From Active Resilience to Autonomous Operations: AI, Knowledge Graphs, and Human-Centred Frameworks for Future-Ready Manufacturing

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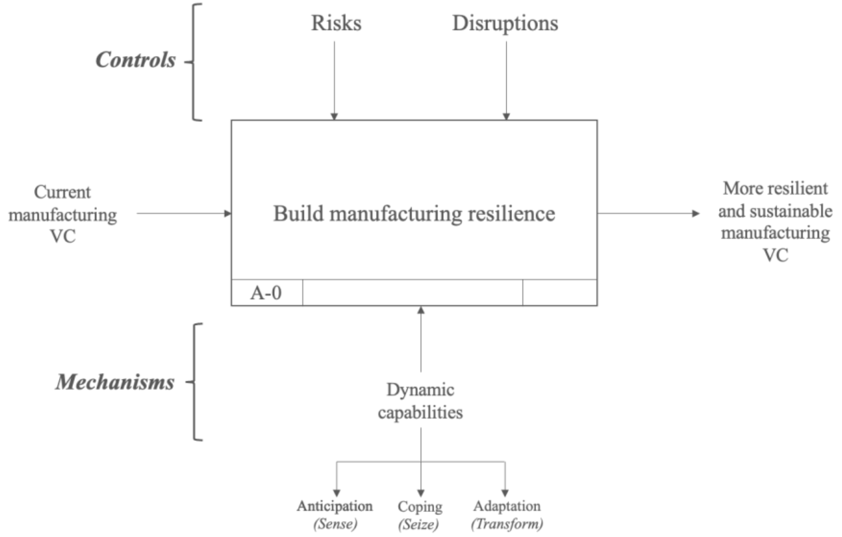
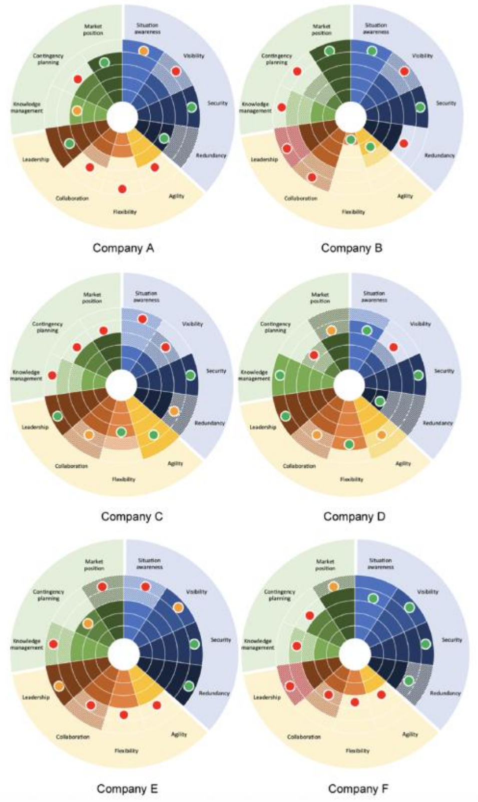
Active Resilience Framework



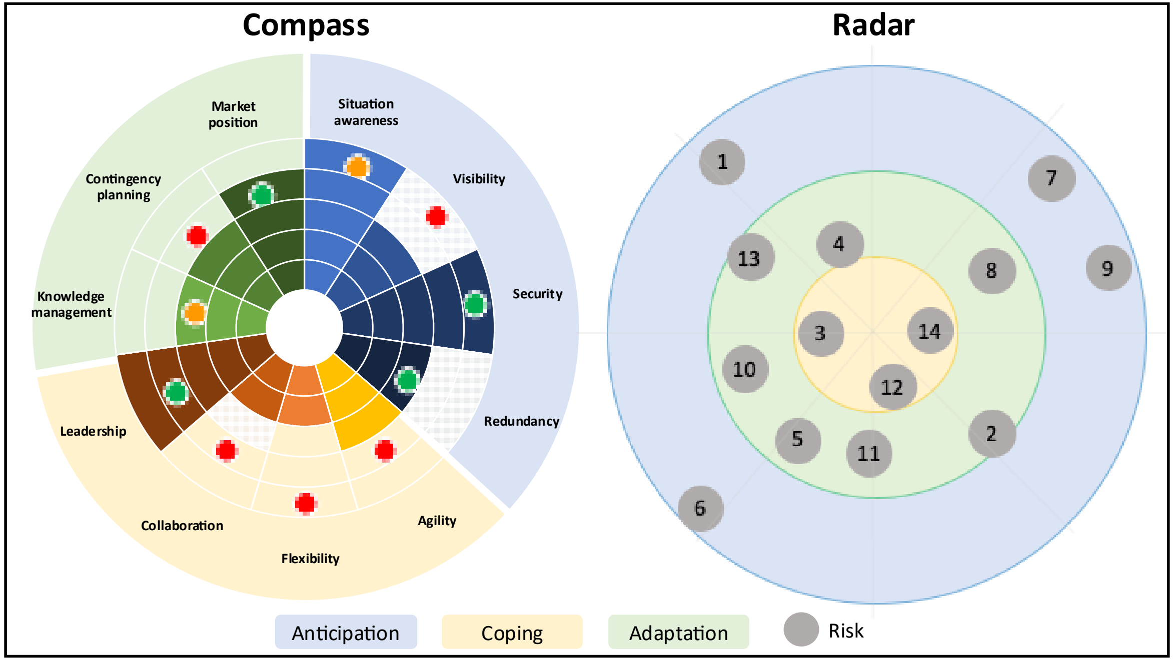
The initial IDEF0-based resilience framework



Resilience compass application in the pilots

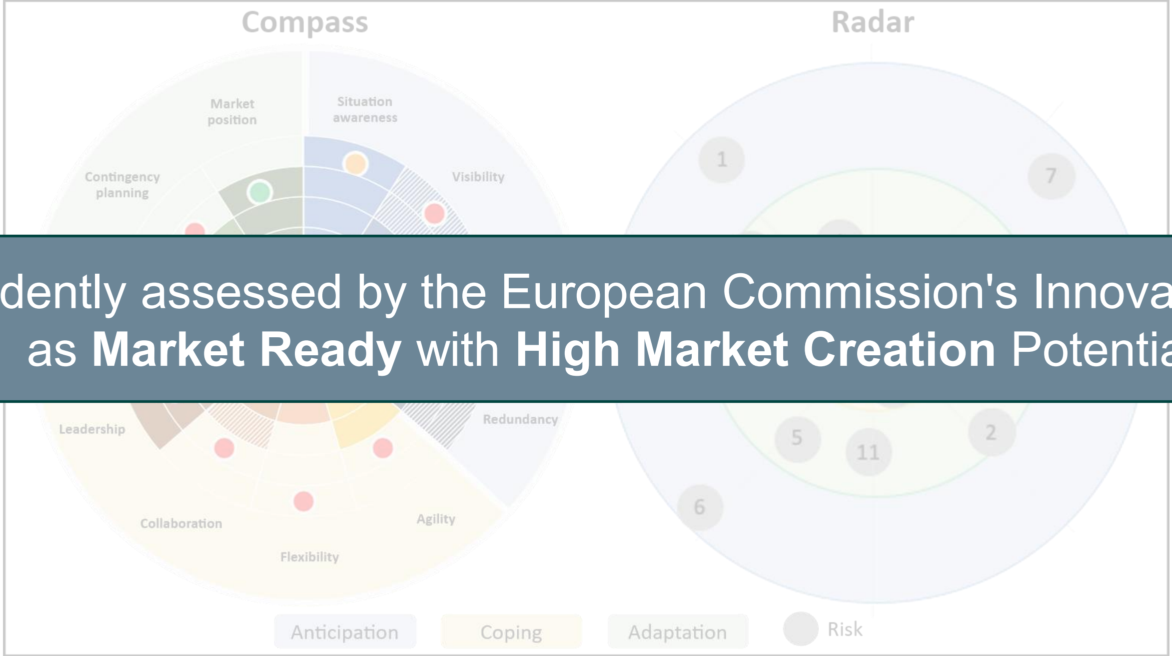
Chari et al. 2024_Resilience Compass Navigation through Manufacturing Organization Uncertainty - a Dynamic Capabilities Approach using Mixed Methods

The Manufacturing Resilience Dashboard



Chari et al. 2025_The manufacturing resilience dashboard – compass and radar navigation through uncertainty

The Manufacturing Resilience Dashboard



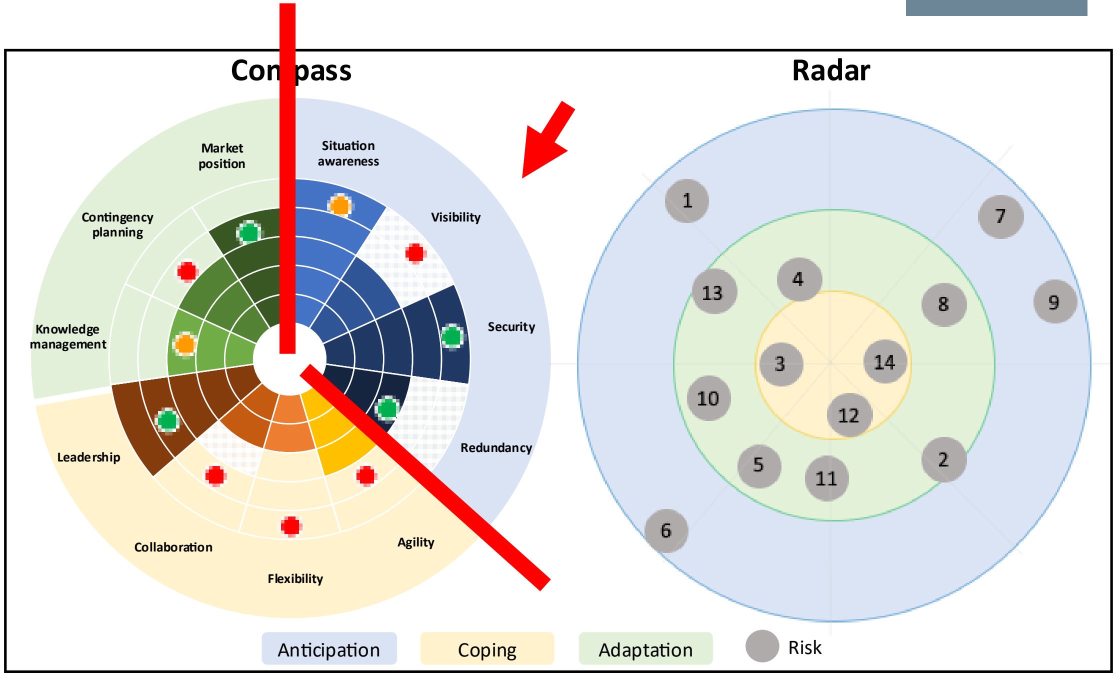
Independently assessed by the European Commission's Innovation Radar as **Market Ready** with **High Market Creation** Potential

Chari et al. 2025_The manufacturing resilience dashboard – compass and radar navigation through uncertainty

Industrial Resilience Needs Better Data Understanding – AI and Agentic Systems need Structured Data

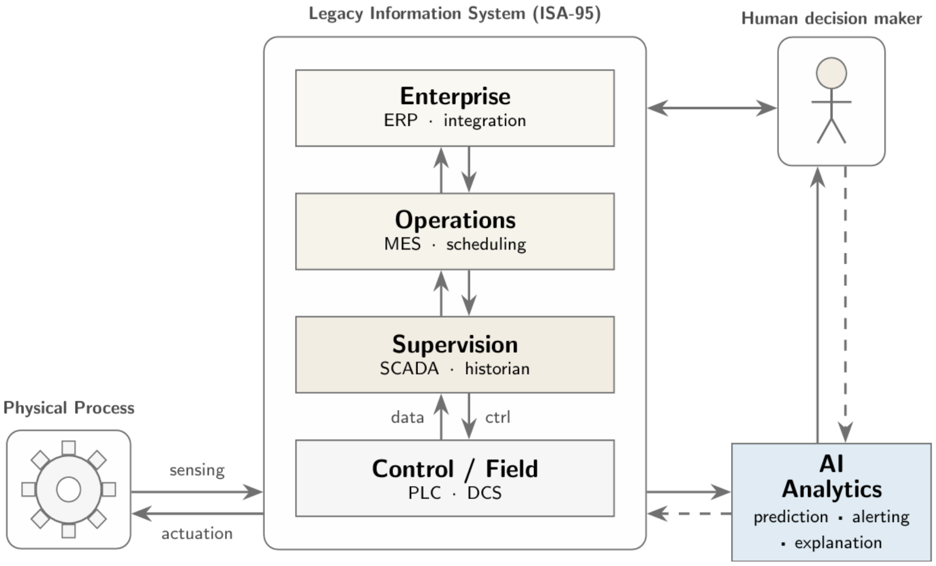
- Industry generates huge amounts of sensor data, logs and other time-stamped data.
- That data contains precious information to improve resilience
- but it is **irregular, noisy, incomplete**, and difficult to use directly in AI

- To enable this, we need a robust way to *structure and represent* industrial data continuously.



AI in Manufacturing: The Data Problem Nobody Talks About

- Manufacturers want AI-assisted decisions: prediction, alerting, explanation
- Legacy systems (ISA-95: SCADA, MES, ERP) were built for control, not analytics
- The data they produce is irregular, asynchronous, and full of gaps
- Standard AI methods assume clean, uniform time-series - a poor fit
- AI in manufacturing is not plug-and-play



What we did -
Mapping AI Methods to Manufacturing Data

- Reviewed and categorised AI approaches relevant to manufacturing decision support
- Simulated realistic manufacturing data traces - irregular timing, observational gaps
- Identified which method families make which assumptions about the data
- Result: a structured way to match AI methods to what your data actually looks like

What We Are Working On

- Where does the data come from? Tracing how ISA-95 systems shape what gets recorded - before any AI touches it
- Detecting anomalies on messy timestamps: AI that flags problems directly from unevenly spaced data, without cleaning it first
- Making event logs readable for AI: turning sequences of machine and process events into something a model can learn from
- Together: AI that fits the data industry actually has, not the data it wishes it had

EuroFMX

European tr**U**stworthy gene**R**ative AI & auton**O**misation **F**rontier **M**odels for **M**anufacturing-**X** competitiveness

HORIZON-CL4-2025-03 | 48 months

Project details

The Challenge

European manufacturing faces:
- **supply chain volatility**
- rapid product change
- a **2.4M worker skills deficit**, and
- growing dependency on **non-European AI**

which threatens industrial sovereignty and competitiveness.

The Vision

Europe's first **industrial-native autonomisation foundation model** built in Europe, by Europeans, for European industry.

Shifting factories from reactive automation to **proactive autonomisation**.

Consortium at a Glance

69 partners across **20 European countries**

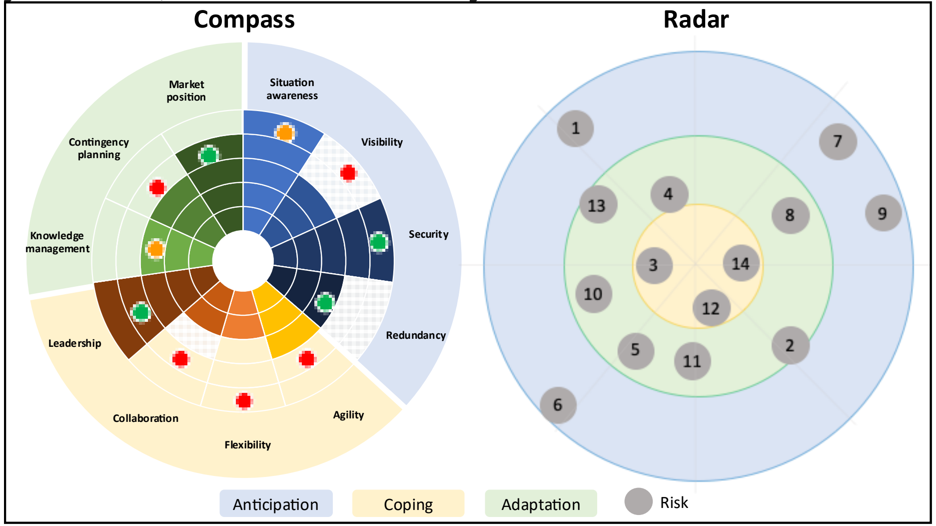
21 research orgs · 19 large industries
17 SMEs · 12 associations

Total budget: **€45 million**

Siemens · Bosch · Schneider Electric · SKF · Continental · Philips · Leonardo · COMAU · Fraunhofer · AVL

Chalmers' role

- Develop a **multi-dimensional measurement model** to assess and benchmark **competitiveness** of autonomisation solutions across dimensions like *resilience, agility, human-automation symbiosis, and sustainability*

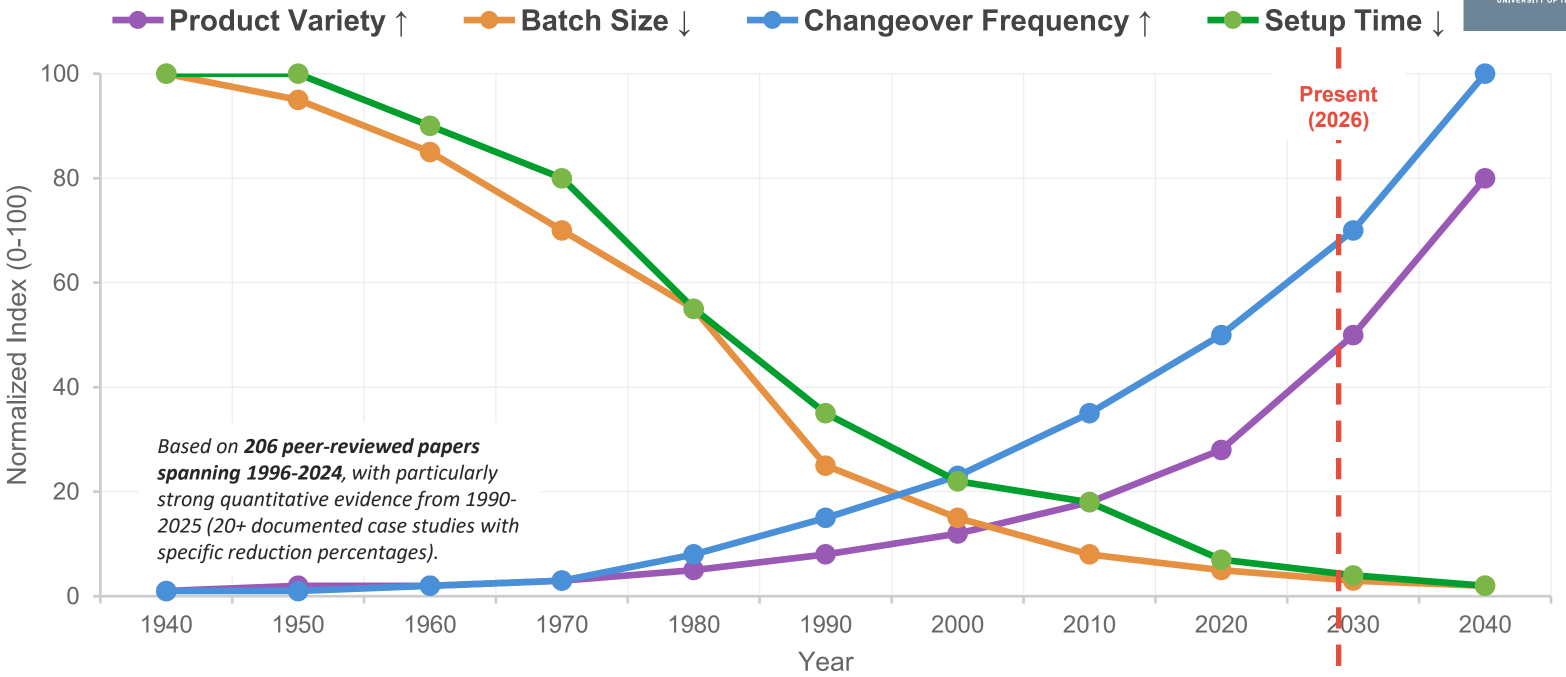


- Participate in **high productivity automated machining reconfiguration** pilots

Vinnova Projects

Factory SensAI & DTIT

Global trend: Mass production to advanced automation (1940–2030)



1940
Mass Production
Few changeovers needed

1980
Lean & SMED
Quick changeover methods

2000
Mass Customization
Product variety grows

2020
HMLV & Industry 4.0
High-mix, low-volume

2030
AI-Guided Resets
Automated optimization

Research Questions & Approach

RQ1

What AI capabilities provide the highest impact on changeover performance in discrete manufacturing?

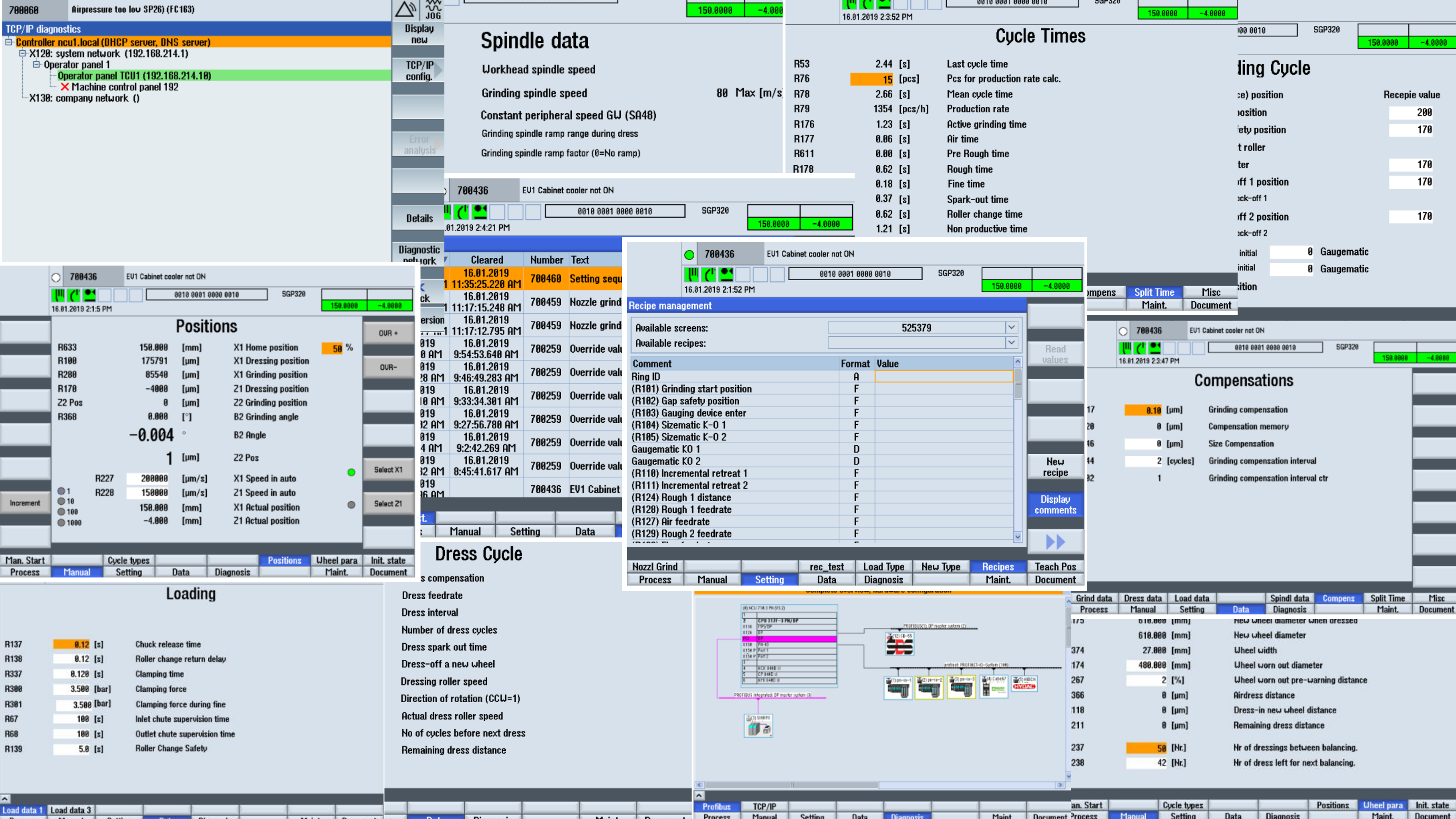
RQ2

What organizational readiness factors and technical infrastructure investments are necessary for successful AI solution lifecycle management?

Research Design

Exploratory mixed-methods case study

- Literature review
- Empirical field studies at SKF incl. Shop floor observations
- Documentation analysis (SOPs)
- Stakeholder discussions
- Two channels:
  - DD01 (World Class - 2017)
  - DD11 (Automatic Resetting - 2025)


700060 Airpressure too low SP26) (FC163)
TCP/IP diagnostics
Controller ncu1.local (DHCP server, DNS server)
X120: system network (192.168.214.1)
Operator panel 1
Operator panel TCU1 (192.168.214.10)
Machine control panel 192
X130: company network ()
Display new
TCP/IP config.
Error analysis
Details
Diagnostic network
Spindle data
Workhead spindle speed
Grinding spindle speed 80 Max [m/s
Constant peripheral speed GW (SA40)
Grinding spindle ramp range during dress
Grinding spindle ramp factor (0=No ramp)
Cycle Times
R53 2.44 [s] Last cycle time
R76 15 [pcs] Pcs for production rate calc.
R78 2.66 [s] Mean cycle time
R79 1354 [pcs/h] Production rate
R176 1.23 [s] Active grinding time
R177 0.06 [s] Air time
R611 0.00 [s] Pre Rough time
R178 0.62 [s] Rough time
0.18 [s] Fine time
0.37 [s] Spark-out time
0.62 [s] Roller change time
1.21 [s] Non productive time
16.01.2019 2:3:52 PM
Recepie value
700436 EU1 Cabinet cooler not ON
0010 0001 0000 0010
SGP320
150.0000 -4.0000
16.01.2019 2:4:21 PM
Cleared Number Text
16.01.2019 11:35:25.220 AM 700460 Setting sequ
16.01.2019 11:17:15.248 AM 700459 Nozzle grind
16.01.2019 11:17:12.795 AM 700459 Nozzle grind
16.01.2019 9:54:53.640 AM 700259 Override valu
16.01.2019 9:46:49.283 AM 700259 Override valu
16.01.2019 9:33:34.301 AM 700259 Override valu
16.01.2019 9:27:56.780 AM 700259 Override valu
16.01.2019 9:2:42.269 AM 700259 Override valu
16.01.2019 8:45:41.617 AM 700259 Override valu
700436 EU1 Cabinet
Manual Setting Data
Recipe management
Available screens: 525379
Available recipes:
Comment Format Value
Ring ID A
(R101) Grinding start position F
(R102) Gap safety position F
(R103) Gauging device enter F
(R104) Sizematic K-O 1 F
(R105) Sizematic K-O 2 F
Gaugematic KO 1 D
Gaugematic KO 2 D
(R110) Incremental retreat 1 F
(R111) Incremental retreat 2 F
(R124) Rough 1 distance F
(R120) Rough 1 feedrate F
(R127) Air feedrate F
(R129) Rough 2 feedrate F
Read values
New recipe
Display comments
Nozzl Grind rec_test Load Type New Type Recipes Teach Pos
Process Manual Setting Data Diagnosis Maint. Document
16.01.2019 2:1:52 PM
Positions
R633 150.000 [mm] X1 Home position
R100 175791 [µm] X1 Dressing position
R200 85540 [µm] X1 Grinding position
R170 -4000 [µm] Z1 Dressing position
Z2 Pos 0 [µm] Z2 Grinding position
R360 0.000 [°] B2 Grinding angle
-0.004 ° B2 Angle
1 [µm] Z2 Pos
R227 200000 [µm/s] X1 Speed in auto
R228 150000 [µm/s] Z1 Speed in auto
150.000 [mm] X1 Actual position
-4.000 [mm] Z1 Actual position
OVR + OVR- Select X1 Select Z1 Increment
50 %
16.01.2019 2:1:5 PM
Man. Start Cycle types Positions Wheel para Init. state
Process Manual Setting Data Diagnosis Maint. Document
Loading
R137 0.12 [s] Chuck release time
R138 0.12 [s] Roller change return delay
R337 0.120 [s] Clamping time
R300 3.500 [bar] Clamping force
R301 3.500 [bar] Clamping force during fine
R67 100 [s] Inlet chute supervision time
R68 100 [s] Outlet chute supervision time
R139 5.0 [s] Roller Change Safety
Load data 1 Load data 3
Dress Cycle
s compensation
Dress feedrate
Dress interval
Number of dress cycles
Dress spark out time
Dress-off a new wheel
Dressing roller speed
Direction of rotation (CCW=1)
Actual dress roller speed
No of cycles before next dress
Remaining dress distance
ding Cycle
position
Gaugematic
Split Time Misc
Maint. Document
16.01.2019 2:3:47 PM
Compensations
0.10 [µm] Grinding compensation
0 [µm] Compensation memory
0 [µm] Size Compensation
2 [cycles] Grinding compensation interval
1 Grinding compensation interval ctr
Grind data Dress data Load data Spindl data Compens Split Time Misc
Process Manual Setting Data Diagnosis Maint. Document
610.000 [mm] New wheel diameter
27.000 [mm] Wheel width
400.000 [mm] Wheel worn out diameter
2 [%] Wheel worn out pre-warning distance
0 [µm] Airdress distance
0 [µm] Dress-in new wheel distance
0 [µm] Remaining dress distance
50 [Nr.] Nr of dressings between balancing.
42 [Nr.] Nr of dress left for next balancing.
Profibus TCP/IP
Process Manual Setting Data Diagnosis Maint. Document

The Vast Decision Space

Each changeover = combinatorial explosion of possible configurations

Set-Up Tactics

Offline prep, direct adjust, staging use

Tooling Choices

5–10 tools, selection order, wear status

Parameters

Wheel speed, feed rate, coolant, dressing

Quality Approach

Aggressive, incremental, measurement timing

Economic Trade-Offs

Speed vs quality, tool life vs cost

Context Factors

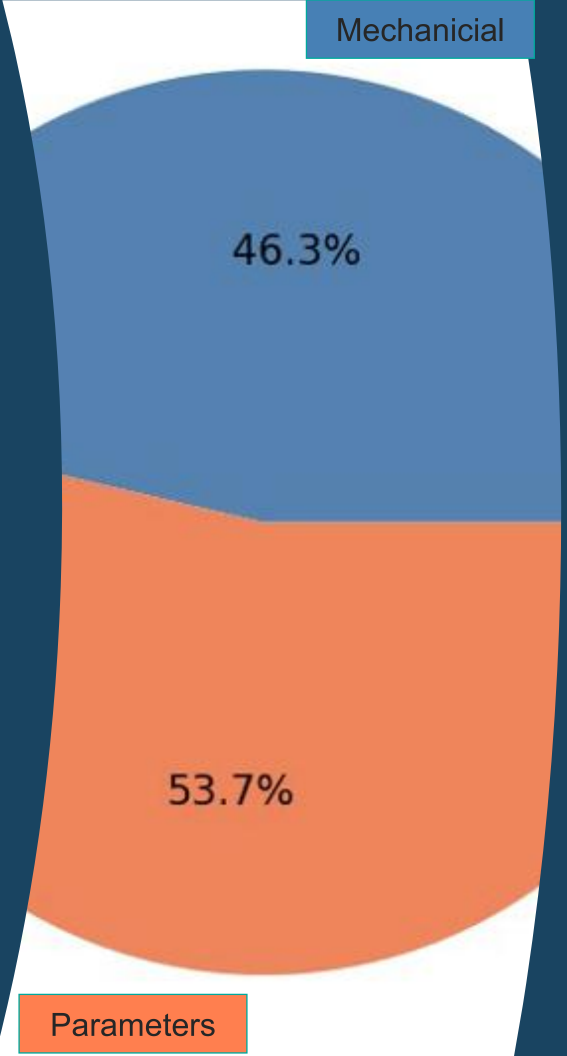
Machine type, product family, operator skill

Each decision interacts with others → AI must find patterns
across high-dimensional space that even experts may not recognize

Operator Changeover Work & Decisions

Time spent on

Mechanical
vs
Configuration
(parameter changes)



1. When should the changeover start?
2. How many operators are needed for the reset?
3. Which components should be picked from inventory?
4. How precise should the shoe presetting be?
5. Which grinding process should be selected?
6. Should the grinding wheel be kept or replaced?
7. Should the coolant nozzle be reused or changed?
8. If runout is borderline, should the plate be accepted or reground?
9. What coolant nozzle angle and distance should be used?
10. When should parallel loader adjustments begin?
11. Does the grinding wheel pass or fail the sound test?
12. Which grinding wheel should be selected?
13. How much should the wheel be dressed?
14. Which initial grinding parameters should be set?
15. Which parameter should be adjusted after a failed trial part?

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Grinding Parameter Adjustment Guide

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Parameter	What it influences	When to adjust it	Typical risk
Offset X	Directly affects outer diameter	When measured diameter (R166/R246) is outside tolerance	Overshoot → oscillating adjustments
Offset Z	Axial position and geometry alignment	When axial positioning or flange clearance is incorrect	Misalignment causing geometry errors
R127 – Air feed rate	Initial contact behavior and cycle stability	When entry into grinding zone is unstable	Too aggressive → vibration or burn
R128 – Rough feed rate	Material removal rate and cycle time	When cycle time too long or removal insufficient	Too high → diameter instability or surface damage
R130 – Finish feed rate	Surface finish and dimensional stability	When surface finish poor or diameter fluctuates	Too fast → rough surface; too slow → long cycle
R131 – Spark-out	Roundness and diameter stabilization	When roundness errors appear	Too long → cycle time increase
R101–R105 – Start/end positions	Grinding location, taper and geometry	When taper or wrong removal location occurs	Systematic geometry errors
R136 – Workpiece RPM rough	Grinding stability and removal dynamics	When grinding unstable or removal too slow	Too high → vibration
R153 – Workpiece RPM finish	Surface finish and final accuracy	When finish quality poor	High RPM → chatter
R842 – Speed ratio qs	Interaction wheel/workpiece speeds	When grinding unstable or finish inconsistent	Wrong ratio → poor surface
R115 – Dressing infeed	Wheel sharpness and surface quality	When wheel dull or finish deteriorates	Too much → wheel wear
R116 – Dressing feed	Dressing efficiency	When wheel becomes glazed	Aggressive dressing damages wheel
R817 – Dressing speed ratio	Wheel geometry after dressing	When dressing inconsistent	Uneven wheel condition
R456 – Coolant pressure rough	Thermal stability	When burn marks appear	Too high → process disturbance
R457 – Coolant pressure finish	Final cooling and surface quality	When heat damage occurs	Too low → burn marks

10 ML Selection Criteria for Changeover

Bridging operational requirements with ML model feasibility - result of a structured selection process based on literature and expert knowledge

#	Criteria	Why It Matters	Key Technologies
1	**Temporal Awareness**	Time-sensitive sequences and duration	RNN, LSTM, TCN
2	**Multivariate Input**	Multiple data sources simultaneously	XGBoost, RF, DNN
3	**Explainability**	Operators must trust recommendations	SHAP, Decision Trees
4	**Real-Time Inference**	Decisions needed instantly	ONNX, TinyML
5	**Edge-Cloud Compatibility**	Local + central environments	TF Lite, PyTorch Mobile
6	**Robustness to Noise**	Imperfect factory data	Ensemble, AutoML
7	**Optimization Capability**	Learn optimal strategies over time	DQN, PPO (RL)
8	**Transfer Learning**	Leverage knowledge when data is sparse	CNNs, BERT, Domain Adapt.
9	**Human-in-the-Loop**	Operator oversight and feedback	Active Learning
10	**Lifecycle Maintainability**	Retraining, monitoring, updating	MLOps, Drift Detection

Where the project stands today

The project has moved from concept to first technical implementation. We are no longer designing architecture in the abstract — we are building it.

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First real changeover captured at SKF

Full product A → B changeover recorded on a SGP 320 grinder with dual-camera setup, HMI screen capture, and ~50 internal machine parameters via OPC trigger scripts. Quality data on first parts measured in lab.

Solution architecture agreed

Aligned on an input → processing → output design with interfaces between agents. Knowledge graph + RAG approach for the Operator Knowledge Assistant.

AI taxonomy & labeling proof of concept

Team used Claude Opus 4.7 to label simulated changeover video at high and low level (e.g. "machine preparation → visual check spindle"). Foundation for training a recognition model.

Open architectural decisions on the table

Multi-tenant vs single-tenant cloud, public vs local LLMs, data governance per site.

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