Minitab

EXCHANGE

Build Better with the Connected Factory

16 June 2026
BMW Welt

Today's Agenda

Registration	08:30 - 09:30
• Introduction & event kick-off • AI in Manufacturing - Practical applications of AI, Machine learning and connected data • The Hidden Factory - Reduce downtime and uncover hidden capacity losses	09:30 - 10:50
Networking Break	10:50 - 11:15
• Process Variation - Reduce scrap, rework and quality issues • From Monitoring to Mastery - Root cause analysis and process optimization • Designing Better Processes - DOE, predictive modelling and simulation	11:15 - 12:45
Networking Lunch	12:45 - 13:30
• Case Study by Beatrice - 30 Years of DOE, Data and Expensive Surprises	13:30 - 14:00
• Live Deep Dive - Solving manufacturing challenges with the Minitab Solution Center	14:00 - 15:30
Networking Drinks	15:30 - 16:00
BMW Welt & BMW Museum tours	16:00 - 17:00

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AI in Manufacturing: Behind Smoke and Mirrors

Mikhail Golovnya
Senior Advisory Data Scientist

In this session, we'll talk about...

- Digital Transformation
- Data Universe
- Data Analytics
- Machine Learning
- Generative AI
- Agentic AI and AGI

Digital Transformation

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- **Digital Transformation** integrating digital technologies to **fundamentally change how a company operates**, delivers value to customers, and responds to market dynamics
- **Digital Transformation** is about rethinking everything you do —internally and externally.

What is Digital Transformation?

Key Aspects

- Technology integration (**data analytics**, cloud computing, AI, automation, IT infrastructure, etc.)
- Data-Driven Decision Making (**predictive analytics** to inform strategic and day-to-day choices)
- Cultural and Organizational Change (innovation, agility, embracing new technologies)
- Business Process Optimization (automating manual tasks, workflows, efficiency, productivity)
- Enhanced Customer Experience (aps, social media, chat bots, support, personalized services)

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Data Universe: Half a Century of Growth

- **1970s–1980s: Megabytes**
  Thousands to hundreds of thousands of records, Apollo
- **1990s: Gigabytes Become Common**
  Internet, transactions, server logs, Human Genome
- **2000s: Terabyte Era**
  Digital and social media, Google, Facebook, CERN
- **2010s: Petabyte and Exabyte Scale**
  Big data revolution, YouTube, Climate Modeling
- **2020s: Zettabyte Era and Beyond**
  IoT, social media, video, sensor data

- Exponential Growth for the past 50 years!
  150 dB Growth

Data Universe: YouTube Growth

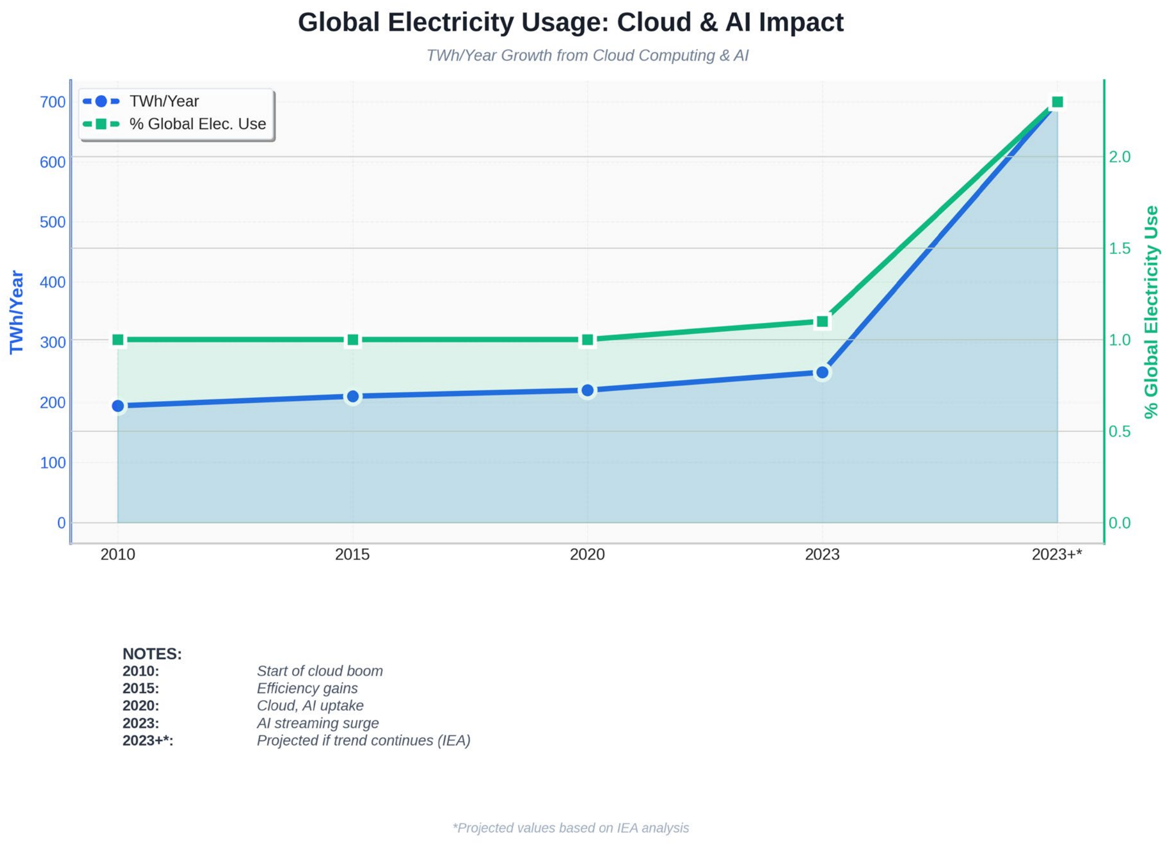
Key Milestones

Hours of videos uploaded per minute

YEAR	HRS/MIN	HRS/DAY	NOTES
2007	~6	8,640	Early rapid growth
2010	24	34,560	Social and smartphone era begins
2012	72	103,680	YouTube mainstream, HD videos rise
2014	300	432,000	Explosion in global smartphone use
2017	400	576,000	Live streaming, 4K, mobile creators
2019	500	720,000	Global user base, monetization
2022	500+	720,000+	Number stayed stable but content length increases
2024	600 - 700	864,000–1M+	Continued grown (unofficial estimates)

Global Data Center Power Consumption

Estimated Global Data Center Power Consumption by Year



Key Takeaways

- **Current**: Data centers use ~250 TWH/year (2023-24), about 1% of all global electricity.
- **Trend**: After years of efficiency, demand is rising rapidly due to AI and digitization.
- **Future**: Could triple by 2030 unless efficiency and renewable adoption keep up.

Data Analytics – The Quest for AI

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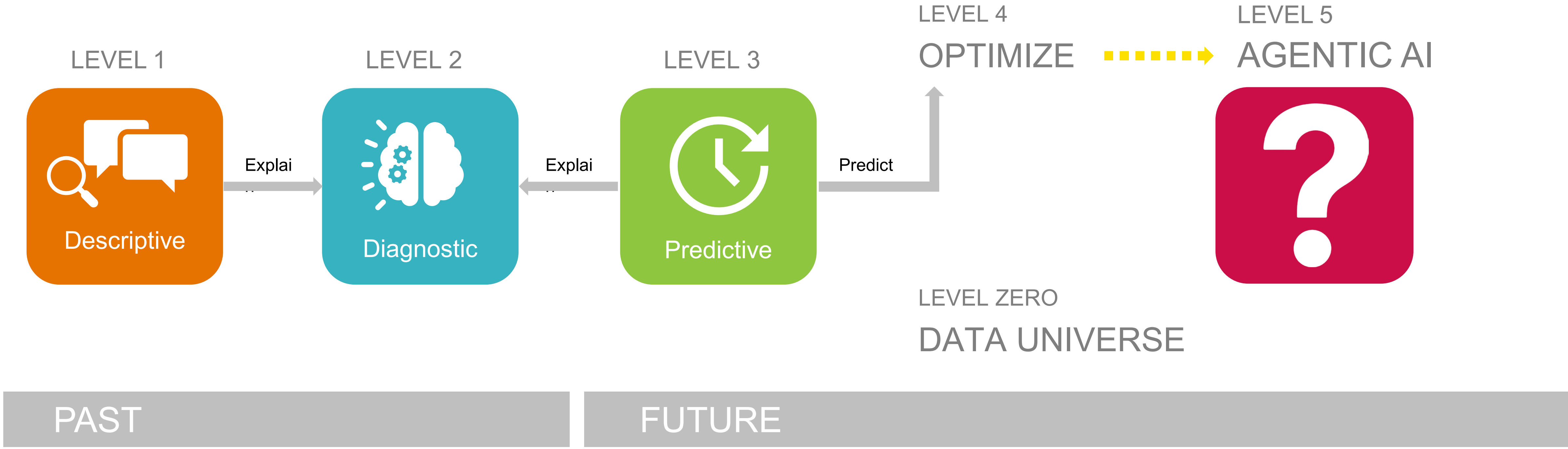

AI Developments: 20th Century 1st Track

- **Reactive Machines:**
  - These are basic rule-based systems that operate based on predefined rules.
- **Expert Systems:**
  - These are computer systems that mimic the decision-making ability of a human expert in a specific domain.

KNOWING

AI Developments: 20th Century
2nd Track

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Machine Learning (ML) Systems:

- ML is a subset of AI that focuses on developing algorithms and models that enable computers to learn from data.
- Types of ML systems include **supervised learning (PA)**, unsupervised learning, and reinforcement learning.

LEARNING

AI Developments: Modern Landscape

Machine Learning (ML) Systems:

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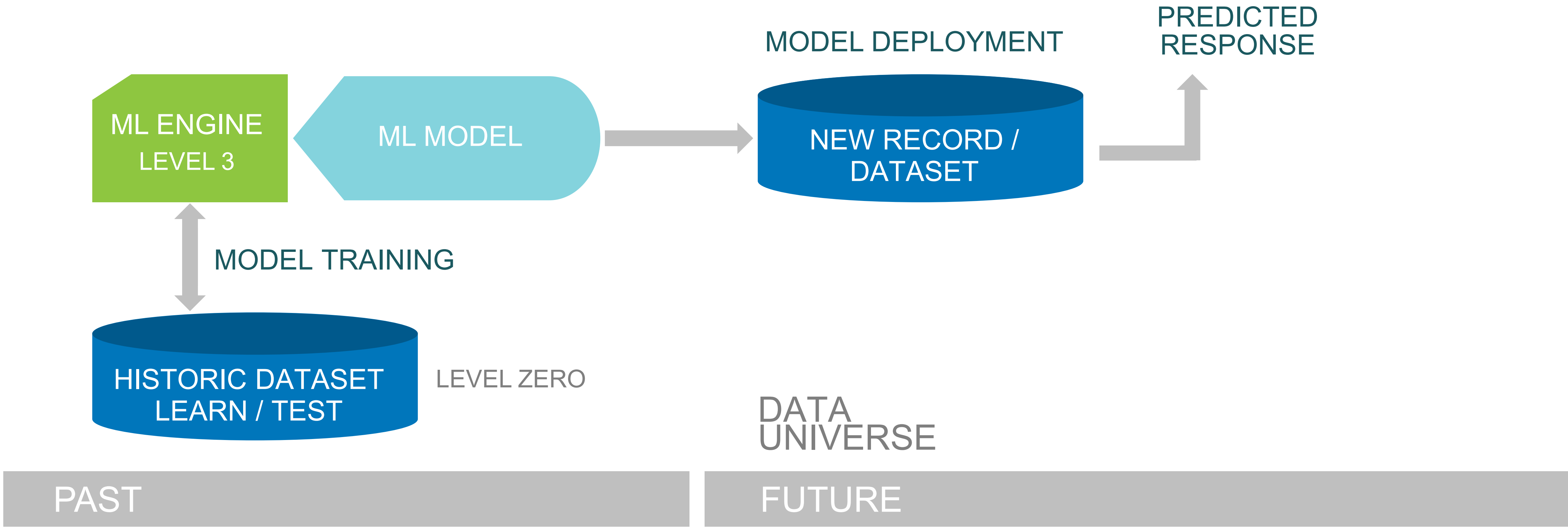
Neural Networks:

- Inspired by the human brain, neural networks are a key component of many AI systems.

NUMBERS

Machine Learning Process



Machine Learning in Manufacturing

- Quality Control and Defect Detection
- Fault Diagnosis
- Predictive Maintenance
- Process Optimization
- Demand Forecasting
- Supply Chain Risk Prediction
- Yield Prediction
- Energy Consumption Prediction

Example: Predicting Equipment Failure

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- Problem

  Predict the probability of a machine failure based on the current operating conditions (real-time sensor data)

Impact

Capture the problem before things blow up!

Example: Steel Plate Fault Detection

- Problem

  Automatic detection of surface defects during steel manufacturing process using real time sensor and process-derived measurements

Impact

Reduce waste of material and resources

OEE – Overall Equipment Effectiveness

- A key metric that measures how efficiently and effectively manufacturing equipment is utilized
- Percentage of planned production time that is truly productive
- Components:
  - Availability
  - Performance/Speed
  - Quality

Major Hurdles to Digital Transformation

- Reluctance (fear) to adopt innovation
- Not understanding the actual business need
- Accommodating technology for the sake of technology
- New Features/Capability over Reliability
- Gathering the data we don’t need
- Don’t gathering the data we do need
- Fundamental limitations of machine learning
- Moore’s law yielding to the 80/20 rule
- Regulatory constraints (emissions, etc.)

GPT: Generative Pretrained Transformer

- Genuine **revolution in Data Analytics** ability to communicate with the machines using natural human language (**conversational retrieval**)
- Transformer technology introduced by Google to convert words to word vectors
- Pretrained on humongous volume of various on-line text sources
- Generative – sequential generation of words to produce large blocks of text
- Made computationally feasible by the advent of **GPUs** and large parallel processing arrays

TEXT

Training Corpora in Perspective

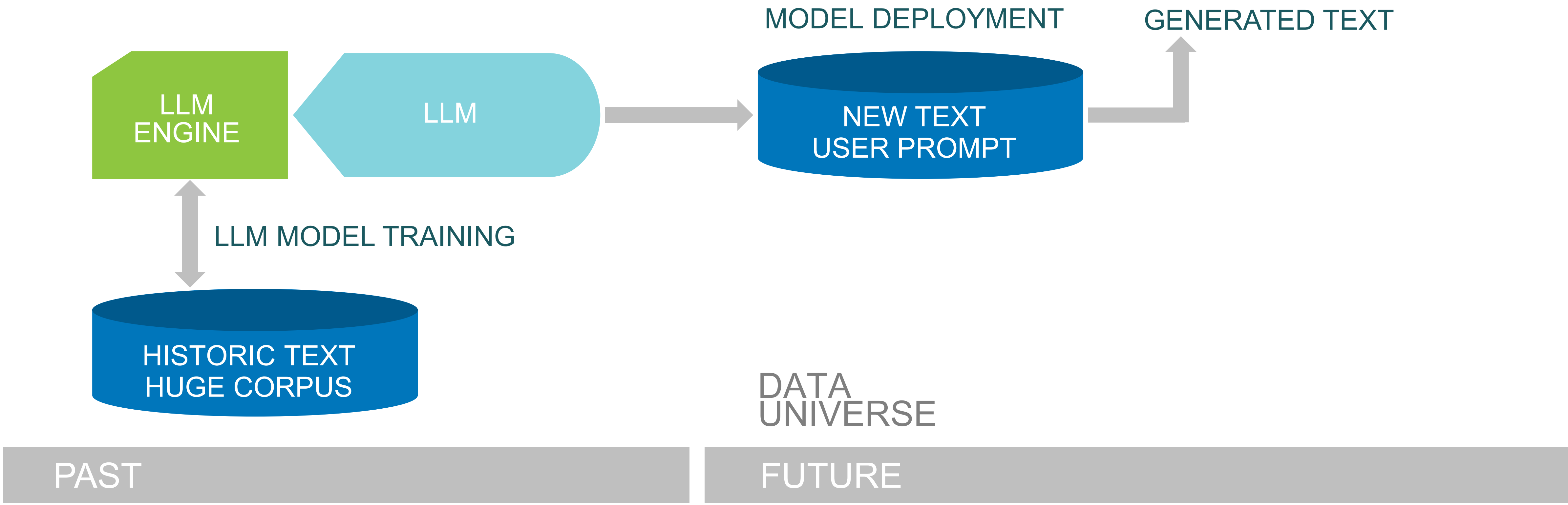
ALL GPT models are trained on a human-supplied source text!

- The Complete Works of William Shakespeare (or the Bible)
  - 0.006G (3 months of reading)
- Babylonian Talmud
  - 0.040G (1.5 years of reading)
- Complete works of Vladimir Lenin
  - 0.100G (4 years of reading)
- Encyclopedia Britannica
  - 0.250G (10 years of reading)

- GPT-1 (2018)
  - 5G (180 years of reading)
- GPT-2 (2019)
  - 40G (1,500 years of reading)
- GPT-3 (2020)
  - 570G (20,000 years of reading)
- GPT-4 (2023)
  - 5,000G
- GPT-5 (2025)
  - 20,000G

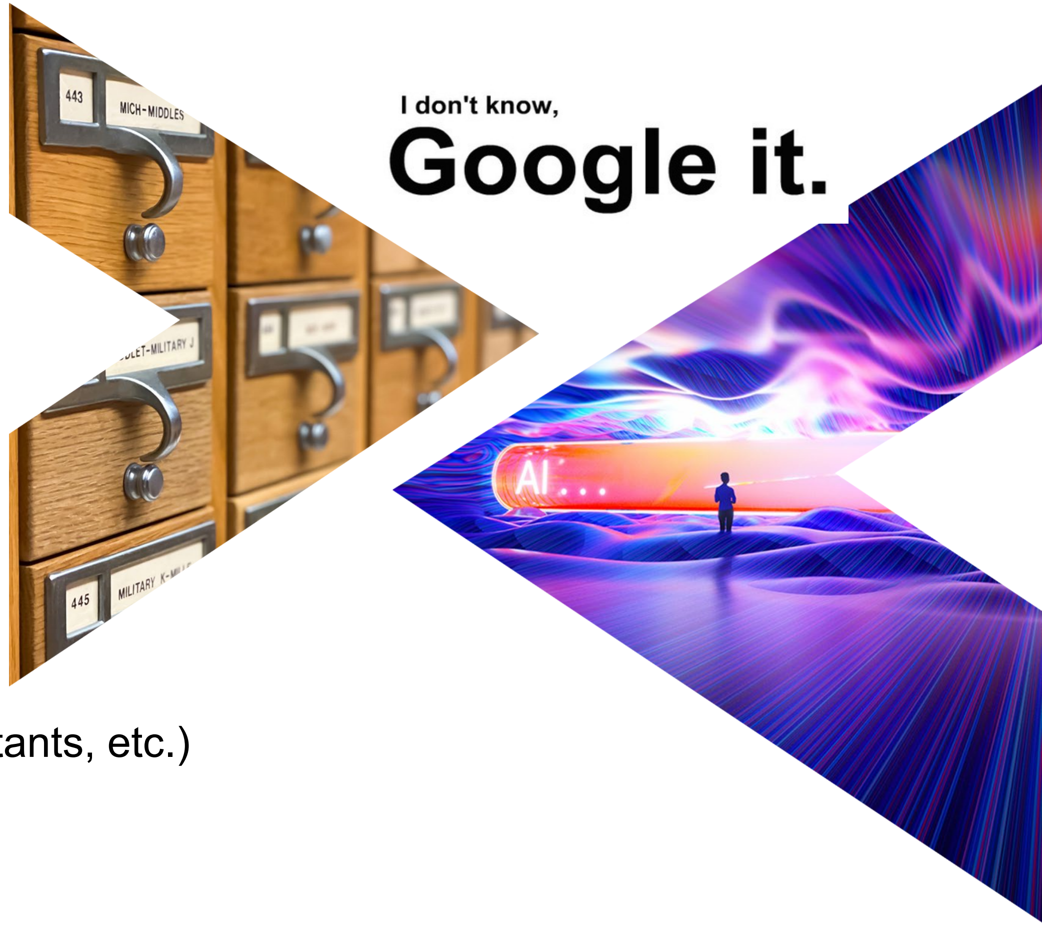
- Wikipedia
  - 500G (Comparable to GPT-3)
- US Library of Congress
  - 100,000G
- Public crawlable web
  - 5,000,000G

Large Language Model Process



GenAI as Information Retrieval System

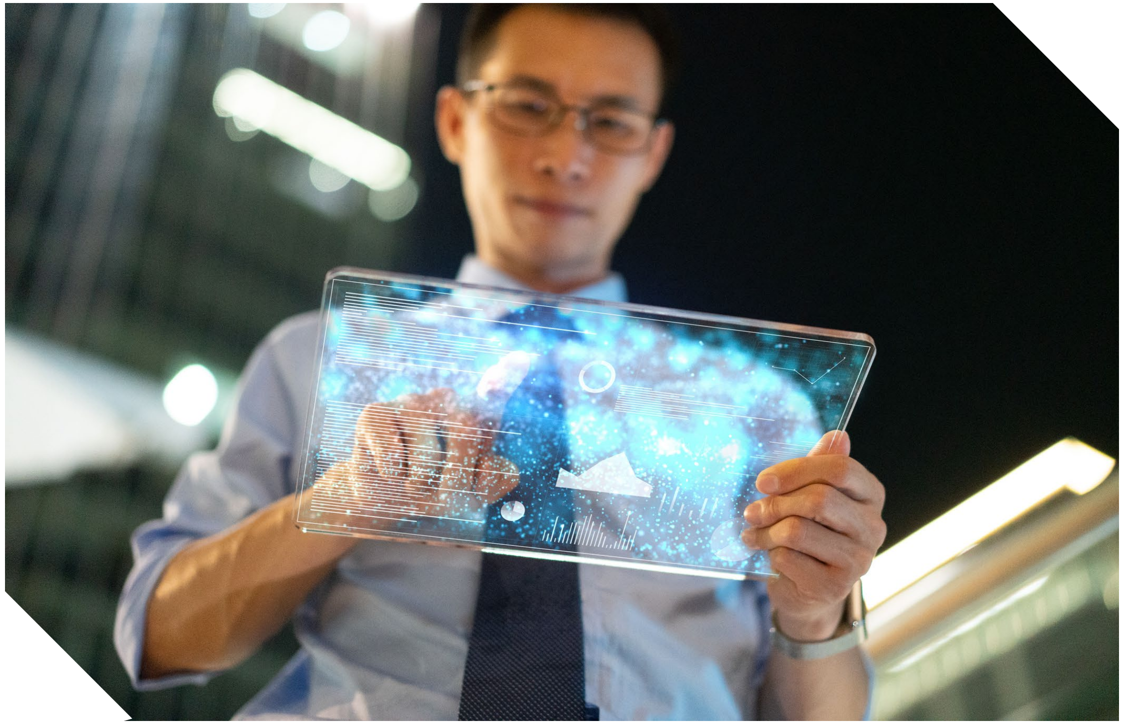
- **Libraries**
  - As old as ancient Greece and Egypt
  - Culminated in the Library of Congress Classification
- **Pre-digital Mechanization**
  (19th-20th centuries: index cards, punch cards, etc.)
- **Early Computerized IR**
  (1940s-1960s: Boolean searches, etc.)
- **Search Databases**
  (1970s-1980s: electronic abstracts, indices, etc.)
- **Web-search era**
  (1990s-2000s: Web Crawler, Alta Vista, Yahoo, Google, etc.)
- **Big Data and ML**
  (2010s: collaborative filtering, recommender systems, personal assistants, etc.)
- Generative AI and Conversational Retrieval
  (2020s: ChatGPT and its likes)



How Should We Handle Generative AI?

DIVINATION

INTERROGATION



GenAI in Manufacturing

- Generative Design (Product Development)
- Synthetic Data Generation for Training Models
- Process Optimization and Simulation
- Scenario Generation
- Automated Documentation
- Digital Twins

GenAI Fundamental Flaws

- The abrupt end of scalability with the release of GPT 5.0
  (Moore's law yielding to the 80/20 rule)
- Creation vs Regurgitation
- Unacceptable Liability (Code Generation vs Medical Advice)
- Hacking and code/prompt injection attacks
- Emotional attachments
- Ethical considerations
- Inherently prone to hallucinations
- Flooding the Data Universe with the superfluous content
  - Amazon book mills
  - Science paper mills
  - Web-bot comments and reviews

What About AGI?

Self-aware AI:

- This refers to hypothetical AI systems with self-awareness and consciousness.

Theory of Mind:

- This is a more advanced form of AI that can understand human emotions, beliefs, intentions, and thoughts.

General AI (Strong AI):

- General AI systems can understand, learn, and apply knowledge across diverse domains.
- They can perform any intellectual task that a human being can do.

Superintelligent AI:

- This is a theoretical AI that surpasses human intelligence in every aspect.

AGI

SCI FI

RELIGION

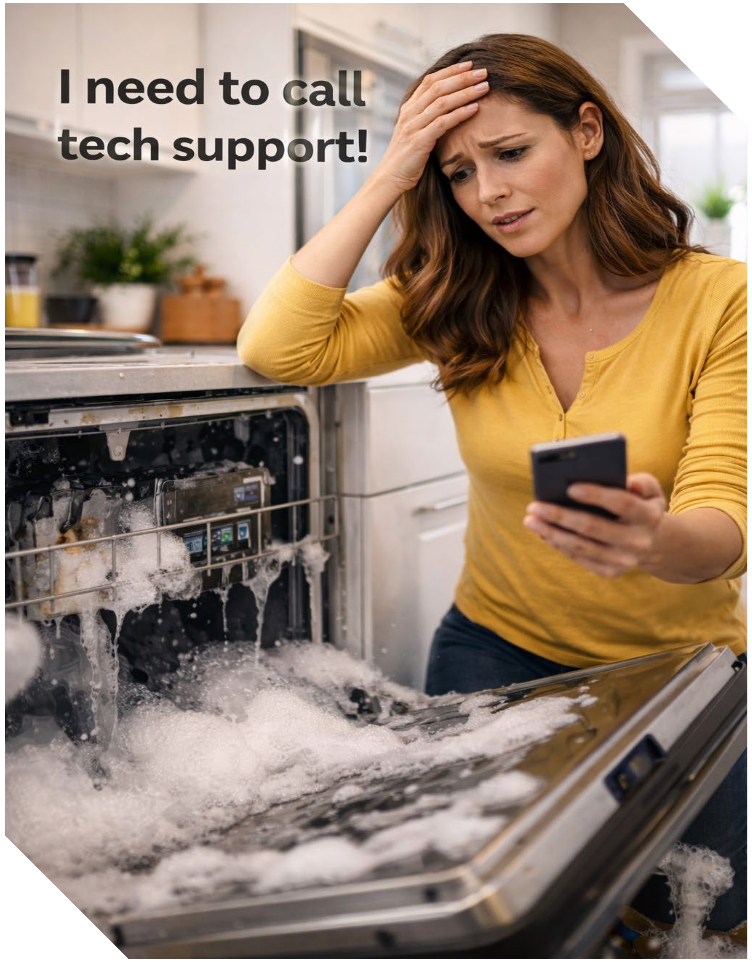
Obstacles to Reaching AGI

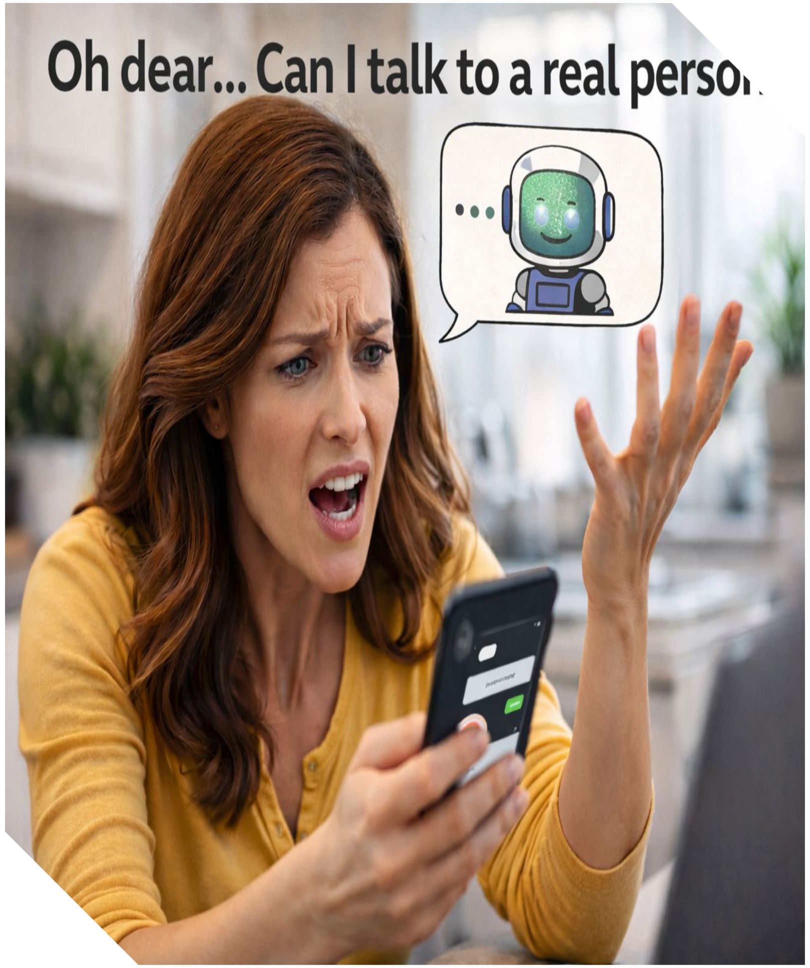
- Narrow AI (Gen AI) alone is not enough!
- The world is **open-ended** – the modern AI systems are **closed**
- Five Areas Where Human Intelligence Remains Superior
  - Understanding **language**
  - Understanding the **world**
  - **Adapting** to new circumstances
  - Learning **new things** quickly bypassing data
  - **Reasoning** in the face of incomplete and inconsistent information
- Presence of non-verbal inferred context/information in most human interactions
- The elusive idea of common sense
- Issues of trust and accountability

Agentic AI: Dangerous Crossroads

- Agentic AI (inductive): systems that can **act autonomously** to pursue goals, **make decisions and** take multi-step actions **with limited or no human intervention.**
  - Very challenging to develop, maintain, and monitor
  - Rewards speed for scrutiny
  - Trades short term operational gains for long-term lack of resilience
  - Dissolution of trust and accountability
  - May trigger **costly avalanche-like failures**
  - Ignores qualified minority views
  - Maximizes efficiency and minimizes exploration
  - May unintentionally lead to technocratic tyranny

And What About Customer Experience?





Agentic AI: Dangerous Crossroads

- **Hybrid Cognition** as a viable alternative
  - Human intelligence at the center of decision making
  - AI serves as memory assist and cognitive amplifier
  - Interpretation is separated from authority
  - Preserves vigilance and accountability

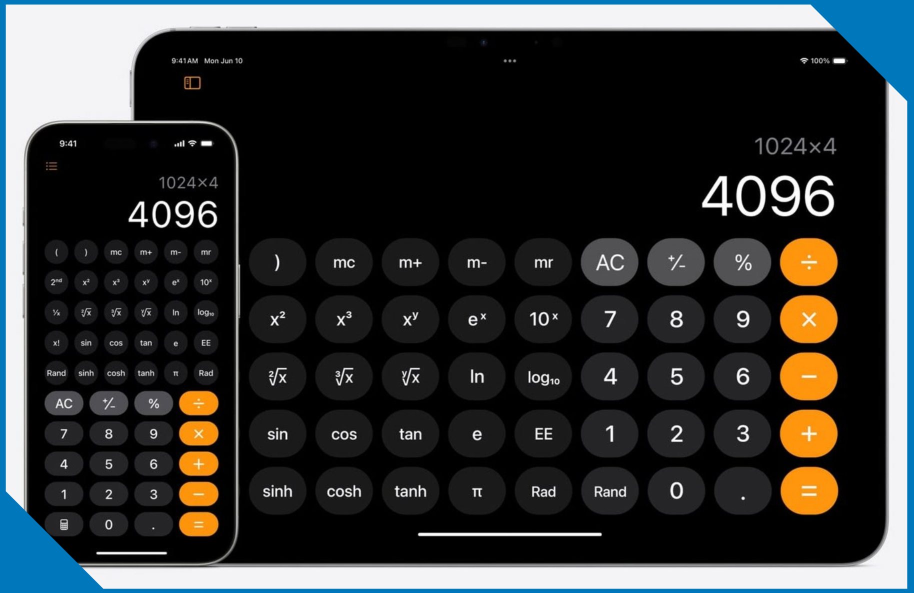
A car moves faster than me …

… but it will never fly!

An excavator lifts more than me …

… but it will never build a sandcastle!

A calculator adds faster than me …



… but it will never have an eureka moment!

The Deep Blue computer plays chess better than me …

… but it will never play hockey like my son!

ChatGPT creates an illusion of a relationship …

… but it will never have a soul!

"The only thing more dangerous than ignorance is arrogance.

Imagination is more important than knowledge."

– Albert Einstein

THE ULTIMATE DANGER

We Become Like AI

Thank you

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OEE: Insights, Blind Spots and Better Decisions

Marco Massa and Tony Smith

What OEE Actually Measures

Availability x **Performance** x **Quality**

Availability

Unplanned breakdowns
Mechanical/Electrical failures
Planned maintenance
Tool/die/product changeovers
Product changeovers/setups
Material shortages
Waiting for personnel
Safety stops or utility outages

Performance

Reduced machine speed
Repeated stops/interruptions
Material feed issues
Operator speed reduction
Increased cycle time
Equipment bottlenecks
Frequent adjustments
Suboptimal settings

Quality

Out-of-spec parts
Surface defects
Assembly errors
Packaging/labeling errors
Material contamination
Weld defects
Paint/coating defects
Rework or scrap

Recent Acquisitions around OEE

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Availability
Performance
Quality

SCYTEC DATA XCHANGE

- Real-time OEE
- Downtime and runtime tracking
- Machine + operator data

Quality

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- CMM, gage, PLC data collection
- SPC reporting
- Automated and real-time

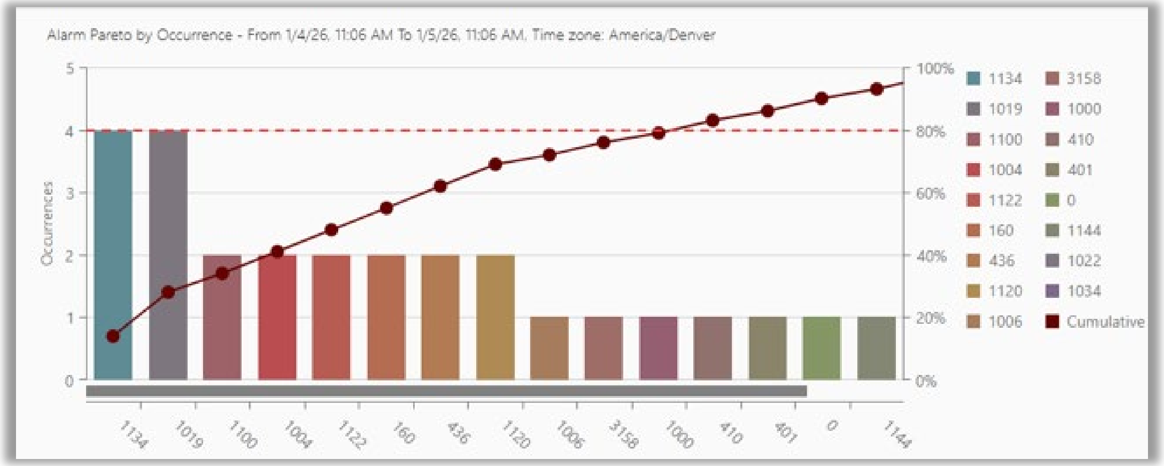
Process
Simulation

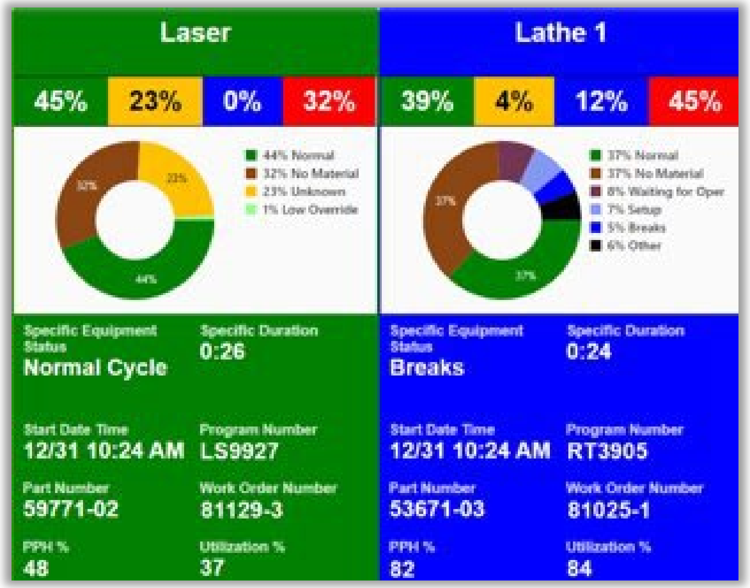
SIMUL8

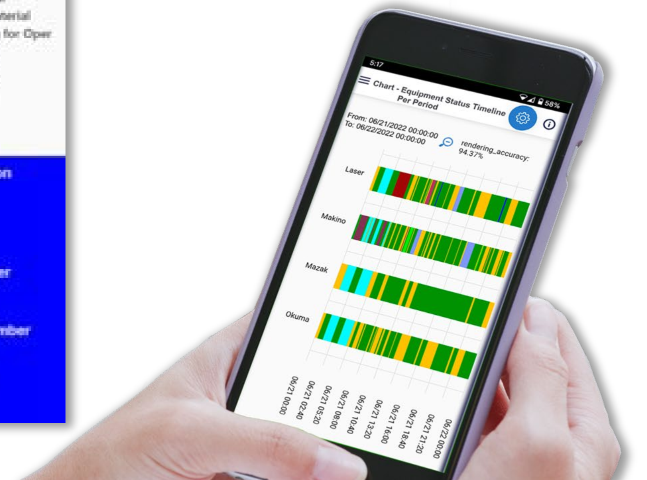
- Process simulation
- Digital twins
- Process mining + simulation

Drive Performance with Real-Time Data

- Replace manual tracking with real-time data
- Identify downtime root causes
- Improve utilization and throughput
- Standardize OEE across operations







Problem #1
85% OEE, why?

- Machine breakdowns
- Reduced speed
- Scrap/Rework

How To Collect Data?

Automatic collection

Operator Input

Integration

Automatic Data Collection

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- Standard protocols
- Proprietary machine protocols
- Hardware based options and sensors
- Custom integrations

Case Study

Utilization Increase and Improved Processes with Machine Monitoring

Business Outcomes at AMT senior Aerospace

- 15–20% higher utilization
- Greater visibility into downtime causes
- Increased production capacity
- Better process insights from tool & probe data

Thank you

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Process Variation: The Silent Profit Killer

Marco Massa and Tony Smith

Where Do You Lose Profit?

Missed deliveries

High scrape rates

Product recalls

Lost Profit

Customer Returns

Work on scrapped parts

Process variation can be the driving force behind all these factors!

Contributing Factors in Process Variation

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- Inconsistent Data Collection
- Operators rely on guesswork
- Variability in raw material properties
- Untracked tool wear
- Environmental Factors
- Setup Variations
- Lack of data

Manufacturers often struggle to address these problems because they do not have a strong data strategy

Not collecting the right data

Data quality is inconsistent

Data exists in siloes

Digital Thread is incomplete

Data Strategy

Data analytics and AI are NOT intelligent.
They are only able to work with the data that is provided.

Rubbish In → ML model → Rubbish Out

Incomplete Data → AI model → Hallucinations

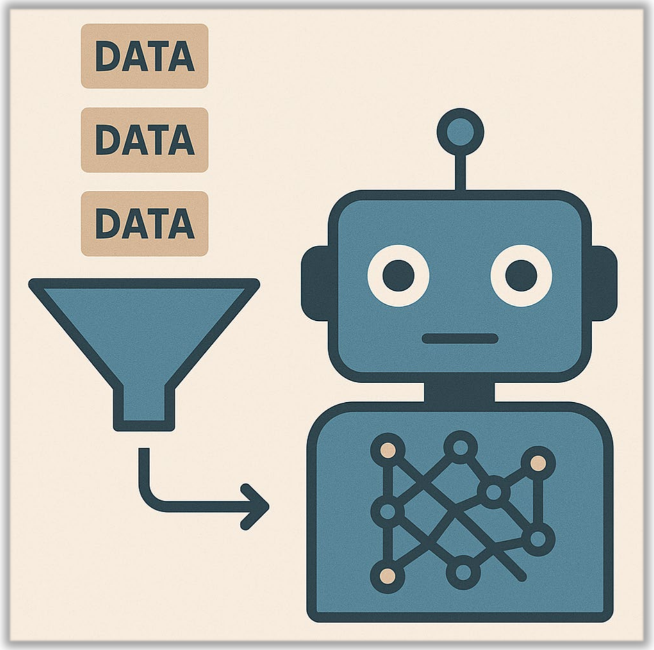
For analytics to deliver real value to an organisation, data needs to be holistic, accurate and reliable.

1 Data Capture

2 Data Validation

3 Data Centralisation & Preparation

Objective Driven



1 Data Capture

How Minitab can help to capture data across a plant:

- Incoming Inspection
- Moulding Operations
- Machining Operations
- Final Inspection

Real-time insights and better decisions

Reduces waste and errors in manual data collection

Incoming Inspection Common Challenges

- Measurements recorded on paper
- Results results disconnected from downstream production data
- Limited visibility of supplier performance over time

Without connected data, incoming inspection becomes a pass/fail activity rather than a source of insight into process variation.

Incoming Inspection - Solutions

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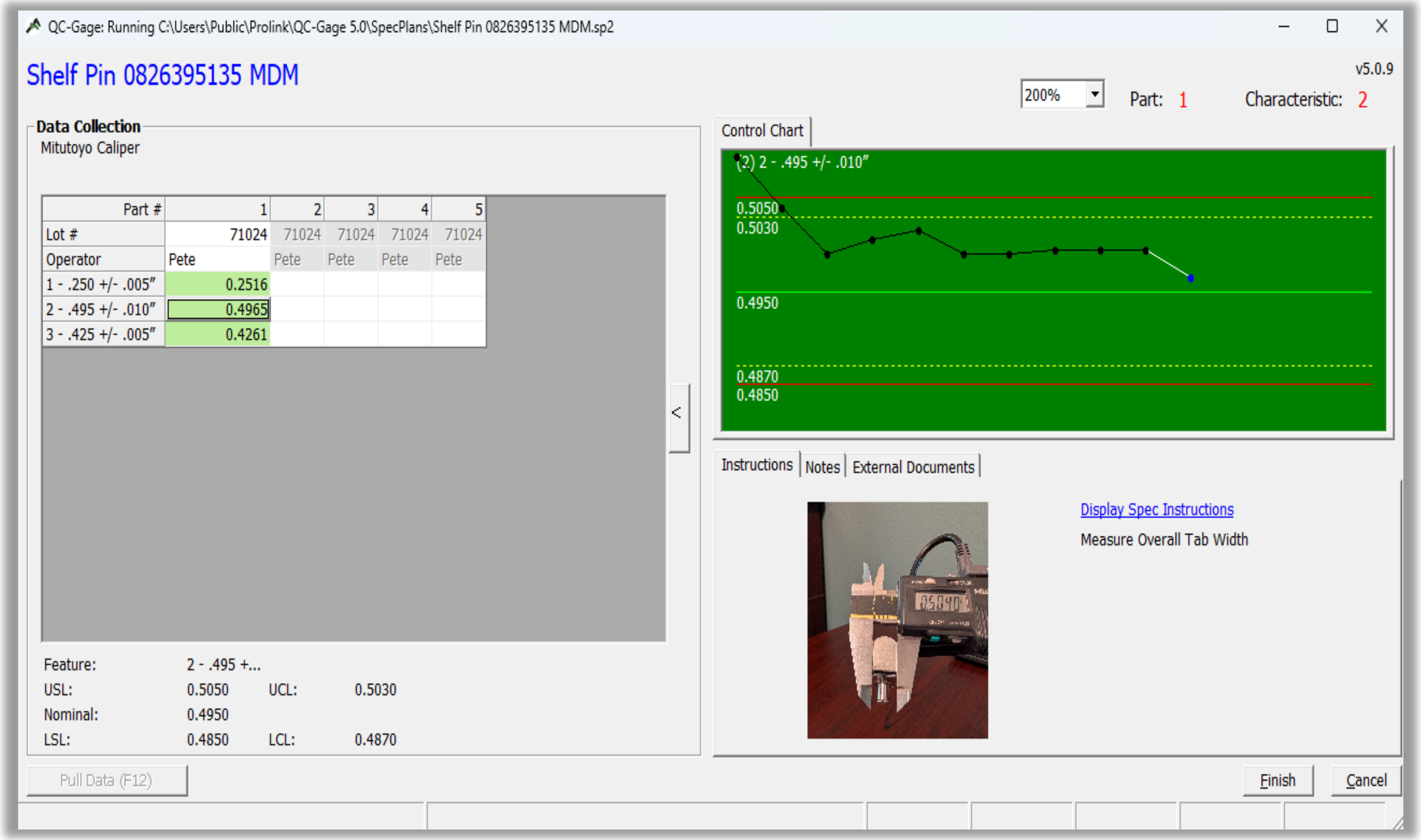


By automatically capturing inspection data and linking it to supplier and material information, manufacturers gain visibility into variation before it enters production.

Moulding Department Common Challenges

- Moulding processes are highly sensitive to process conditions
- Small changes in temperature, pressure or time can introduce lots of variation
- Process data is often available but trapped in PLCs
- This limits the ability for root-cause analysis and process optimisation

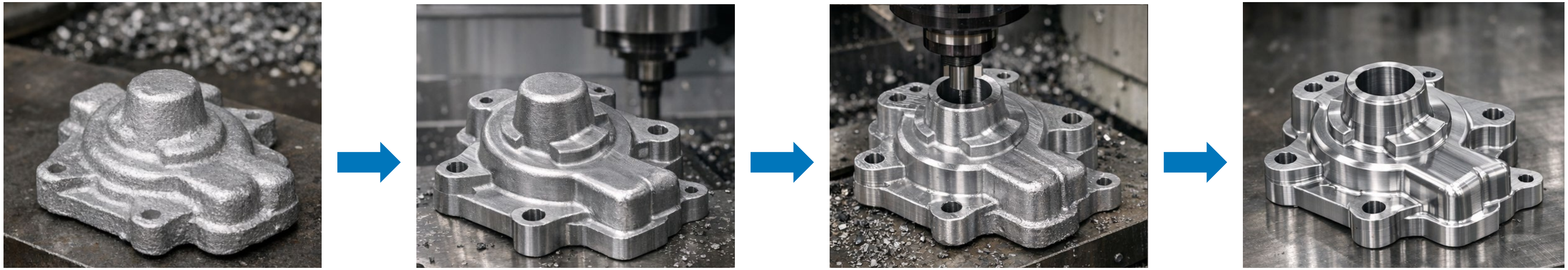
Moulding Department Solutions

- Minitab can integrate directly with every mainstream PLC
- Critical process data is captured and connected to material, production and quality data

Manufacturers gain the ability to correlate process conditions with quality outcomes

Machining Department

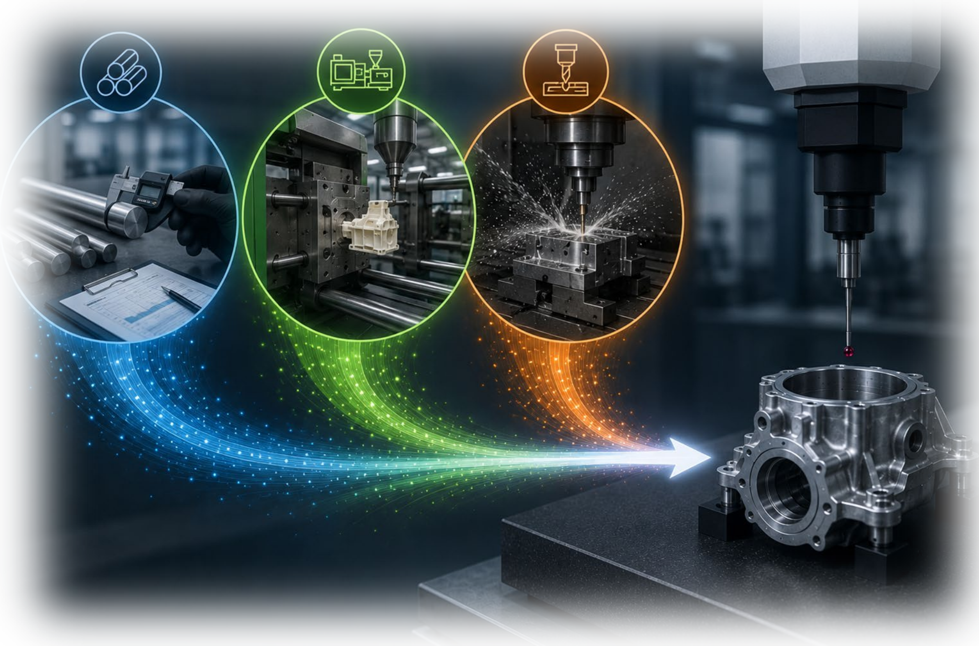
Measure parts after each operation to ensure additional cost is not added to a part that should have been scrapped or recycled.



Why keep machining if there was an out of specification condition in an earlier operation that scrapped the part?

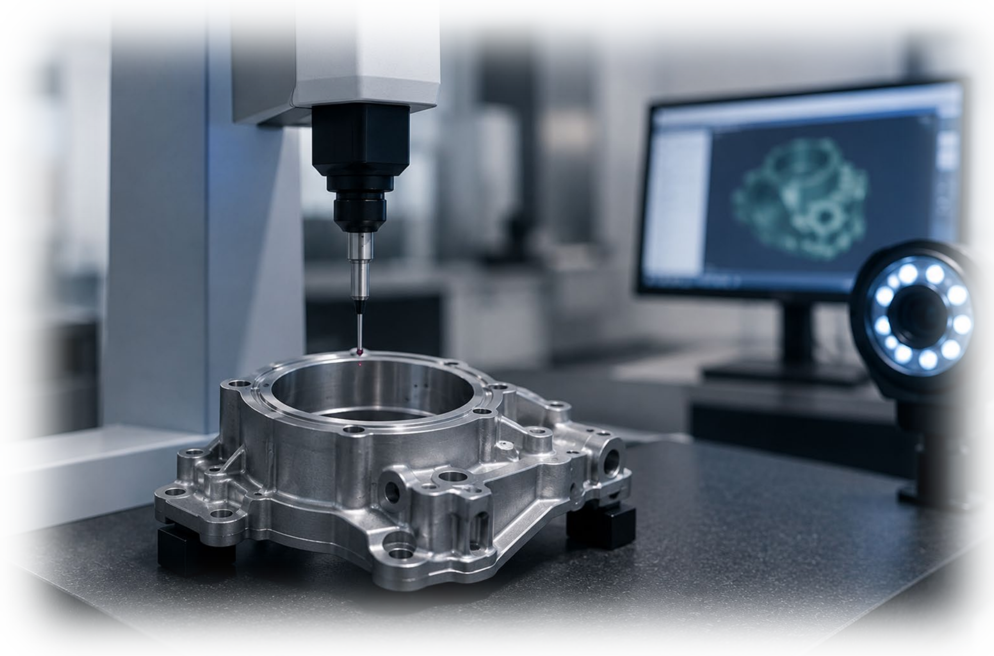
Final Inspection Challenges

- Final inspection is where the impact of variation introduced throughout the manufacturing process becomes visible.
- However, when quality data remains disconnected from the product's history, defects can be identified but their root causes often remain unclear.



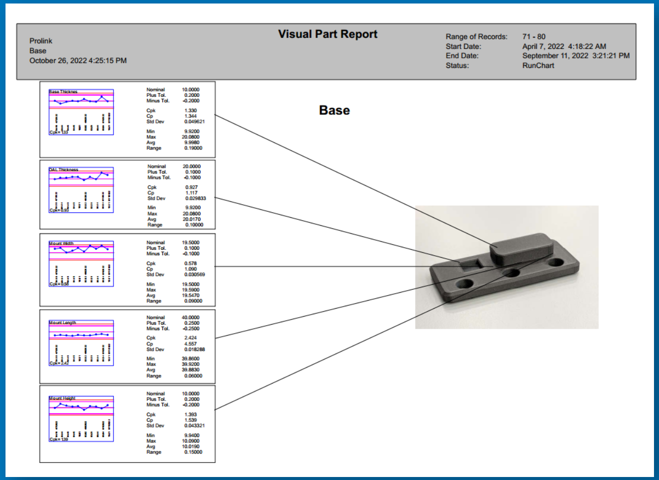
Final Inspection Challenges

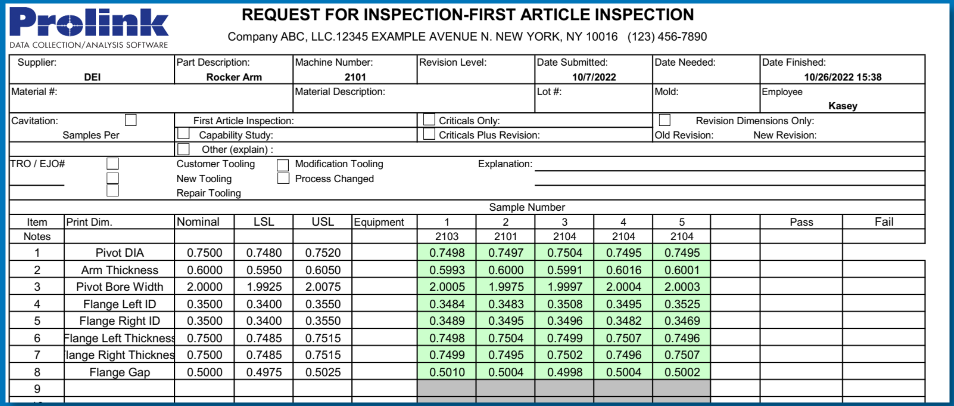
- Measurement data isolated within CMM and vision systems
- Manual reporting and customer documentation
- Limited visibility into the sources of variation
- Difficult root cause investigations



Final Inspection Solutions

- Real-time integration with CMMs to unlock data
- Save time with automated report generation
- Export data to Minitab for root-cause investigations





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DATA COLLECTION/ANALYSIS SOFTWARE

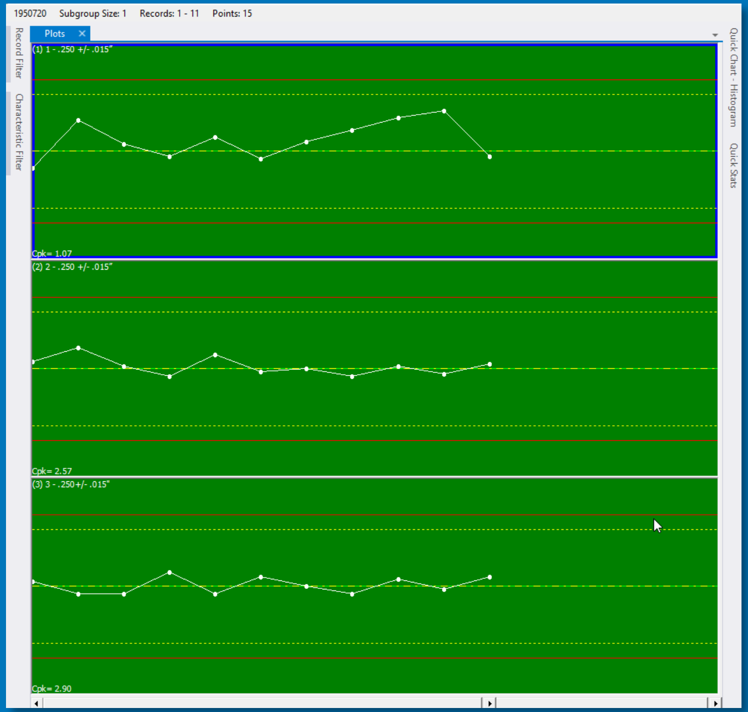
REQUEST FOR INSPECTION-FIRST ARTICLE INSPECTION

Company ABC, LLC.12345 EXAMPLE AVENUE N. NEW YORK, NY 10016 (123) 456-7890

Supplier: **DEI**	Part Description: **Rocker Arm**	Machine Number: **2101**	Revision Level:	Date Submitted: **10/7/2022**	Date Needed:	Date Finished: **10/26/2022 15:38**
Material #:		Material Description:		Lot #:	Mold:	Employee **Kasey**

Cavitation: Samples Per
First Article Inspection:
Capability Study:
Other (explain) :
Criticals Only:
Criticals Plus Revision:
Revision Dimensions Only:
Old Revision: New Revision:
TRO / EJO#
Customer Tooling
New Tooling
Repair Tooling
Modification Tooling
Process Changed
Explanation:

Item	Print Dim.	Nominal	LSL	USL	Equipment	Sample Number 1	2	3	4	5		Pass	Fail
Notes						2103	2101	2104	2104	2104			
1	Pivot DIA	0.7500	0.7480	0.7520		0.7498	0.7497	0.7504	0.7495	0.7495			
2	Arm Thickness	0.6000	0.5950	0.6050		0.5993	0.6000	0.5991	0.6016	0.6001			
3	Pivot Bore Width	2.0000	1.9925	2.0075		2.0005	1.9975	1.9997	2.0004	2.0003			
4	Flange Left ID	0.3500	0.3400	0.3550		0.3484	0.3483	0.3508	0.3495	0.3525			
5	Flange Right ID	0.3500	0.3400	0.3550		0.3489	0.3495	0.3496	0.3482	0.3469			
6	Flange Left Thicknes	0.7500	0.7485	0.7515		0.7498	0.7504	0.7499	0.7507	0.7496			
7	lange Right Thicknes	0.7500	0.7485	0.7515		0.7499	0.7495	0.7502	0.7496	0.7507			
8	Flange Gap	0.5000	0.4975	0.5025		0.5010	0.5004	0.4998	0.5004	0.5002			
9													



Data Strategy

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They are only able to work with the data that is provided.

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1 Data Capture

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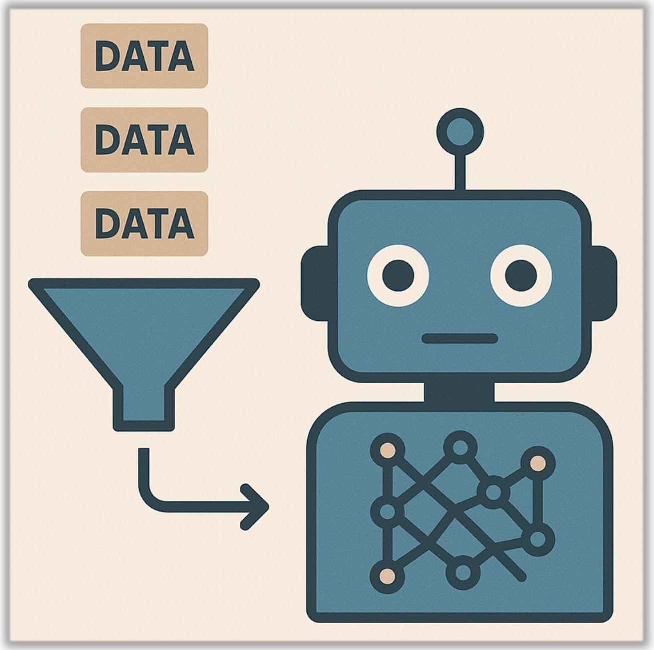
3 Data Centralisation & Preparation

Objective Driven



2 Data Validation
Measurement System Analysis (MSA)

📌 What is it?

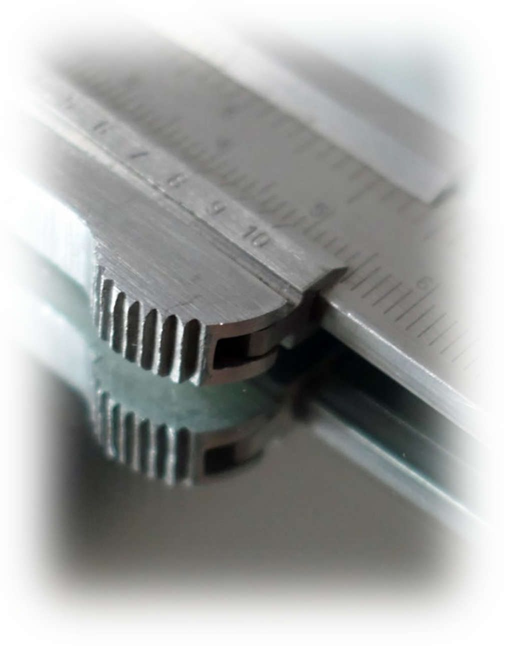
Structured tests to reveal if a measuring system is reliable & consistent

⚠️ Why is it important?

Poor systems lead to false rejects, missed defects, wrong decisions

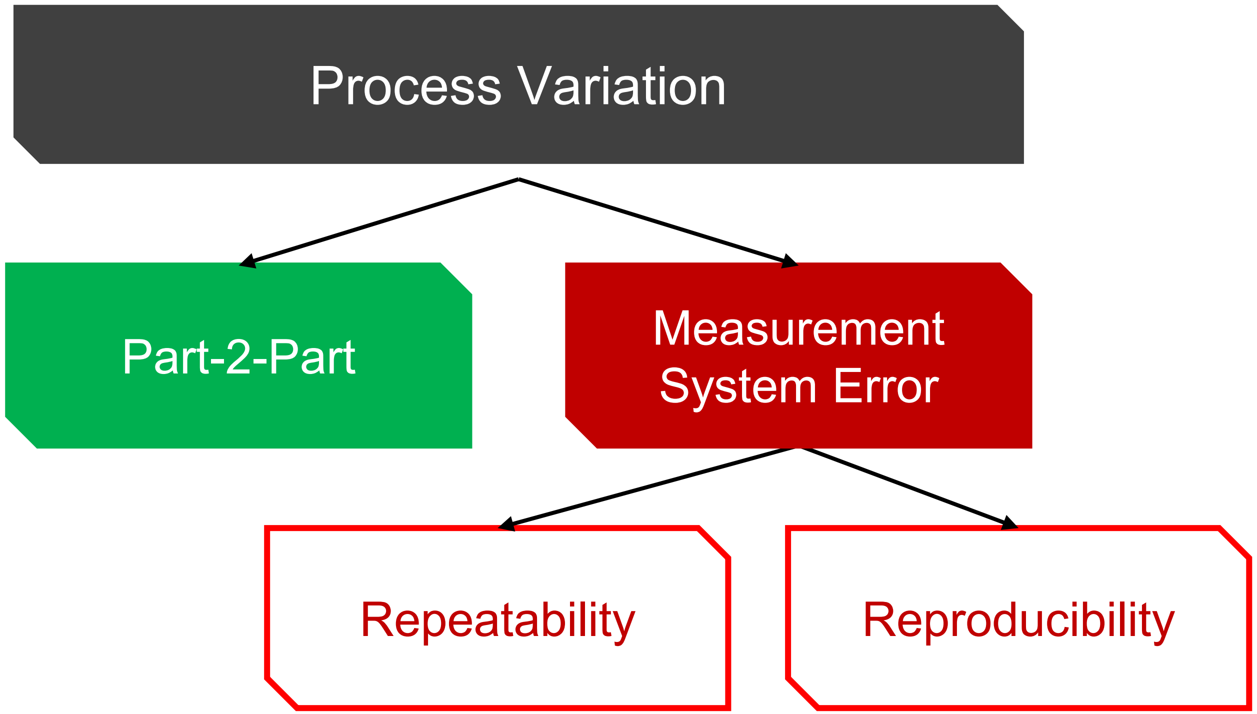
⏰ When to use?

New systems / Equipment changes / Disputes / Routine checks



Confidence in data → Reduced risks → Stronger decisions → Compliance

Partitioning of Process Variation

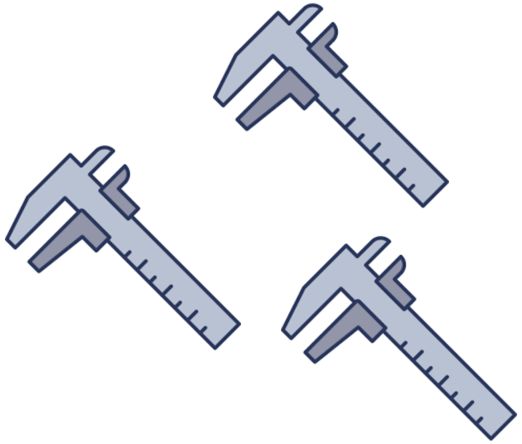


→ variation caused by **measurement system**

→ variation caused by **the operator**
→ ???

0 - 10% = ✅ acceptable
10 - 30% = ⚠️ marginal
> 30% = ❌ unacceptable

But How to Handle Additional Factors?



Top diameter

Bottom diameter

Include more than one measurement system within a study

Measure a dimension in multiple locations

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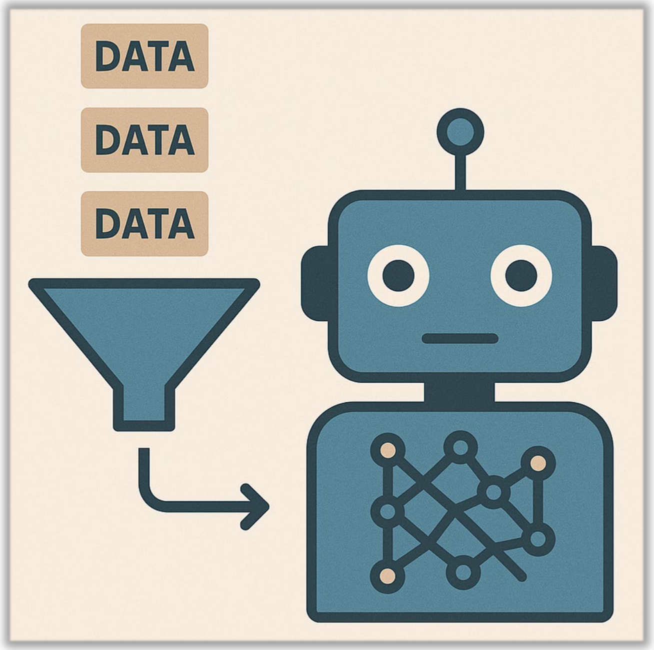
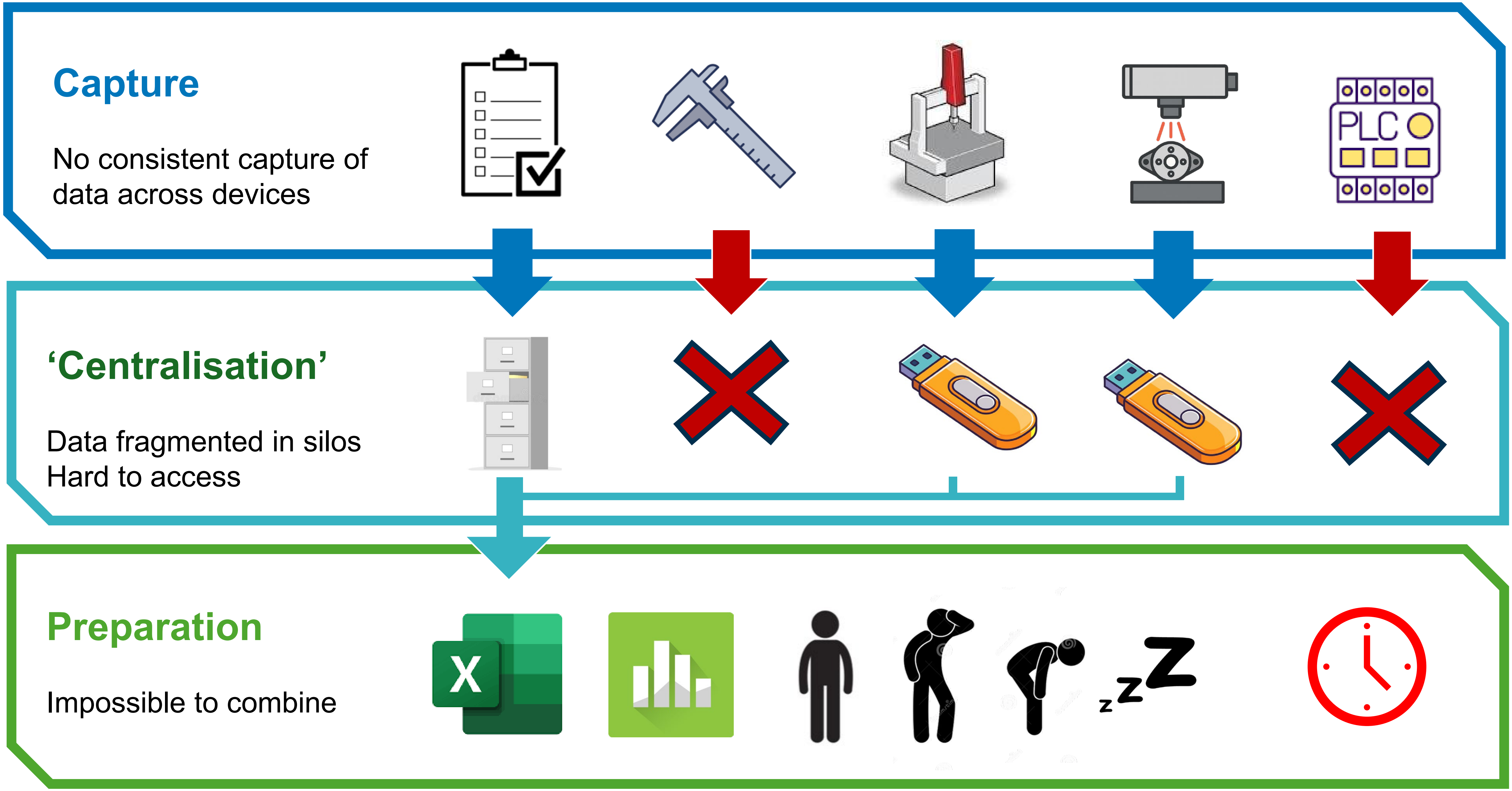
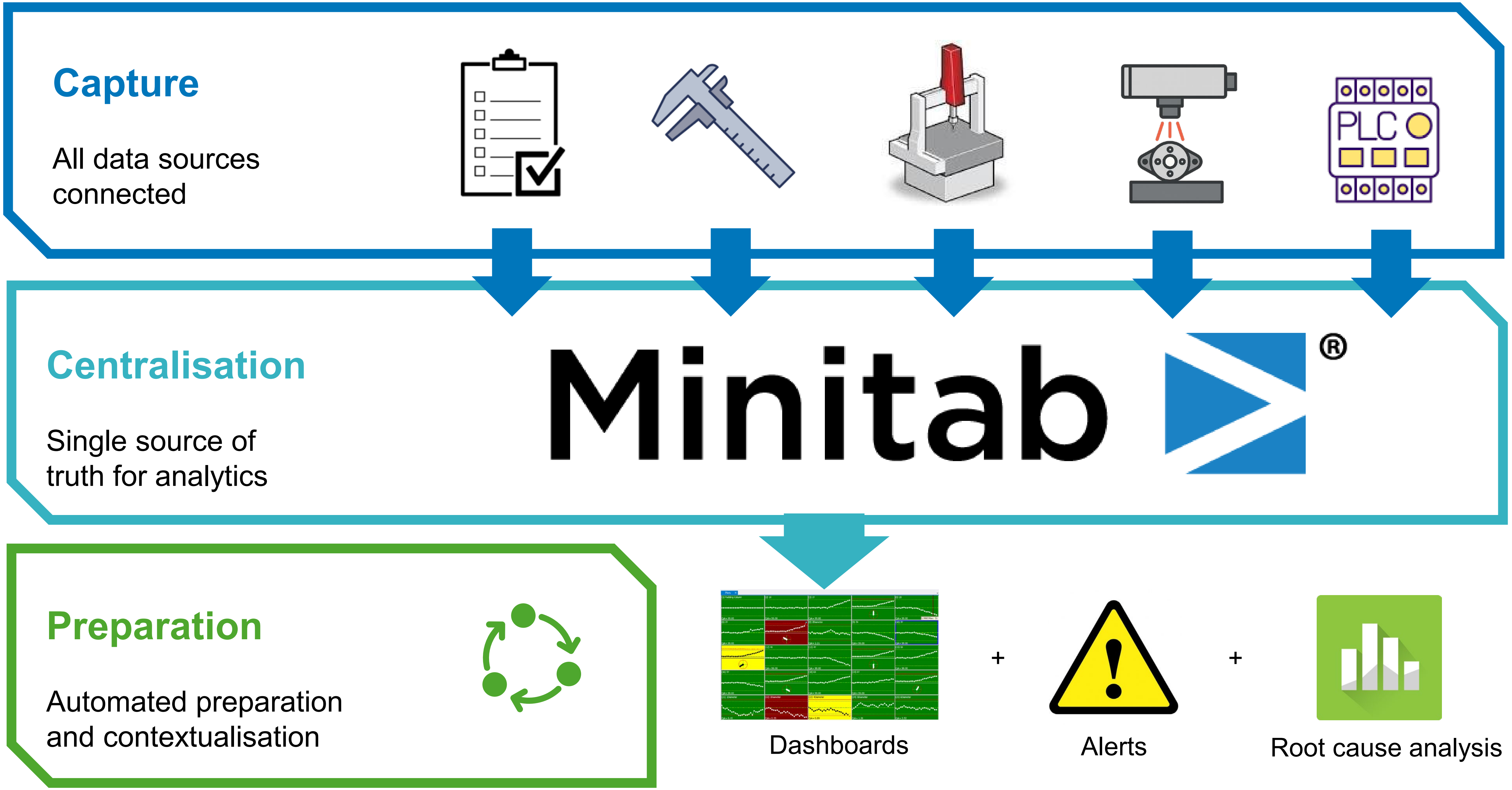
3 Data Centralisation & Preparation

Objective Driven




Capture
No consistent capture of data across devices
PLC
'Centralisation'
Data fragmented in silos
Hard to access
Preparation
Impossible to combine
X
z
z
Z



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Summary

Creating a strong data strategy and a digital thread transforms production data into actionable information:

Identify, understand, and reduce process variation

See the Health of the Plant:

- Factory floor view
- Red / Amber / Green status indicators
- Immediate visibility of problem areas

Monitor Process Stability

- Real-time SPC
- Trends
- Alerts
- Capability metrics

Drill Down into Issues

- Production line
- Machine
- Product
- Characteristic

Questions?

Thank you

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From Monitoring to Mastery: Root Cause Analysis

Marco Massa and Tony Smith

Root Symptom Analysis (RSA)

"Everyone doing the wrong thing together, enthusiastically, accelerating short-term solutions with long-term consequences"

Root Symptom Analysis (RSA)

Reactive symptom analysis keeps the factory busy but the root cause alive

Trial-and-error is not a root-cause method

Root Symptom Analysis RSA	**Symptom** an alarm, defect, or low-yield batch appears	**Containment** a quick change is made to stop the pain	**Temporary relief** performance improves for a shift or a run	**Recurrence** the issue returns because the mechanism was never isolated
Root Cause Analysis RCA	**Collect the Data** machines, sensors, lab systems	**Find key drivers** rank what actually drives the response	**Validate & Quantify** prove change was real	**Scale learning** repeat the learning line to line

Monitoring shows what changed, not why

Monitoring tells you when & how much something changed but it does not automatically tell you why it changed and what changed

Monitoring Detects

- Yield loss
- Process shifts
- Increased scrap
- Out-of-control conditions
- Declining capability

Beyond Detection: Critical Decisions

- ✓ Identify the driver
- ✓ Prioritize the inputs
- ✓ Verify process capability
- ✓ Confirm effectiveness
- ✓ Prevent recurrence

The signal is the beginning of the conversation not the end. It starts the investigation, it doesn't close it!

From Y to X

Monitoring shows the Y, root cause analytics helps identify the Xs that matter

Ys: Process outcomes

- ✓ Scrap
- ✓ Defect rate
- ✓ Diameter deviation
- ✓ Downtime
- ✓ Customer quality

$$Y = f(X)$$

Xs: Process drivers

- ✓ Tool age
- ✓ Vibration
- ✓ Speed
- ✓ Pressure
- ✓ Temperature

The improvement question: which Xs are meaningful, measurable and actionable

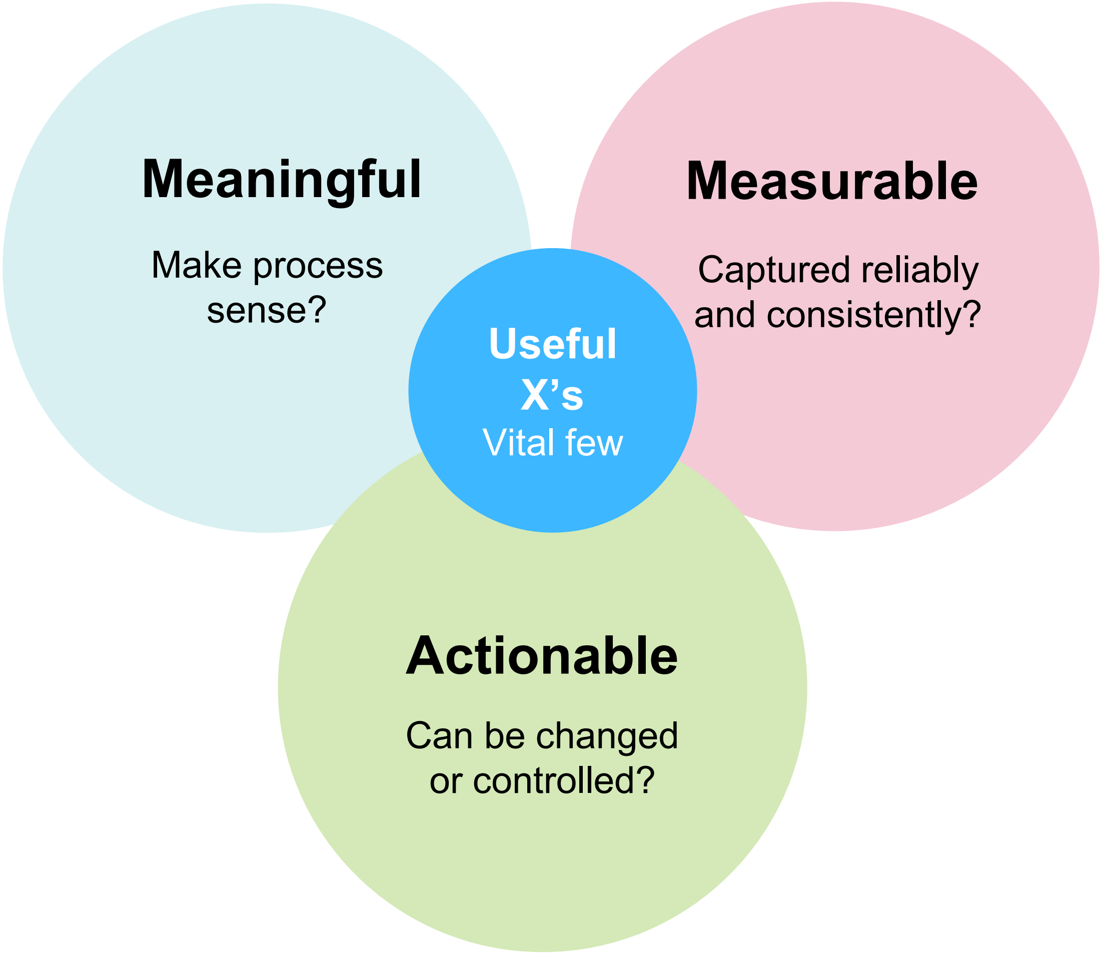
Root Cause Starts Before the Model

Manufacturers have more data than ever, but more data is not the same as better process knowledge

Ask better questions, but don’t filter too early

Questions to ask:

1. Meaningful
   Does this variable make process sense?
2. Measurable
   Can we capture it reliably and consistently?
3. Actionable
   Can the team actually change or control it?



Example

A manufacturer is producing precision-machined pump housings. The engineering team tracks real-time process variables during machining and inspection data from the finished part.

First-pass yield ≈ 94%

Finished Pump Housing

Quality Metric (Target)
Bore Diameter Deviation
Target = 0 µm
Spec = ± 10 µm

Potential Drivers of Variation

Field	Type	Description
Timestamp	Datetime	Production timestamp at roughly 8-minute intervals
Part ID	Text	Unique finished part identifier.
Machine ID	Categorical	CNC machine producing the part
Material Lot	Categorical	Incoming material lot
Material Hardness Rc	Numeric	Rockwell hardness
Spindle_Speed_RPM	Numeric	Machining speed
Tool_Age_parts	Numeric	Parts since tool change
Coolant Temp C	Numeric	Coolant temperature
Vibration RMS mm s	Numeric	Measured vibration
Ambient_Temp_C	Numeric	Ambient shop temperature
Clamp Pressure bar	Numeric	Fixturing pressure
Bore Diameter Deviation microns	Numeric target	Finished-part dimensional quality metric
Surface Roughness Ra um	Numeric target	Secondary finished-part quality metric.
Pass/Fail	Categorical target	Classification target: Fail when dimensional or roughness specification is missed.

Thank you

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Design Better Processes

Marco Massa and Tony Smith

Design Better Processes

Proactive quality with DOE. Digital validation with simulation

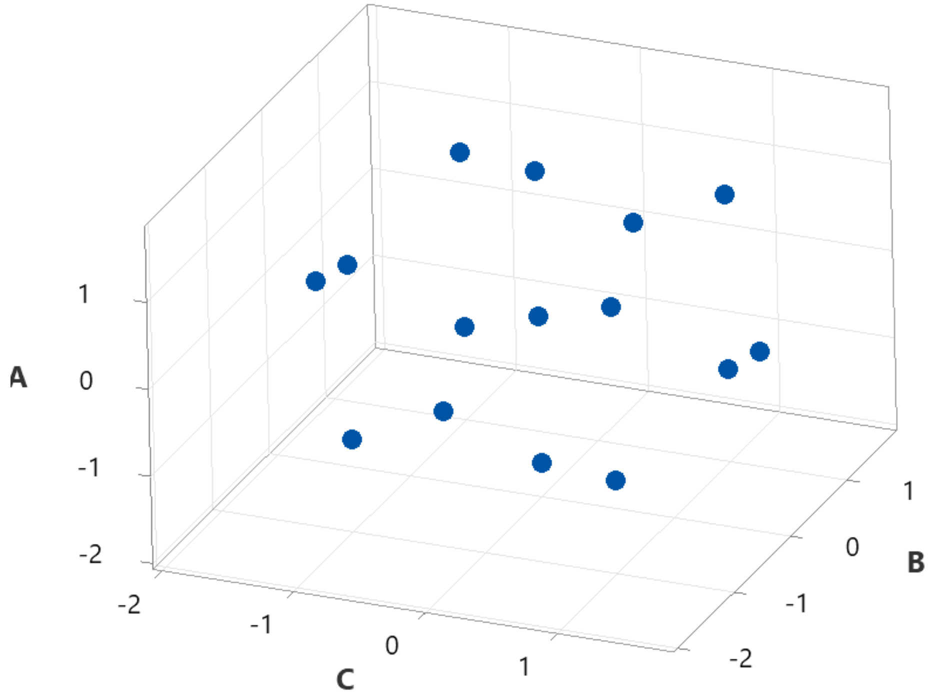
Experiment → Optimize → Simulate → Decide

Design of experiments and simulation reduce the number of physical trial loops needed to reach a stable operating window in both discrete and process manufacturing.

Design Better Processes

DOE systematically changes multiple inputs simultaneously to determine:

- ✓ Which factors matter most
- ✓ How factors interact
- ✓ Where the optimal operating region exists
- ✓ How robust the process is to variation



DOE
Why One-Factor-at-a-Time Improvement Falls Short

Traditional Approach

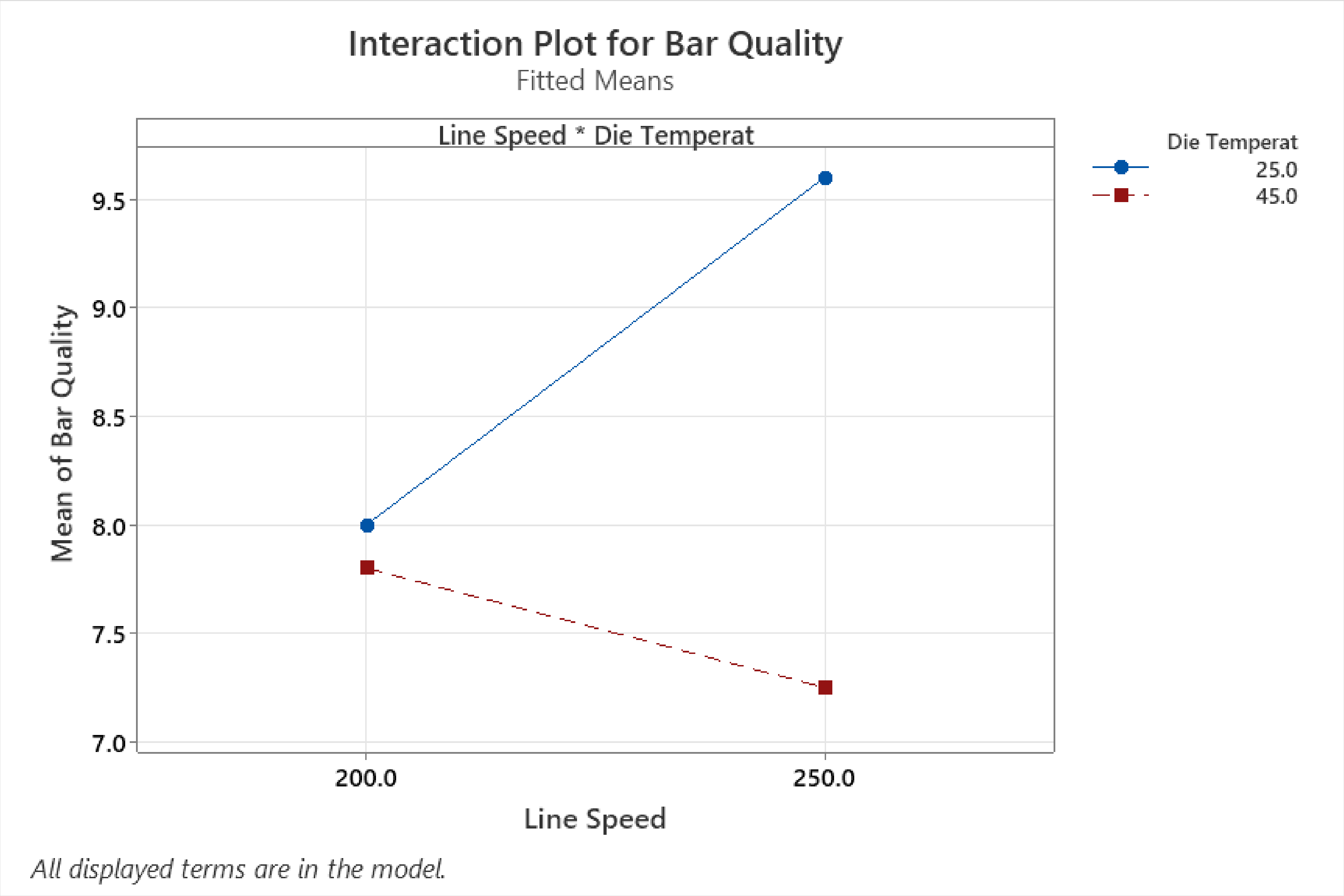
- Change one variable
- Observe the outcome
- Repeat until performance improves

The Problem

Interactions between variables are missed

Optimization becomes slow and expensive

Engineering conclusions are often incomplete


Interaction Plot for Bar Quality
Fitted Means
Line Speed * Die Temperat
Die Temperat
25.0
45.0
9.5
9.0
8.5
8.0
7.5
7.0
Mean of Bar Quality
200.0
250.0
Line Speed
All displayed terms are in the model.

The Evolution of Experimental Designs Minitab DOE by Effex

Why Modern DOE Matters

Manufacturing systems are becoming:

- More complex
- More constrained
- More expensive to test
- More multi-objective

Minitab DOE by Effex adds

- ✓ Advanced optimal designs
- ✓ OMARS® experimental designs
- ✓ AI-assisted design selection
- ✓ Reduced experimental runs
- ✓ Integrated optimization workflows
- ✓ Better performance for high-factor systems

DOE Use Case: Pressure-Differential Drying

Persimmon Chips

Factors

- Pressure differential
- Drying temperature
- Drying time

Responses

- Moisture
- Crispness
- Sensory quality

Minitab turns experimental data into candidate process recipes

Published DOE Dataset

Hezhou University
Guilin University of Technology

Batched Drying Process

Taking raw persimmons, preparing, baking, and packing

Quality Responses

Pressure effects puffiness,
Higher temperatures increases browning
Drying time impacts crispness

Scrap

Prepare › Batch › Dry › Cool › Inspect › Pack › Ship

Minitab DOE by Effex Demo

Data → Optimal Design → Candidate Recipes

A Process Can Be Optimized…
…and still fail operationally

Bottlenecks and Shifts Downstream

Buffers Overflow

Labor Becomes Constrained

Changeovers Disrupt Schedules

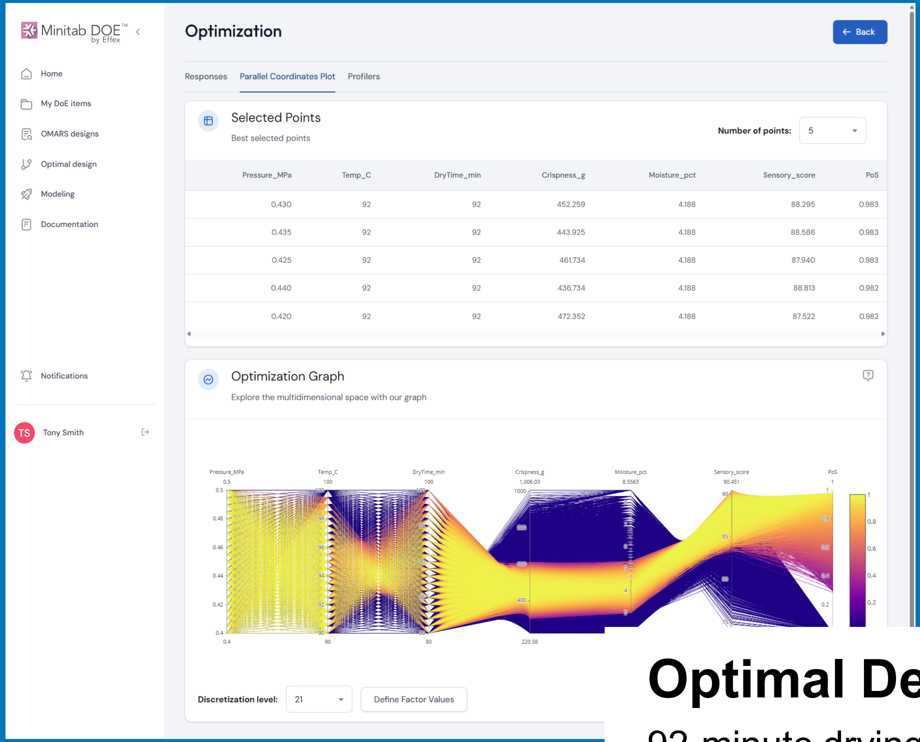
WIP Inventory Grows

Throughput Stalls

Optimization must balance the system

Current Design

90-minute drying time, Estimated Pass Rate: 93%

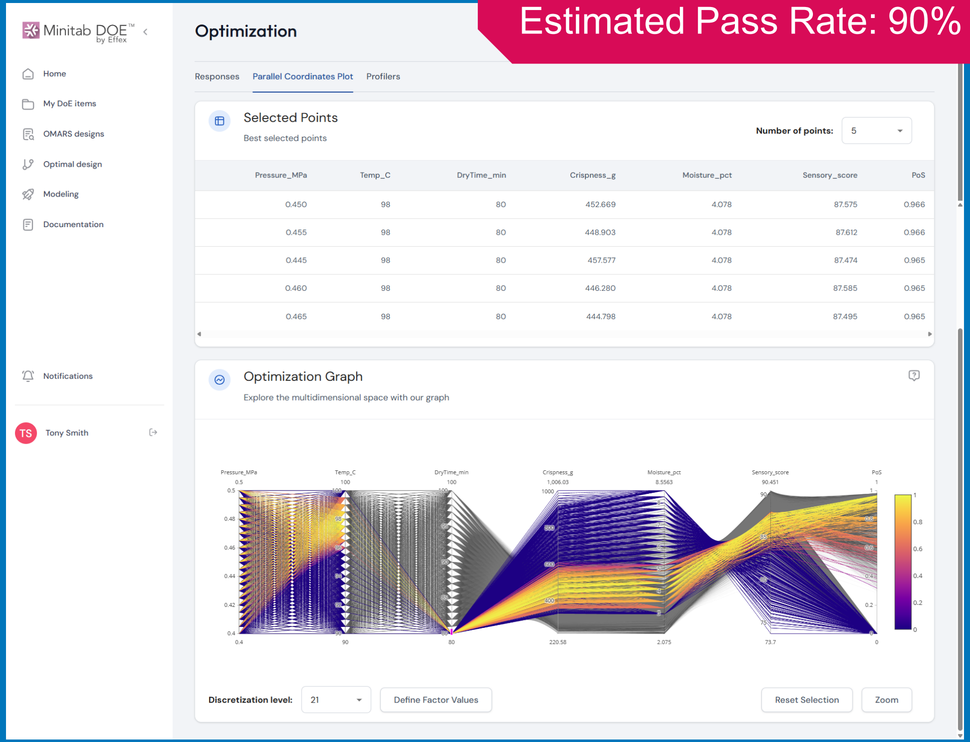


Optimal Design

92-minute drying time
Estimated Pass Rate: 97%

Fast Design

80-minute drying time
Estimated Pass Rate: 90%



What is Discrete Event Simulation?

A digital representation of a manufacturing system that models:

- Machines
- Operators
- Queues
- Material flow
- Downtime
- Shift schedules
- Variability

Current Design
90-minute drying time
Estimated Pass Rate: 93%

Optimal Design
92-minute drying time
Estimated Pass Rate: 97%

Fast Design
80-minute drying time
Estimated Pass Rate: 90%

DOE Informed Simulation

Simulation allows us to see the impact of candidate process designs on the wider system.

Map your process › **Simulate the DOE recipes** › **Compare scenarios** › **Move forward with evidence**

A model or simulation does not replace engineering judgment. It helps the team spend physical trials only where the odds of success are meaningfully higher.

Virtual experiments reduce the cost of being wrong.

Same

Demand, process and resources

Scenarios

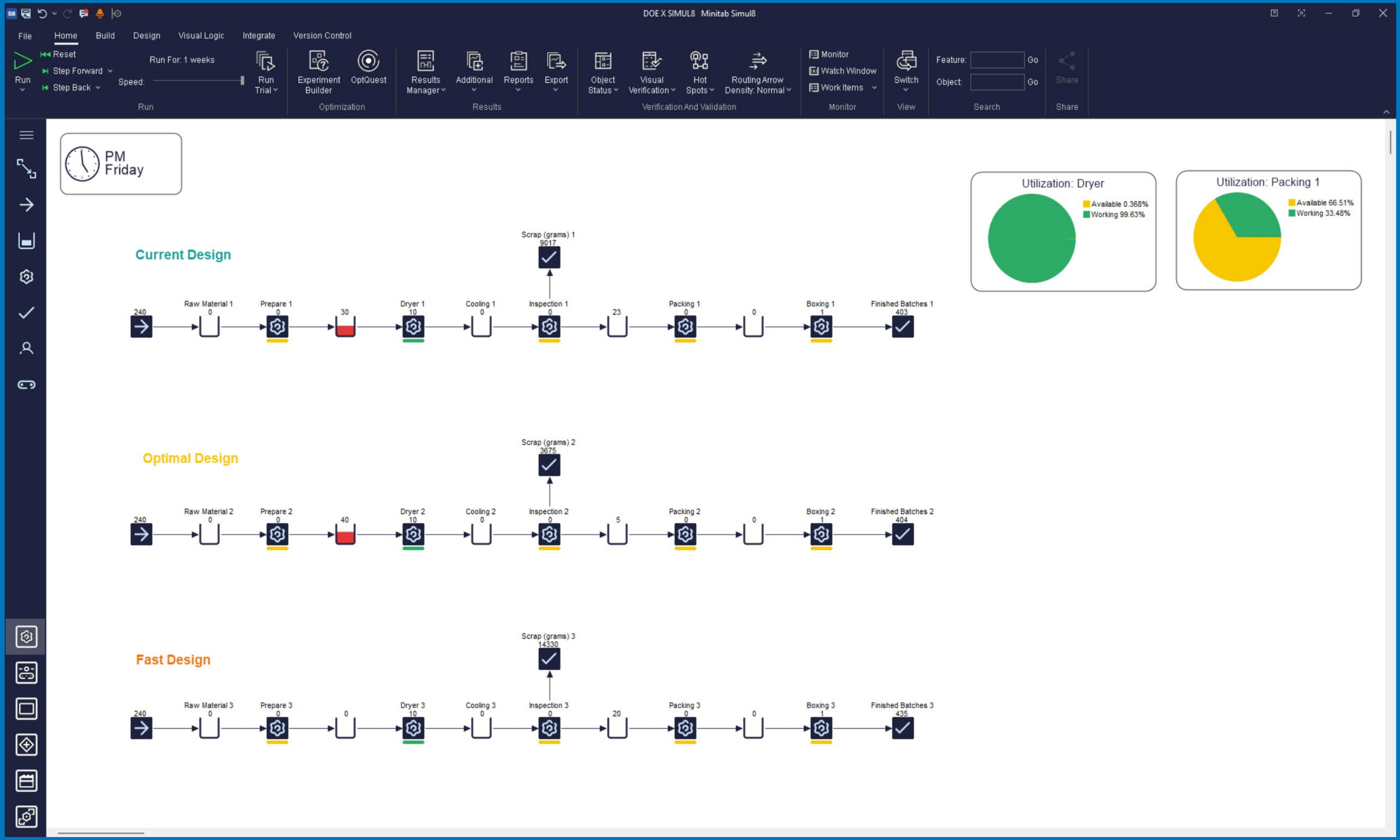
Drying time: Excepted pass rate (impact of temp.)

Results

Output, scrap, WIP & utilization

Insights from the Simulation

Which recipe gives the best operating balance?



Current Design

Finished Cases Shipped: **403**
Scrap Volume: **9090g**
WIP: 30 **Batches**
Dryer Utilization: **99.6%**

Optimal Design

Finished Cases Shipped: **404**
Scrap Volume: **3748g**
WIP: **40 Batches**
Dryer Utilization: **99.6%**

Fast Design

Finished Cases Shipped: **435**
Scrap Volume: **14481g**
WIP: **0 Batches**
Dryer Utilization: **99.5%**

Takeaways

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One-factor-at-a-time optimization leaves performance undiscovered

DOE accelerates learning and identifies true process relationships

Combining experimentation and simulation creates smarter manufacturing decisions

Minitab DOE by Effex expands DOE capability for complex systems

Simul8 allows manufacturers to predict operational behavior before implementation

Thank you

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Yes, We Tested It…

30 Years of DOE, Data and Expensive Surprises

Beatrice Blum, Solutions Architect
ex Procter&Gamble statistician

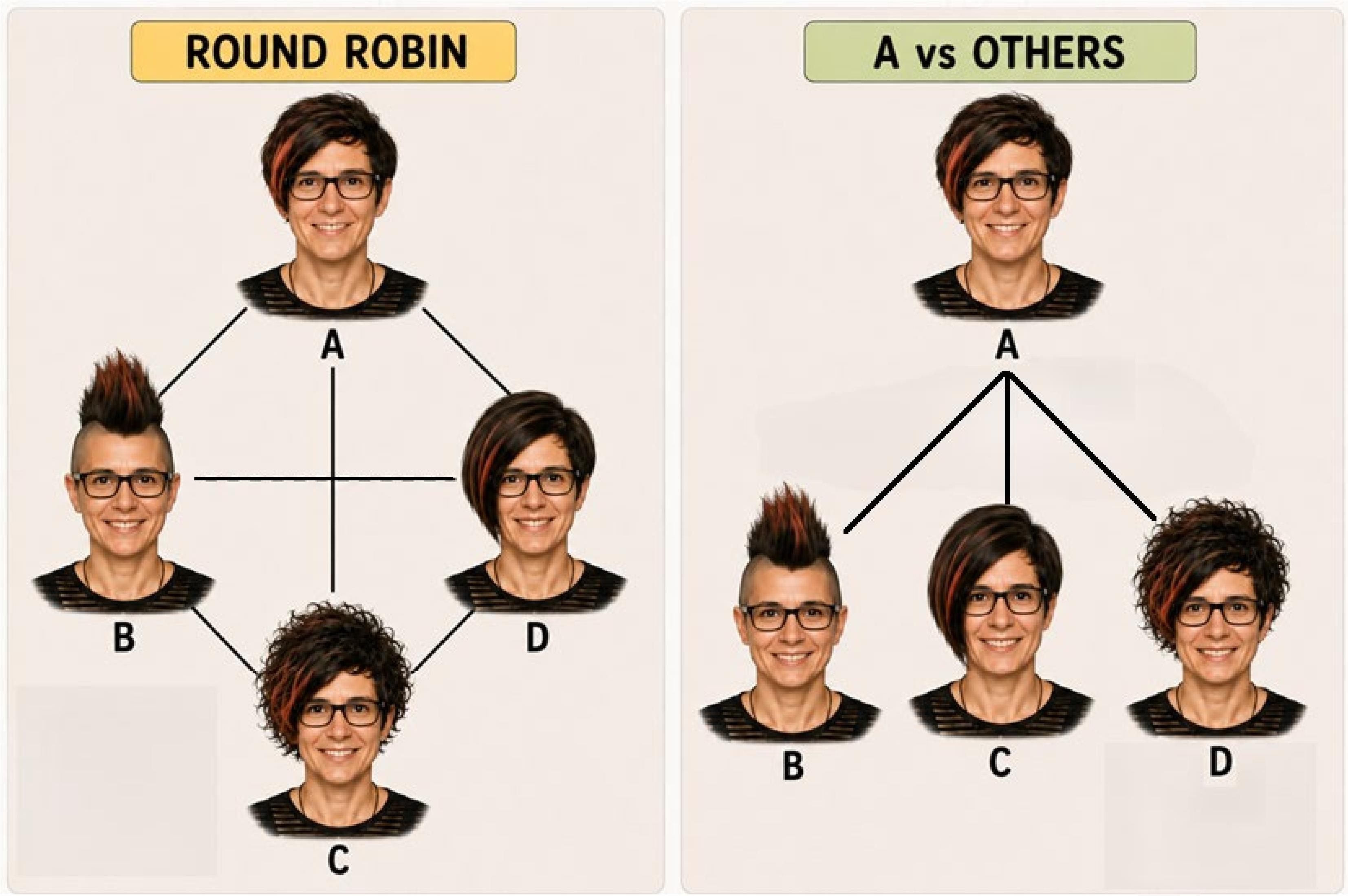
This is a story of trying…

How it all began…

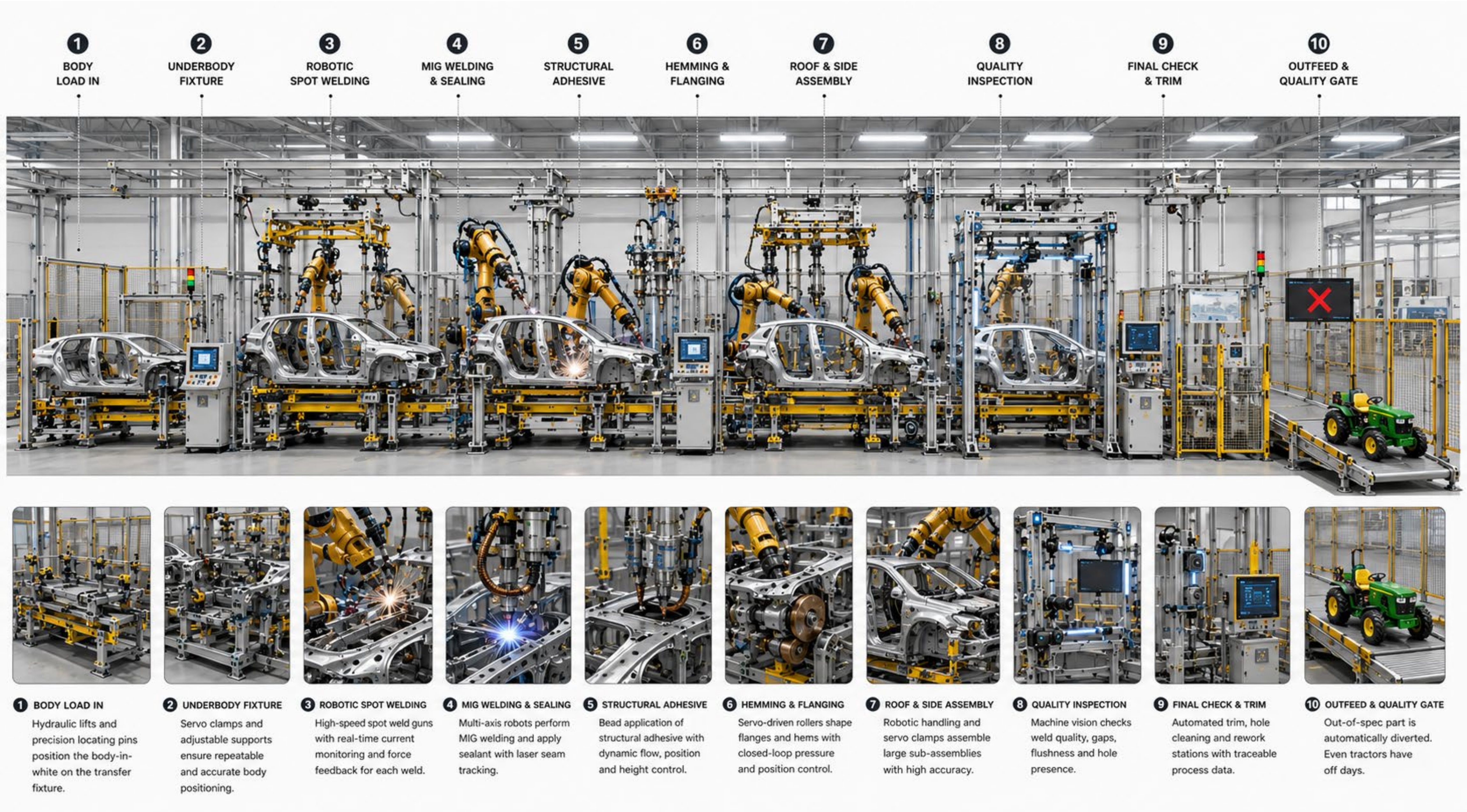
Before data and DOE, there was:

“looking”

Your vote !



A car manufacturing line



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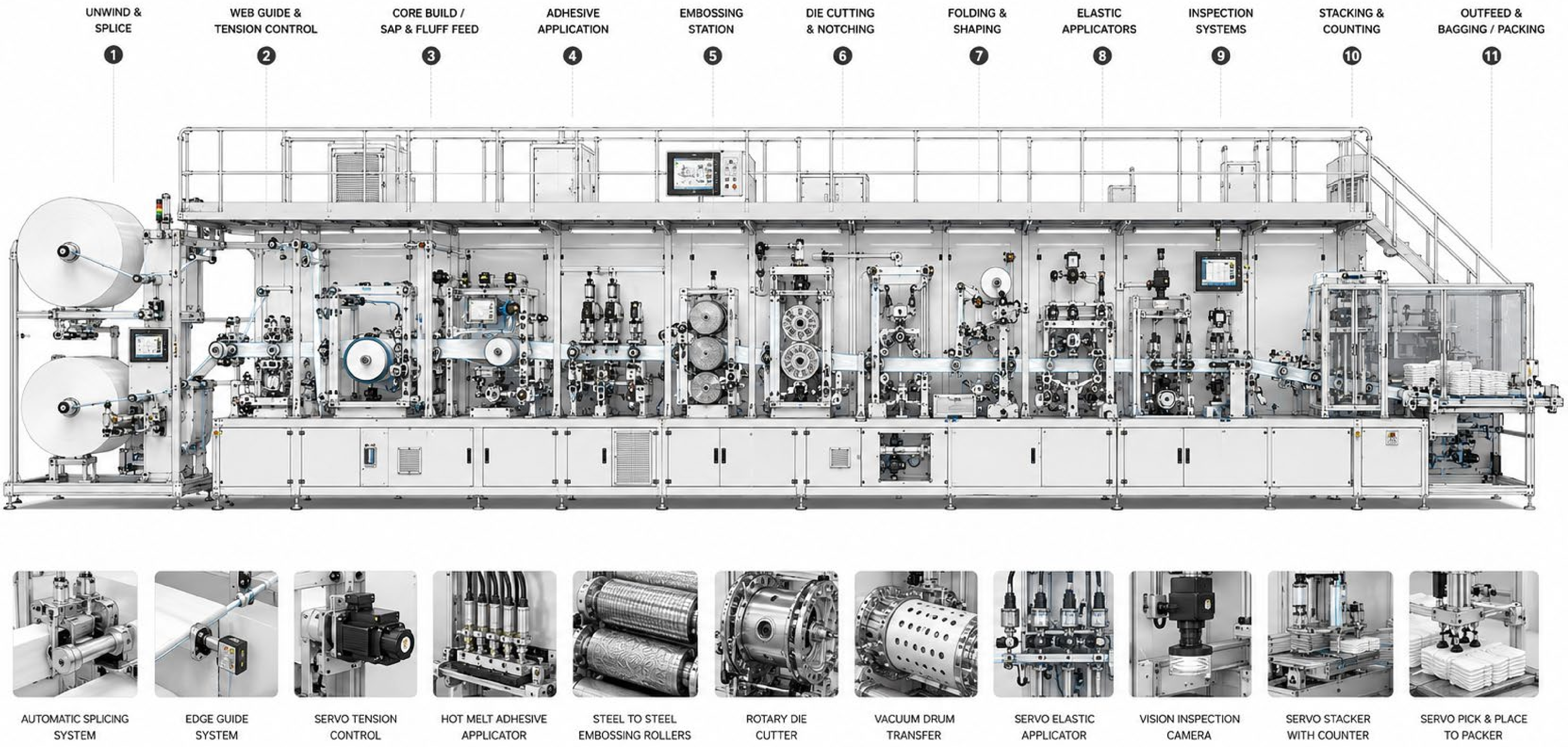
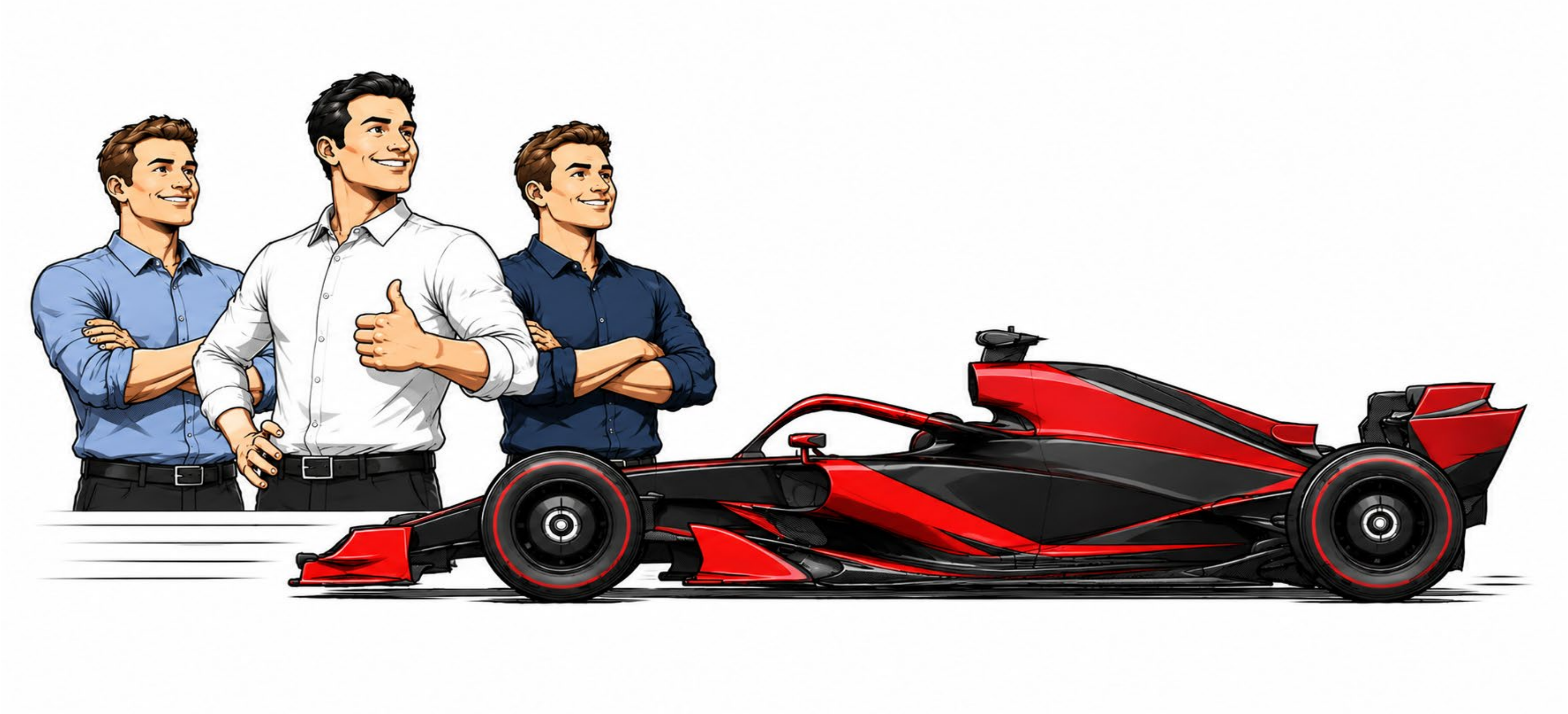
A roll-to-roll manufacturing line

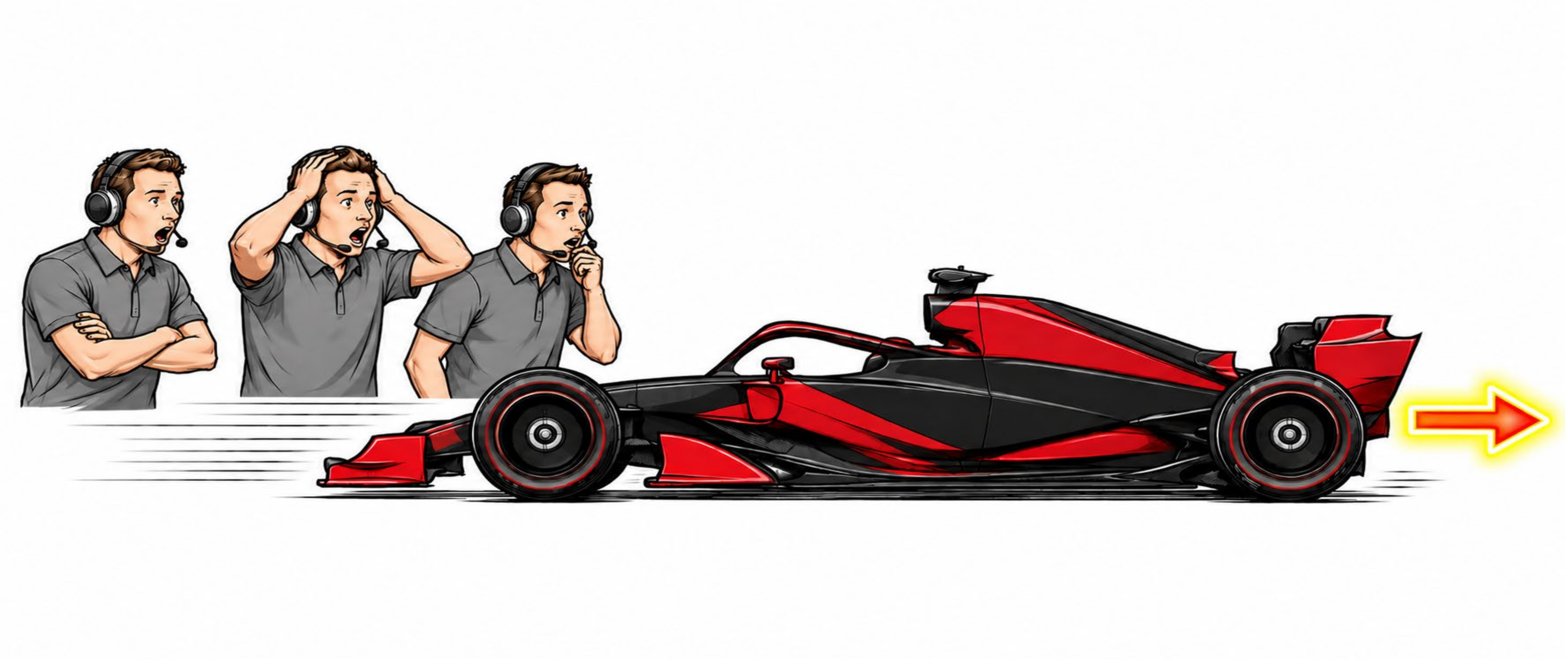


AI generated

Formula 1 – an engineering masterpiece!



Formula 1 – an engineering masterpiece?



DoE and AI

- Build robust measurement systems and validate them: accuracy, uncertainty, bias, and reproducibility
- Optimize quality output, energy consumption, safety, and environmental footprint simultaneously
- Quantify societal trade-offs: safety, fairness, sustainability, and access
- Reveal critical interactions hidden by one-factor-at-a-time tuning
- Systematically stress-test guardrails, robustness, and failure modes

A DoE Lover's Confessions

- I have a deep affection for DoE. It is something almost magical when it's allowed to work
- Competence and rigor are not the same
- An everlasting awe at how durable the immunity to doing it right turns out to be
- Every "we already know" is an unexplored corner waiting to surprise you

So, what…

I've spent 30 years explaining DOE.

I've spent 31 years being politely ignored.

Then again...

I keep trying.

Thank you

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Deeper Dive:

Turning Process Data into Operational Confidence

Marco Massa, Tony Smith
and José Nunez Ares

What We'll Explore Today

A Manufacturing Challenge

Identify and reduce process variability in a real-world polymer production case

From Data to Decisions

Centralize data, automate workflows and enable trusted, scalable decision-making

Design, Optimize, Innovate

Enable faster innovation and more robust process development with advanced experimental designs

Key Take Aways

Build a foundation for proactive operational excellence

When Consistency Becomes a Challenge

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Rising Variability

Despite unchanged process settings

Operational Impact

Scrap increased, specifications became harder to meet, and supplier variability grew

Engineering Challenge

More troubleshooting, less time for optimization

The Root Problem Emerges

After reviewing historical production data, a major source of variability was identified:

1 critical raw material was being supplied by 3 different vendors, each introducing subtle but significant differences into the process.

The challenge was no longer just technical, it became operational and organizational.

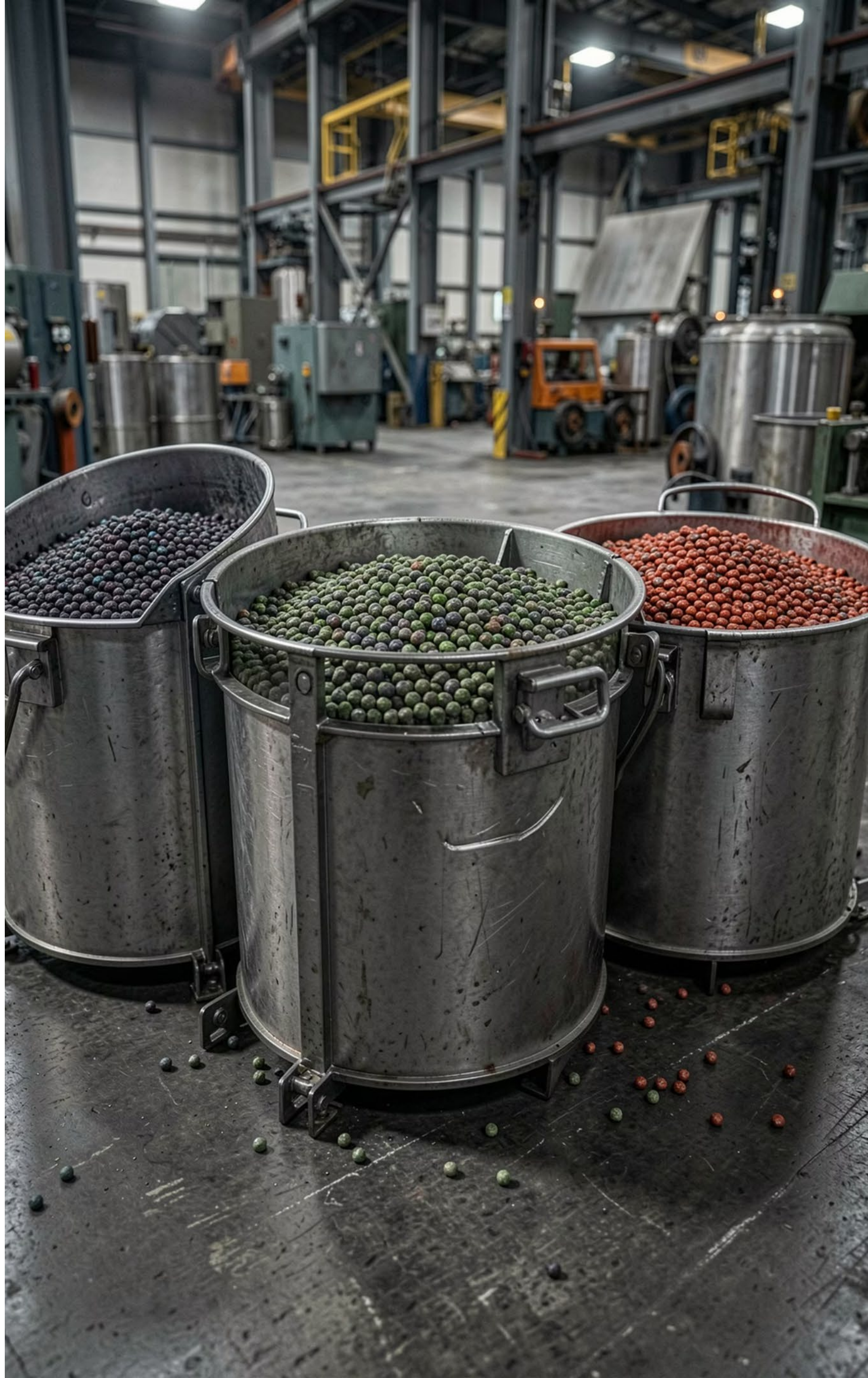
Scrap Increased

More material wasted per batch as variability grew

Specs Harder to Hold

Customer requirements increasingly difficult to maintain

Engineers Stretched



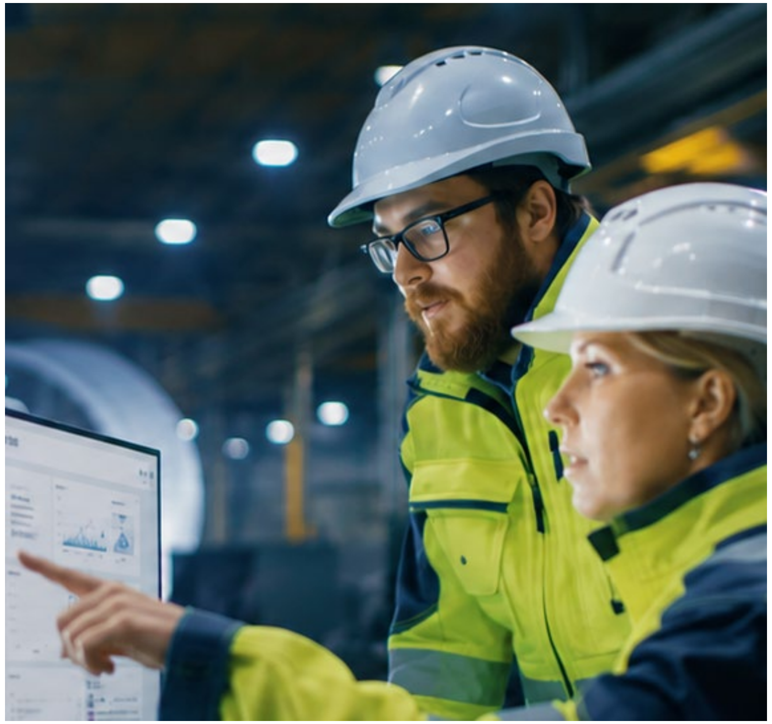
The benefit of using our solution

Data Ingestion

Preparation Workflows

Automation

Dashboard-Ready Datasets



Reduced Manual Effort

Faster Reporting Cycles

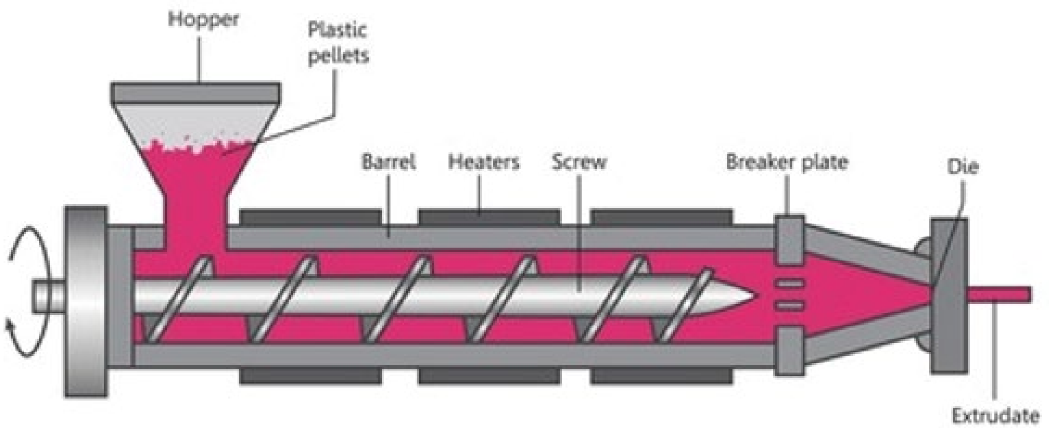
Consistent KPIs

Better Collaboration

Once visibility is established, the next step is optimization

The experimental challenge

- ✓ Product variability increasing
- ✓ Raw material differences identified as the root cause
- ✓ Robust process settings required
- ✓ Experiments are expensive



Polymer extrusion

5-Step DOE Process

1. Prepare

Define your experiment goals and desired outputs

2. Setup

Choose the combinations of input values to be tested, which is your experimental design.

3. Experiment

Conduct tests according to the selected experimental design

4. Analyze

Discover the influence of the inputs on the outputs through interactive graphs

5. Optimize

Find the best inputs for the desired outputs

Data Collection (steps 1–3)

Data Analytics (steps 4–5)

Setting up the experiment

Critical material attributes

Critical process parameters

Polymer extrusion

Critical quality attributes that characterize the product/process

Limited to 24 tests due to high cost and time

Experimental factors and responses

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Factor type	Factor name	Factor range
CMA	Supplier (categorical)	A, B, C
CPP	Die Temperature (°C)	[180,200]
	Residence Time (min)	[7,9]
	Pressure (MPa)	[75,84]

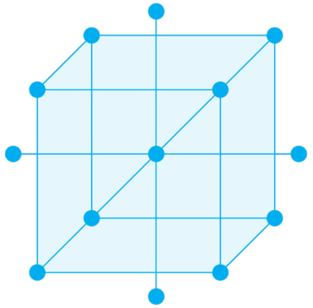
CQA	Optimization sense	Value	Target value
Residual (ppm)	Minimization	<50	25
Density (g/cm3)	On target	[0.86, 0.90]	0.88
Melting temperature (°C)	Maximization	>170	172

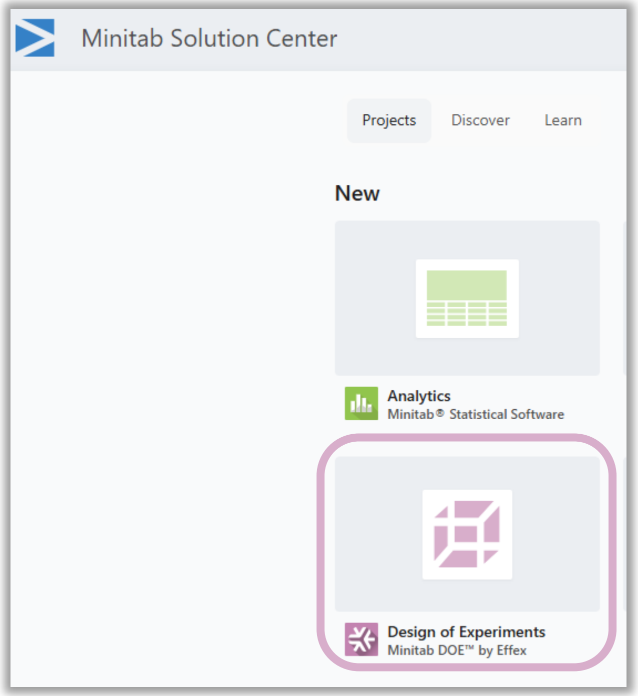
1 Critical Material Attribute:
- ✓ One categorical with three levels

3 Critical Process Parameters
- ✓ All controllable
- ✓ All numerical
- ✓ Crucial to determine the factor ranges

3 Critical Quality Attributes with specs

Minitab DOE by Effex Demo





Obtain an experimental design for the polymer extrusion robustness challenge

Analyze the experimental data

Optimize the models

Demo Key Take Aways

Minitab DOE™ by Effex

Minitab EXCHANGE

What we've done:

Selected the optimal experimental design balancing tests and information

Modeled multiple responses with significant linear and nonlinear effects

Identified robust operating conditions across three raw material suppliers

Benefits:

Fewer tests, better designs

Guided design & model selection

Interactive, intuitive and visual multi-response optimization

Unlocking Operational Intelligence From Data to Decisions

The combined value of data management and decision optimization

Business Impact

Faster operational decisions

Proactive management

Reduced variability

Better resource allocation

Transformation Journey

Integration of fragmented data

End-to-end operational intelligence

Confident decision-making

Potential Areas

Time savings

Faster decisions

Improved KPI consistency

Operational agility

Scalability

Data visibility & trust → Real-time optimization of decisions & actions → Measurable business impact → One integrated journey

What Now?

Scale

Expand adoption across functions, sites, and global operations

Predict

Leverage advanced analytical models to anticipate outcomes and risks

Expand optimization use cases

Drive more value by solving new operational and business challenges.

Stronger decisions → **Smarter operations** → **Lasting impact**

Thank you

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Next: Let Minitab Visit You!

- **See and advise** on your challenges firsthand
- **Involve your team on-site** at your workplace
- **Identify quick wins** and strategic moves

Thank you!