

In collaboration with MEXT Technology Center

# Unlocking Value from Artificial Intelligence in Manufacturing

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# Foreword



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Türkiye has established itself as a key global player in advanced manufacturing and aims to boost its position through Fourth Industrial Revolution technologies. In recent decades, the country has made significant efforts to position itself as a global innovation hub, excelling in developing state-of-the-art technologies in ground-breaking companies in various fields. Artificial intelligence (AI) technology applications are part of this effort. In principle, AI could unlock more than \$13 trillion in the global economy and boost GDP by 2% per year.<sup>1</sup> However, companies struggle to tap into the value that AI applications can create.

This paper seeks to uncover the hidden potential of AI in the manufacturing sector and the respective end-to-end systems by providing practical use cases and critical enablers to help harness its potential. Coupled with the energy crisis and material shortages facing the world, manufacturing players need to go beyond traditional operating methods to drive efficiency and sustainability.

The twin challenges of technological progress and socio-political distress call for new forms of cooperation that respond to heightened demand for localization while recognizing the drivers of connectivity that shape global impact. Acknowledging this, the Centre for the Fourth Industrial Revolution in Türkiye – mandated by the

Ministry of Industry and Technology and established by the Turkish Employers' Association of Metal Industries (MESS) – joined the World Economic Forum's Centre for the Fourth Industrial Revolution Network, the foremost platform helping leaders anticipate emerging technologies and drive their inclusive and sustainable adoption. The network links on-the-ground experience and action with global network-based collaboration, learning and scaling.

This white paper is an output of the ongoing partnership between the Forum's Platform for Shaping the Future of Advanced Manufacturing and Value Chains and Platform for Shaping the Future of Technology Governance: Artificial Intelligence and Machine Learning, the Centre for the Fourth Industrial Revolution Affiliate in Türkiye and MESS. It highlights case studies from organizations on the impact, feasibility and scalability of AI in manufacturing. It identifies several opportunities and lessons from the community on how to increase operational efficiency, sustainability and workforce engagement in manufacturing and value chains by using AI.

We hope this report will provide decision-makers with a better understanding of how to unlock the untapped potential of industrial artificial intelligence (AI). We look forward to collaborating with you to deploy these technologies responsibly.

# Executive summary

Recent global developments and an ever-growing list of shocks and disruptions have put further strain on already shaken global value chains. The complexity of current challenges impacting manufacturing and value chains calls for the need to go beyond the traditional means of driving productivity to uncover the next wave of value for businesses, the workforce and the environment. Artificial intelligence (AI) is a crucial enabler of industry transformation, opening new ways to address business problems and unlock innovation while driving operational performance, sustainability and inclusion. Even though the impact of AI applications on manufacturing processes is known, the full opportunity from their deployment is still to be uncovered due to a number of organizational and technical roadblocks.

Recognizing this need, the Centre for the Fourth Industrial Revolution Türkiye, together with the World Economic Forum's Platform for Shaping the Future of Advanced Manufacturing and Value Chains and Platform for Shaping the Future of Technology Governance: Artificial Intelligence and Machine Learning, convened industry, technology and academic experts to shed light on these challenges and propose a step-by-step approach to overcome them. The consultations revealed six main challenges hindering the adoption and scaling of AI applications in manufacturing:

1. A mismatch between AI capabilities and operational needs
2. The absence of a strategic approach and leadership communication
3. Insufficient skills at the intersection of AI and operations
4. Data availability and the absence of a data governance structure
5. A lack of explainable AI models in manufacturing
6. Significant customization efforts across manufacturing use cases

The consultations show that leading manufacturers have successfully overcome the challenges mentioned above, implementing a variety of AI applications and achieving a positive impact on operational performance, sustainability and workforce engagement, mainly in six areas: health and safety, quality, maintenance, production processes, the supply chain, and energy management.

While opportunities enabled by AI in manufacturing are promising and attracting many leaders, organizations are looking for a common framework that outlines how to implement AI solutions and ensure a successful return on investment.

Based on the consultations, this white paper presents one step-by-step process as an example of how it is possible to overcome barriers, using the AI Navigator<sup>2</sup> developed by the INC Invention Center as a reference:

Phase 0: Initiation to build the fundamentals – strategy, data and workforce

Phase 1: Ideation to identify potential use cases and conduct a pre-selection

Phase 2: Assessment to select use cases and identify priorities via gap analysis

Phase 3: Feasibility to complete all required tests and studies

Phase 4: Implementation, which requires iteration and piloting using agile project management

Moving forward, the World Economic Forum and the Centre for the Fourth Industrial Revolution Türkiye will continue to work closely with stakeholders in the Centre for the Fourth Industrial Revolution Network and across industries to accelerate the journey to capture value from AI in manufacturing globally. It will offer the Turkish Employers' Association of Metal Industries (MESS) Technology Centre as a unique testing and collaboration system for businesses to pilot new AI applications and foster a collaborative approach among a diverse group of stakeholders to ensure the right AI capabilities are built in manufacturing and rolled out worldwide.

# Introduction

Companies across value chains are now facing an energy crisis and material and key component shortages, even as they are still recovering from and adapting to COVID-19 impacts. The complexity of the challenges impacting operations calls for the need to go beyond the traditional means of driving productivity to uncover the next wave of value and address sustainability and workforce challenges. Artificial intelligence (AI) can enable a new era in the digital transformation journey, offering tremendous potential to transform industries to gain greater efficiency, sustainability and workforce engagement by generating new insights from large amounts of data. However, despite this promising value creation potential, the deployment of AI in manufacturing and value chains is still below expected levels.

Based on a global survey conducted over the last four years of more than 3,000 companies across industries and geographies, a growing number of companies recognize the business imperative to improve their AI competencies:

- 70% of respondents understand how AI can generate business value
- 59% have an AI strategy in place
- 57% affirm that their companies are piloting or deploying AI.

Despite these trends, only 1 in 10 companies believe they generate significant financial benefits with AI.<sup>3</sup>

While manufacturers acknowledge the importance and urgency of embedding AI in their processes and while leading companies have already internalized it in their business processes, many are becoming disillusioned with their efforts to capture value from it and lag in developing the right AI capabilities.

Understanding the purpose and role of AI is key to solving manufacturing challenges. With a problem-oriented approach, AI efforts can be linked to clear business targets, giving business units and business functions a joint interest in making the transformation successful.<sup>4</sup>

This white paper sheds light on the benefits that can be achieved through industrial AI and the successful AI applications implemented across industries, lessons learned and tangible impacts. Consultations conducted with the multistakeholder initiative community find that industrial AI helps people work in a smarter, safer and more efficient way. However, to unlock its full potential, companies require an understanding of current barriers to adoption and a structured approach to overcome them. Therefore, this paper also presents one example of a step-by-step guide to successfully implementing scalable industrial AI use cases.

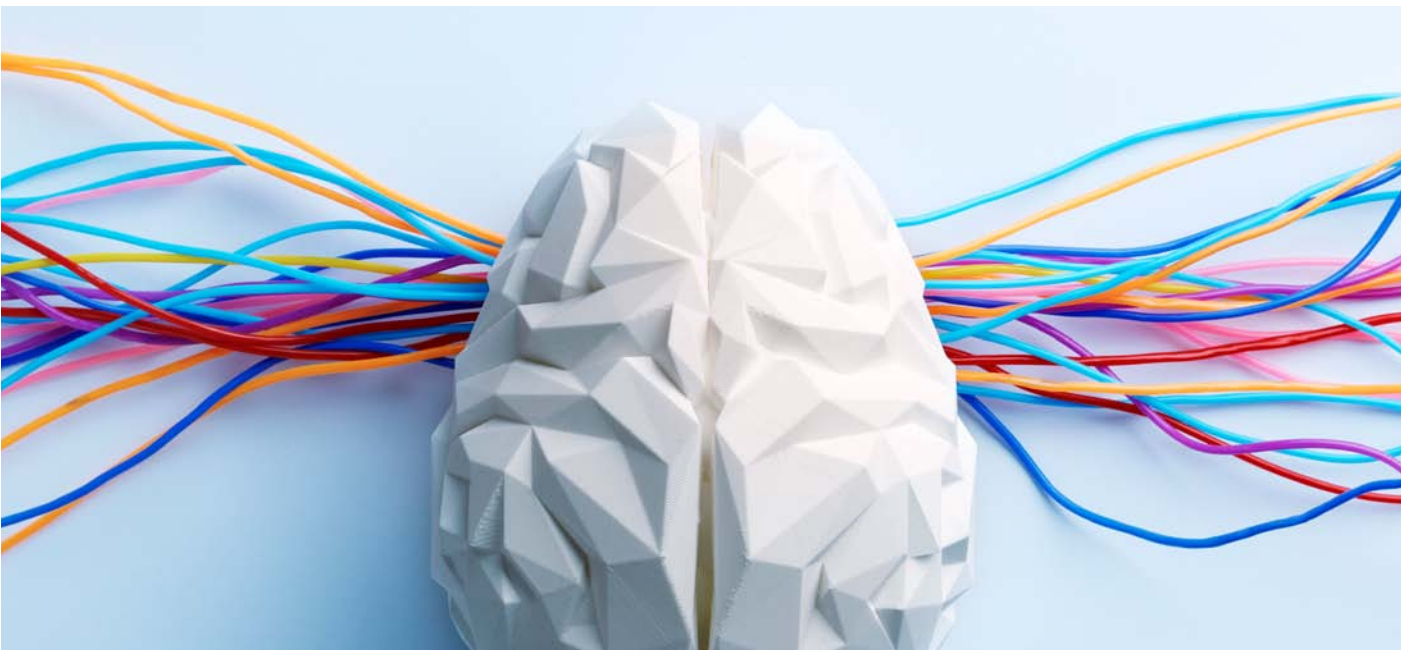




1

# Unlocking value in manufacturing through AI

AI applications in manufacturing help increase operational performance, drive the sustainability agenda and empower the workforce.



The artificial intelligence (AI) revolution allows the conversion of large amounts of data into actionable insights and predictions that can provide impetus to data-driven processes. Manufacturing companies capture value from AI using different mechanisms, the most common being eliminating redundant work, solving existing problems and revealing hidden value by analysing and recognizing patterns in data. AI is applied to augment tasks such as classification, continuous estimation, clustering, optimization, anomaly detection, rankings, recommendations and data generation to solve industrial problems.<sup>5</sup>

Consultations with senior executives from the World Economic Forum's Platform for Shaping the Future of Advanced Manufacturing and Value Chains and Platform for Shaping the Future of Technology Governance: Artificial Intelligence and Machine Learning, as well as members and partners of the Centre for the Fourth Industrial Revolution

Türkiye, find that AI can help drive a step-change in manufacturing, yielding significant benefits in three categories (figure 1):

- **Operational performance** by automating and optimizing routine processes and tasks, increasing productivity and operational efficiencies, improving quality (e.g. reducing defects, forecasting unwanted failures) and optimizing production parameters
- **Sustainability** by optimizing material and energy usage, increasing energy efficiencies, reducing scrap rates and extending machine lifespans
- **Workforce augmentation** by guiding the decision-making process and parameter setting, enhancing the accuracy of predictions and forecasting, reducing repetitive tasks and increasing human-robot interactions

FIGURE 1 | Dimensions of value creation with AI in manufacturing



2

# Shedding light on common barriers to industrial AI adoption

Implementing AI solutions requires continuous project management efforts, expectation management and the necessary resources.



Despite this potential, companies have not yet fully realized the vision of AI-powered manufacturing systems. To unlock the untapped value of industrial AI, pinpointing the source of a company's struggles and defining the roadblocks open a new path to think through and derive the right solutions to overcome them. As the barriers to AI adoption stem mainly from organizational, strategic and technical

components, understanding them will help identify a pathway to implement scalable AI applications.

Consultations with the community of over 35 senior operations executives, technology experts and academics have identified six challenges hindering the adoption of AI in manufacturing and value chains (figure 2).

FIGURE 2 Barriers to AI adoption in manufacturing



Mismatch between AI capabilities and operational needs



Absence of a strategic approach and leadership communication



Insufficient skills at the intersection of AI and operations



Data availability and absence of a data governance structure



Lack of explainable AI models in manufacturing



Significant customization efforts across manufacturing use cases





## Mismatch between AI capabilities and operational needs

Manufacturers have often selected AI projects based on existing technical capabilities instead of focusing on the impact on business operations. The match between business pain points and AI technologies is not always thoroughly considered. Therefore, AI solutions may be technically feasible but fail to solve a relevant, impactful problem in

operations. This causes a mismatch of expectations and hinders their wider adoption in manufacturing. Building a solid business case with a problem-oriented approach that clearly defines business needs and evaluating the value of an AI solution compared to alternative solutions are the first steps in overcoming that barrier to adoption and scale.



## Absence of a strategic approach and leadership communication

A clear company-wide AI strategy and communication plan are often ignored. Without the right sponsors and committed leaders to start the dialogue and collect the buy-in from end-users, the onboarding of AI applications across the company can't occur due

to workforce reluctance. As AI is changing the ways of working, communicating the strategic approach, benefits and new processes can help increase end-users' willingness to embrace it in their routines.



## Insufficient skills at the intersection of AI and operations

External consultants or information technology (IT) experts who have a limited understanding of the manufacturing requirements on the shop floor often lead AI projects. However, to be successful, AI applications require development

and implementation by cross-functional teams with diverse expertise at the convergence of IT, operational technology (OT), data and AI technologies. This requires upskilling the workforce and attracting new talent in manufacturing.



## Data availability and the absence of a data governance structure

Applying machine learning models requires training on large amounts of data to recognize patterns and relationships.<sup>6</sup> However, manufacturing companies often rely on small data sets and fragmented data, hindering the accuracy of the resulting insights. Even when available, these data sets may not represent appropriate failure cases or relevant process situations and are mostly not interoperable.

Creating a single source of information ensures that businesses operate based on standardized, relevant data across the organization. To overcome this challenge, sharing data across companies' boundaries can support joint efforts to adopt artificial intelligence techniques in the manufacturing sector and rely, in turn, on a set of organizational and technological success factors.<sup>7</sup>



## Lack of explainable AI models in manufacturing

The perception of AI models as complex, non-transparent and uninterpretable systems hinders their deployment. Manufacturers need AI models that are either open and transparent to build trust in the predictions and specific results or interpretable for domain experts to accept them. AI-provided predictions need to be meaningful, explainable

and accurate and have a warning mechanism in place to minimize risks. Explainable AI tools and techniques allow experts to obtain justifications for their results in a format that manufacturing users can understand. The greater the confidence in the AI-powered output, the faster and more widely AI deployment can happen.

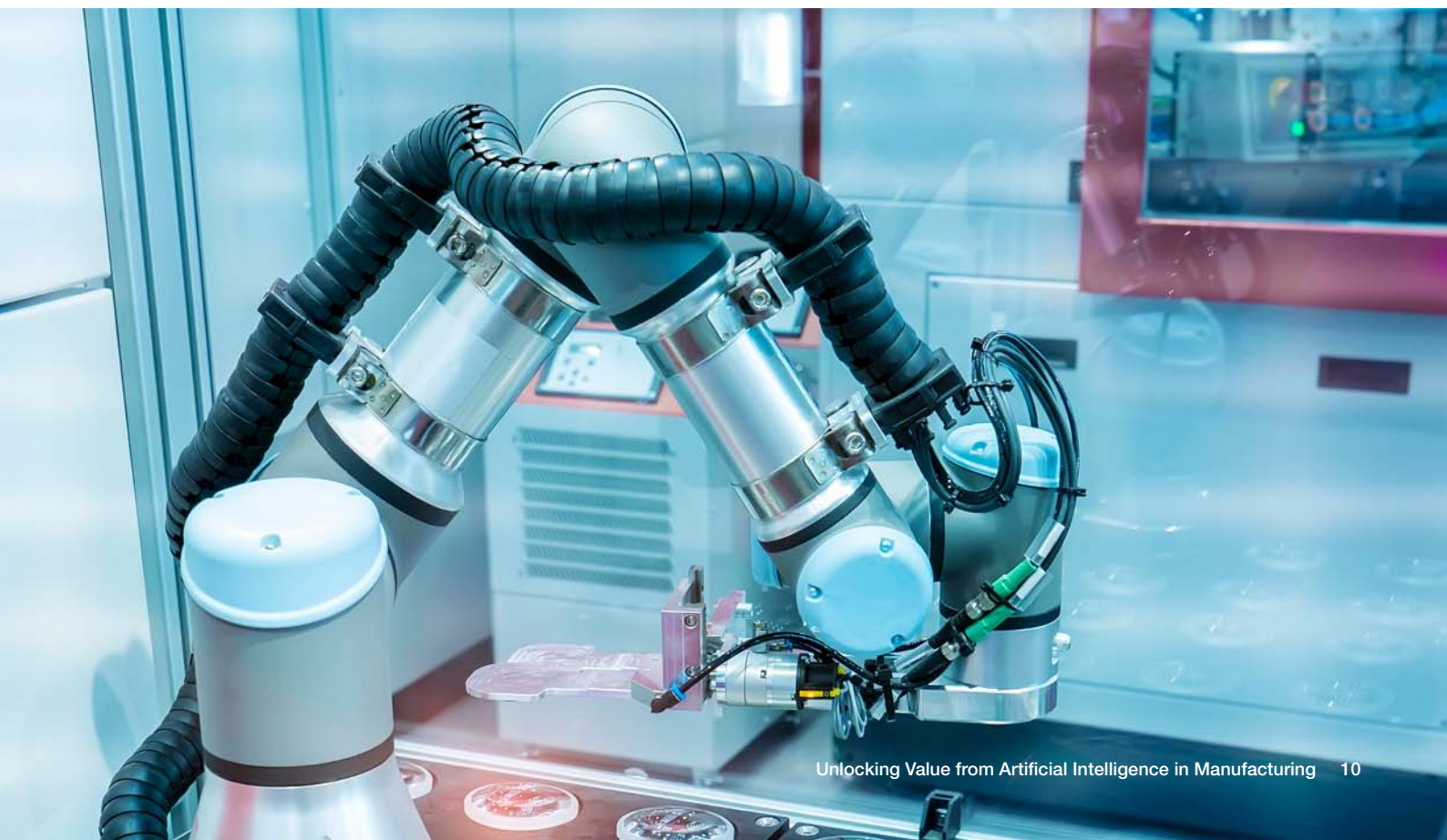


## Significant customization efforts across manufacturing use cases

Factories are complex engineered systems and AI models need configuration to be adapted to each process and conform to its constraints. Hence, it is not possible to simply apply trained AI models or pipelines from one manufacturing use case to another. The design of the machine learning pipeline and the pre-processing, training and

testing of AI models still need manual intervention for customization, which is not yet fully automated. Additionally, industrial companies struggle to find commercially available hardware and software with off-the-shelf AI features that require minor customization.

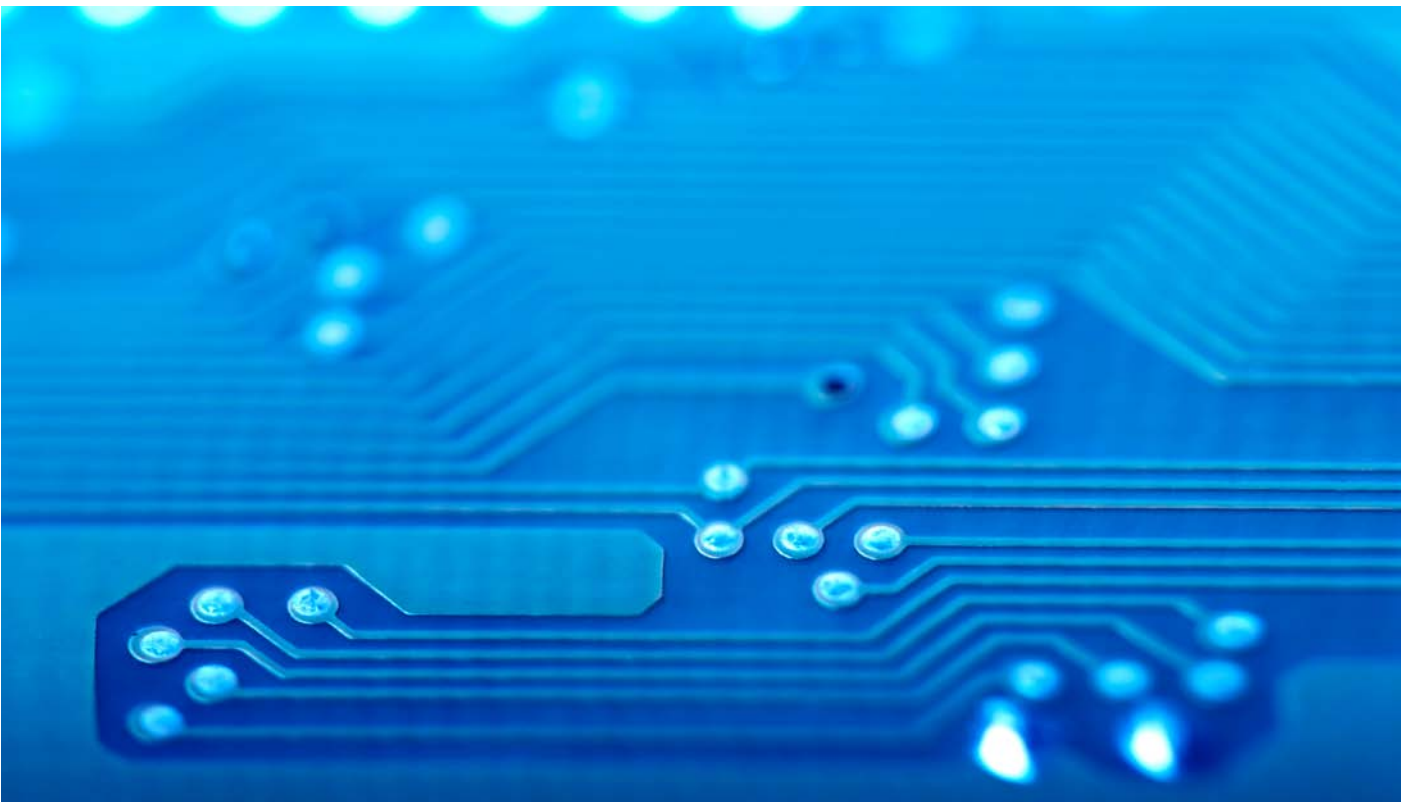
Shedding light on these challenges and understanding them can help identify the right solutions and approaches to overcome them.



3

# A collection of AI applications in manufacturing

AI applications can boost operational performance and lead to a positive impact on sustainability and workforce engagement.



Consultations with over 35 senior operations executives and technology experts find that leading manufacturing companies have successfully managed to approach and overcome the challenges mentioned above by starting with their business needs, outlining a clear strategy, building cross-functional capabilities and putting a stronger focus on data governance, and selecting AI models that meet their needs.

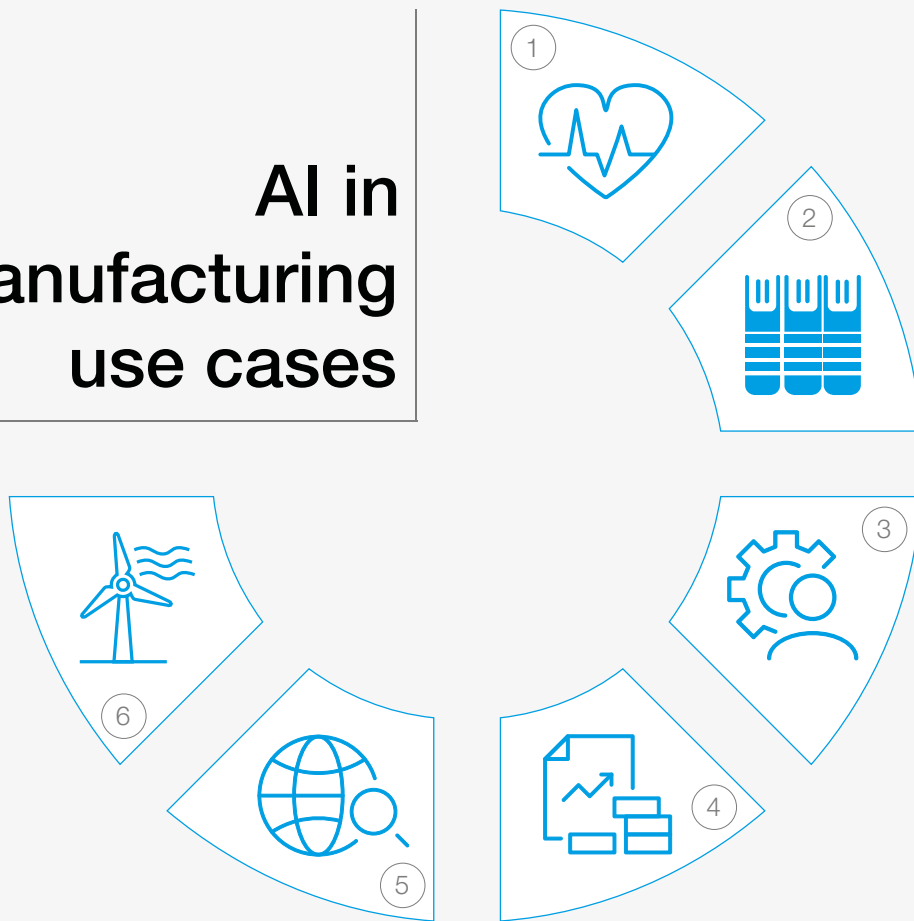
They have implemented a variety of AI applications that have boosted their operational performance and led to a positive impact on sustainability and workforce engagement.

To illustrate the potential and feasibility of AI in manufacturing, the creation of an industrial AI use case library with input from the community has started. The 23 use cases collected across different industries cover six main application areas: health and safety, quality, maintenance, production process, supply chains, and energy management (figure 3).



FIGURE 3 | Leading manufacturers are implementing a variety of AI applications

# AI in manufacturing use cases



Source: Company interviews



## Health and safety

- Employee health & safety: incident prevention
- Process safety: advanced alarm analytics



## Quality

- Quality inspection in assembly
- Quality assurance/defect inspection
- Quality testing
- Quality prediction



## Maintenance

- Machine health monitoring: predictive maintenance
- Maintenance planning



## Energy management

- Energy optimization
- Electricity demand forecasting
- Heating and cooling optimization



## Supply chains

- Future demand and price forecasting
- Supply chain control tower
- Warranty and service management



## Production process

- Process optimization
- Line balancing
- Product design and development
- Process parameter optimization
- Production planning/decision support

The use cases collected provide valuable insights indicating the business need, the solution implemented and the impact achieved. The applications show that the return on investment (ROI) is positive and the payback period of the

investments is usually tangible within 1-2 years. After piloting the AI applications in one division, manufacturing companies either have already deployed to multiple divisions or have the vision to scale.

TABLE 1 | A collection of AI in manufacturing use cases

	Use case	Company	Sector	AI application	Impact
Health & safety	Process safety: advanced alarm analytics	Tüpraş, Türkiye	Energy	Model designed as an experienced operator/engineer in continuous estimation and classification of alarms, detection of nuisance alarms, alarm flood analysis and recommendation of better configurations. Root causes, next-best actions and set points extracted from the historical data through basic descriptive analytics and data science pre-process techniques	<ul style="list-style-type: none"> <li>– Total time of alarm floods decreased by 40%</li> <li>– Number of alarms decreased by 50%</li> <li>– Time efficiency: Alarm rationalization meetings shortened from 4 hours to 30 minutes</li> </ul>
	Employee health & safety: incident prevention	Intenseye, USA	Manufacturing	Image recognition by monitoring the shop floor with existing cameras, receiving real-time alert notifications and enhancing employee health and safety (EHS) to eliminate life-altering injuries	<ul style="list-style-type: none"> <li>– Unsafe situations and actions reduced by 70-80%</li> <li>– With a safer environment, a more productive workforce with increased business uptime created</li> </ul>
Quality	Real-time spot weld quality prediction	Martur Fompak, Türkiye	Automotive	Examining the effective parameters on the frames being welded in robotic spot weld stations (weld quality) and predicting the spot nugget diameter realized in line in real time	<ul style="list-style-type: none"> <li>– Up to 40% savings achieved in energy use</li> <li>– Scrap rate reduced while ensuring sustainability in production</li> <li>– Costs reduced by 60% by preventing the use of excess welding materials</li> </ul>
	Detection of carbon coating defects	Bosch, Türkiye	Automotive	Visual inspection to ensure the coating quality is good by checking parts and searching for coating defects in four different classes: scratches, damages, black in black, silver	<ul style="list-style-type: none"> <li>– Productivity increased by 11%</li> <li>– 15 million parts checked had no incidents</li> </ul>
	Quality assurance with federated learning in control	Huawei, China	Production	Optimizing quality inspection of customized products by deploying cloud services and a federated learning approach (local data collected, global optimum interpolated and in turn shared back to all local facilities without disclosing sensible product or process data)	<ul style="list-style-type: none"> <li>– Productivity increased by 30-40%</li> <li>– Lead time reduced</li> </ul>
	Quality inspection in assembly verification	Ethon AI, Switzerland	Electronics	Explainable computer vision methods used to support factory workers in detecting assembly errors on printed circuit boards (e.g. missing, faulty, or wrong components) via a human-AI interface (camera system with live feedback)	<ul style="list-style-type: none"> <li>– 10x less implementation effort expended</li> <li>– Trustworthiness of the system increased with the explainable model</li> </ul>



	Use case	Company	Sector	AI application	Impact
Quality	Quality testing	Karsu, Türkiye	Textile	Visual inspection of fibre ratio in yarn content using microscopic images to check production quality and to analyse customer complaints	<ul style="list-style-type: none"> <li>Report preparation time for customer complaints and analysis expected to decrease by 90%</li> <li>Expert requirement for the subject will be eliminated</li> </ul>
	Quality inspection in drug-and patient safety	Körber Digital, Germany	Pharmaceuticals	Visual inspection of the quality of pharmaceuticals while AI recognizes patterns instead of measuring physical image values, which decreases the false-reject of products	<ul style="list-style-type: none"> <li>Reduction of false-reject rate by an average of 88%</li> <li>Detection rate increased by an average of 38%</li> <li>Approximately 2x faster time-to-market achieved (transferability) in vision setup</li> </ul>
	Predictive quality	Schneider Electric, France	Electronics	An AI engine that predicts the demagnetization voltage to reduce the number of iterations during relay tests in residual current device product range	<ul style="list-style-type: none"> <li>Machine capacity increased</li> <li>Capex investment reduced</li> <li>Rejections reduced</li> </ul>
	Quality prediction	Obeikan Digital Solutions, Saudi Arabia	Packaging	<p>Through a smart manufacturing platform combination of digital twin and innovative AI, as well as lean operational excellence with end-to-end integration of all functions, process anomaly conditions and drivers detected</p> <p>Statistical process control algorithm, a proven approach of quality control, used</p>	<ul style="list-style-type: none"> <li>Productivity and quality sustainability increased</li> <li>Overall equipment effectiveness in PET lines improved by 20%</li> <li>Customer complaints reduced</li> </ul>
Production process	Process optimization	Fero Labs, USA	Steel	Providing automated software to take preventive actions early in the production process with explainable AI models to reduce raw material use and minimize costs and emissions during steel production	<ul style="list-style-type: none"> <li>Alloy use reduced by 9% at steel mills</li> <li>Failure rate eliminated</li> </ul>
	Line balancing	Khenda, Türkiye	Automotive	AI-based video analytics to label the actions of manual tasks to eliminate operator-related errors and improve manual manufacturing processes and optimize line balancing	<ul style="list-style-type: none"> <li>Productivity increased by 25%</li> <li>By increasing quality and efficiency, error costs eliminated and waste and defective products avoided</li> </ul>
	Production parameter optimization	Dataprophet, South Africa	Foundry	<p>Generating insights into the complex interactions between hundreds of process parameters and their impact on final quality by using deep learning algorithms</p> <p>Application then prescribes next-best step to optimize production without poor quality</p>	<ul style="list-style-type: none"> <li>Defects reduced to 0% from a 6% of historical defect rate</li> <li>Number of quality stops reduced from 81 to 20 per week</li> </ul>

	Use case	Company	Sector	AI application	Impact
Production process	Advanced decision support system on performance test	Arçelik, Türkiye	Home Appliance	Improving cooling test performance in different and dynamically changing climatic conditions to shorten the test duration by an in-house decision-making system based on AI and machine learning (ML)	<ul style="list-style-type: none"> <li>– Service call rate improved by 15.3%.</li> <li>– 17.8% of test capacity increased by decreasing the test time from 80 min. to 65 min.</li> <li>– 17.8% in energy savings per unit in LPT (long performance test) system</li> <li>– 16.7% of warranty cost improvement per unit achieved</li> </ul>
	Process management	GEP, USA	Chemicals	Implementing AI-enabled process controls to manage catalyst ingestion based on pressure and temperature changes in the reactor and to manage the transfer rates	<ul style="list-style-type: none"> <li>– Overall batch cycle time reduced by 22% and need to add new reactor capacity alleviated</li> </ul>
Maintenance	Predictive maintenance: machine health monitoring and maintenance planning	Sensemore, Türkiye	Cement	Detecting the machinery failure mode by collecting the continuous vibration data through fault estimation, early warning and maintenance planning with AI on fans and electric motors	<ul style="list-style-type: none"> <li>– Downtime reduced by 90%</li> <li>– Maintenance cost reduced by 25%</li> <li>– Machine life increased by 20%</li> <li>– Operation productivity improved by 25%</li> </ul>
	Predictive maintenance	The Center for Intelligent Maintenance Systems (IMS), USA	Electronics	Predicting the concentration of contaminative particles before it can negatively impact the production yield, allowing chamber cleaning to be performed in a proactive manner Solution is for dry etching chamber in semiconductor manufacturing to monitor the deposit accumulation process inside the processing chamber	<ul style="list-style-type: none"> <li>– 70% reduction in the costs of unplanned downtime</li> <li>– Competitiveness improved</li> </ul>
	Predictive maintenance	Predictronics, USA	Automotive	AI-based predictive solutions for industrial robots for an automotive manufacturing client to monitor welding robot health and ultimately predict and prevent failure events and schedule maintenance, saving time, money and resources	<ul style="list-style-type: none"> <li>– 50% reduction in unplanned downtime</li> <li>– Inefficient maintenance practices reduced</li> </ul>

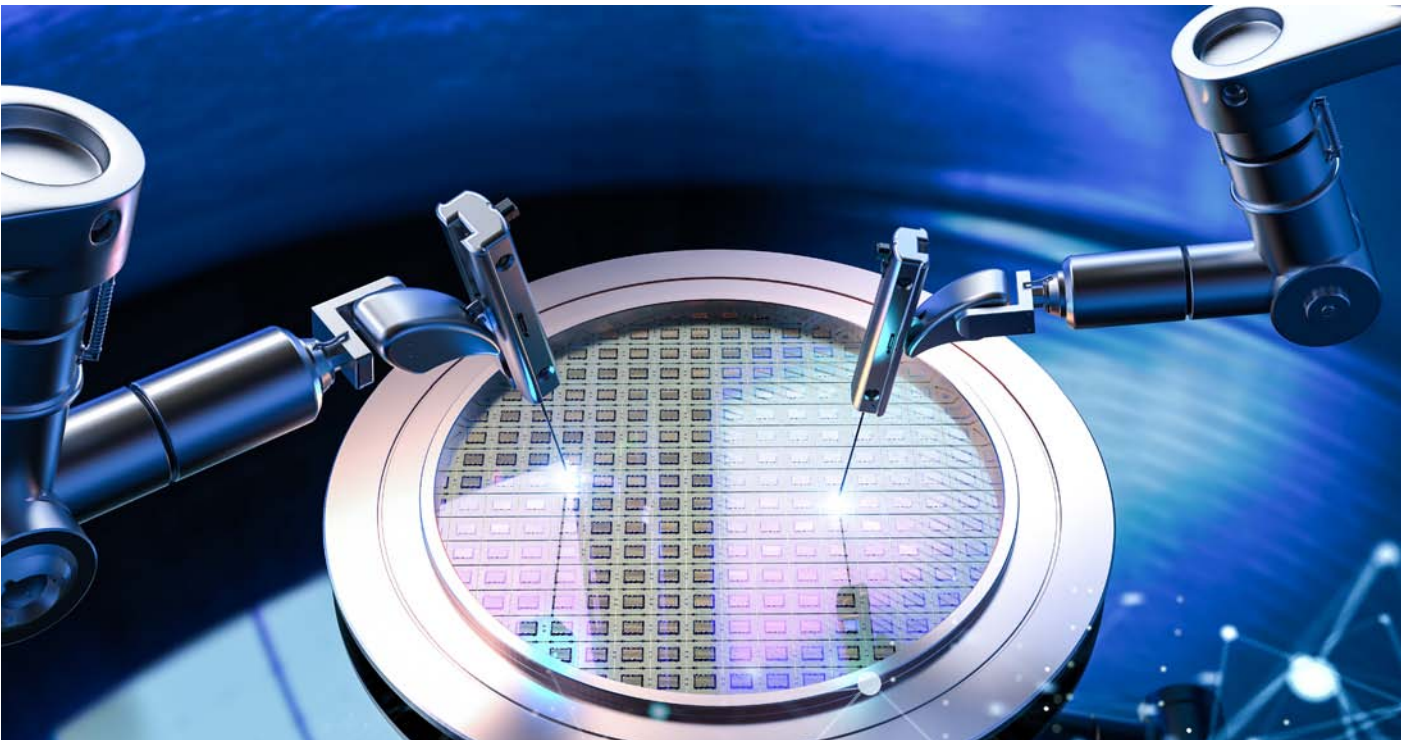
	Use case	Company	Sector	AI application	Impact
Supply chain	Future demand and price forecasting	SmartOpt, Türkiye	Chemical	Forecasting future demand for products, services and raw material prices by automatically training AI model and tuning the model parameters automatically without user input	<ul style="list-style-type: none"> <li>Forecasting accuracies for the next 6 months reached 85-99%</li> </ul>
	Warranty and service management	Tofaş, Türkiye	Automotive	Component-based prediction granularity as the components of the vehicles affected by different factors to determine warranty expenditure of the coming years for the sold vehicles	<ul style="list-style-type: none"> <li>Prediction accuracy increased from 70% (manual prediction) to 95%, which resulted in reduction of reserve fund by 10% per year</li> </ul>
Energy management	Energy optimization	Canvass AI, Canada	Food and Beverage	Analysing thermal efficiencies, ambient conditions to control real-time natural gas optimization and consumption targets across turbines; electricity production targets and steam demand from downstream boilers	<ul style="list-style-type: none"> <li>5.09% gain in thermal efficiency, which translates to 9M lbs/yr and energy cost savings achieved</li> <li>CO<sub>2</sub> emissions reduced</li> <li>Overall equipment effectiveness improved</li> </ul>
	Electricity demand forecasting	Ford Otosan, Türkiye	Automotive	Predicting electricity usage with changing periods in the 12 different regions of the factory with a model that worked automatically in predetermined periods and eliminated error factors	<ul style="list-style-type: none"> <li>Prediction accuracy score varies between 80-95% for the total consumption of the factory</li> <li>The pre-emptive right to buy the electricity is reserved with the electricity provider</li> </ul>
	Heating and cooling optimization	Makinarocks, Republic of Korea	Electric vehicle	Optimizing energy management system (vehicle temperature) of electric vehicles by simulating the control environment using a deep neural network-based dynamics model and implementing a reinforcement learning method to improve energy efficiency through optimized control inputs	<ul style="list-style-type: none"> <li>Improved the energy management system's energy efficiency in electric vehicles by 10% on average, with a maximum increase of 25%</li> <li>An additional 5-7% increase in driving distance per every 10-15% increase in energy management system energy efficiency</li> </ul>

Source: Company interviews

4

# A step-by-step approach to implementing scalable industrial AI applications

It is possible to uncover AI's untapped potential with a holistic approach.



Digital and AI can power a new era for continuous improvement in manufacturing beyond the traditional means of driving productivity, thereby unlocking additional value. Although leading manufacturers have already captured significant benefits from AI applications, some are still trying to get started and are looking for a common framework that paves the way for the deployment of AI in manufacturing with a positive return on investment.

This study has demonstrated that it is possible to uncover AI's untapped potential with a holistic approach. The development of AI-based applications starts by laying the groundwork and some fundamental steps. With a step-by-

step approach and the required toolset, the manufacturing sector can gain new perspectives to overcome the most pressing challenges.

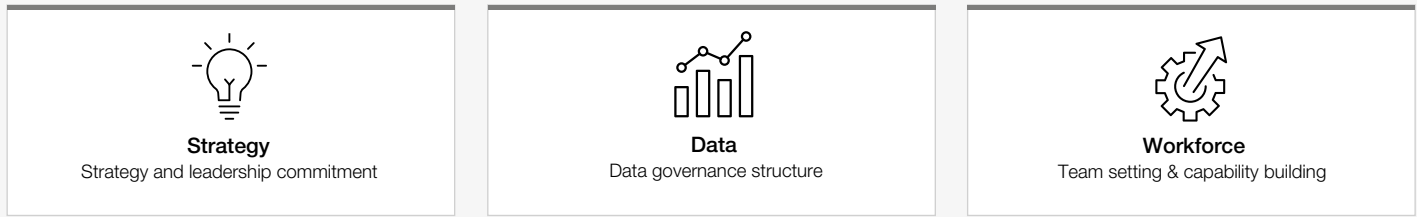
To do so, the INC Invention Center has developed the AI Navigator,<sup>8</sup> a structured toolset to help companies reach the untapped potential of AI and identify use cases with the strongest chance of successful implementation. The step-by-step guide presented here (figure 4) – based on the AI Navigator and consultations from the initiative community – provides an example of how to develop application-specific roadmaps and companywide actions, from idea generation through evaluation and feasibility analysis to successful implementation.

FIGURE 4 | A step-by-step guide to implementing AI in manufacturing

## Phase 0

### Initiation

Kick-off preparation



## Phase 1

### Ideation

Problem – solution fit

- Discover
- Define
- Empathize
- Confront

Use case pre-selection

## Phase 2

### Assessment

AI readiness level

- Infrastructure
- Data
- Process
- Mindset/culture

Use case prioritization

## Phase 3

### Feasibility

Implementation concept check

- Business feasibility
- Technical feasibility
- Data testing
- Technology scouting
- Competence validation

Use case decision

## Phase 4

### Implementation

Product-market fit

- Agile approach
- Explainable model
- Testing
- Evaluation
- Deployment

Use case validation

Source: Adapted from the work of the INC Invention Center

## Phase 0: Initiation

AI is an emerging discipline intended to create a system that amplifies and expands human abilities. To implement a holistic approach independent from industry specifics, there are three fundamentals: strategy, data and workforce.

**1. Strategic approach and leadership commitment** to cultivate the AI transition comprehensively, from business units to production facilities. To successfully translate the strategy into action, leading manufacturers have placed significant efforts on change management by actively communicating the set vision and its benefits, investing in workforce upskilling and infrastructure upgrades and establishing a digital company culture. For AI governance and data ethics mechanisms to be responsible and explainable, they have to be incorporated into this strategy.

**2. Data governance** will be an indispensable part of the process. While collecting the data, it is necessary to build a hub for data flows to manage data availability, usability, integrity and security. AI applications are only built when the data is available; therefore, the most prominent, easily applicable and transferable data structure needs to be built beforehand.

**3. Cross-functional teams** with multi-disciplinary in-depth knowledge in IT, OT, data, analytics and technology engineering and how to organize these with business acumen. Therefore, it is crucial to build an agile team structure for AI projects that revives the collaboration between the technology team and business professionals. AI solutions require collaboration with different skill sets and expertise. Even though external sources are used in the transition, in-house experts need to be upskilled.



## Phase 1: Identification

AI projects have the greatest probability of success when businesses conduct a critical early analysis of potential use cases resulting from a problem-oriented approach. After setting the stage in Phase 0, this first phase of the AI Navigator enables the early prioritization of use cases based on a problem-solution-fit analysis.

To discover a set of potential value-adding use cases, a cross-functional team that can analyse and

define the main pain points and thus develop the relevant requirements for the solutions needs to be involved.

Close communication and collaboration with relevant colleagues and end-users at an early stage help ensure the developed solution meets their needs and allows them to adapt progressively to the introduced change. Ultimately, this will increase the acceptance of the deployed application's use.<sup>9</sup>

## Phase 2: Assessment

The second phase of the AI Navigator methodology focuses on a much more precise assessment of the maturity level of the company-specific AI use case preselected in phase 1 in order to establish the current status quo.<sup>10</sup> This phase aims to determine whether the use case can be successfully integrated with the existing data set, process perspective, infrastructure and culture/mindset. Subsequently, a rough solution hypothesis is to be defined, whereby the target maturity can be specified. Usually, there is a gap between the current and target maturity levels. To close this gap, well-founded recommendations for action must

be formulated. Later implementation can only be made possible after all to-dos have been processed and the resulting gap between the maturity levels has been closed. Consequently, based on the assessment results, a statement about the expected implementation effort can be made with a high degree of accuracy.

The completion of phase 2 further narrows down or focuses on the use cases that offer comparatively high added value and fulfil the necessary prerequisites for later implementation.

## Phase 3: Feasibility

The third phase of the AI Navigator focuses on business and technical feasibility. In addition to ROI estimations, critical elements of this phase include:

- **Data testing:** This ensures that enough structured and labelled data sets of the right quality are available to produce the required results. This provides initial insights into the general feasibility of the use case in preparation for implementation. This is essential to the development of the specific technology concept.<sup>11</sup>
- **Technology scouting:** To check whether the previously established solution hypothesis might be developed or purchased, it is recommended to carry out the technology scouting as a next step. In technology scouting, solutions

available on the market or at the research and development stage are analysed, considering the company's individual tech stack. In the best case, existing solutions can be used directly or at least built upon.

- **Competence analysis:** If the company requires or desires in-house development, a well-founded competence analysis of the employees' skills is necessary to decide which cooperation partners are needed externally and which skills can be covered or built up internally.<sup>12</sup>

During this phase, the solution hypothesis becomes increasingly concrete. If the resulting implementation concept deviates from the original solution hypothesis, it may be necessary to perform the individual steps in phase 3 again.

## Phase 4: Implementation

The focus of the fourth phase is to clearly define the implementation roadmap. Industrial AI applications need modification, testing and validation of models with iterations, which takes time. Using agile project management methodologies across an open, collaborative environment, including internal and external team members, can help streamline

the process, ensure the implemented application addresses the need of the end-user, and provide a space for innovation and co-creation.

It is not enough to pilot an AI use case to leverage the potential of existing data. Scaling the solutions developed is critical to success. For this, it is also

necessary to consider the data available and the parameters of related use cases, data access, data governance and security, and the required skills early on.<sup>13</sup>

Not many organizations have experience with AI. It is crucial to ensure employees join the transformation to a data-driven future, eliminate fears and prejudices, and establish a culture open to failure.<sup>14</sup> To build and sustain trust in AI, transparent and explainable AI models must be implemented and the domain expert must be aligned with AI recommendations. Leading the projects with agile sprints makes this progress smoother. The maturity of AI models improves over time, which means it is not necessary to change the model according to the first sprint results, as adding additional data sources and increasing the size of available data yields better results. To accelerate the model training curve collaboratively, “federated learning (an approach to machine learning in which the training data are not managed centrally)”<sup>15</sup> can distribute the effort for multiple parties across multiple decentralized edge devices or servers holding local data samples without exchanging them.

The systematic approach such as that of the AI Navigator enables an additional benefit in terms of the comparability of different ideas and use cases and alignment of the strategy. While it is often possible to develop many technology-oriented ideas, the challenge lies in prioritizing different topics, even in the same department. Using an approach like the AI Navigator and a well-defined evaluation logic allows for the comparison of different use cases across the four phases to determine how relevant they are and what the potential implementation effort will be in terms of technology, mindset and culture. In addition to building cross-functional teams and involving the domain expert in the development process, the cultural component of a guide such as the AI Navigator enables the early identification of potential action points.<sup>16</sup> Developing the AI literacy of domain experts by collaborating with academia and capability-building centres without focusing on vendor-specific tools is crucial to building the team.



## CASE STUDY

### Pilot implementation at MEXT Technology Center



The Turkish Employers' Association of Metal Industries (MESS), one of Türkiye's largest and most active employer associations, has built the MEXT Technology and Capability Building Center to help its members and companies leverage digital transformation and technologies. The digital factory uses cutting-edge 5G technology on two production lines – a discrete production line (end-to-end connected manufacturing) and a continuous production line (digital twin of integrated steel production) – on which it has implemented over 160 use cases.

MEXT is a real-world demonstration of the initiation phase of the guide.

With a strategy to have a state-of-the-art digital model factory, leadership has prioritized AI-related initiatives and use case development with a clear vision. The AI Lab for Manufacturing is now being built and jointly works on various AI technology governance initiatives with the World Economic Forum's Platform for Shaping the Future of Technology Governance: Artificial Intelligence and Machine Learning and with public authorities.

MEXT is an openly available space to work with academics, manufacturing companies, technology providers and start-ups. It uses a Maestro smart data layer as a data governance

solution to serve as a testbed for new technologies, minimize integration efforts and manage all data flows.

This approach has shortened the time to value for AI studies due to the availability of clean data with real-time automated contextualization.

To accelerate the pace of the implementation of AI solutions, an agile team was built comprising digital transformation and business strategy professionals, data governance experts and AI experts from member companies. Additionally, the in-house team has received training on artificial intelligence (AI)-specific knowledge.

MEXT has completed more than 150 smart industry readiness index (SIRI) assessments in the automotive, machinery and equipment producers, steel, textile, cement, chemical and food processing industries. Based on the SIRI insights, industry-specific pain points have been defined with the structured pathway of the AI Navigator. The AI use cases prioritized for implementation are workplace safety, AI-based machine health monitoring and forecasting, quality inspection, process optimization and predictive maintenance use cases. With in-house experts and upstream and downstream partners, additional AI use cases are being added and continuously updated.

# Conclusion

With a holistic approach, AI can solve some of the most persistent problems in manufacturing and tap into new opportunities that allow companies to increase their operational performance, drive the sustainability agenda and empower the workforce.

While organizational and technological challenges are still hindering the deployment of AI applications at scale, leading manufacturers have successfully seized the AI-derived potential and implemented a wide range of use cases for health and safety, quality, maintenance, production process, supply chains, and resource and energy management.

By using a step-by-step approach such as the one highlighted in this white paper, leaders can identify relevant applications and successfully implement them.

Moving forward, the World Economic Forum and the Centre for the Fourth Industrial Revolution Türkiye will continue to work closely with stakeholders across industries and the Centre for the Fourth Industrial Revolution Network, offering MEXT as a unique testing and collaboration system for businesses to:

- Collectively pilot next-generation AI applications and unlock the untapped value of AI in manufacturing, building on the capabilities of the technology centre, which has positioned itself as a testbed for industry and technology companies that carry out research and development innovations and proof of concept studies to accelerate inclusive technology adoption;
- Foster a collaborative approach among a diverse system of industry leaders, technology experts and academics to develop the right capabilities needed for AI deployment and digital transformation in manufacturing.

Manufacturing companies are invited to engage with the Centre for the Fourth Industrial Revolution Türkiye and the Forum's Platform for Shaping the Future of Advanced Manufacturing and Value Chains and Platform for Shaping the Future of Technology Governance: Artificial Intelligence and Machine Learning to collectively make progress on the AI journey in manufacturing and further scale AI capabilities globally, unlocking value for businesses, workers, society and the environment.



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# Endnotes

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