Industrial AI
Approaches and lessons

Gerhard Kreß,
SVP Portfolio and digital business, Siemens AG

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Our purpose »

We create **technology** to transform the everyday, for **everyone**

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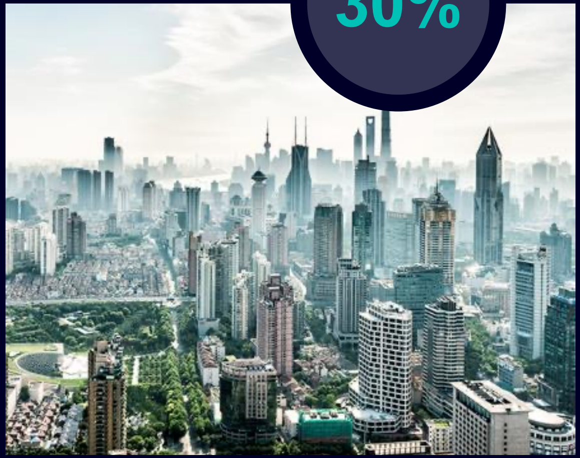
Siemens focuses on key industries – these industries have a great potential to reduce resource consumption and drive progress and growth

50%

Industry

material savings
can be realized using digital twins and innovative production technologies such as additive manufacturing.

30%



Infrastructure

of energy worldwide
is consumed by building operations. Data analytics & automated building mgmt. can unlock large saving potentials.

30%

Mobility

higher network capacity
can be achieved through automatic train operation and by optimizing train flows and rail operations.

44%

Healthcare

faster door-in-door-out[1]
time for stroke patients is possible with AI-supported analysis of brain scans.

1 Time interval between patient arriving at the hospital and leaving from mechanical thrombectomy | **Source:** International Energy Agency, Royal Berkshire Hospital NHS Foundation Trust

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Siemens focusses on eleven Company Core Technologies

Strategic R&D across all Siemens businesses

Company Core Technologies

- Connectivity & Edge
- Advanced Manufacturing & Circularity
- Future of Automation
- Data Analytics & Artificial Intelligence
- Cybersecurity & Trust
- Simulation & Digital Twin
- Power Electronics
- Integrated Circuits & Electronics
- User Experience
- Sustainable Energy & Infrastructure
- Software Systems & Processes

Siemens R&D
(FY2023)

€6.2 bn

~€500 m

stringent investments in future growth fields

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As a global technology company, we **empower our customers** to make their industries **more sustainable**

320,000 Employees[1]	**€77.8 bn** Revenue[2]
€8.5 bn Net income[3]	**15.4%** Profit margin Industrial Business[2]

1 As of September 30, 2023 | **2** In fiscal 2023 | **3** Continuing and discontinued operations

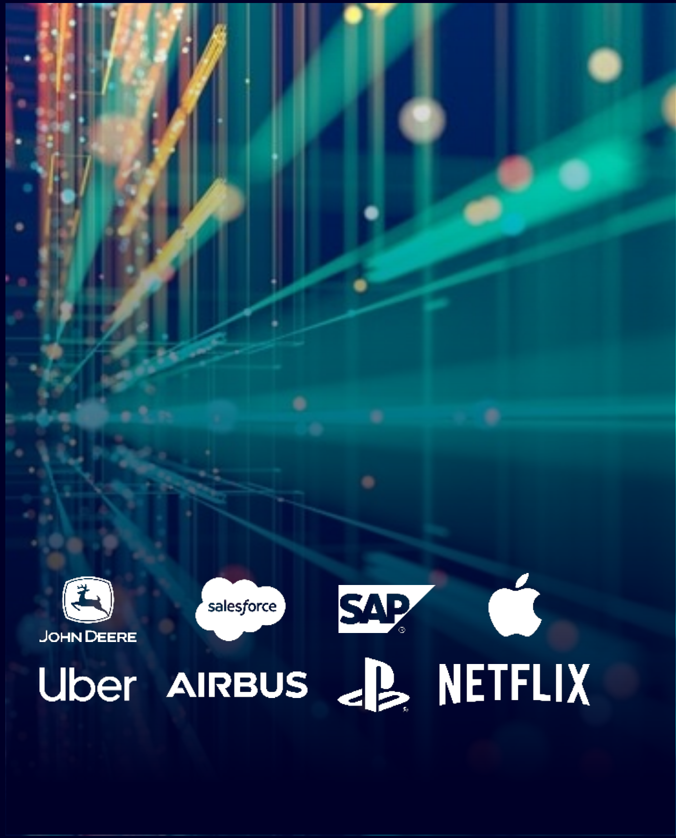
Digital disruptions drive the digital transformation in the industrial space and create an abundance of accessible data

Transfer of hardware to software

Software defined hardware

Digital twin

Platform economy



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Market challenges are also driving industrial players towards digital transformation
but there are systemic issues slowing down progress

Industrial players are facing many different types of business challenges

- Supply Chain Disruptions
- Lack of accessible talent
- Regulatory compliance
- Energy cost
- Market volatility
- Sustainability targets and regulations
- Global competition and cost pressure
- Global competition and cost pressure
- Product personalization leading to smaller lot sizes and more variants

These challenges often require a
digital transformation

Accessible data is increased

Business models start to change

However, the digital transformation faces issues in the industrial environment:

- Brownfield hardware/system environment with partially old assets in place
- Unclear cost/return/ROI situation with often high upfront cost for connectivity
- Partially unproven digital solutions for the long run
- Missing skills and capabilities for digital topics
- Cybersecurity risks

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Digital transformation increases accessible data and drives business model change due to superior insights

Guaranteed availability

Customer value

100%	>15%
availability of the schedule	reduction in lifecycle cost

Insights-as-a-Service

Software-as-a-Service

Digital transformation:

- Accessible data is increased
- Business models start to change

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Therefore, Siemens created

Siemens Xcelerator

The open digital business platform

A comprehensive, curated **portfolio** that includes digital and IoT-enabled offerings from Siemens and certified partners.

A continuously growing, powerful **ecosystem** of partners.

A **marketplace** to explore, educate and exchange with a community of cust-omers, partners and developers, and to purchase products, solutions and services.

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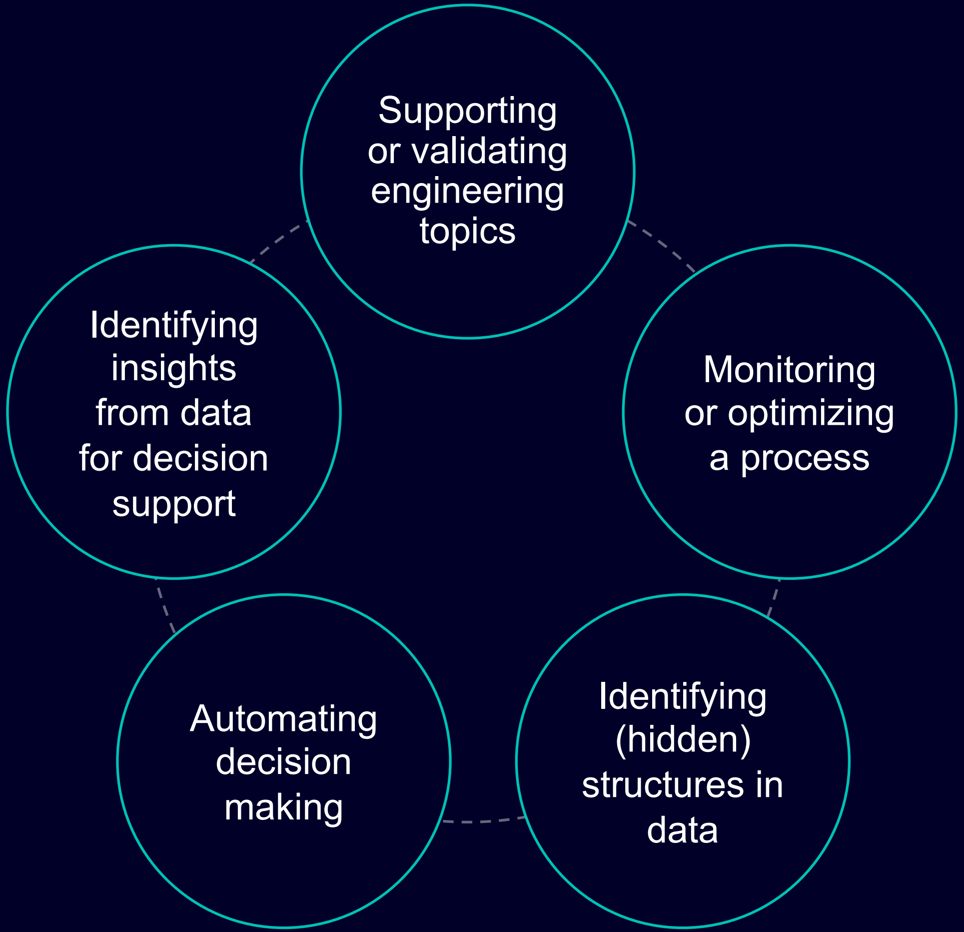
Industrial AI will become more relevant in 5 different sets of value levers, enabling different clusters of use cases

Industrial AI:

Application of **artificial intelligence** technologies in the **industrial sector** to enhance **productivity**, **efficiency**, and **decision-making** processes



Clusters of industrial AI use cases:

- Develop better products
- Develop smarter products
- Produce products better/cheaper
- Improve product usage/integration
- Provide aftermarket services (e.g., predictive maintenance)
- Provide on-top services for products
- Change product value proposition

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What makes industrial AI so difficult?

Industrial AI is more difficult due to a set of inherent reasons:

- **Cost of failure** or false predictions are very high – requires very high prediction accuracies
- Models **operate 24/7 for many years** – requires robust model operationalization and a stringent monitoring
- Difficulty to ensure inclusion of all relevant environmental parameters into the model – danger of model is being used **outside of trained space**
- Industrial systems are engineered systems – large number of **internal correlations by design**
- Number of measured data points much higher than the number of external influencing factors – **System massively over defined** with many direct or indirect correlations
- Data often comes from sensors that are prone to temporary or permanent **disturbances** – requires constant data validation
- **Assets fail seldomly** – data set for model training is unbalanced or not enough failure cases available
- **Brownfield environments** contain machinery from different generations with **legacy standards / protocols** – making gathering and analysis of data challenging

To harvest savings potentials in industrial environments, customers need to **adapt processes to the AI** created insights and **reduce buffers or personnel** – reducing possibility to counteract false insights

Example of train doors: A predictive model in standard quality would not create value for customers

A train door is one of the most often failing items. Let us try to predict one week in advance if it will fail a week later using time series data on door motor current.

Assumptions:

The train door open appr. 300 times per day and is in operation on 350 days per year. It is experiencing failures on 3 days per year. The prediction accuracy of the failure model is 80%

	Prediction	
Reality	**Failure**	**No failure**
Failure	3	0
No failure	70	277

Results:

The model will create over 20 times more false alarms then real alarms. This is destroying value!

Predictive maintenance uses data analysis and machine learning algorithms to predict equipment failures before they occur, optimizing maintenance schedules and reducing downtime.
Condition-based maintenance relies on monitoring of the condition to determine when maintenance should be performed, ensuring optimal performance and reducing unnecessary maintenance activities

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Approaches to resolve issues with industrial AI

The challenges with industrial AI can be tackled, but it is not simple:

- Validation of sensor data for trustworthiness
- Utilization of artificial data to train models
- Implementation of industrial grade anomaly detection including identification of typology of anomaly
- Incorporation of system specific (engineering) frame conditions to reduce false positives
- Implementation of “expert in the loop” approach to validate potential findings
- Utilization of sophisticated data labeling solutions to identify unclear conditions
- Development of new basic models taking into account the specific situations in industrial AI

Most of these approaches reduce scalability of solutions and require significant interaction with system engineers

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Example: Senseye relies on mapped asset types and focuses on the attention index, keeping the engineer in the loop

AGVs
FANS
CONVEYORS
GEARBOXES
PUMPS
MIXERS
ROBOTS
POWER & DRIVES
MOTORS
BUCKET ELEVATOR
CHILLERS
MANY MORE

Senseye Predective Maintenance monitors **over 500+** different types of assets across diverse industries, sectors & verticals

Automated learning from condition indicators

- Pressure
- Current
- Torque
- Vibration

Normal / Deviation from norm vs Live Data / known failures

Diagnostics & Condition monitoring

Prognostics

Attention index

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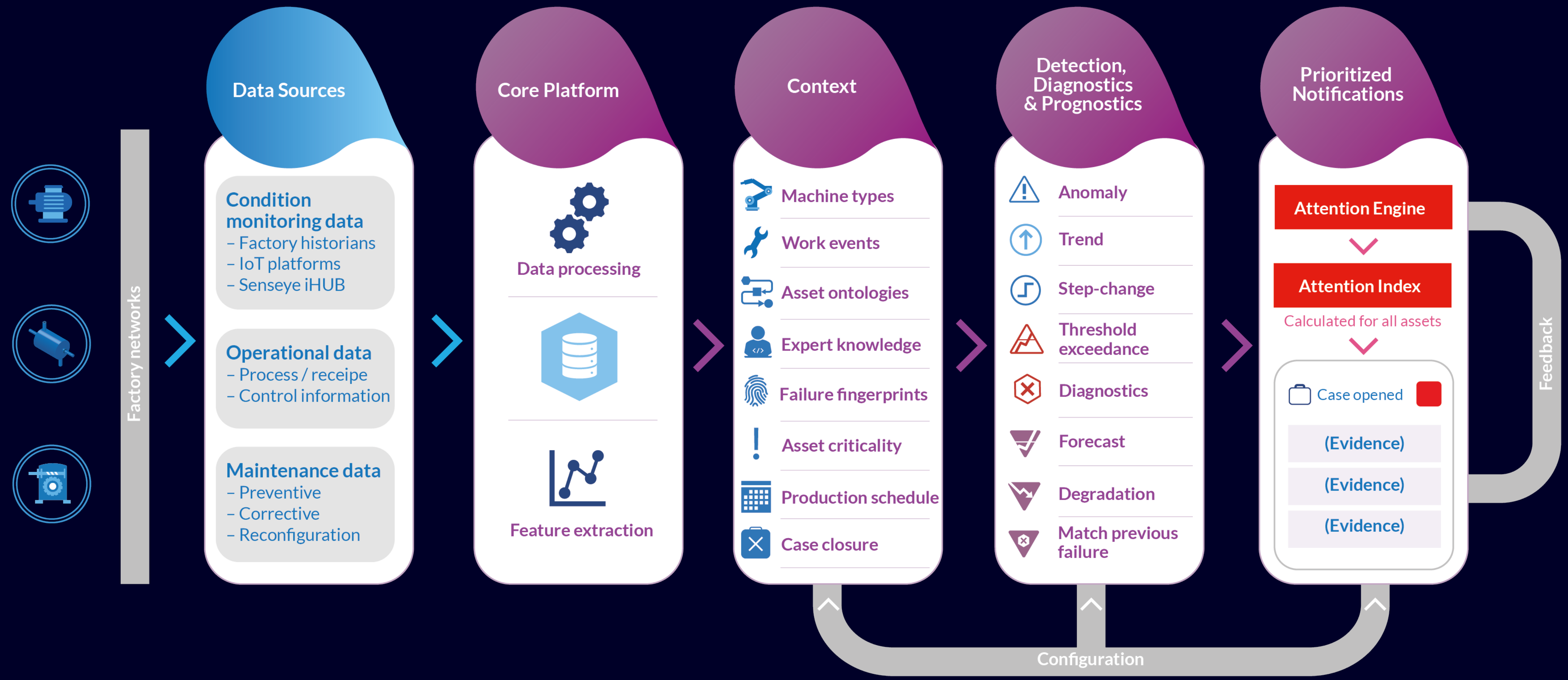
Example: Senseye Predictive Maintenance – Functional pipeline



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Example: For Singapore LTA, REAMS reduces lifecycle cost. The AI models all include Siemens experience and design expertise

Up to
13%
LCC savings

Lifecycle Management

Asset Monitoring
- Asset Information Overview
- Monitoring of Performance, LCC, Risk (Moving 30 Years Forecast)

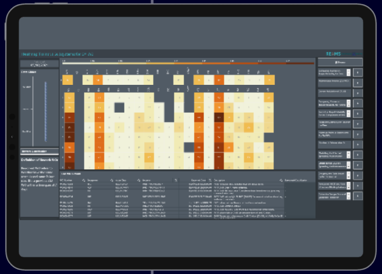
Up to
+8 year
Life extension

Trigger!

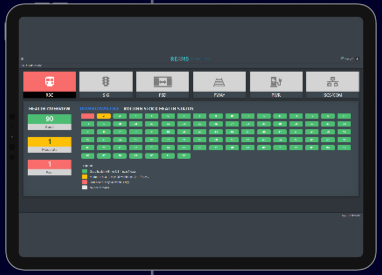
Trigger!

Operation & Maintenance

Maintenance Optimization
- Reliability Analysis
- Identification of Failure Drivers to improve reliability
- Enabling Stretching maintenance (PM & OH) intervention



Asset Health Prediction
Health prediction for advance warning of impending failures



Continuous
Feedback & Update

Downtown
Line

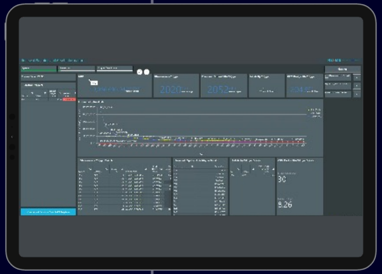
Basis: Experience and design expertise

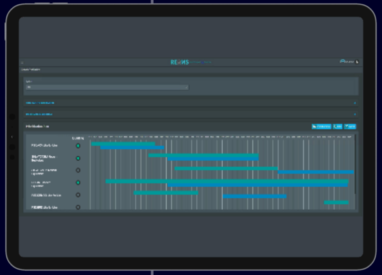
Land Transport Authority
SBS Transit

Knowledge Transfer

Renewal Planning

Renewal Planning
- Advanced renewal planning based on user-defined renewal triggers
- Generation of renewal/extension recommendations based on reliability and cost





LTA = Land Transport Authority, REAMS = Rail Enterprise Asset Management System, LCC = lifecycle cost

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Example: AI prediction can save almost 40% effort for a standard simulation approach with same quality of the results by incorporating design expertise

Target:
Crash Safety Optimization

Objective:
- Minimize Vehicle Mass (crash critical parts)
- Maximize Energy Absorption (crash crit. parts)

Constraints: (for safety ratings)
- Intrusion
- Head Injury Criteria
- Chest Severity Index

SHERPA — 600 Evaluations

SHERPA + HEEDS AI Simulation Predictor — 387 Evaluations

774 hours

18 days of time savings!

213 Evaluations

Real CAE Simulations

AI Model Predictions Only

Heeds AI simulation predictor relies on many years of design expertise to speed up result generation

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Summary and conclusion

- Industrial AI is a critical element for realizing benefits from digital transformation in the industrial environment
- All approaches need to incorporate topic expertise, customer process know how and physical frame conditions
- Industrial AI needs to address and resolve a multitude of challenges in a robust and reliable way to ensure the benefits for the customer
- Data integration and data abstraction is key to the economic viability of such an approach
- However, industrial AI models will be very powerful if implemented correctly

Contact

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