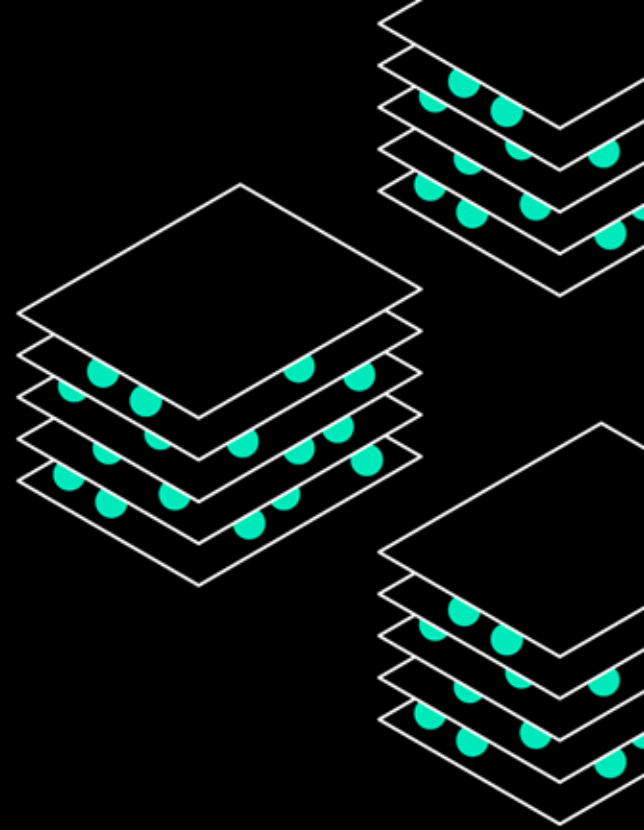


VOLTAIQ

De-risking and accelerating space power system development and production with **AI-assisted battery analytics**

Tal Shoklapper, CEO & Co-Founder

Space Power Workshop
Energy Storage I — Space Battery Level Topics
April 22, 2026

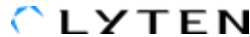


VOLTAIQ

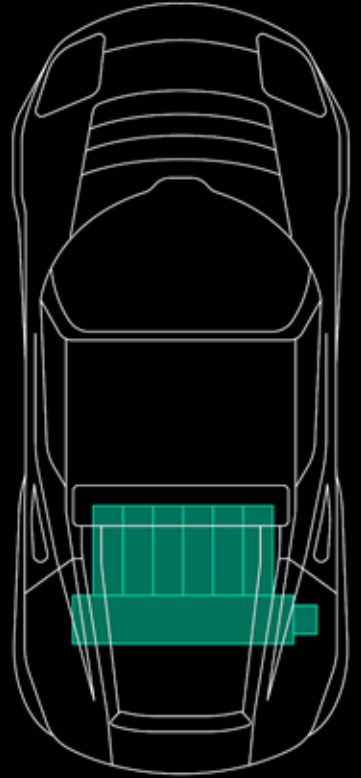
Bringing batteries and battery-powered products to market faster since 2012

The first and only battery-specific analytics solution, Voltaiq is the world's most trusted platform for developing, producing, and optimizing batteries and battery-powered products.

Voltaiq is trusted by over 100 organizations across the battery lifecycle



Market realities and the traditional approach



The market realities of space battery programs

**Small teams, low-
volumes**

**Every cell and pack
matters**

**Mission-critical
applications**

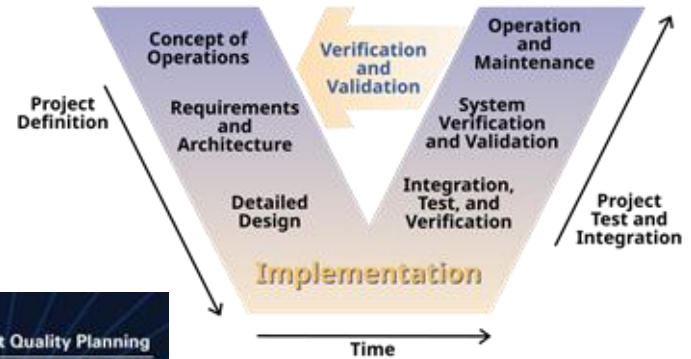
**Failures are not
recoverable**

Rising demands

**Adopt new tech
while maintaining
rigorous standards**

The “gold standard” development methodology

- “Stage-gate” or “waterfall” processes
- Developed around 3-5 year product design cycles
- Generally intended to be performed once per cycle



Does any of this sound familiar?

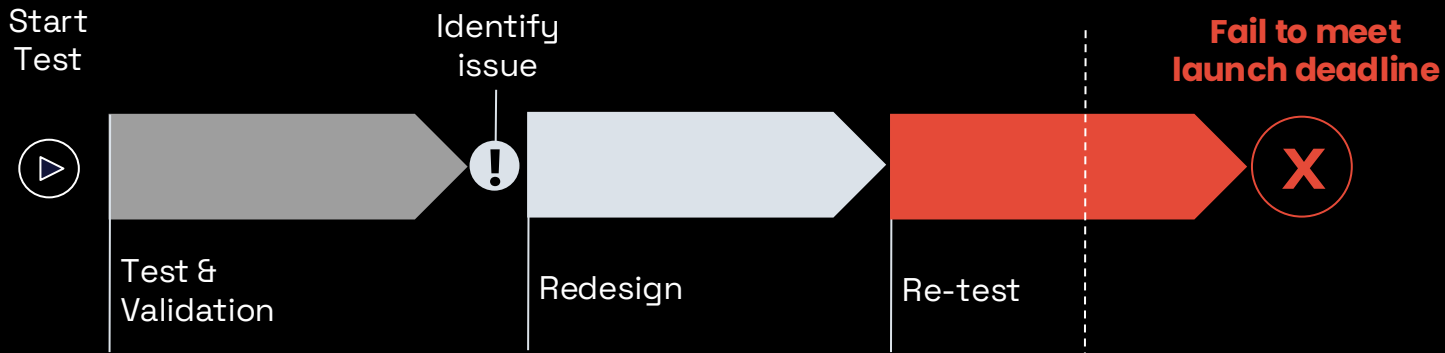
Problem 1:

You find battery issues too late
(and miss too many)

Problem 2:

Once you find a problem you don't have
time to fix it (miss launch window)

Battery issues jeopardize product launch timelines



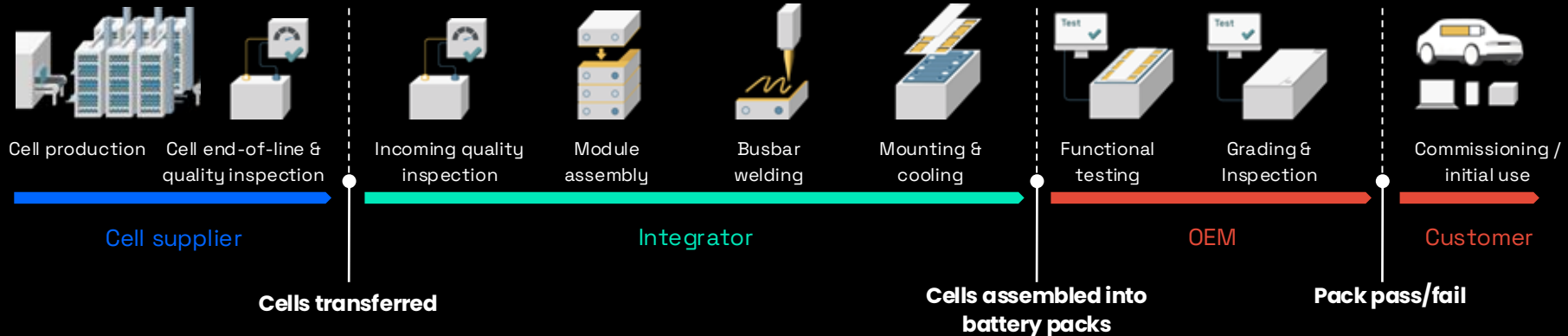
And downstream production issues are extremely costly

Problem 1:

You find battery issues too late
(and miss too many)

Problem 2:

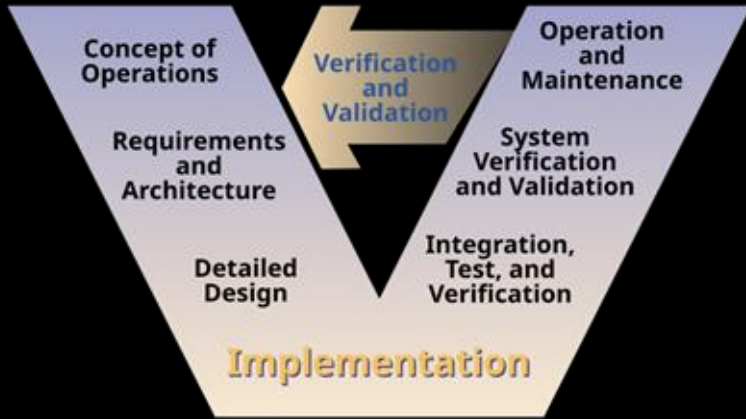
You take too long
to fix the ones you find



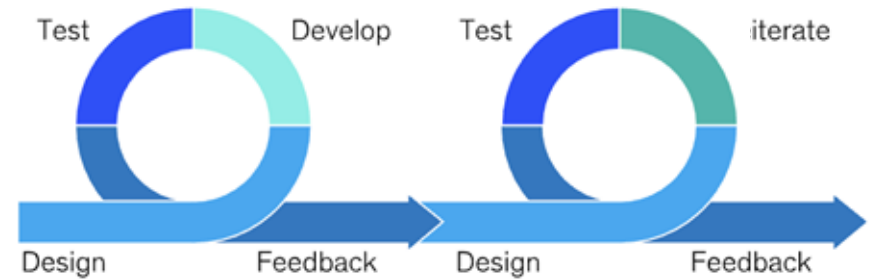
The approaches needed to stay competitive and how to enable them



A shift from stage gate



To agile



Unlike linear waterfall processes, agile uses continual test-and-feedback loops to refine designs

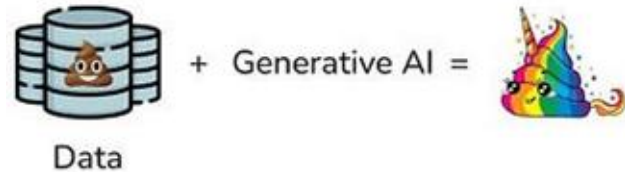
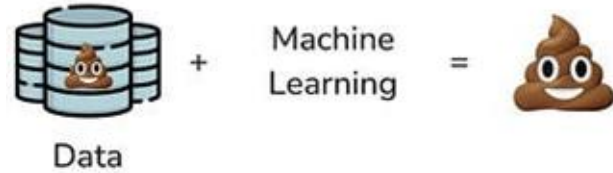
<https://www.mckinsey.com/capabilities/operations/our-insights/its-coming-home-the-return-of-agile-hardware-product-development>

ML & AI are all the rage

But, what we're actually seeing in production

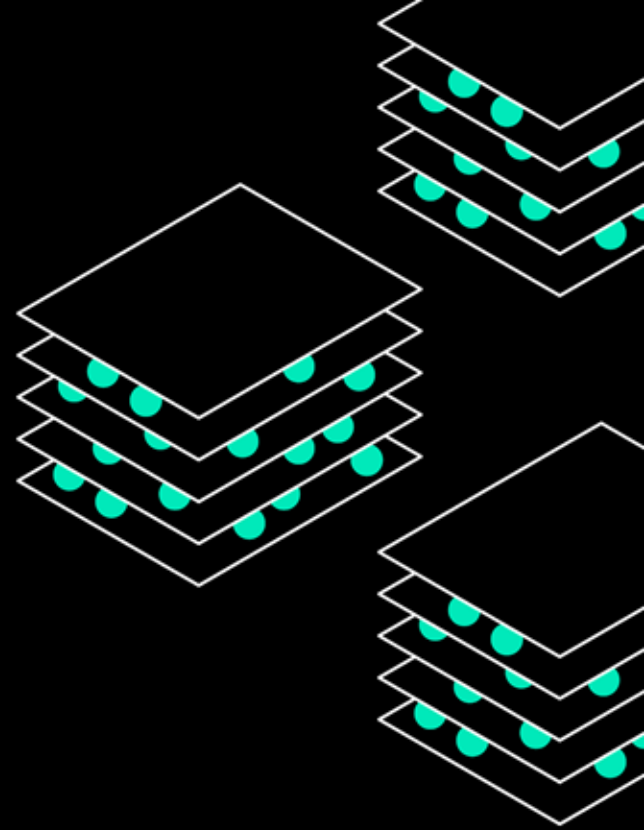
- Automation chains being marketed as AI
- Months spent curating small data sets
- Showcases of proof-of-concepts
- Overfit models that don't scale
- Narrow AI for siloed applications like image analysis
- Examples where a simple regression actually does a better job

The current state of battery AI

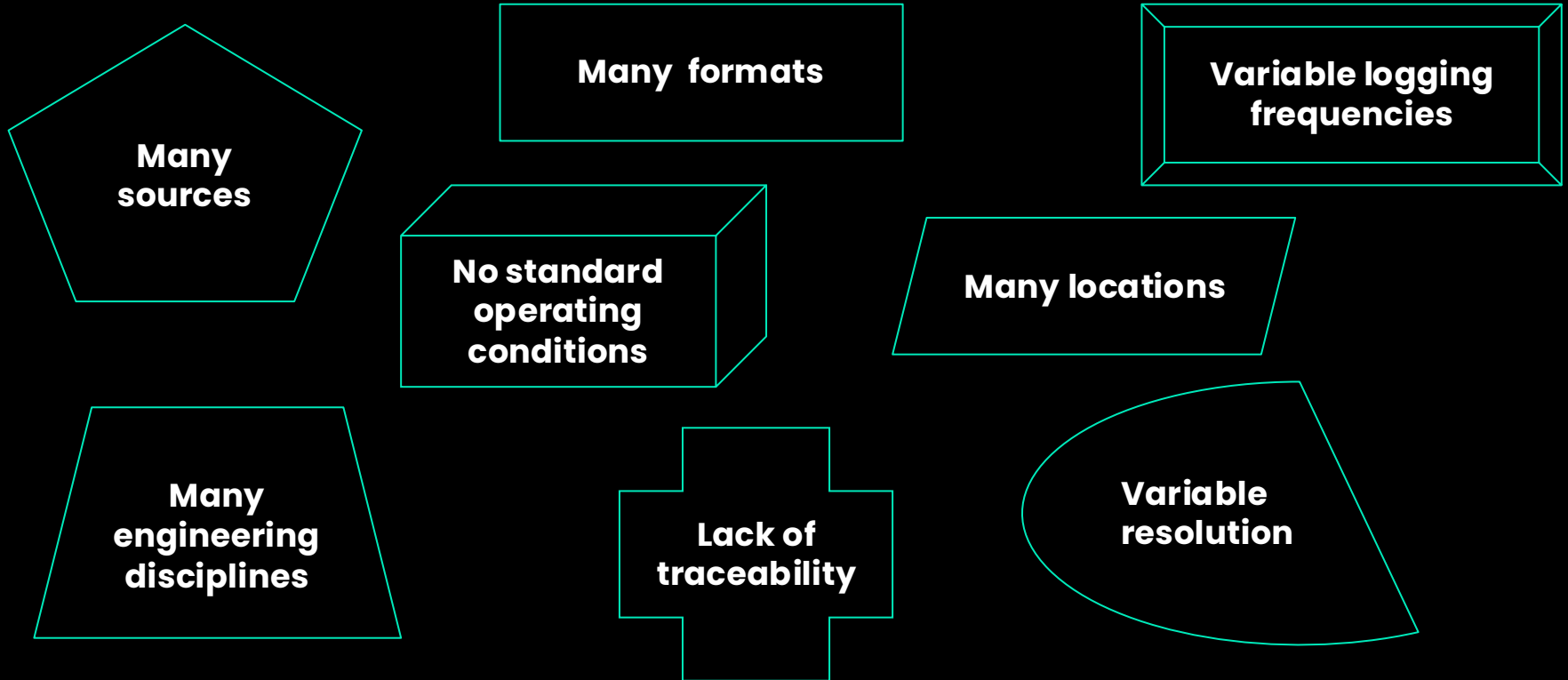


To enable agile product development cycles that utilize virtual development, ML & AI

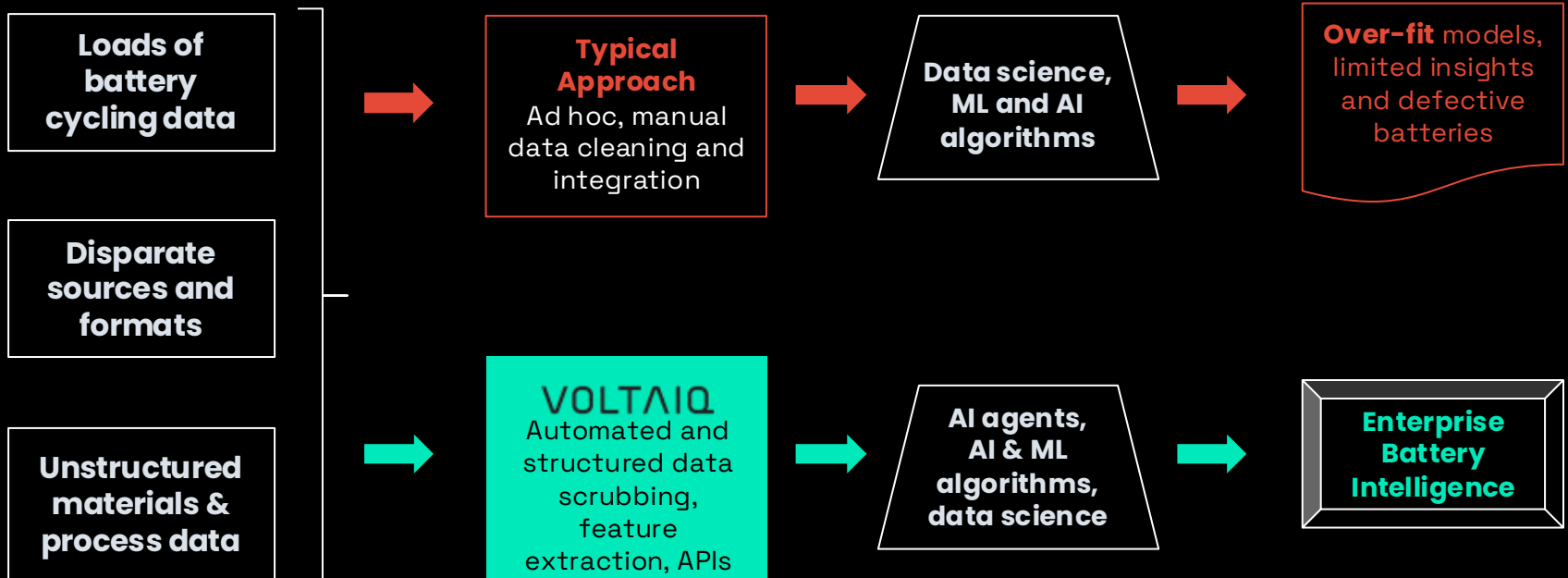
You need good data, and lots of it



The “Elephant in the Room” challenge with AI: You need super-clean and well-structured data AT SCALE, but...



Most companies still struggle just to get all the relevant data in one system, in one format, accessible to all stakeholders



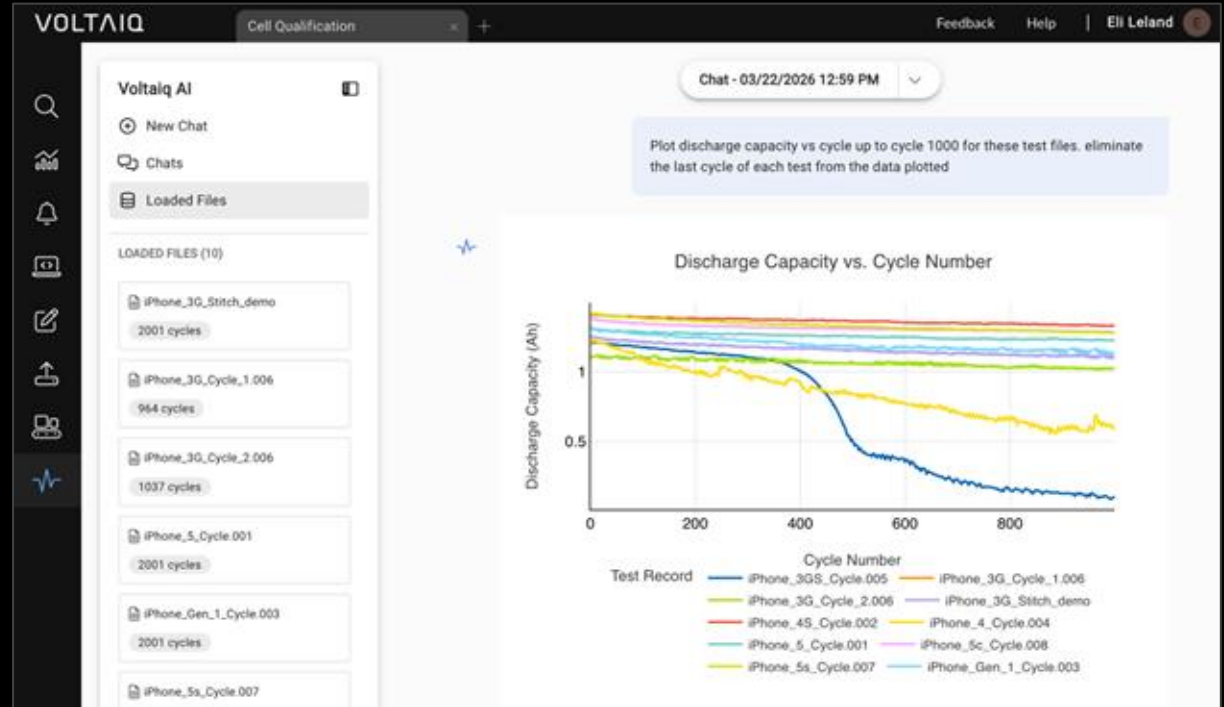
Introducing Voltaiq AI

Natural language in, battery data science out

Voltaiq AI puts advanced battery analysis in everyone's hands, not just the coders.

In minutes instead of hours or days.

Voltaiq AI, in alpha release with select customers



Case study: R&D

Differential capacity analysis

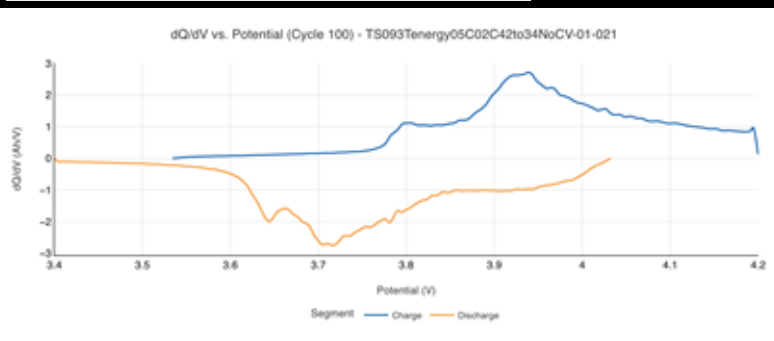
Before:

Hunt-and-pecking through spreadsheets or writing Python

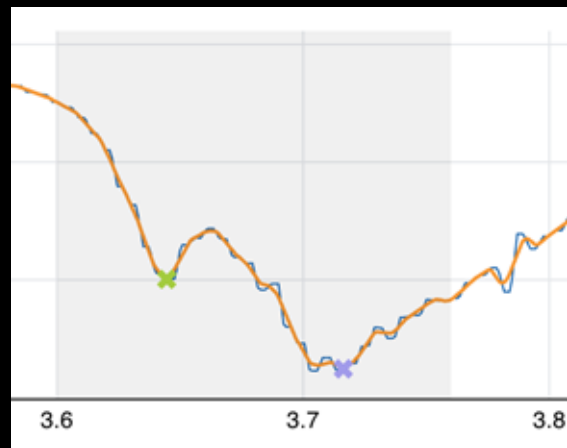
With Voltaiq AI:

Asking questions, getting answers.

plot dq/dv vs potential for cycle 100



Find the local minima between 3.65 and 3.75V



How much capacity was discharged between these two local minima for this cycle

the discharged capacity difference is:

- $Q(V_1) = 0.541195$ Ah
- $Q(V_2) = 0.390823$ Ah
- $\Delta Q = Q(V_2) - Q(V_1) = -0.150372$ Ah

Deep electrochemical characterization in minutes, with plain English

Case study: Cell qualification

Analyzing a cycling protocol study

Before:

Hand-wavy DOEs, “eyeballed” analysis and intuition-based next steps.

With Voltaiq AI:

A virtual data scientist, offering statistics-based conclusions and next steps.

Show an overview table of my cycling protocol study

DOE overview (protocol combinations and replicate counts)

Each row below is a unique cycling protocol defined by: (temperature, lower cutoff V, upper cutoff V, charge C-rate, discharge C-rate, CV step) with the number of cells run under that protocol.

Top of the DOE by replicate count:

temp (°C)	LCV (V)	UCV (V)	charge C	discharge C	CV step	n cells
25	3.0	4.2	0.5C	0.5C	Yes	14
50	3.0	4.2	0.5C	0.5C	Yes	5
25	3.0	4.2	0.5C	0.2C	No	4
25	3.4	4.2	0.5C	0.2C	No	4
25	3.0	4.2	1C	1C	Yes	3
25	3.0	4.2	0.5C	0.2C	Yes	2
25	3.0	4.0	0.5C	0.2C	No	1
25	3.0	4.0	0.5C	0.5C	No	1

which protocols show 80% capacity retention at cycle 500?

What protocols look best?

A) Charge and discharge rates are the strongest drivers in your data

Charge C-rate

- 0.5C charge: 46 evaluated cells, 32 pass (~69.6%)
- 1C charge: only 1 evaluated cell, 0 pass (retention ~0.758)

Observation: All of the “good” results are essentially at 0.5C charge. There isn’t enough 1C data to be definitive, but the limited evidence is not encouraging.

Discharge C-rate

- 0.2C discharge: 18/18 pass (100%), median retention ~0.88
- 0.5C discharge: 11/22 pass (50%), median ~0.80
- 1C discharge: 3/7 pass (43%), median ~0.79

Observation: If your goal is to reliably hit ≥80% at cycle 500, the most robust setting in your dataset is 0.2C discharge. As you push discharge rate up to 0.5C and 1C, the probability of passing drops substantially.

B) CV step: “No CV” looks better overall, but it’s not the primary lever

Across all evaluated cells:

- CV = No: 16/20 pass (80%), median retention ~0.866
- CV = Yes: 16/27 pass (59%), median retention ~0.821

Observation: “No CV” is associated with better retention in this dataset, and it’s not based on tiny sample sizes (n=20 vs n=27).

However, CV step is partially confounded with other settings (especially discharge rate), so I’d treat this as a *real signal* worth testing rather than a final causal conclusion.

Bottom line (what the data says enables ≥80% at cycle 500)

1. 0.5C charge (in your data, that’s where the successes are)
2. Lower discharge rate is key: 0.2C discharge is extremely reliable; 0.5C and 1C are mixed/risky
3. No CV step correlates with better outcomes, but you should validate it with matched comparisons because of confounding

If you want, I can also produce a short “recommended protocol set” ranked by (a) pass probability and (b) highest discharge rate, while enforcing a minimum replicate count so we don’t pick winners from 1–2 cells.

Case study: Cell qualification, continued

Analyzing a cycling protocol study

Before:

Hand-wavy DOEs, “eyeballed” analysis and intuition-based next steps.

With Voltaiq AI:

A virtual data scientist, offering statistics-based conclusions and next steps.

Learn more from past results, plan your next set of experiments

If I were to cycle 40 more cells with the objectives of both determining whether the CV step matters and also identifying the maximum discharge rate that still meets 80% capacity retention at cycle 500, what protocols should I run and how many replicates?

Recommended 40-cell plan

Part A – Main study (32 cells): 2x2 factorial

This directly answers “does CV matter?” and tests whether 1C discharge can still hit the 80%@500 goal.

Run 8 replicates per condition:

1. 0.5C charge / 0.5C discharge / CV = No → n=8
2. 0.5C charge / 0.5C discharge / CV = Yes → n=8
3. 0.5C charge / 1C discharge / CV = No → n=8
4. 0.5C charge / 1C discharge / CV = Yes → n=8

All at 25°C, 3.0–4.2 V.

What this gives you

- CV effect at 0.5C discharge: compare (1) vs (2)
- CV effect at 1C discharge: compare (3) vs (4)
- Whether 1C discharge is viable at all (pass rates of groups 3 & 4)
- Whether CV interacts with discharge rate (if CV helps at 1C but not at 0.5C, etc.)

Part B – Anchors/controls (8 cells): confirm baseline & detect “lab drift”

Your current data strongly suggests 0.2C discharge is the safest way to meet the target. Use it as a contemporaneous control so you can interpret failures at higher discharge without wondering if the whole batch shifted.

5. 0.5C charge / 0.2C discharge / CV = No → n=4
6. 0.5C charge / 0.2C discharge / CV = Yes → n=4

All at 25°C, 3.0–4.2 V.

Case study: Production issue root-cause analysis

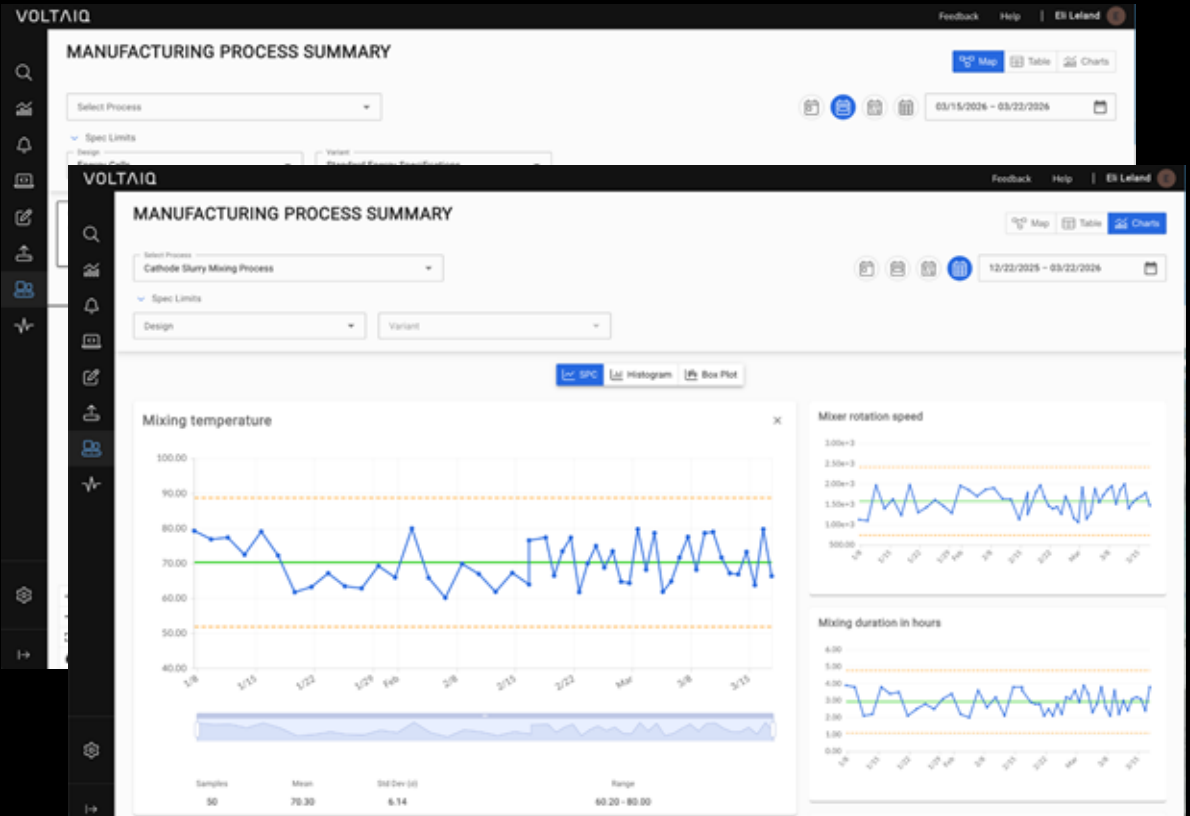
Investigating low capacity at formation

Before:

Weeks of manually pulling data from different equipment and systems, sifting through spreadsheets.

With Voltaiq AI:

All production process data is already imported, cleaned, structured, and ready for automated correlation and analysis at scale.



Case study: Production issue root-cause analysis, continued

Investigating low capacity at formation

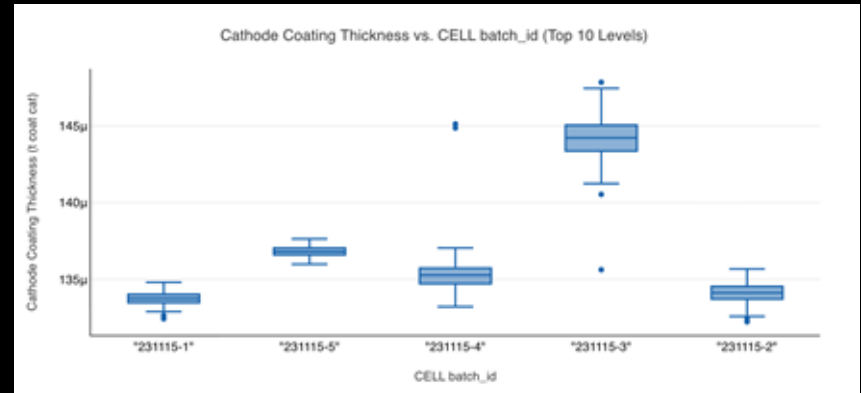
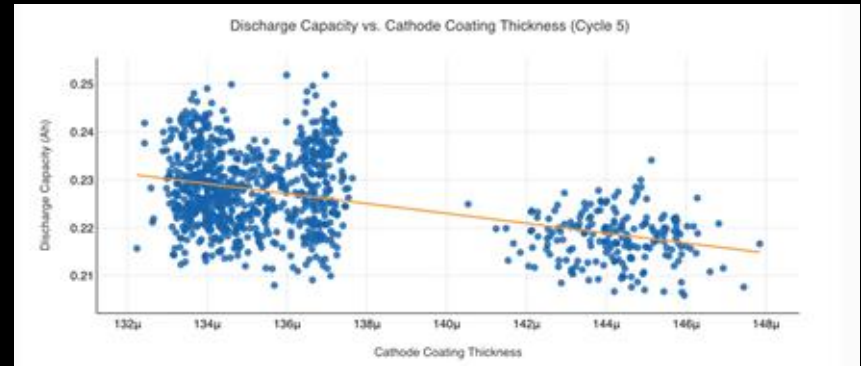
Before:

Weeks of manually pulling data from different equipment and systems, sifting through spreadsheets.

With Voltaiq AI:

All production process data is already imported, cleaned, structured, and ready for automated correlation and analysis at scale.

What relationship do you observe between this thickness and discharge capacity at cycle 5? Generate one or more visualizations to illustrate



Case study: Production issue root-cause analysis, continued

Investigating low capacity at formation

Before:

Weeks of manually pulling data from different equipment and systems, sifting through spreadsheets.

With Voltaiq AI:

All production process data is already imported, cleaned, structured, and ready for automated correlation and analysis at scale.

Accelerate root-cause analysis to ramp production faster and maintain yield

Can you find any further correlation to upstream process or material parameters that could result in the higher coating thickness?

A) Strongest upstream associations (categorical / "recipe-like")

Using a one-way effect size (η^2 , fraction of thickness variance explained by grouping):

- CELL_batch_id - $\eta^2 = 0.9469$ (5 levels)
- CELL_cat_slur_mix_eqid_id - $\eta^2 = 0.9469$ (5 levels)
- CELL_a_slur_mix_time - $\eta^2 = 0.9460$ (4 levels)
- CELL_cat_slur_mix_time - $\eta^2 = 0.9312$ (3 levels)
- CELL_cathode_busid_date - $\eta^2 = 0.3660$ (2 levels)

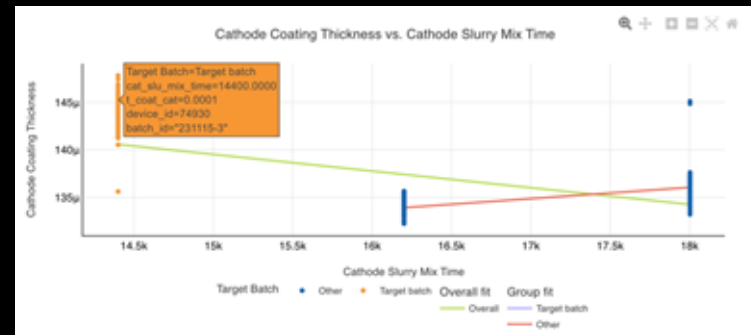
Interpretation: thickness is very likely being driven by a small number of discrete upstream process regimes (batch/equipment/mix-time settings) rather than purely continuous drift.

B) Strongest numeric correlations with thickness

Pearson / Spearman correlations vs CELL_t_coat_cat :

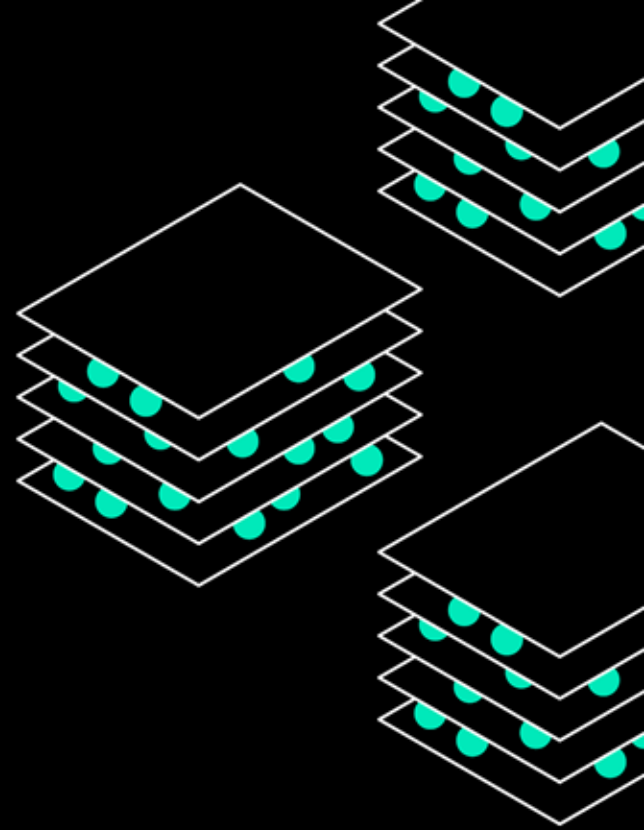
- CELL_cat_p_a : $r = +0.5897$ (Spearman 0.3434)
- CELL_a_p_a : $r = +0.3892$ (Spearman 0.3022)
- CELL_cat_m_a : $r = +0.3465$ (Spearman 0.1736)
- CELL_v1_th_a : $r = +0.0715$ (small)

These look like "parameter" fields (possibly pressures/areal loadings/masses/etc.; names are ambiguous), but empirically they move with thickness.

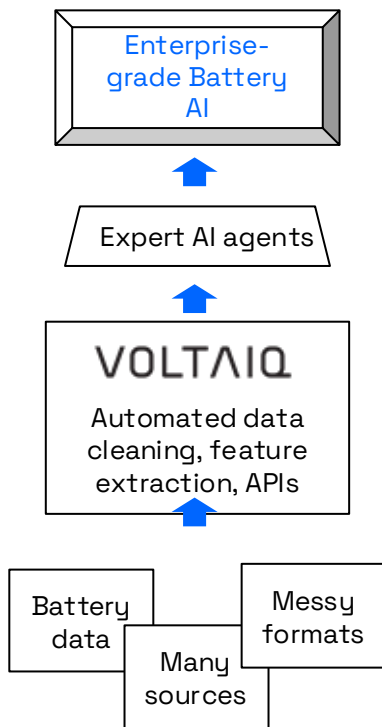


VOLTAIQ

Enabling **Battery AI** for the enterprise



Voltaiq Enables and Accelerates Battery AI for the Enterprise

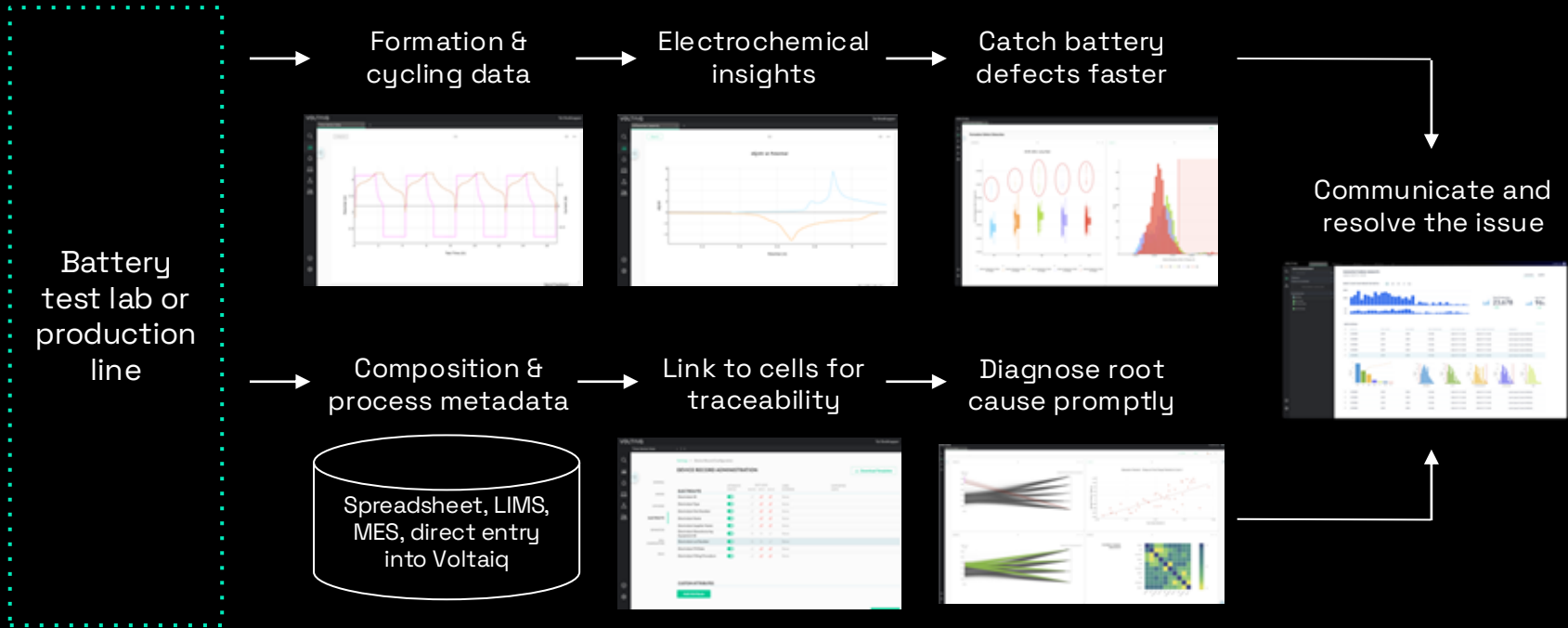


Automated clean, labeled, featurized data unlocks the value of AI

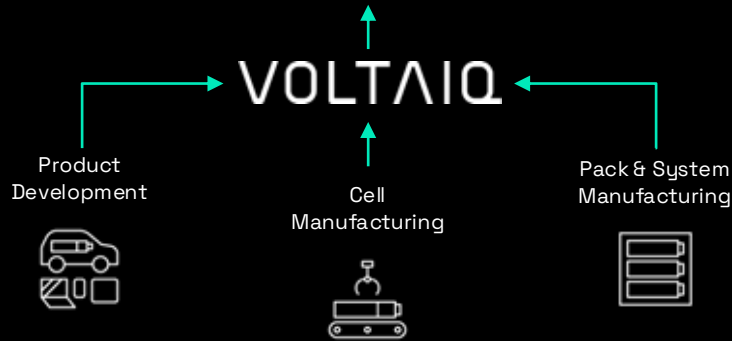
You're going to want to try a lot of models, to find one that **you understand and that works for **your application****

Enterprise-scale data automation infrastructure enables **rapid iteration, up front and over time**

How it works:



Voltaiq: the standard for enterprise-grade battery analytics



Built-in battery workflows and expertise
Now powered by AI

Customizable for your battery application

Get up and running in under a month

Proven success at enterprise scale

Work with the leader in battery intelligence to unlock the full value of your data, today and tomorrow

The Voltaiq Effect

1. Get your new battery tech to market faster

2. Ensure high quality battery & materials supply

3. Identify quality issues earlier

4. Find root cause faster, maintain & optimize yield

Enterprise Battery Intelligence Platform

*20-20,000x engineering workflow acceleration**

Battery Lifecycle



Product Development



Cell Manufacturing



System Manufacturing



In-field Operations

VOLTAIQ

Thank you

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