

# Designing, Growing, and Evaluating Biomaterials with AI

A systems-level workshop on  
decision-making across the  
biomaterials lifecycle

# A Biomaterials Journey

Scale up/out

Commercialization

Execution

Research/IP

Innovation



Mycelium-based food scale-up  
sold over +2000 stores (500 Wholefoods)

Mycelium textiles R&D for luxury and  
consumer electronics

Mycelium foam R&D



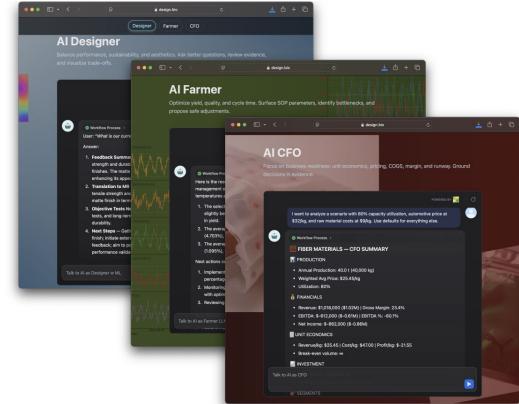
Led Data Systems &  
Intelligence at Ecovative

Co-founder, CTO of Biorealize  
Portable Bioreactor for R&D

UPenn - Faculty  
Biodesign (2011-2021)

# Session Structure

- 0.** Designing or Engineering Biomaterials
- 1.** Designing under uncertainty
- 2.** Operating & Scaling Biomaterials
- 3.** Evaluating Techno-economics
- 4.** Integration & discussion



Test decisions under guided simulations

# Learning Outcomes

## Systems Reasoning

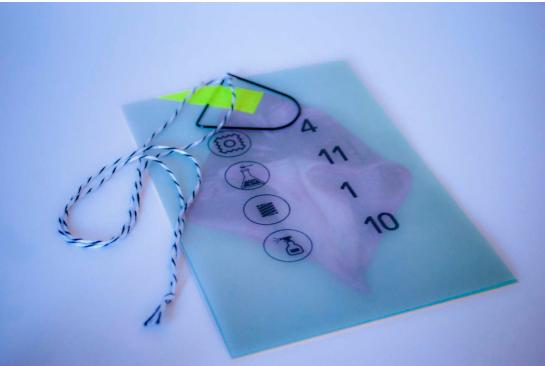
- Identify where AI can meaningfully support engineering decision-making (in biomaterials)
- Reason about experimental design, process operation, and economics as a coupled system

## Trade-off Evaluation

Evaluate trade-offs between technical performance, scalability, and market viability

## Role of AI

Critically assess the limits of AI in complex biological and manufacturing contexts





# Why This Workshop?

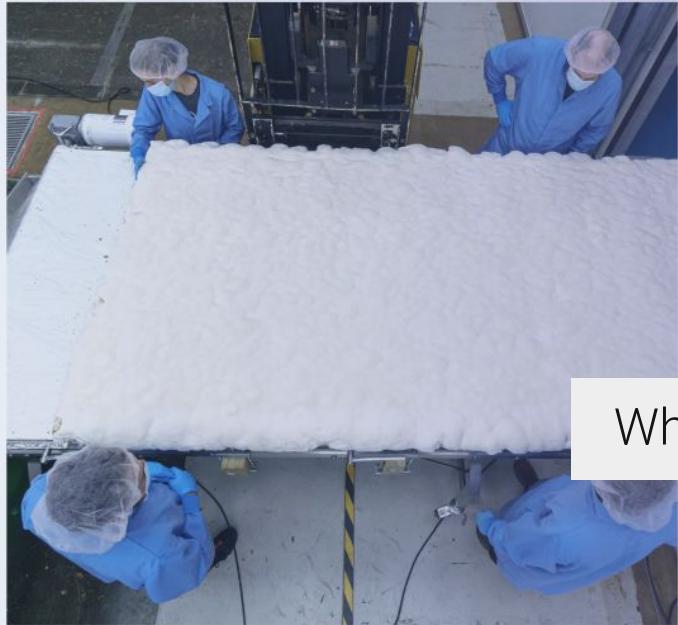
**Biomaterials** (*and many other innovation*) **often**  
**don't come out of the studio or lab**

– they fail at the boundaries:

- Experiment ↔ Scale
- Process ↔ Economics
- Technical success ≠ Market success

CAPEX

PIVOT-  
ABILITY



Investment  
readiness

DESTINY  
CONTROL

Why things fail?

SCALE-READINESS

uncertainty

RATE of  
LEARNING



ALCOFO

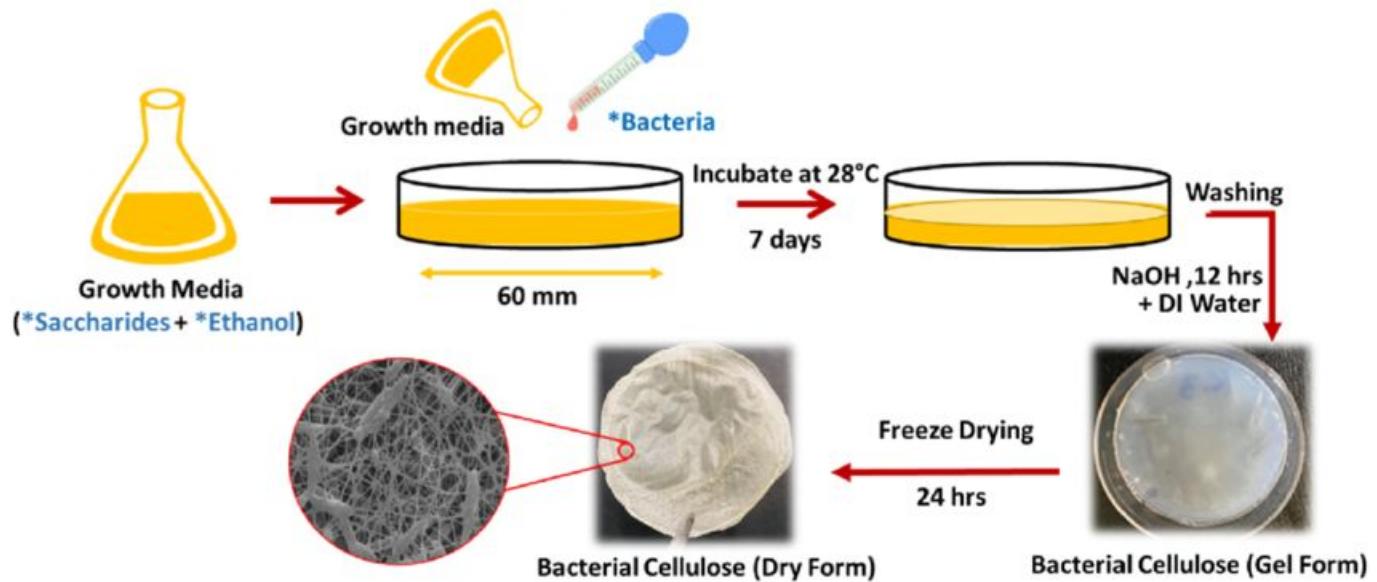
# Why Biomaterials & AI

- **Using AI for decision-support** across the full biomaterials design lifecycle—from early material innovation, to production and scale-up, to techno-economic evaluation.
- Broadening access, allowing other fields to contribute their expertise.
- AI can support three interconnected roles:
  - **Designing** materials under performance and sustainability constraints;
  - **Operating** biological production processes under uncertainty; and
  - **Evaluating** unit economics and market viability.



Can we grow a wallet?

# How to grow BC pellets at the lab?



*Komagataeibacter xylinus*

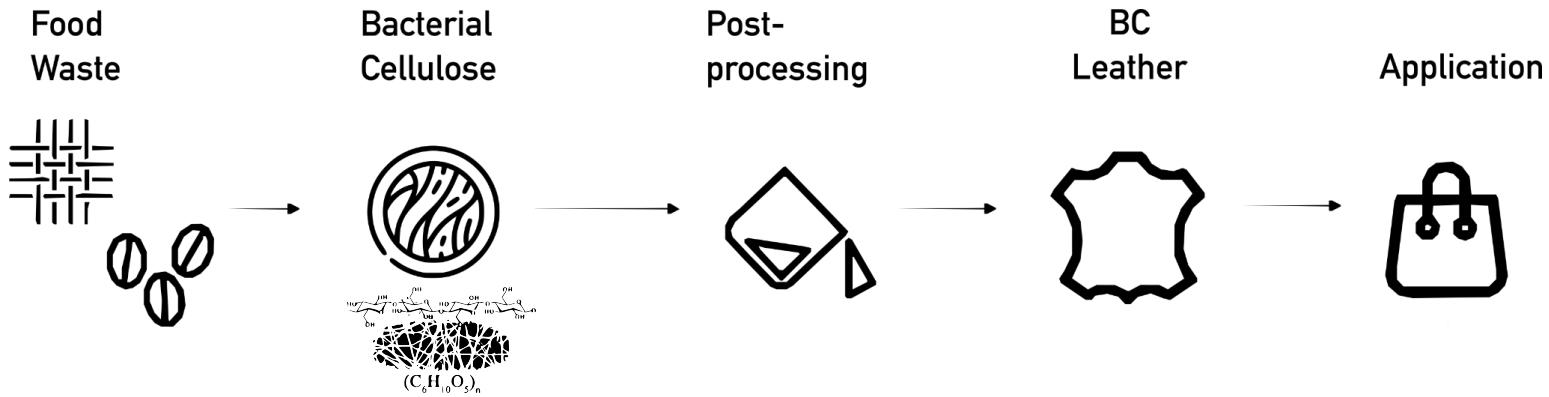
Nano-scale fibers (~20-100 nm diameter) but  
forms a macro-scale mat  
Pure culture (not SCOBY)

By Francisco X Nascimento

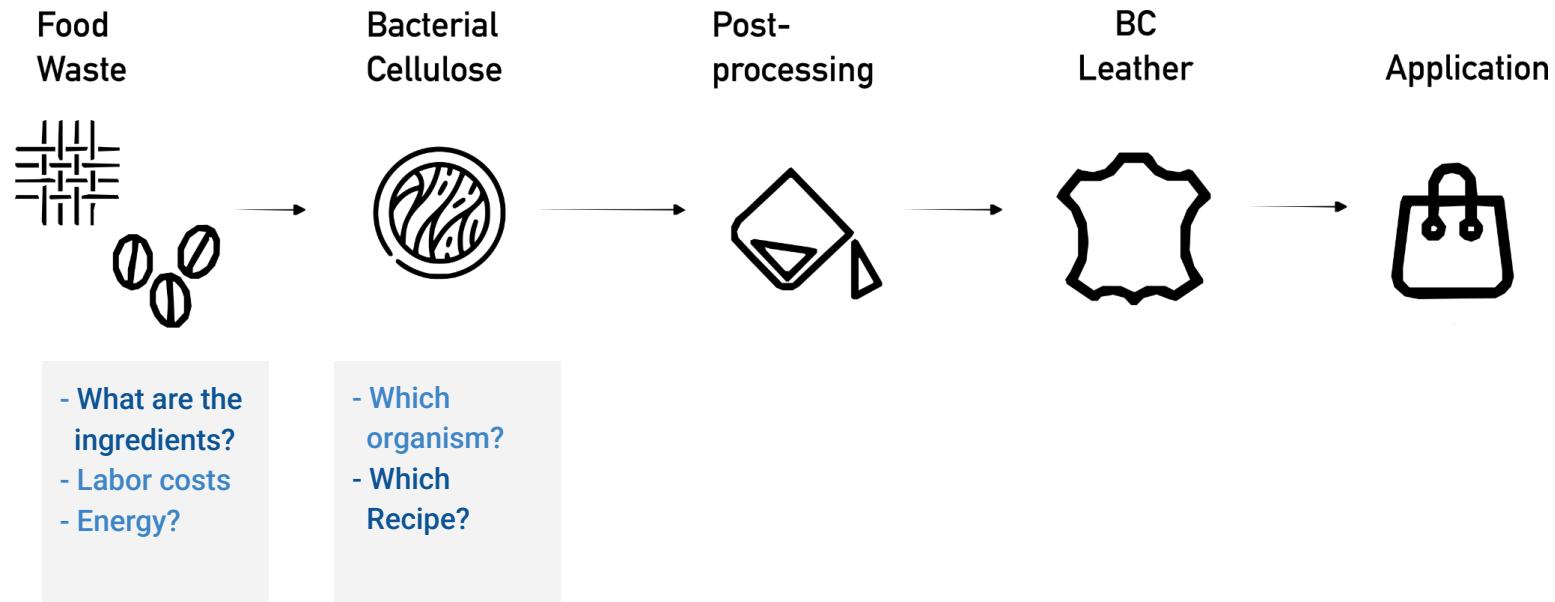


Where do wallets grow?

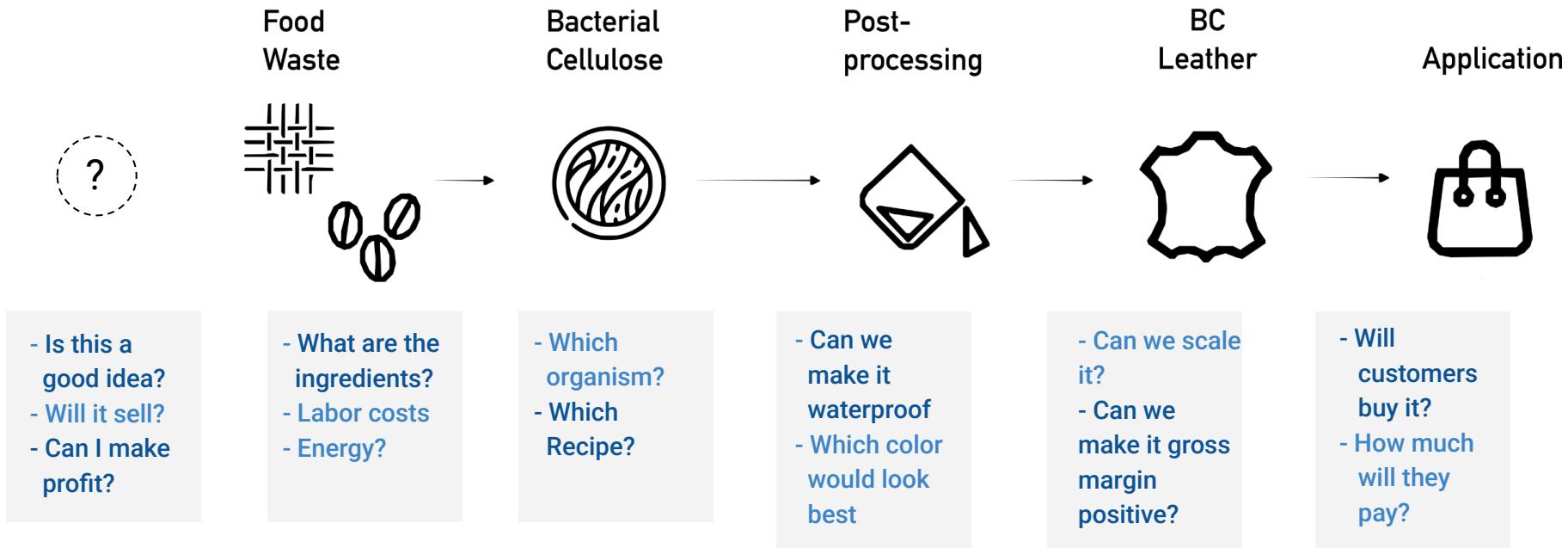
# Scale up Pipeline



# Pipeline (of uncertainties)



# Pipeline (of uncertainties)



# 1. Designing Under Uncertainty

- Translating material performance, sustainability, and aesthetic goals into measurable criteria
- Using AI-assisted analysis to compare formulations, prototypes, and experimental results
- Identifying which uncertainties matter most—and which experiments are worth running next
- Design of Experiments as an economic, not purely statistical, problem

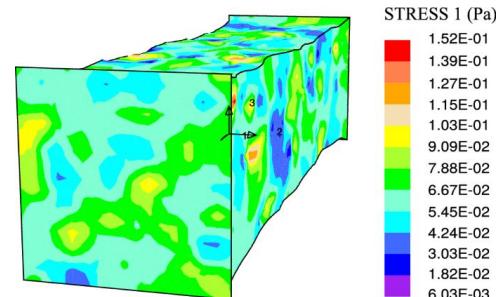
# How do we make a reliable material?



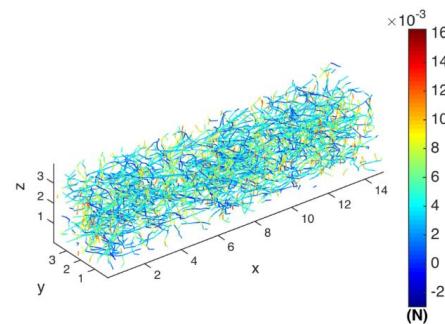
How do you use AI for quantitative & quantitative assessment?

## Optical Testing

What is uniformity?  
(Surface regularity)



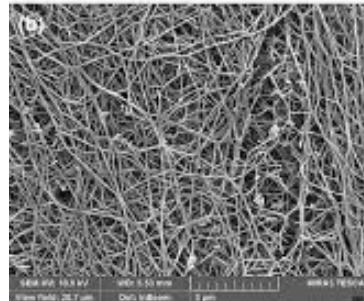
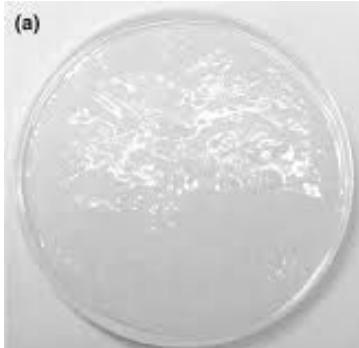
(a) Stress  $\sigma_{11}$  (Pa) in the matrix



(b) Fiber force  $f_{fiber}$  (N) in the network

Jin, T. A computational framework for biomaterials containing three-dimensional random fiber networks based on the affine kinematics. *Biomech Model Mechanobiol* 21, 685–708 (2022).  
<https://doi.org/10.1007/s10237-022-01557-6>

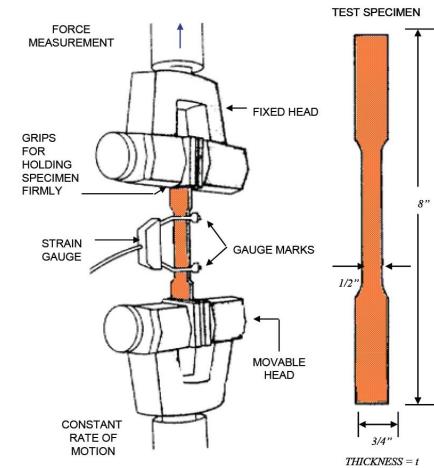
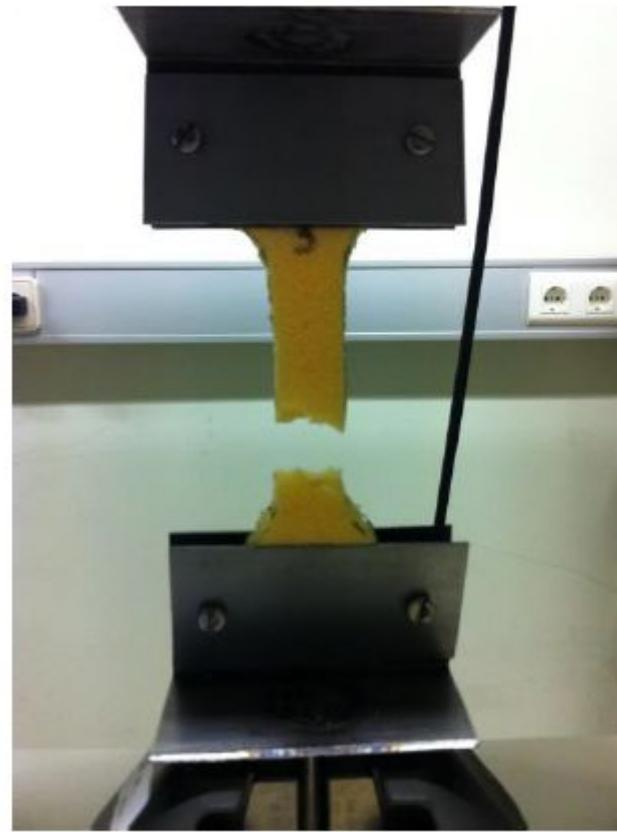
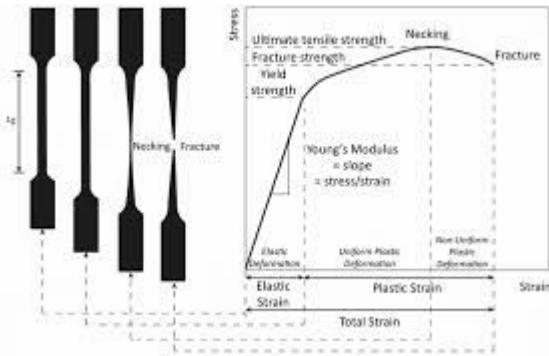
What makes a good  
BC pellicle?



- Growing is expensive
- Testing is expensive
- How do we decide which parameters matters more

Image → QC  
Mechanical Properties

Quality category



## Mechanical Testing

- What is the tensile strength?
- What is elongation at break?
- Stiffness?



Which one will the client like?

**How do you use AI for qualitative experience?**

#### Preferences

What is the user feedback on the textured finish?

How about color?

## AI-ASSISTED DECISION MAKING

### Designer/Engineer/Scientist

- Formulation (Recipe) Experiments
- Mechanical Testing
- Product Prototypes
- User feedback forms
- Historical data
- Experience data

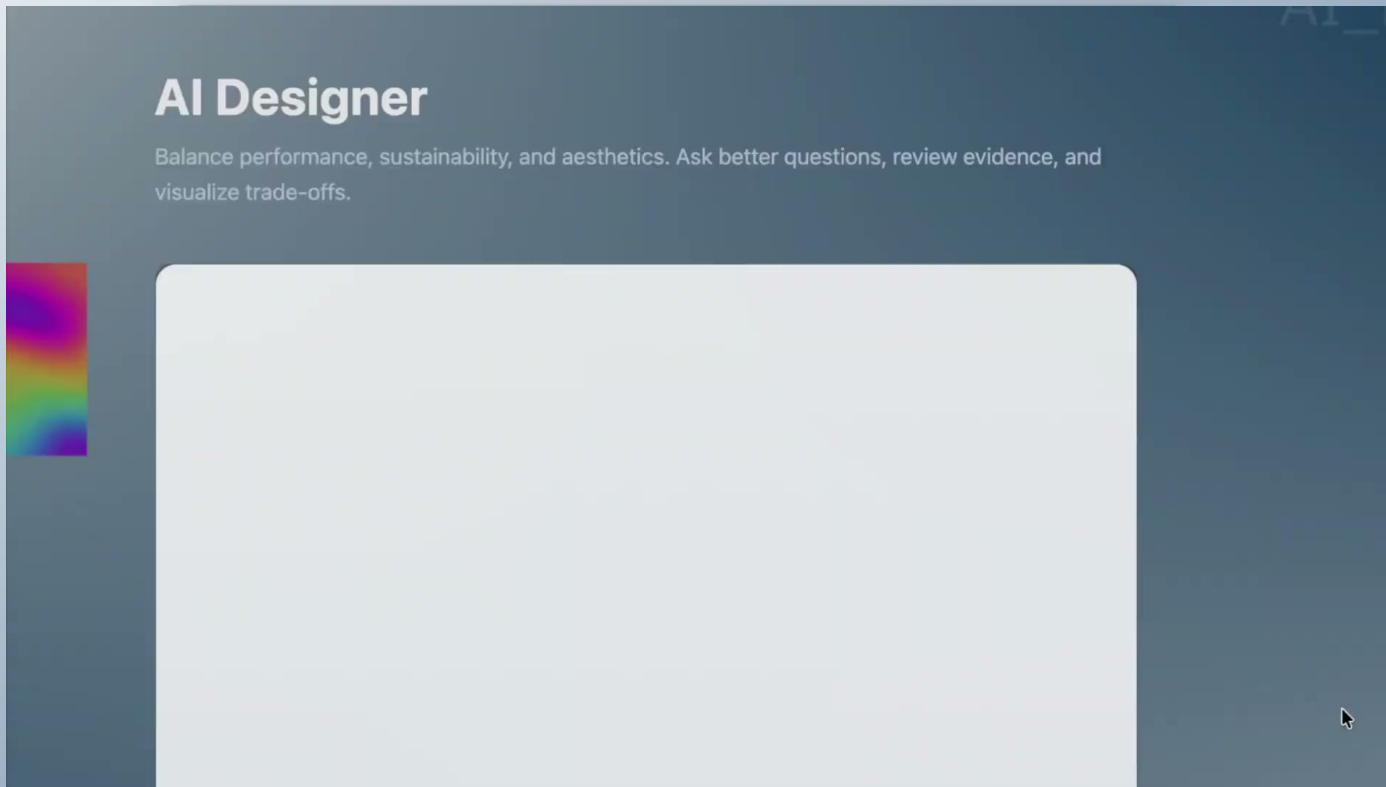
Spreadsheets, recipe databases, forms, ML

AI as DATA MANAGER  
AI as KPI TRACKER

AI as ASSUMPTION VALIDATOR  
AI as ANALYST

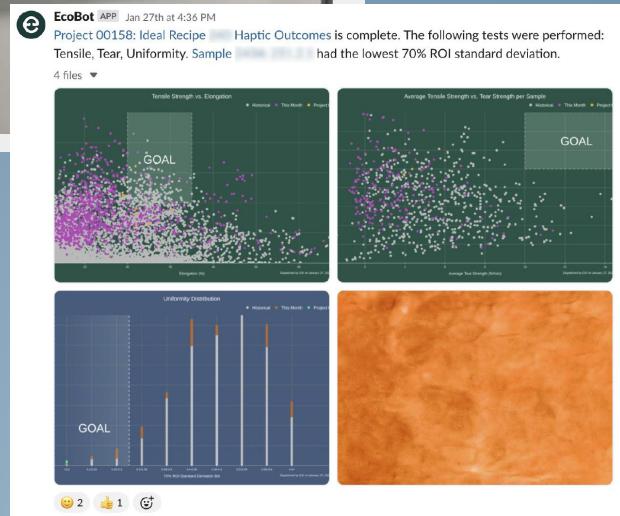
AI as REPORT MAKER  
AI as PREDICTOR

One platform



## AI as Designer

How does AI support material readiness by helping you navigate the trade-offs between performance, sustainability, and aesthetics?



## Classifier Model

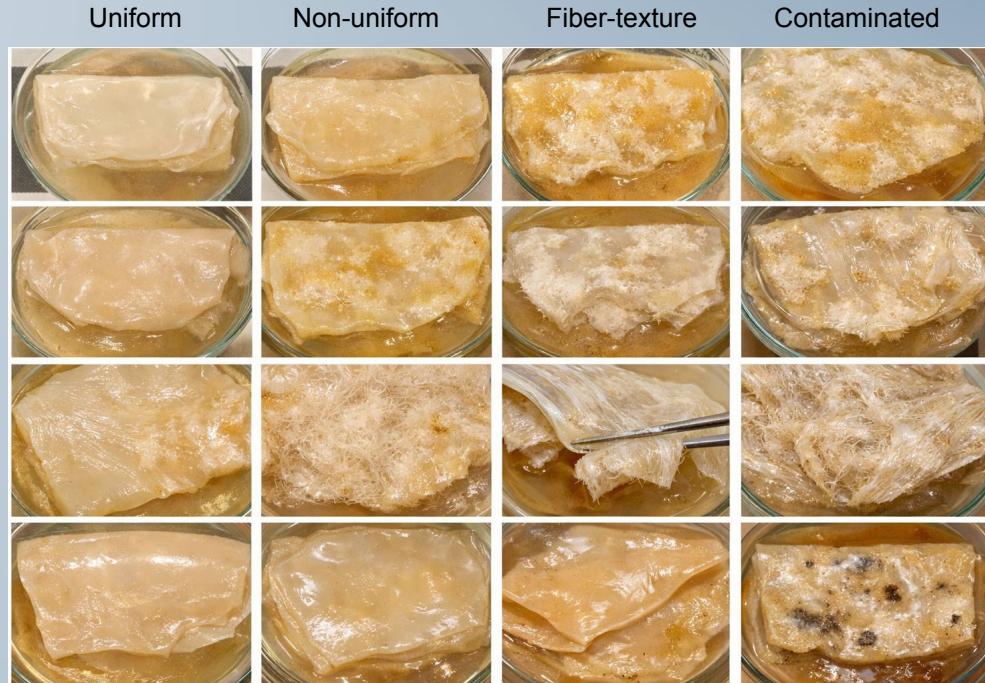


*The material looks good visually, but I'm worried about brittleness. What would be the best next experiment to improve it without losing the surface quality?*

**Predicted class:** uniform

Top probabilities:

{'contaminated': 0.2413543462753296,  
'fiber\_texture': 0.0203  
05141806602478, 'non\_uniform':  
0.23074842989444733, 'uniform':  
0.5075921416282654}



## Regressor Model

- Tensile Strength (0-50 MPa)
- Elongation (0-100%)
- Stiffness (0-1)
- Uniformity (0-1)

## Uniform



## Non-Uniform

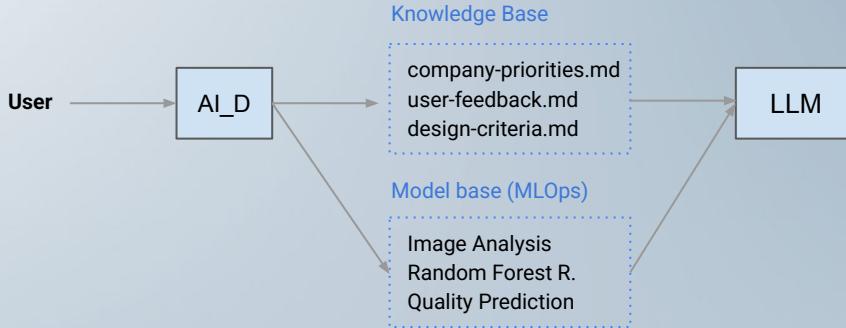


## Fiber Texture



## Contaminated





## Designer

You are in charge of material readiness, but need to know if you meet performance, sustainability criteria.

You are worried about aesthetics. Which interventions will still yield the best aesthetic results

## Questions to AI

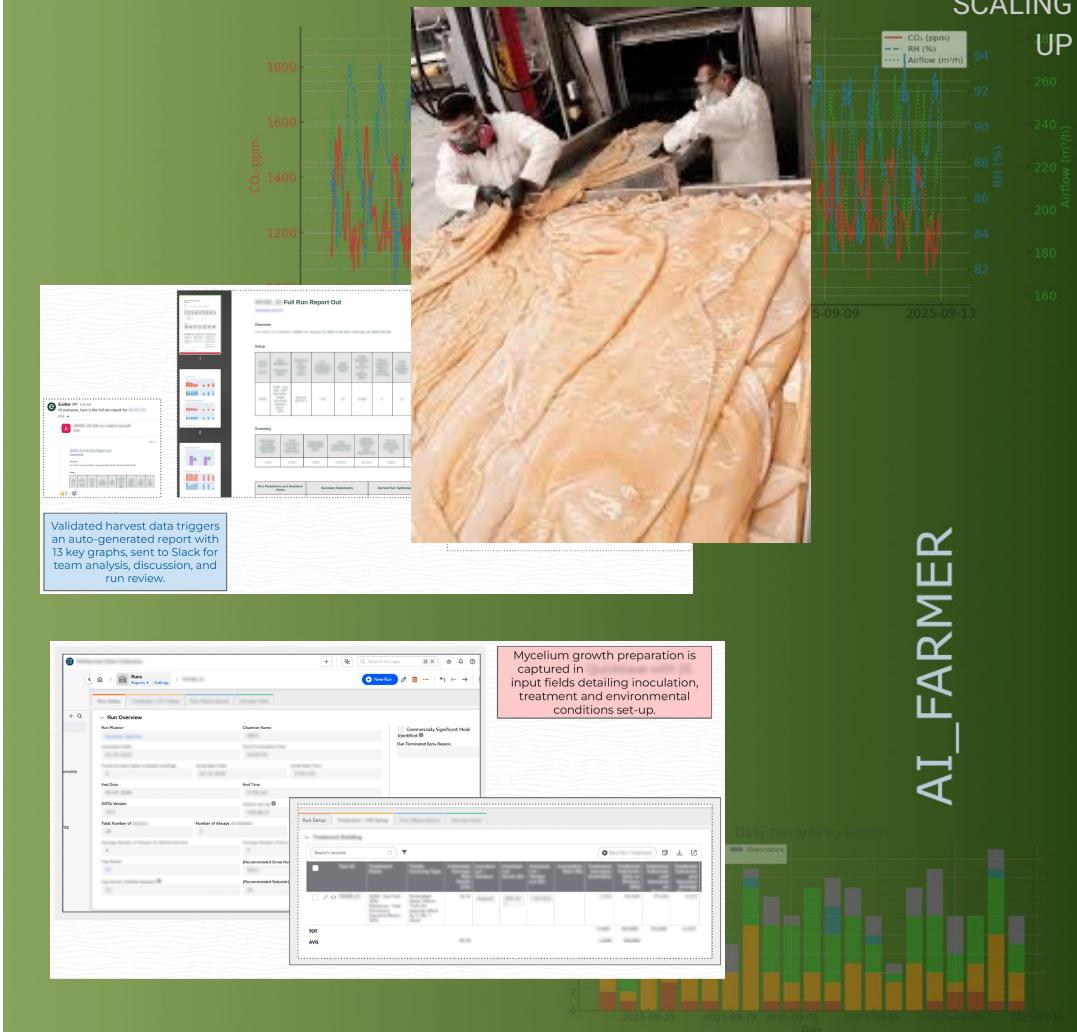
- **Material Readiness (MR1-3)**  
*Based on this image, is this material ready to be used as a hanging interior panel, or should I treat it as exploratory? What MR level would you place it in?"*
- **Qualitative DoE:**  
*The material looks good visually, but I'm worried about brittleness. What would be the best next experiment to improve it without losing the surface quality?"*
- **Trade-off**  
*This sample scores lower on tensile strength but has the most compelling surface texture so far. Is it reasonable to move forward with this version, and what risks should I acknowledge?*
- **Use and Framing**  
*If I used this material as-is, what kinds of uses would it be appropriate for, and what should I avoid using it for?*

## 2. Operating & Scaling Biomaterials

- Moving research to production
- Understanding variability in biological production systems
- Using AI to interpret sensor data, detect anomalies, and reason about yield and quality
- Balancing algorithmic insight with human operational knowledge
- Recognizing when increased automation improves robustness—and when it introduces fragility

## AI as Farmer (Grower)

- How does AI support scale readiness by predicting quality, yield, and production bottlenecks—and by bringing algorithmic insight together with human intuition?
- How do you grow? Move questions from research to operations.



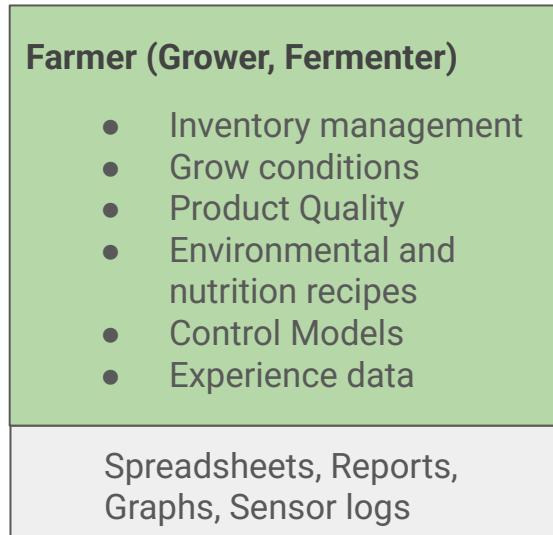


POLYBION



ModernSynthesis

## AI-ASSISTED DECISION MAKING

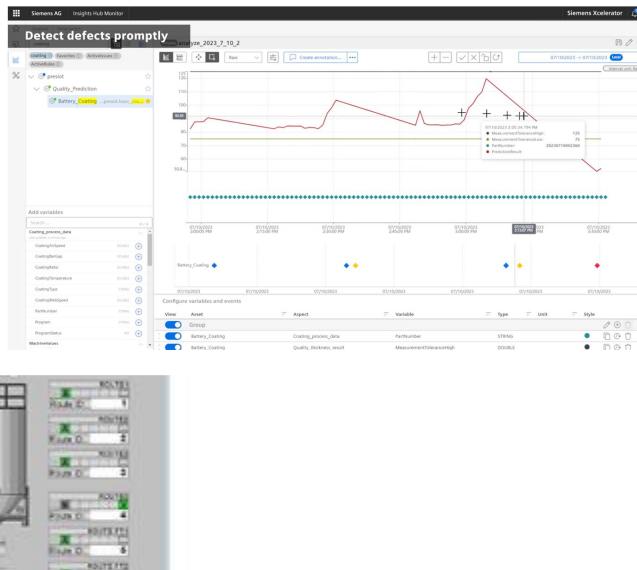


AI as DATA MANAGER  
AI as KPI TRACKER

AI as ASSUMPTION VALIDATOR  
AI as ANALYST

AI as REPORT MAKER  
AI as PREDICTOR

One platform



## Environmental monitoring

- **Temperature:** 28-30°C optimal for *Komagataeibacter* (strict control  $\pm 1^\circ\text{C}$ )
- **pH:** 4-6 range, typically 5.0 (acetic acid production lowers pH over time)
- **Dissolved oxygen (DO):** Critical - BC production is aerobic, typically maintain >20% saturation

## bc\_runs\_2024\_2025.csv

**One row = one fermentation run (static tray batch)**

**Purpose:** operations/anomaly detection, yield benchmarking, run-to-run comparisons.

### Identifiers

- run\_id (*string, unique*) — e.g., BC\_RUN\_2024\_001
- start\_date (*YYYY-MM-DD*)
- end\_date (*YYYY-MM-DD*)
- year (*int*)
- recipe (*recipe\_1 | recipe\_2 | recipe\_3*)

### Process (static tray)

- fermentation\_mode (*fixed string: static\_tray*)
- fermentation\_temp\_c (*number*)
- run\_period\_days (*int*)
- initial\_ph (*number*)
- inoculum\_pct (*number; v/v %*)

### Media

- carbon\_source\_type (*glucose | sucrose | glycerol | molasses*)
- carbon\_concentration\_gL (*number*)
- nitrogen\_source\_type (*yeast\_extract | peptone | mixed | none*)
- yeast\_extract\_gL (*number; allow blank if not used*)
- peptone\_gL (*number; allow blank if not used*)

### Geometry / scale

- tray\_count (*int*)
- tray\_area\_m2 (*number; total surface area across trays*)
- liquid\_depth\_cm (*number*)

### Run outputs (at harvest)

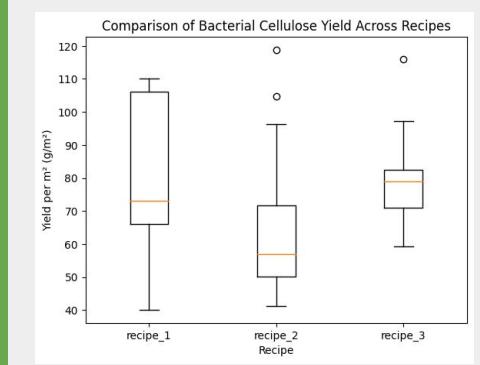
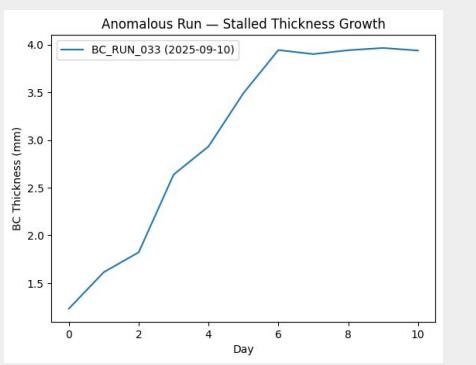
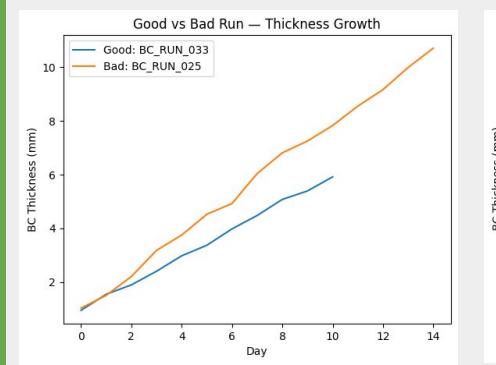
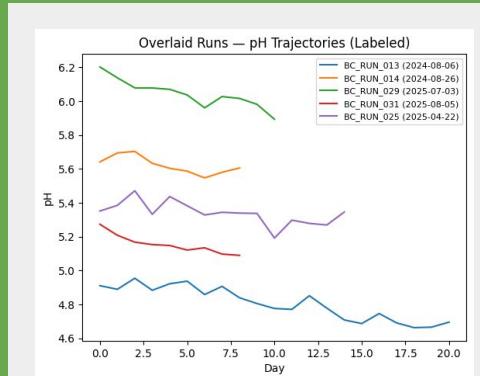
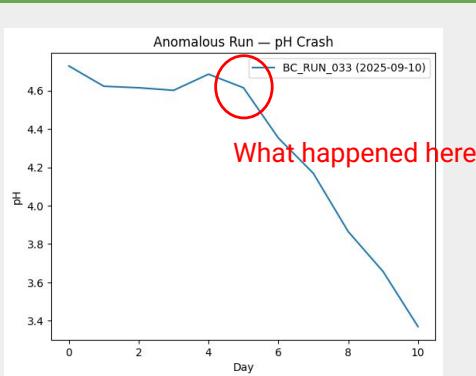
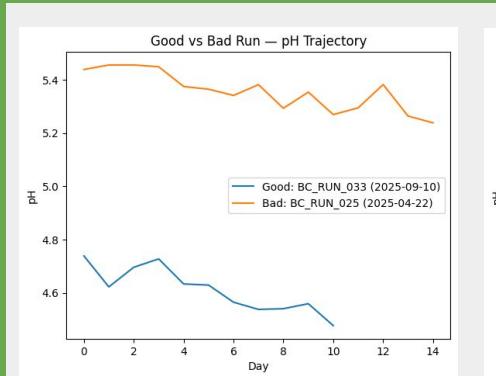
- wet\_mass\_total\_g (*number or blank if not tracked*)
- dry\_mass\_total\_g (*number*)
- yield\_per\_m2\_gm2 (*number; dry\_mass\_total\_g / tray\_area\_m2*)
- avg\_thickness\_mm (*number; mean across sampling points*)
- thickness\_variation\_pct (*number; std/mean100 across points; optional but very useful*)\*

### Quality/process flags

- defects\_pct (*number; your operational QC score*)
- contamination\_flag (*0/1*)
- avg\_process\_deviation\_pct (*number; aggregate deviation metric you already like*)

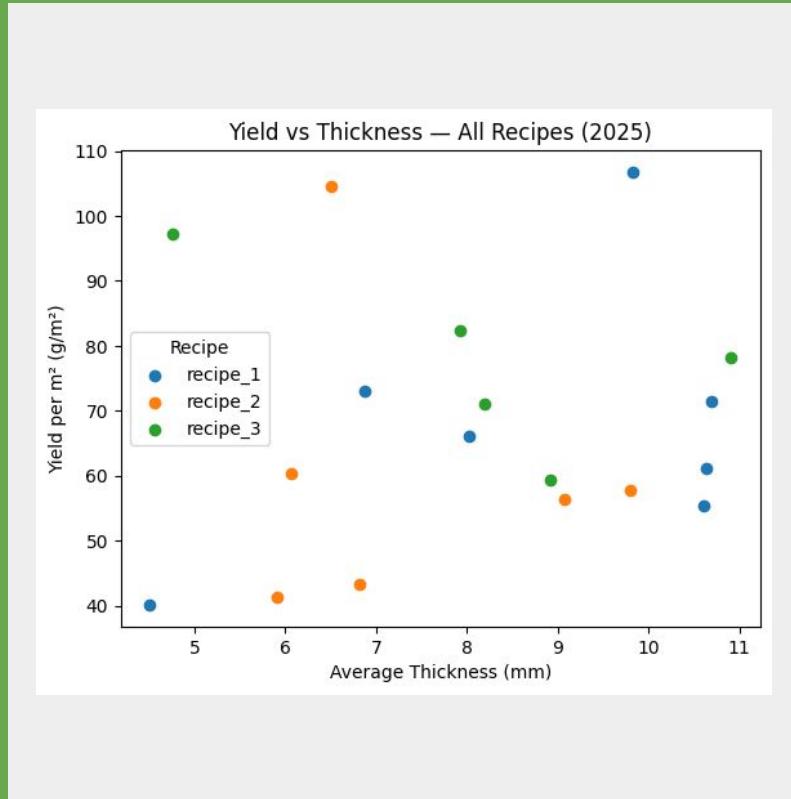
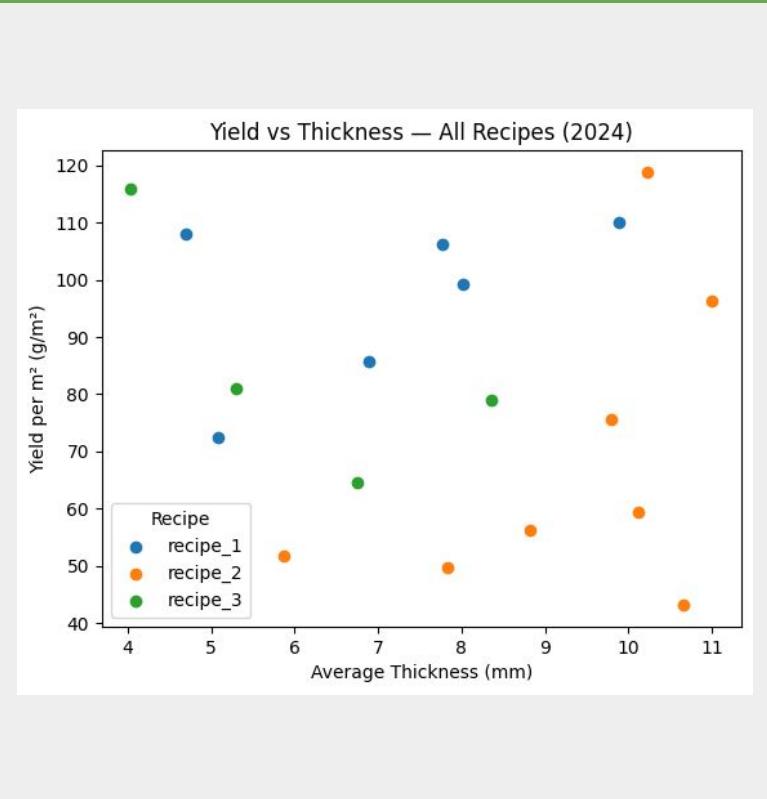
### Notes

- notes (*string; optional*)

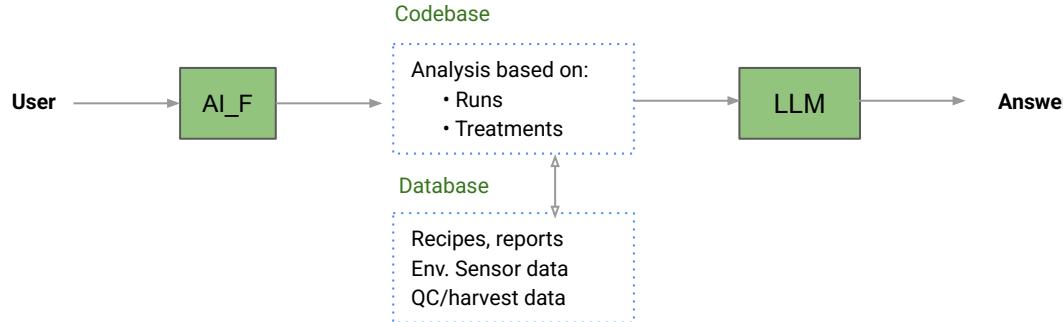


## Common issues

Finding causes for deviations



Recipe & treatment optimization



## Farmer

Moving from data to insights

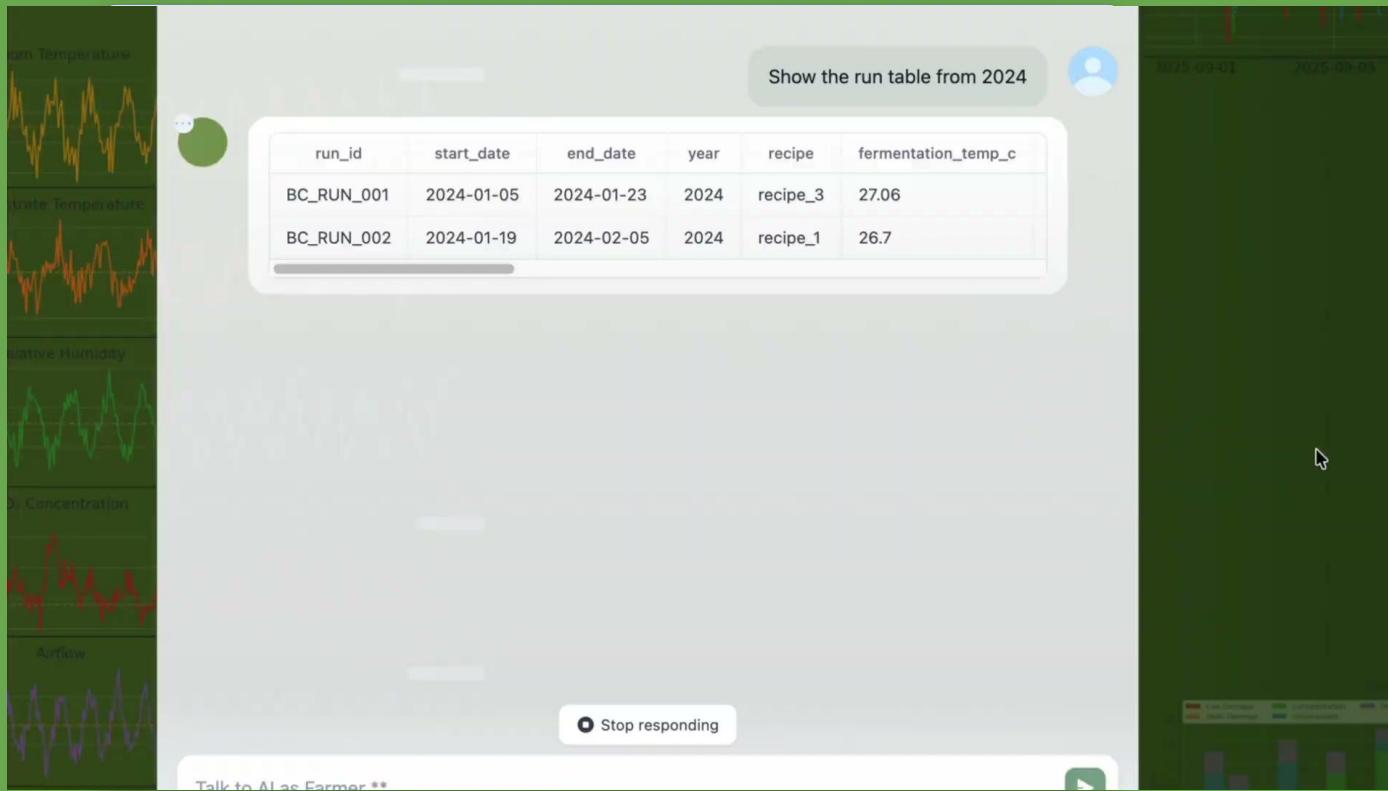
What are the insights we can get from our production and treatment runs from 2024-2025?

How do you interpret anomalies?

What is unique to a farmer?

## Questions to AI Farmer

- **Production and Yield**  
*What was our best recipe for yield in 2024?  
How did total dry mass production change from 2024 to 2025?*
  - **Process Inputs → Outputs**  
*Which variables explain variation in yield the best?  
Which process parameter most strongly correlates with defects?*
  - **Anomaly Detection and Q&C**  
*Which runs were flagged as anomalous in 2024 and why?*
  - **Recipes and Process Comparison**  
*What was our best recipe for yield in 2024?  
Did recipe performance change between 2024 and 2025?*
- Show yield by recipe as a table*



Let's chat with AI Farmer

### 3. Evaluating Techno-economics

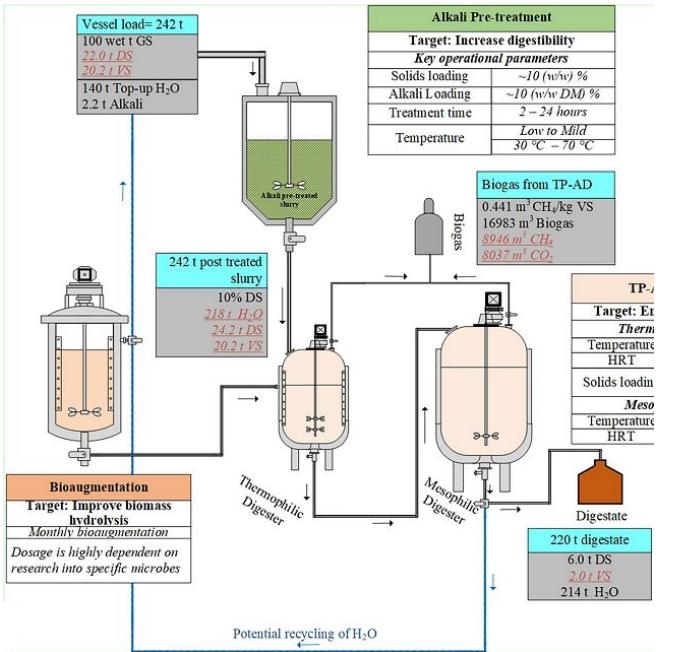
- Moving beyond spreadsheets to link process performance to unit economics
- Exploring how changes in yield, throughput, and recovery affect unit economics, pricing, and total addressable market (TAM)
- Scenario-based evaluation: scale, pivot, or stop
- Treating techno-economic models as living design constraints rather than post-hoc justification

# What is TEM?

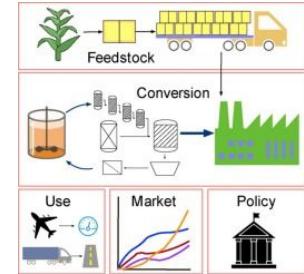
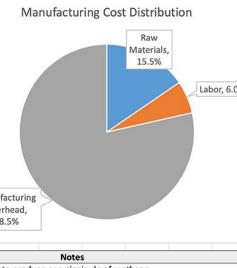
Chris Burk

Techno-Economic Modeling for Chemical and Bioprocess Innovations

WILEY

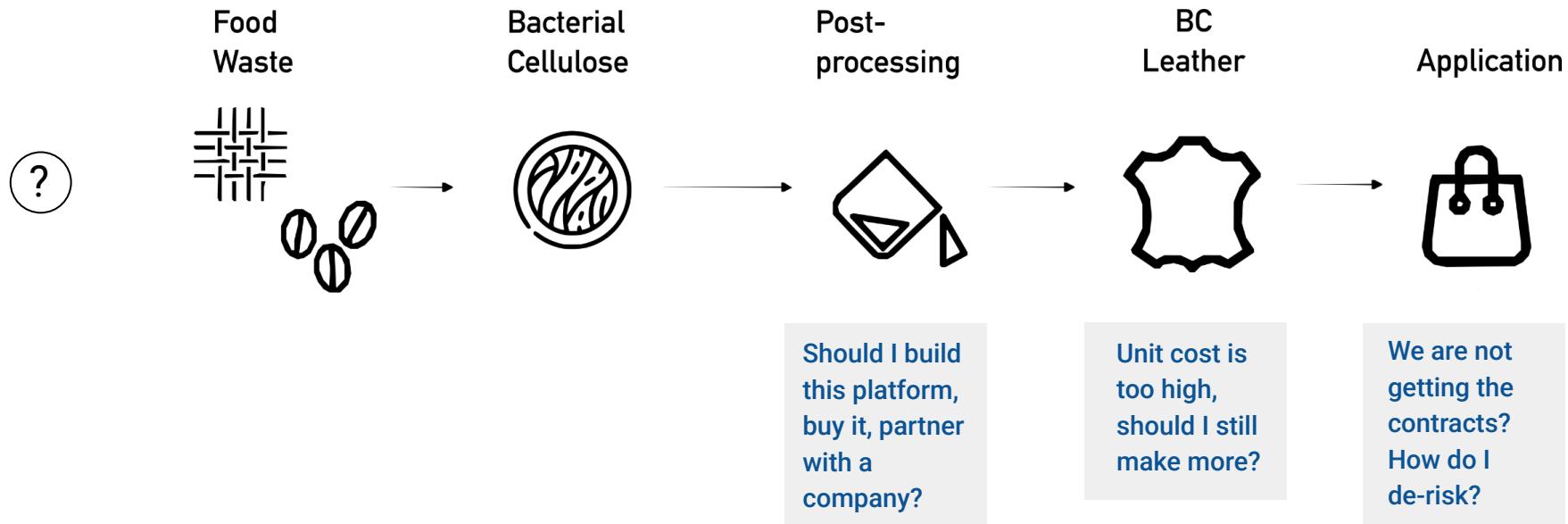


Process Costs	\$/GJ	\$/year	% of Total
Raw Materials	\$ 8	\$ 4,180,394	15.5%
Carbon dioxide	\$ 8	\$ 4,114,924	15.1%
Water	\$ 0	\$ 20,214	0.1%
Catalyst (annual need)	\$ 0	\$ 45,257	0.2%
<b>Labor</b>	\$ 3	\$ 1,620,787	6.0%
Direct labor	\$ 1	\$ 760,933	2.8%
Indirect labor	\$ 1	\$ 380,466	1.4%
Fringe	\$ 1	\$ 479,588	1.8%
<b>Manufacturing Overhead</b>	\$ 39	\$ 21,209,419	78.5%
Factory floor space	\$ 0	\$ 5,602	0.0%
Capital equipment	\$ 3	\$ 1,846,189	6.8%
Maintenance	\$ 1	\$ 656,204	2.4%
Insurance	\$ 0	\$ 164,051	0.6%
Utilities - electricity	\$ 34	\$ 18,536,474	68.6%
<b>Total Manufacturing Cost</b>	\$ 50	\$ 27,010,600	100.0%
<b>Energy Consumption</b>			
Process energy per GJ methane produced	1.77 GJ/GJ		Notes
			energy used by this process to produce one gigajoule of methane



- Combines technical + financial data:** Links process parameters (yields, energy use, throughput) with costs (CAPEX, OPEX, materials) to assess commercial viability
- Calculates key metrics:** Produces cost per unit, payback period, ROI, and break-even points for a technology or process
- Identifies cost drivers:** Shows which technical or operational factors most impact economics, guiding R&D priorities
- Guides scale-up decisions:** Evaluates whether lab/pilot innovations can compete economically at commercial scale

# Evaluation Techno-economics



## AI as CFO

- How does this product turn into a business?
  - How does AI support business readiness by going beyond spreadsheets to model unit economics and market realities?
- Tracking econometrics KPIs
- Baking techno-economic model into the everyday of the business
- Why do I need to know about EBITDA



AI\_CFO

# AI-ASSISTED DECISION MAKING

## Finance Officer (CFO)

- Techno-economic models (ML)
- Capital expenditure (CAPEX), Operational expenditure (OPEX)
- Cash, loans, grants
- Term sheets

Spreadsheets, Quickbooks, Finance models

AI as DATA MANAGER  
AI as KPI TRACKER

AI as ASSUMPTION VALIDATOR  
AI as ANALYST

AI as REPORT MAKER  
AI as PREDICTOR

One platform

## Bacterial Cellulose Techno Economic Evaluation

I will help you analyze the techno-aesthetic-economic (TAE) performance of your **bacterial cellulose** system. You can use the **default values** as a starting point and override only what you want to change.

### PRODUCTION PARAMETERS

- **Production Capacity:** What's your annual production capacity? (*default: 60 tonnes*)
- **Capacity Utilization:** What percentage of capacity are you currently using? (*default: 75%*)

### PRICING BY SEGMENT (per kg)

- **Fashion Segment:** Current selling price (*default: \$20.00/kg*)
- **Automotive Segment:** Current selling price (*default: \$30.00/kg*)
- **Upholstery Segment:** Current selling price (*default: \$25.00/kg*)

### MARKET MIX (percentages should total 100%)

- **Fashion Mix:** What % of production goes to fashion? (*default: 40%*)
- **Automotive Mix:** What % goes to automotive? (*default: 35%*)
- **Upholstery Mix:** What % goes to upholstery? (*default: 25%*)

### YIELD & QUALITY (TAE core)

- **Fashion Contamination Loss:** % lost to failed runs (*default: 8%*)
- **Drying/Finishing Loss:** % lost during drying/trimming (*default: 10%*)
- **Design-Grade Pass Rate:** % meeting aesthetic/quality criteria (*default: 70%*)

### VARIABLE COSTS (per kg)

- **Raw Materials:** Cost per kg (*default: \$8.00*)
- **Energy:** Cost per kg (*default: \$3.50*)
- **Labor:** Cost per kg (*default: \$2.50*)
- **Maintenance:** Cost per kg (*default: \$1.50*)
- **Quality Control:** Cost per kg (*default: \$1.00*)
- **Packaging & Logistics:** Cost per kg (*default: \$2.00*)

### PROCESS / TREATMENT (farm-app fields)

- **Drying Method:** (*default: air\_dry*)
- **Pressing Level:** (*default: none*)
- **Conditioning RH:** (*default: 50% RH*)
- **Conditioning Temp:** (*default: 23°C*)
- **Final Moisture:** (*default: 10%*)
- **Plasticizer Type:** (*default: none*)
- **Plasticizer %:** (*default: 0%*)

### FIXED COSTS & INVESTMENT (in millions)

- **Initial CAPEX:** Total capital investment (*default: \$2.5M*)
- **Annual Fixed Costs:** Facilities, insurance, etc. (*default: \$0.4M*)
- **R&D Investment:** Annual R&D spending (*default: \$0.15M*)
- **Marketing & Sales:** Annual budget (*default: \$0.1M*)
- **Corporate Overhead:** Annual overhead (*default: \$0.2M*)

### FINANCIAL ASSUMPTIONS

- **Depreciation Period:** Equipment life in years (*default: 10 years*)
- **Discount Rate:** Cost of capital (*default: 12%*)
- **Tax Rate:** Corporate tax rate (*default: 25%*)

The image shows a mobile application interface. On the left, there are five stacked line charts representing different variables over time (from 2023-09-01 to 2025). The charts are labeled from top to bottom: Relative Temperature (yellow), Relative Humidity (orange), Carbon Concentration (green), Airflow (red), and Liquid Depth (purple). The x-axis is labeled "Time". Above the charts, the text "BC\_RUN\_009" and "2024-05-26" is displayed. In the center, a user interface element shows a message bubble with the text "Which variables explain variation in yield the best in 2024?" followed by a blue profile icon. Below this is a table with two columns: "feature" and "corr". The data is as follows:

feature	corr
thickness_variation_pct	0.557
avg_process_deviation_pct	0.453
liquid_depth_cm	-0.419
carbon_concentration_gL	-0.343
tray_area_m2	-0.223

Below the table, there is a bulleted list of three points explaining the correlation results:

- The table shows the top drivers for yield per square meter based on Pearson correlation.
- A positive correlation indicates that as the feature increases, the yield per square meter tends to increase, while a negative correlation suggests the opposite. For example, thickness variation percentage has the highest positive correlation (0.557).

At the bottom of the central panel, there is a button labeled "Talk to AI as Farmer \*\*" with a green play icon to its right. To the right of the central panel, there is a dark vertical bar with a small white cursor icon pointing to it. At the very bottom right, there is a small bar chart with several colored segments (red, green, blue, yellow) and a legend below it.

Let's chat with AI CFO

- Guardrails
- Validation
- Intention discovery

# Good Ideas vs Good Businesses

## Scenario-driven Evaluation

Everything looks great, but why doesn't scale up?

What are my options?

## Risk Assessment

What is in my blindspot?

The product quality is not improving, where else can I focus

## Basic Economics

What are these terms?

- EBITDA:
- CAPEX
- Gross Margin+

## TL;DR:

1. **Sellable yield** (biology + process)
2. **Unit margin** (price – variable cost)
3. **Scale** (spreading fixed costs)

**REVENUE:** Total money the business earns

**EBITDA:** Earnings before Interest, Taxes, Depreciation, Amortization

**EBITDA:** What's left after subtracting operating costs from revenue (but before interest, taxes, depreciation, and amortization)

How well the business runs day-to-day, excluding financial decisions.

You don't really  
need to  
remember  
calculations

```
# --- Calculations ---
util = capacity_utilization_percent / 100.0
mix_f, mix_a, mix_u = fashion_mix_percent/100.0, automotive_mix_percent/100.0,
upholstery_mix_percent/100.0
dr, tax_rate = discount_rate_percent/100.0, tax_rate_percent/100.0

prod_t = production_capacity_tonnes * util
prod_kg = prod_t * 1000.0

avg_price = fashion_price*mix_f + automotive_price*mix_a + upholstery_price*mix_u
var_cost = raw_material_cost + energy_cost + labor_cost + maintenance_cost +
quality_control_cost + packaging_logistics_cost

revenue = prod_kg * avg_price
var = prod_kg * var_cost
gp = revenue - var
gm_pct = (gp/revenue*100.0) if revenue > 0 else 0.0

capex_dollars = initial_capex * 1_000_000.0
fixed_total = (annual_fixed_costs + rd_investment + marketing_sales + corporate_overhead)
* 1_000_000.0
dep = capex_dollars / max(depreciation_period_years, 1)

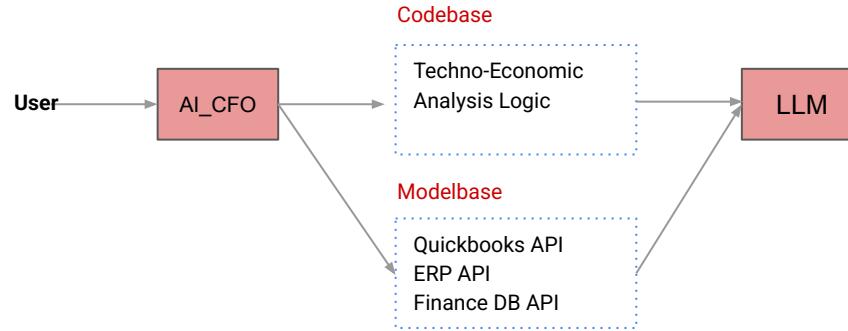
ebitda = gp - fixed_total
ebit = ebitda - dep
ebt = ebit
taxes = max(0.0, ebt*tax_rate) if ebt > 0 else 0.0
ni = ebt - taxes

rev_kg, fixed_kg = avg_price, (fixed_total+dep)/prod_kg if prod_kg > 0 else 0.0
cost_kg, profit_kg = var_cost + fixed_kg, rev_kg - (var_cost+fixed_kg)

payback = (capex_dollars/ni) if ni > 0 else float("inf")
roi_pct = (ni/capex_dollars*100.0) if capex_dollars > 0 else 0.0

npv = -capex_dollars
for y in range(1, 6):
    npv += ni/((1.0+dr)**y)

rev_f, rev_a, rev_u = revenue*mix_f, revenue*mix_a, revenue*mix_u
```



## Human CFO

- What is our burn-rate? Where is the money spent?
- Where are our bottlenecks (i.e., supply-side or demand-side)
- What is ROI expectations?
- What are our capacity requirements?

## Questions to AI CFO

- Run the baseline scenario using all defaults.
- Why is EBITDA negative?
- Which costs are most damaging at small scale?
- What is driving profit/kg?
- What should I change to improve this?
- Run a scenario at 90% capacity utilization. Use defaults for everything else.
- What happens if capacity utilization drops to 60%?
- Run a scenario with contamination loss reduced to 4%.
- What if all sellable material goes to fashion at \$30/kg?

AI Personas — Designer • Far... +

design.bio/workshop/

Focus on business readiness: unit economics, pricing, COGS, margin, and runway. Ground decisions in evidence.

POWERED BY Dify | ⚡

**Raw Analysis: FIBER MATERIALS — CFO SUMMARY**

**PRODUCTION**

- Annual Production: 40.0 t (40,000 kg)
- Weighted Avg Price: \$25.45/kg
- Utilization: 80%

**FINANCIALS**

- Revenue: \$1,018,000 (\$1.02M) | Gross Margin: 23.4%
- EBITDA: \$-612,000 (\$-0.61M) | EBITDA %: -60.1%
- Net Income: \$-862,000 (\$-0.86M)

**UNIT ECONOMICS**

- Revenue/kg: \$25.45 | Cost/kg: \$47.00 | Profit/kg: \$-21.55
- Break-even volume: ∞

**INVESTMENT**

- ROI: -34.5% | Payback: ∞
- NPV (5y): \$-5.61M | CAPEX: \$2.50M

**SEGMENTS**

- Fashion: \$407,200 (40% @ \$20.00/kg)

Talk to AI as CFO

Automotive: \$356,300 (35% @ \$32.00/kg)  
Electronics: \$254,500 (25% @ \$25.00/kg)

Was borrowing money  
a good idea?  
Can I ever make  
money?

AI\_CFO

# Can we ever make money?

## Fast Strategy

- Focus on **design-grade quality**
- Sell into **premium segments early**
- Accept higher costs temporarily

## Primary levers

- ↑ **Design-grade pass rate** (→ 85–95%)
- ↑ **Grade A mix / price multipliers**
- Target **fashion / specialty interiors**
- Maintain **tight process control**

1. What happens if the design-grade pass rate increases to 90%, using defaults for everything else?
2. Now assume premium pricing: fashion price \$30/kg, automotive \$40/kg, with the same 90% pass rate.
3. What if all sellable material goes to fashion at \$30/kg?

## Slow Strategy

- Focus on **biological reliability**
- Drive down **unit costs**
- Scale gradually to amortize fixed costs

## Primary levers

- ↓ **Contamination & drying losses**
- ↑ **Capacity utilization** (80–95%)
- ↓ **Raw material / energy / labor costs**
- Expand **sellable volume**

1. Reduce contamination loss to 2% and drying loss to 5%, using default pricing.
2. Increase capacity utilization to 90% and annual capacity to 120 tonnes.
3. Reduce raw material cost to \$6/kg and energy cost to \$2.5/kg at the same scale.

# What are your levers?

## Scale & Throughput (Volume Levers)

*How much material you can sell.*

- **Annual production capacity** (tonnes/year)  
→ Bigger plant vs pilot scale
- **Capacity utilization (%)**  
→ How hard you run the system
- **Batch cycle time (days) (advanced)**  
→ Faster cycles = more runs per year

## Yield & Quality (Material Levers)

*How much of what you grow is sellable.*

- **Design-grade pass rate\* (%)**  
→ Core quality lever
- **Contamination loss (%)**  
→ Biological reliability
- **Drying loss (%)**  
→ Process damage / shrinkage

## Market Position (Price Lever)

*What customers are willing to pay*

- **Fashion price (\$/kg)**
- **Automotive price (\$/kg)**
- **Upholstery price (\$/kg)**
- **Market mix (%)**  
→ How production is allocated across segments
- **Grade price multipliers (A / B / C)**  
→ Monetizing quality differences

## What are your levers?

### Variable Costs (Efficiency - Unit cost)

How much each kg costs to make.

- **Raw material cost** (\$/kg)
- **Energy cost** (\$/kg)
- **Labor cost** (\$/kg)
- **Maintenance cost** (\$/kg)
- **Quality control cost** (\$/kg)
- **Packaging & logistics** (\$/kg sellable)

### Process Choices (Treatment Levers)

Affect yield, quality, and cost indirectly.

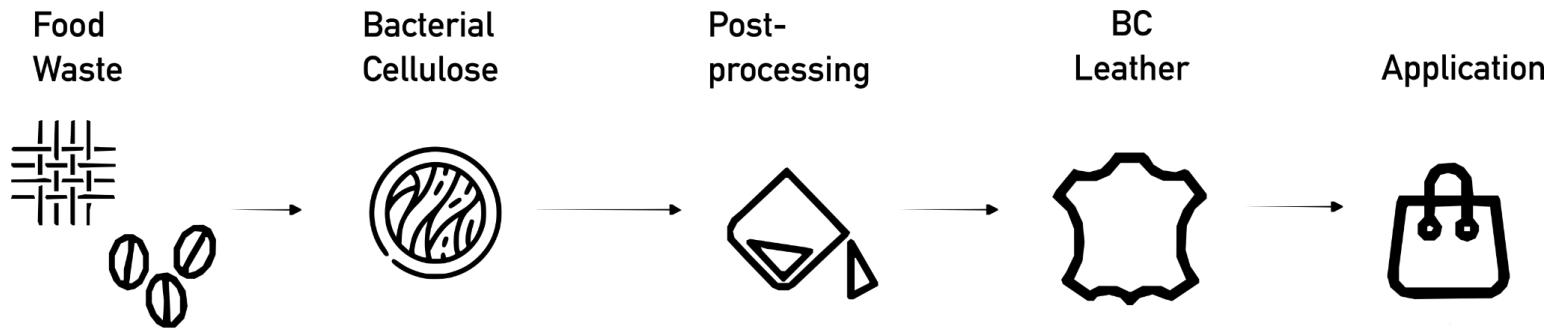
- **Drying method** (air | oven | press)
- **Pressing level** (none | light | heavy)
- **Conditioning** (RH, Temp)
- **Plasticizer** (Type & %)

### Fixed Costs (Business Model Decisions)

What customers are willing to pay

- **Initial Capex** (\$M)
- **Annual fixed costs** (\$M)  
(facilities, R&D, sales, overhead)

# Discussion/Integration



A designer, farmer, and CFO walks into a bar...

bdc

[biodesignchallenge.org](http://biodesignchallenge.org)



**@Columbia check out:**

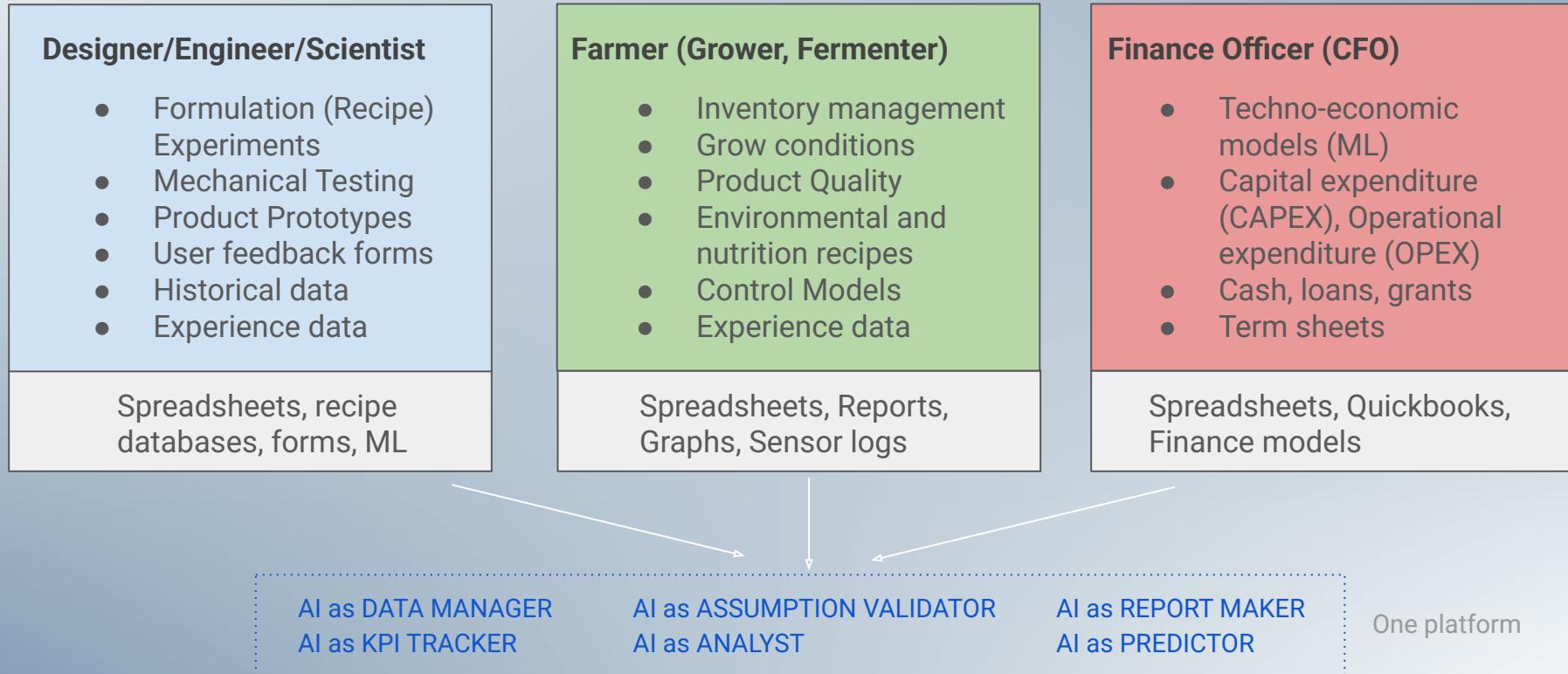
- Lola Ben-Alon, GSAPP
- Tal Danino, Bioengineering
- Theanne Schiros, Research Scientist



PDL Survey 2026

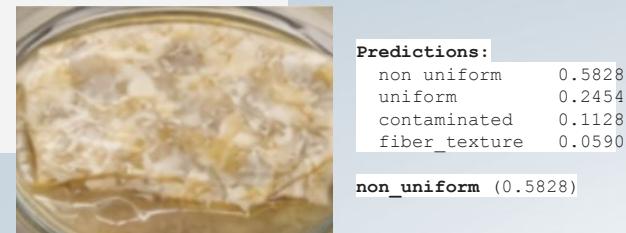
# Appendix

## AI-ASSISTED DECISION MAKING



# Image Classifier: What type of material does this look like?

- Takes an image and assigns it to one of four visual categories (uniform, non-uniform, fiber-textured, contaminated)
- Uses a pretrained vision model to extract texture features
- Learns only a small decision layer on top
- Output = category + confidence



This model names surface conditions it has seen before.

# Image Regressor: What properties might this material have?

- Takes the same image features
- Predicts continuous values (stiffness, strength, elongation, uniformity)
- Trained on proxy labels, not physical measurements
- Output = estimated numbers with uncertainty



```
{'uniformity_score':  
0.548684441566467,  
'stiffness_index':  
0.38718467950820923,  
'elongation_pct':  
8.714523315429688,  
'tensile_strength_mpa':  
43.994346618652344}
```

This model *infers numbers* from visual similarity, not material physics.

## bc\_runs\_2024\_2025.csv

**One row = one fermentation run (static tray batch)**

**Purpose:** operations/anomaly detection, yield benchmarking, run-to-run comparisons.

### Identifiers

- run\_id (*string, unique*) — e.g., BC\_RUN\_2024\_001
- start\_date (*YYYY-MM-DD*)
- end\_date (*YYYY-MM-DD*)
- year (*int*)
- recipe (*recipe\_1 | recipe\_2 | recipe\_3*)

### Process (static tray)

- fermentation\_mode (*fixed string: static\_tray*)
- fermentation\_temp\_c (*number*)
- run\_period\_days (*int*)
- initial\_ph (*number*)
- inoculum\_pct (*number; v/v %*)

### Media

- carbon\_source\_type (*glucose | sucrose | glycerol | molasses*)
- carbon\_concentration\_gL (*number*)
- nitrogen\_source\_type (*yeast\_extract | peptone | mixed | none*)
- yeast\_extract\_gL (*number; allow blank if not used*)
- peptone\_gL (*number; allow blank if not used*)

### Geometry / scale

- tray\_count (*int*)
- tray\_area\_m2 (*number; total surface area across trays*)
- liquid\_depth\_cm (*number*)

### Run outputs (at harvest)

- wet\_mass\_total\_g (*number or blank if not tracked*)
- dry\_mass\_total\_g (*number*)
- yield\_per\_m2\_gm2 (*number; dry\_mass\_total\_g / tray\_area\_m2*)
- avg\_thickness\_mm (*number; mean across sampling points*)
- thickness\_variation\_pct (*number; std/mean100 across points; optional but very useful*)\*

### Quality/process flags

- defects\_pct (*number; your operational QC score*)
- contamination\_flag (*0/1*)
- avg\_process\_deviation\_pct (*number; aggregate deviation metric you already like*)

### Notes

- notes (*string; optional*)



## bc\_treatments\_2024\_2025.csv

**One row = one treated sample (a subset of a run)**

**Purpose:** material quality prediction, comparing treatments, connecting processing → mech properties → surface class.

### Identifiers

- treatment\_id (*string, unique*) — e.g., TRT\_2024\_001\_01
- run\_id (*string; foreign key to bc\_runs*)
- sample\_id (*string; optional but recommended if you cut multiple pieces per tray*)
- tray\_id (*string/int; optional if you want tray-level tracking*)
- treatment\_date (*YYYY-MM-DD; optional*)

### Allocation

- sample\_area\_m2 (*number*)
- sample\_dry\_mass\_g (*number; after treatment*)
- sample\_thickness\_mm (*number; after treatment*)

### Treatment Parameters

- drying\_method (*air\_dry | press\_dry | oven\_low | freeze\_dry*)
- pressing\_level (*none | light | heavy*)
- conditioning\_rh\_pct (*number; optional*)
- conditioning\_temp\_c (*number; optional*)
- final\_moisture\_pct (*number; optional but powerful*)
- plasticizer\_type (*none | glycerol | sorbitol | other*)
- plasticizer\_pct (*number; blank if none*)

### Material Properties

- tray\_count (*int*)
- tray\_area\_m2 (*number; total surface area across trays*)
- liquid\_depth\_cm (*number*)

### Run outputs (at harvest)

- tensile\_strength\_mpa (*number*)
- elongation\_pct (*number*)
- youngs\_modulus\_mpa (*number*)

### Surface class (your categorical label)

- surface\_class (*contaminated | fiber\_texture | non\_uniform | uniform*)

### Notes

- notes (*string; optional*)

### Couple of Clarifications

- tray\_area\_m2 in **Runs** is **total area**, not per-tray. You can always compute per-tray if needed.
- dry\_mass\_total\_g is the **run harvest output**, while sample\_dry\_mass\_g is **post-treatment** and can differ (loss, plasticizer uptake, etc.).
- surface\_class belongs in **Treatments**, because the same run can yield multiple surface outcomes depending on drying/pressing.



## Bridge Outputs

- **Uniformity**
  - **defects\_pct** (highest signal, if defects are scored consistently)
  - **avg\_process\_deviation\_pct** (process instability → non-uniform pellicle)
  - **Derived: thickness\_variation\_pct** (*add this!*)
- **Stiffness** (stiffness ↑ with crystallinity ↑ and density/areal density ↑)**crystallinity\_index\_pct** (higher crystallinity → higher stiffness, generally)
  - **areal\_density\_gm2** (*you have it as yield\_per\_m2\_gm2 but that's dry mass/area; good proxy*)
  - **Derived: density\_gcm3** (*addable*) from dry mass + thickness + area
- **Tensile Strength**
  - **areal\_density\_gm2 / dry\_mass\_yield\_g** (to a point; thicker/denser sheets often test stronger)
  - **crystallinity\_index\_pct** (often positive association)
  - **defects\_pct** (negative association; pinholes/tears crush strength)
- **Elongation**
  - **water\_holding\_capacity\_pct** (more water retention / less brittle sheet often → higher elongation)
  - **crystallinity\_index\_pct** (often *inverse* with elongation; more crystalline tends to be stiffer/brittler)
  - **Post-process moisture / plasticizer** (critical; see below)