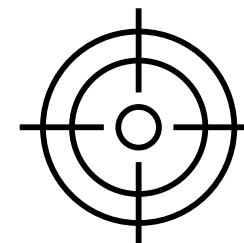
Challenges 

**Investment
risk**

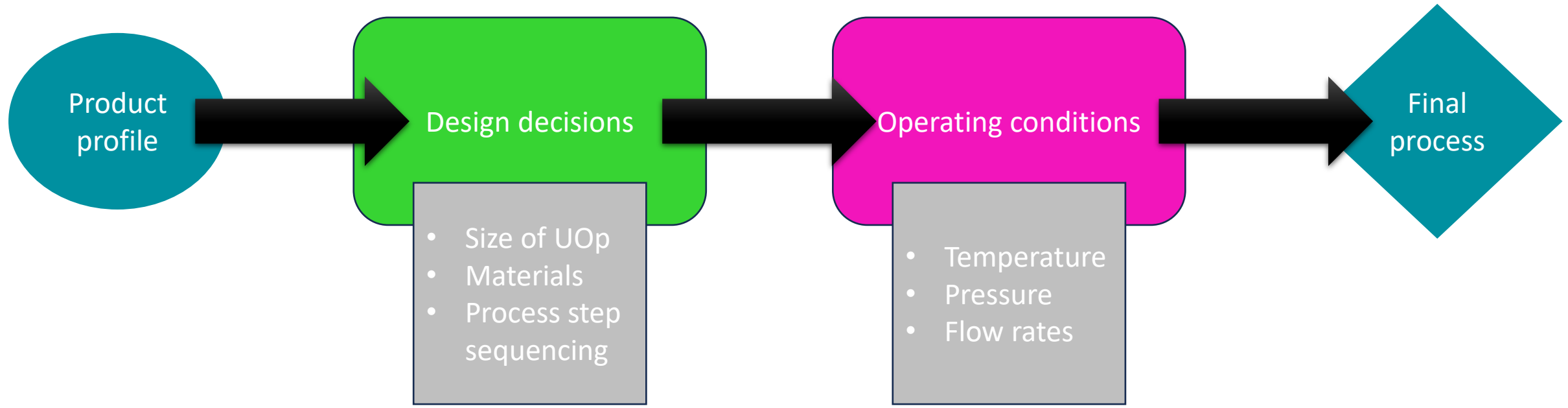
→ **Demand uncertainty:** clinical to commercial

**Impact
quantification**

→ **Awareness and mitigation**



Enough drugs for all, on time.



It works!



It meets the specs



It's inflexible

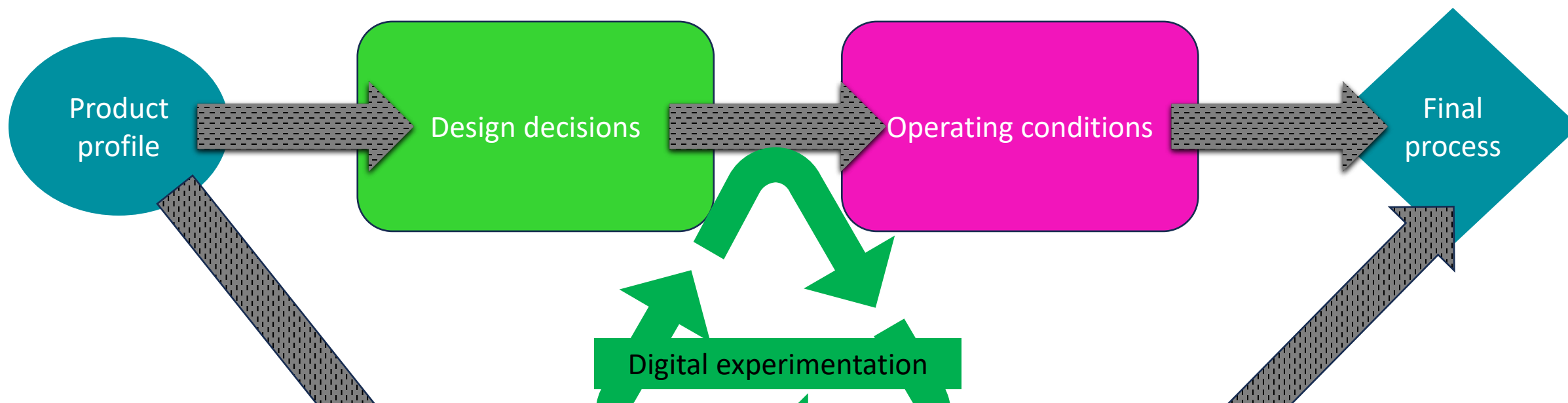


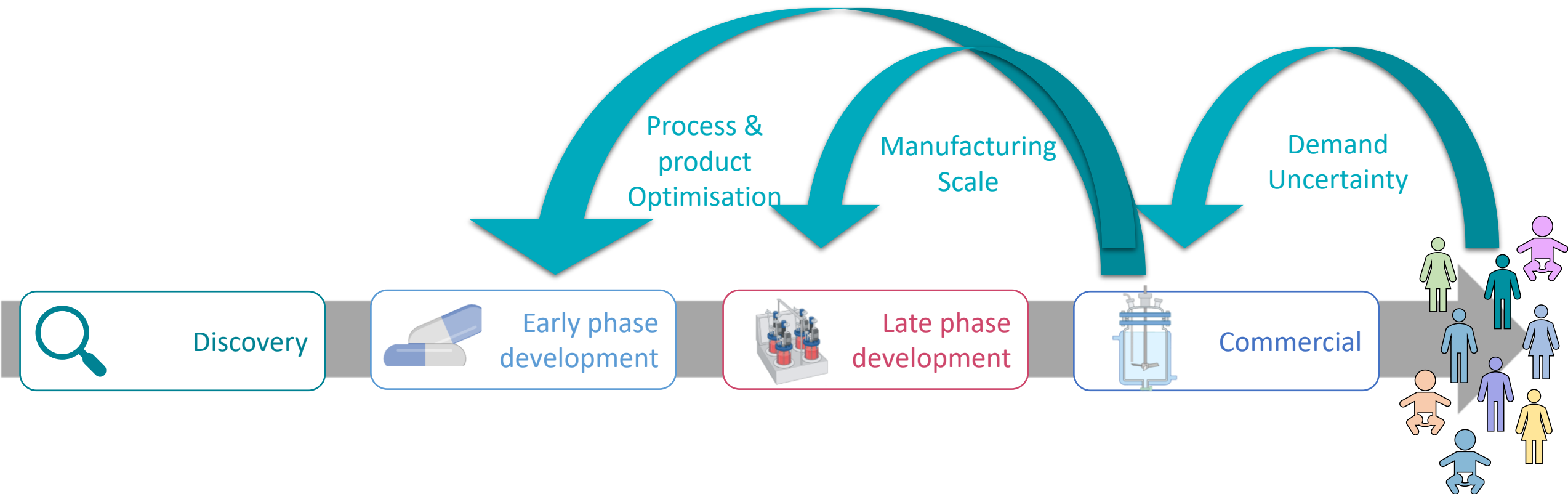
It costs

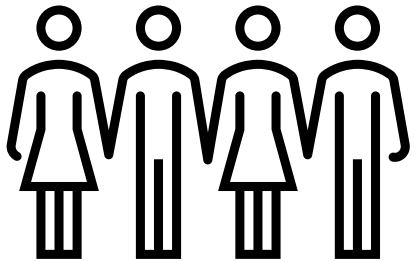


Isolates process steps





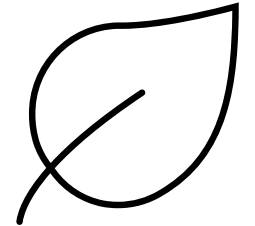




Enough



Accessible



Greener

Optionality

Agility

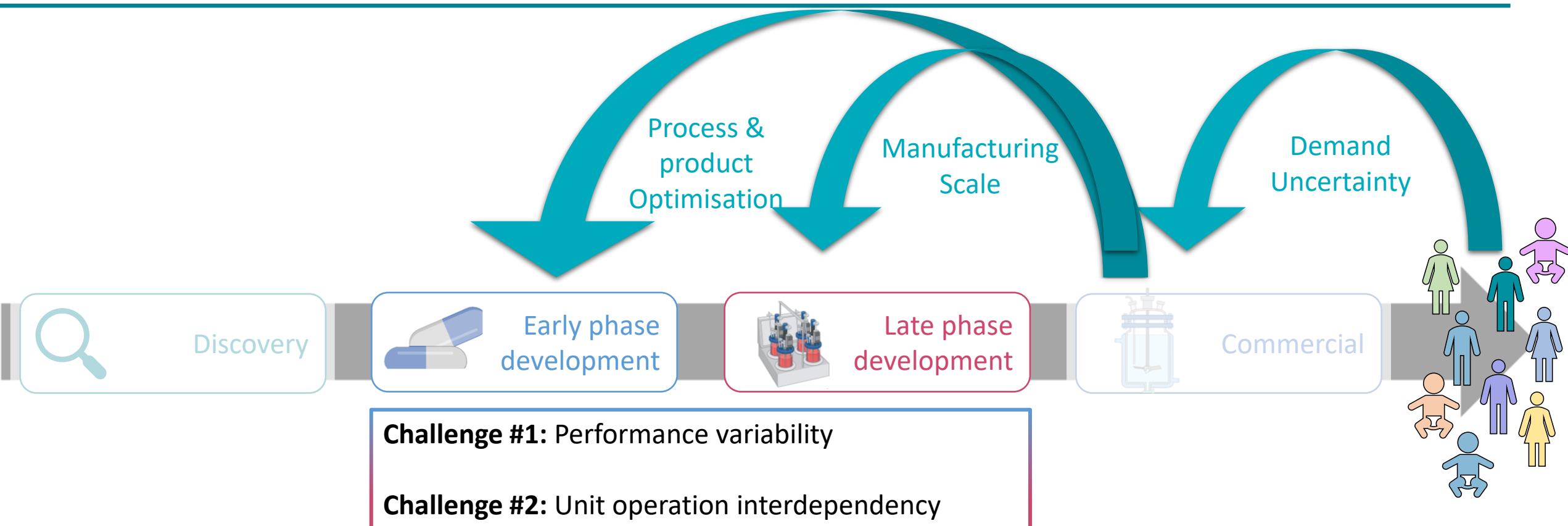
Responsiveness

**DEMAND
UNCERTAINTY**

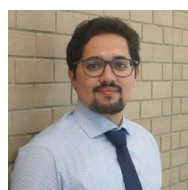
**PERFORMANCE
VARIABILITY**

UNKNOWN

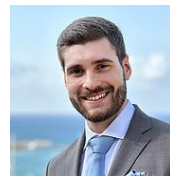
Digital innovation at the service of biopharma



- Sachio *et al.* (2023), *Chem Eng Res Des*, 197, 800-820
- Michalopoulou & Papathanasiou (2025), *Dig ChE*, 14, p.100215
- Galeazzi *et al.* (2025), *J Chrom A*, 21:46619
- Pessina *et al.* (2026), *DChE*, 1;18:100292
- Chiplunkar *et al.* (2026), *Chem Eng Sci*, 16:124255



Dr Ranjith
Chiplunkar



Dr Andrea
Galeazzi



Dr Steven
Sachio



Dr Foteini
Michalopoulou



Daniele
Pessina

- Design space identification
- Hybrid modelling
- Process control

Dr Steven
Sachio



Computer-aided framework for process design

1. Model Development & Problem Formulation

Process modelling & validation

Design problem definition

2. Design Space Identification

Virtual experimentation

Point cloud classification

Alpha Radius
Problem

a) no prior knowledge

b) average prior knowledge

c) established prior knowledge

Tolerance based

Combinatorial

Resolution support

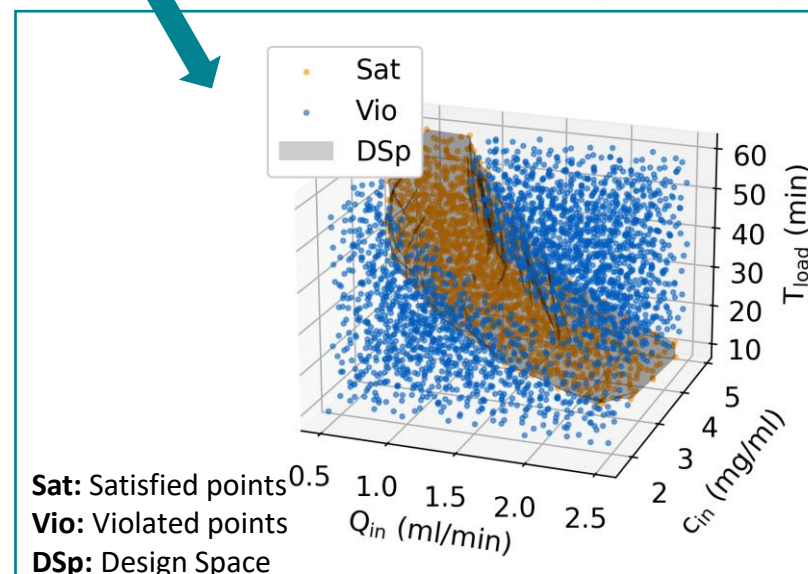
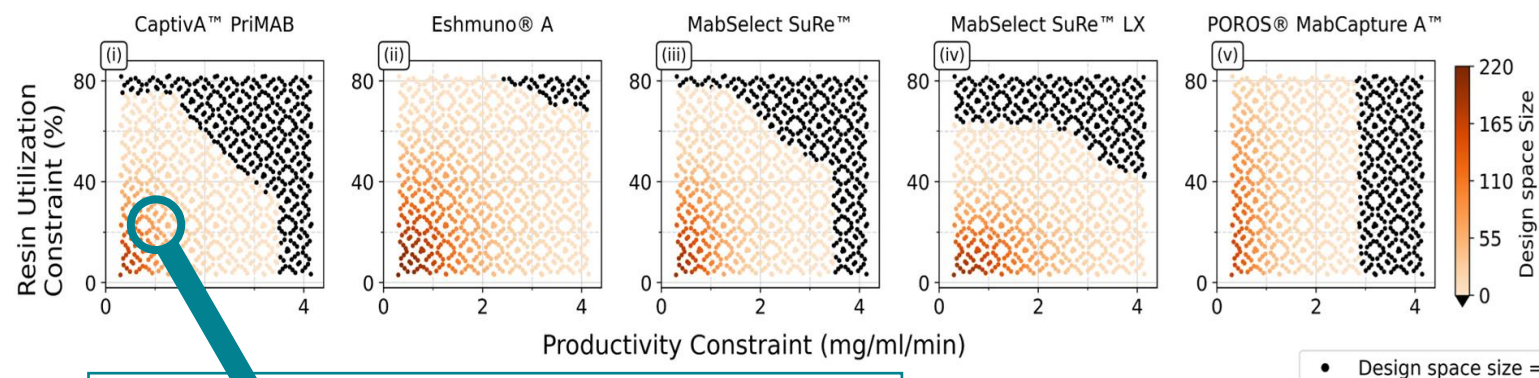
Alpha shape hull

3. Design Space Analysis

Acceptable operating region identification

Acceptable ranges quantification

Material screening in chromatography



- Over 20k combinations screened and assessed
- 5k design spaces generated
- Trade-off quantification
- Process resilience to variations

Sachio et al. (2023), *Chem Eng Res Des*, 197, 800-820
Sachio et al (2024), *J. of Chrom. A*, 1722, p.464890



Python package:
dside.readthedocs.io

Beta software package
also available



Daniele Pessina

Predictive modelling in crystallisation

Transfer Learning Methods

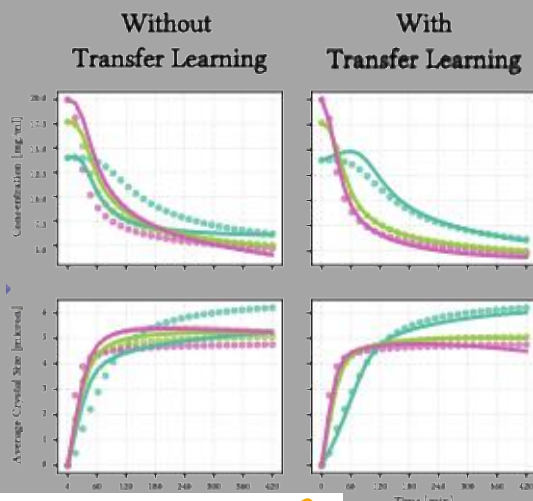
Neural
ODE

Penalise deviations
between network
parameters

Freeze the network
layers

Create an embedding
for the systems

E_{raw}



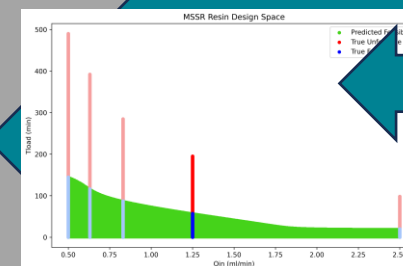
- Transfer learning for crystallisation modelling
- 4 crystallisation systems assessed
- Consumption and growth kinetics captured



Pessina et al. (2026), DChE, 1;18:100292

Pessina et al. (2024), Industr & Eng Chem Res, 64 (24), 12025-12035

Design space for Prot A chromatography



ANN

Generic
mechanistic
model

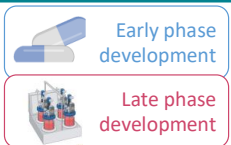
- Good predictions with only 9 experimental runs
- Data quality plays a key role (more than quantity)



Dr Andrea Galeazzi

Galeazzi et al.(2025), J Chrom A, 21:46619





System 1



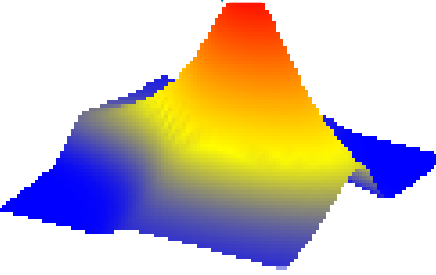
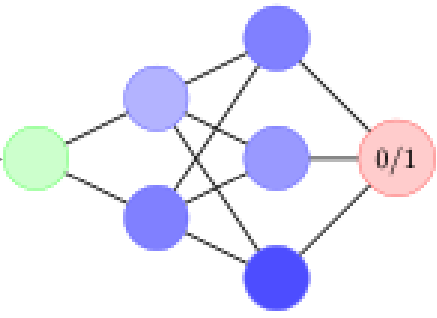
$$\begin{aligned} \varepsilon_c \frac{\partial c}{\partial t} + u \varepsilon_c \frac{\partial c}{\partial z} &= \varepsilon_c D_{\max} \frac{\partial^2 c}{\partial z^2} - \frac{3(1-\varepsilon_c)}{r_p} k(c - c_{p,s}), \\ \varepsilon_p \frac{\partial c_p}{\partial t} &= \frac{1}{r^2} \frac{\partial}{\partial r} \left(r^2 D_{\text{eff}} \frac{\partial c_p}{\partial r} \right) - a \frac{\partial q}{\partial t}, \\ \frac{\partial q}{\partial t} &= k_a c_{p,s} (q_{\max} - q) - k_d q \end{aligned}$$

Mechanistic model

(new) Exper. data

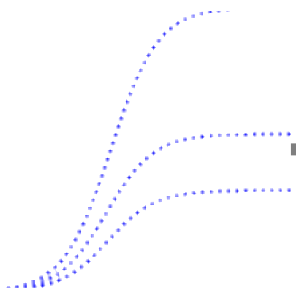
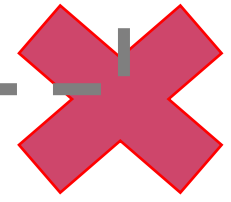
Black box model

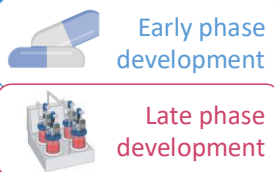
Prediction



Transfer learning

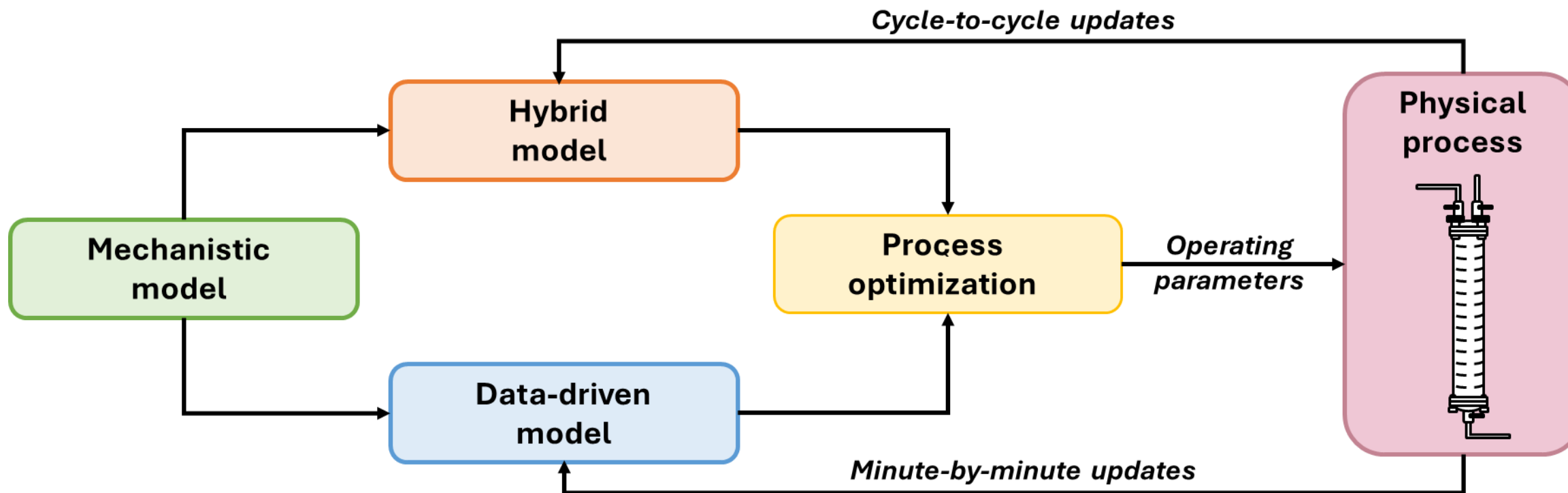
System 2





The case of ion-exchange chromatography

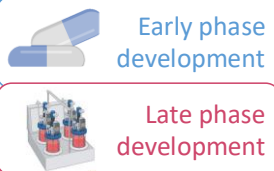
Dr Foteini
Michalopoulou



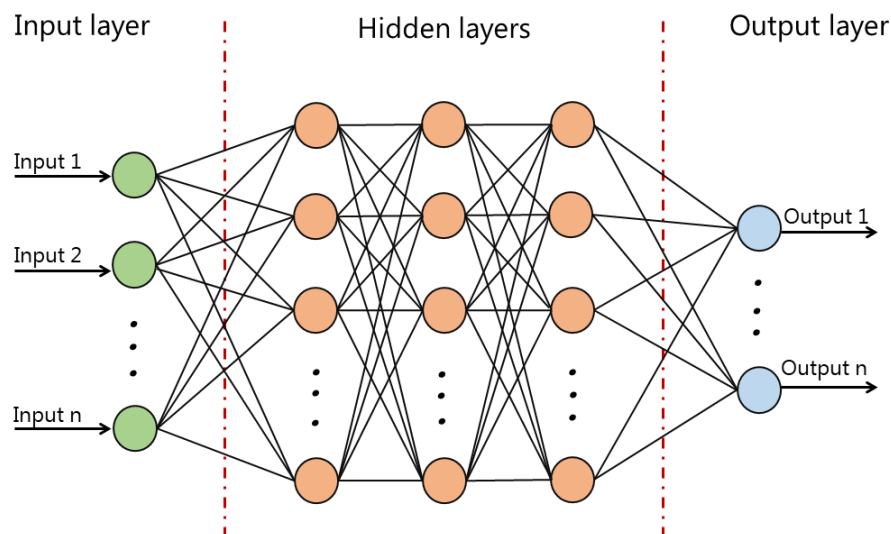
Michalopoulou & Papathanasiou (2024), *AIChE J*, e18600

Michalopoulou & Papathanasiou (2025), *Dig ChE*, 14, p.100215

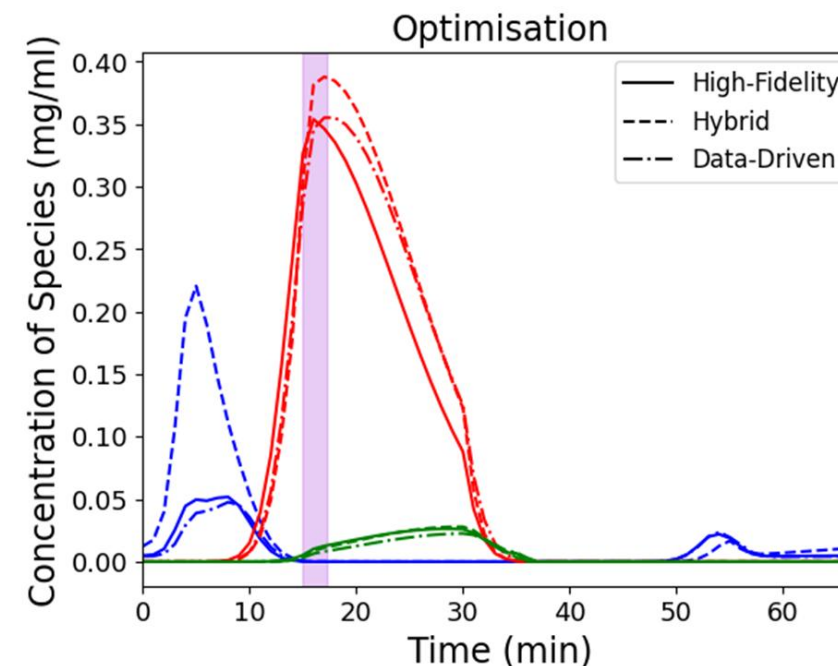
Michalopoulou (2025), *Incorporating AI Tools Into Downstream Process Optimization*, *Bioprocess Online*



Dr Foteini
Michalopoulou



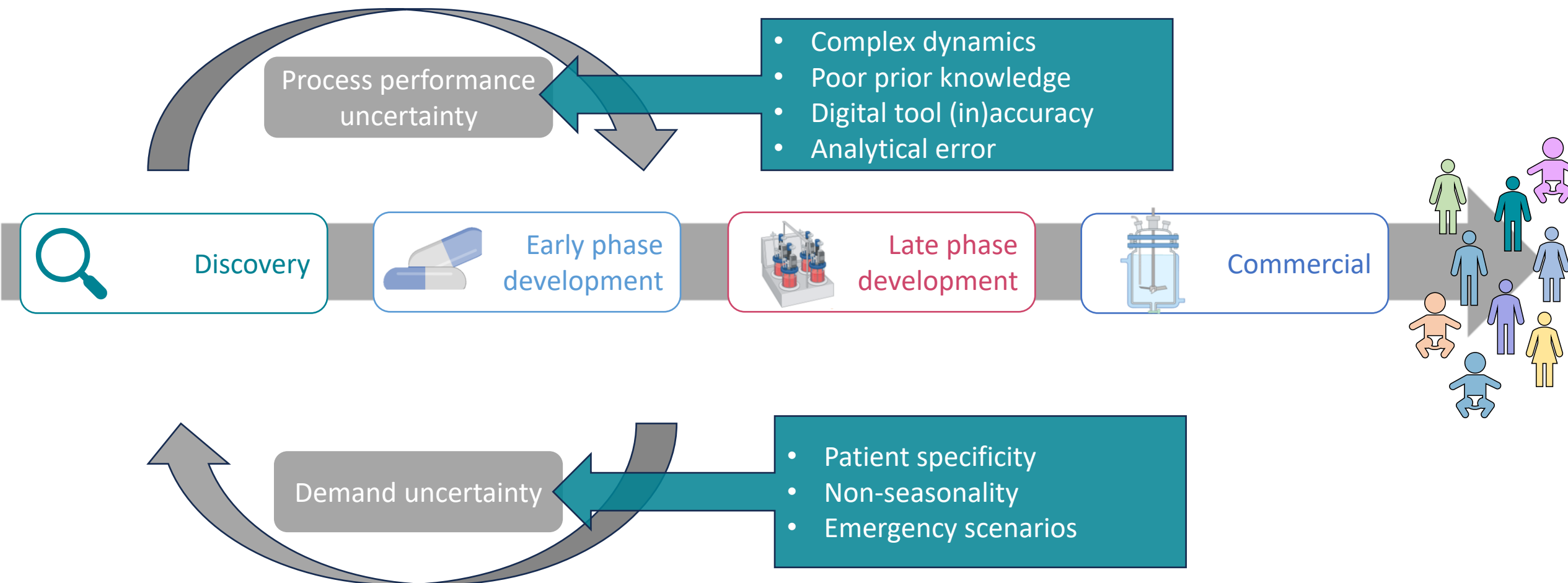
- **Input Layer:**
 - All operating conditions → understanding of the process
 - Dynamic Inputs → understanding of the time step
- **Hidden Layers:**
 - 1-4 hidden layers → uniform structure
 - 16 – 256 neurons
- **Output Layer:**
 - Concentrations at end of column
 - Predictions at CSS



Michalopoulou & Papathanasiou (2024), *AIChE J*, e18600

Michalopoulou & Papathanasiou (2025), *Dig ChE*, 14, p.100215

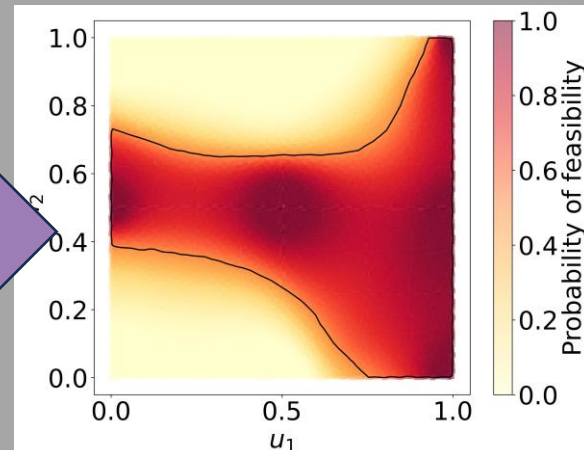
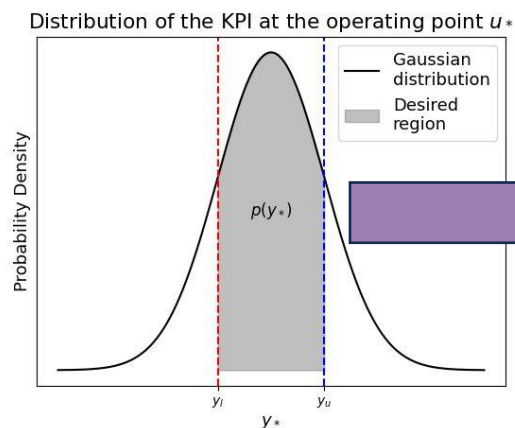
Michalopoulou (2025), Incorporating AI Tools Into Downstream Process Optimization, *Bioprocess Online*



In design

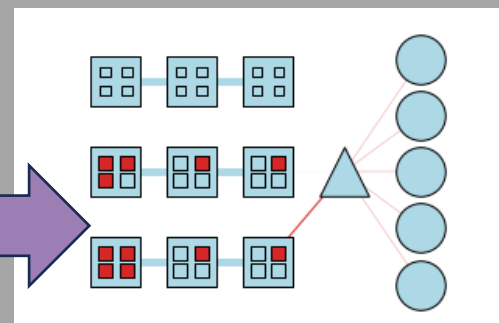
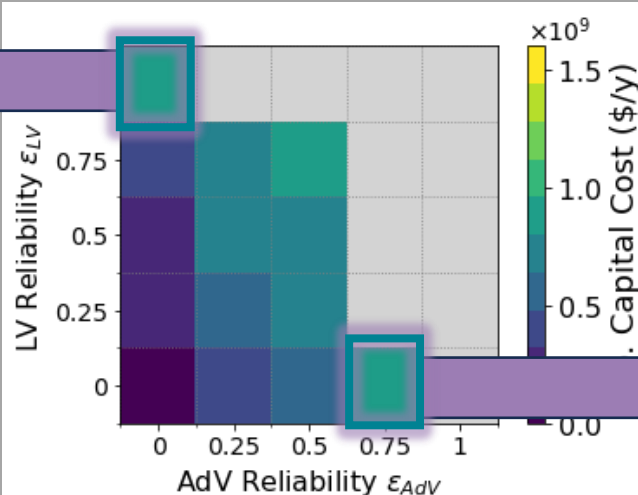
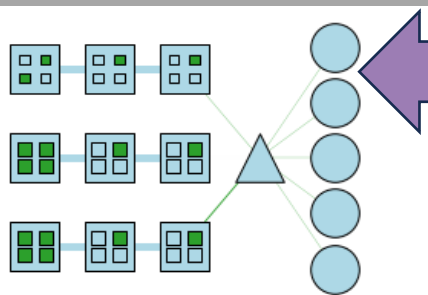


- Data driven design space using GPs
- Guide and minimise experimentation
- Estimation of probability of constraint satisfaction



Dr Ranjith
Chiplunkar

Chiplunkar et al. (2025), Syst and Contr Trans Proceedings of ESCAPE35

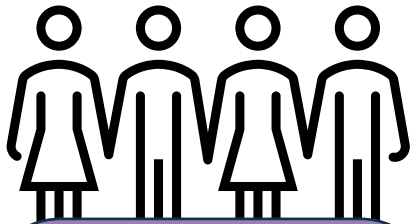


In distribution

Dr Miriam
Sarkis



Sarkis et al. (2025), Comp Chem Eng, p.10901



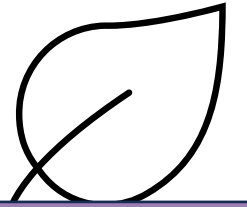
- Demand uncertainty
- Personalised routes
- Unexplored scale up effects

CASSS, CMC Strategy Forum North America



- Rapid scale up
- Costly processes
- (lack of) Analytics

Dr M. M. Papathanasiou



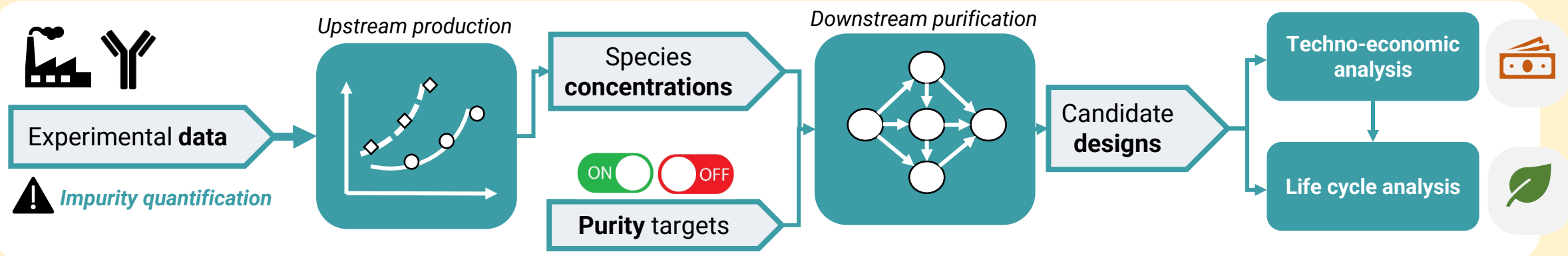
- Wet-lab experiments driving
- Scale-out manufacturing
- Ultra-cold chain logistics

Sarkis et al. *Comp. Chem. Eng. Decarb. And Circ. Economy SI*, 205, 109454

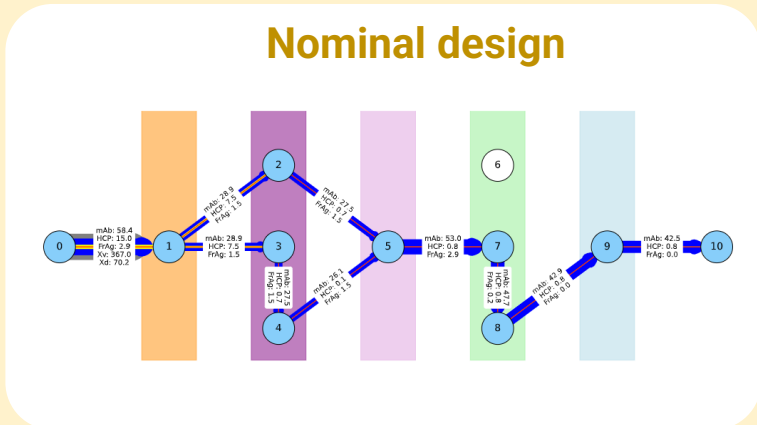
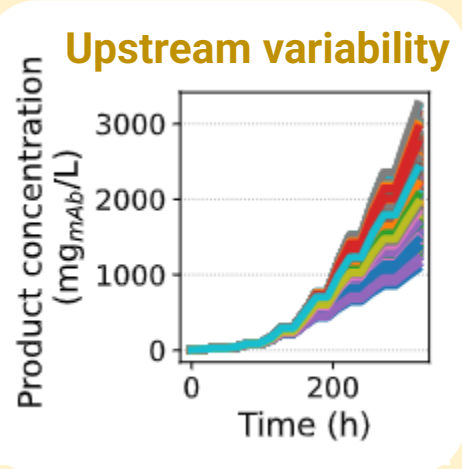
Dr Miriam Sarkis



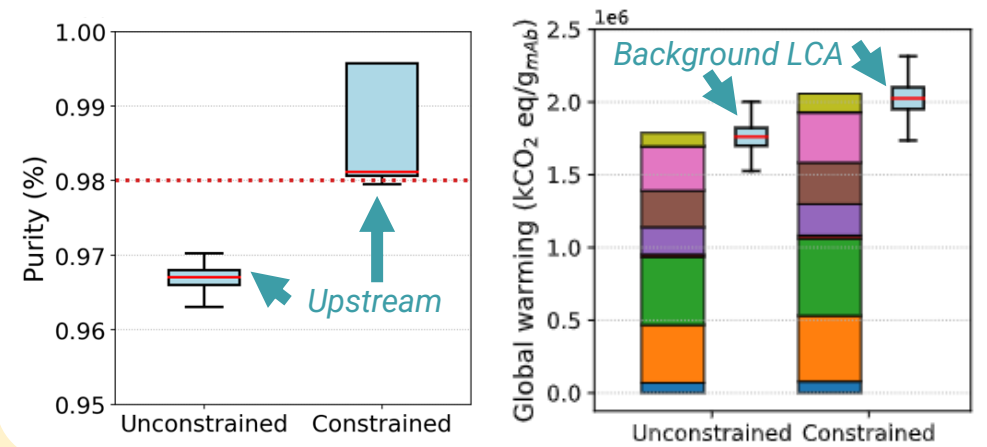
Methodology



Key results



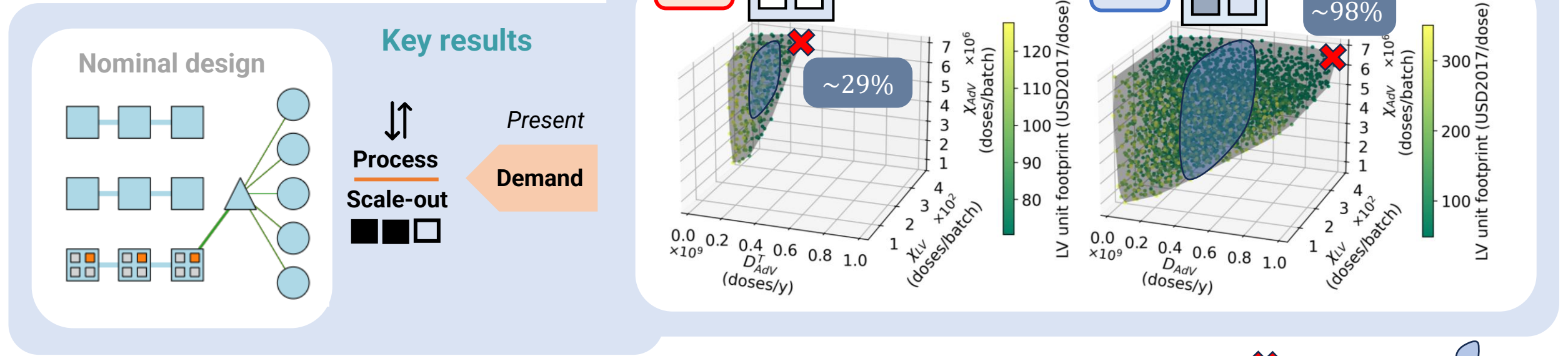
Robustness vs footprint trade-off





Dr Miriam Sarkis

Sarkis et al (2025). *Comp. Chem. Eng. Foundations of Computer Aided Process Design, Special Issue*, 201, 109197



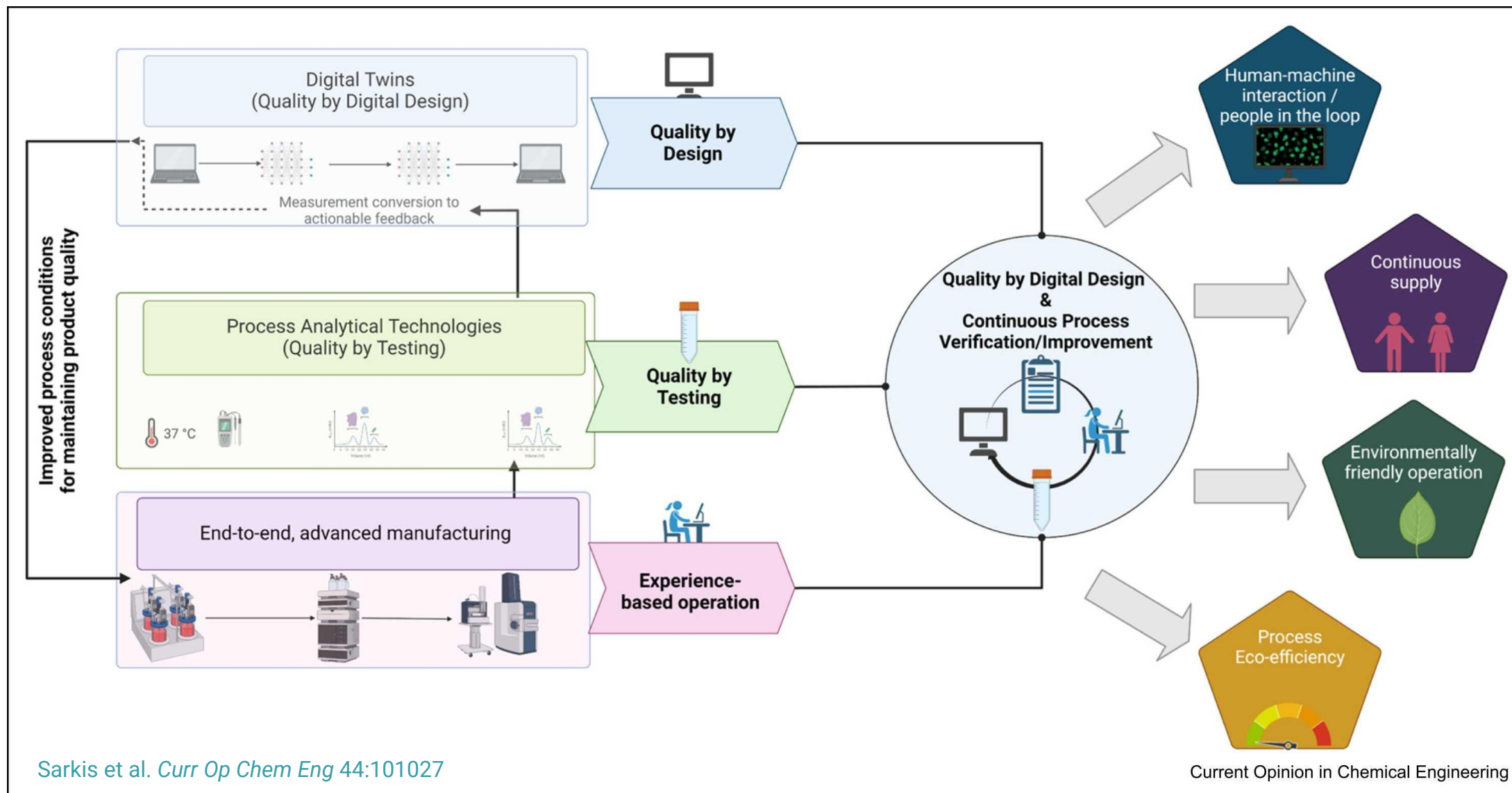
Quantification of **manufacturing trade-offs** between

Cost

Sustainability

Scalability 

Flexibility 



Digital innovation for sustainable, accelerated development in an era of uncertainty

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