TrendMiner

INDUSTRIALIZING AI INTO OPERATIONS

Redefining the landscape of the process manufacturing industry with operational data and insights powered by Artificial Intelligence

Industrializing AI into Operations

Redefining the landscape of the process manufacturing industry with operational data and insights powered by AI

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EXECUTIVE SUMMARY

This White Paper explores the transformative power of Industrial Artificial Intelligence (AI) in the process manufacturing industry. It explains how AI is making production more efficient and how it helps with decision-making by leveraging insights found in operational data. This document is a comprehensive guide to understanding, operationalizing, and benefiting from Industrial AI across various manufacturing landscapes.

Highlights

- Demystifying Industrial AI: A clarification of the concept of Industrial AI with an emphasis on its role to enhance production processes, improve efficiency, and cut costs.

- Evolution of AI in Industry: A historical perspective following the journey of AI from its inception to its current state.

- Operationalizing AI: A deep analysis of the Digitalization Journey that maps the transition from traditional methods of analysis to operations powered by AI. It identifies the phases of digital maturity and the challenges along the way.

- Generative AI – The New Frontier: Groundbreaking capabilities are generating new ideas as well as ethical considerations. The section addresses the potential of Generative AI to revolutionize industrial operations while discussing the importance of managing expectations and ethical concerns.

- Practical Applications and Benefits: These real-world examples show how AI can be used for detecting anomalies, scheduling predictive maintenance, and making other operational improvements. It discusses the benefits of AI, such as increased efficiency, reduced costs, and strategic advantages, as well as how to quantify them.

- The Road Ahead: Looking toward the future, the section addresses the necessary skills for an AI-enhanced workforce and the strategic role of TrendMiner as a partner in the journey.

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01 INTRODUCTION

As Artificial Intelligence (AI) has become part of the common language in the manufacturing industry, many have wondered whether the hype surrounding its capabilities actually results in tangible value. Much of this hype is about the use of Generative AI for industrial applications. While the possible use cases of mainstream Generative AI solutions such as Open AI's ChatGPT are well known, they are less understood for the process manufacturing industry.

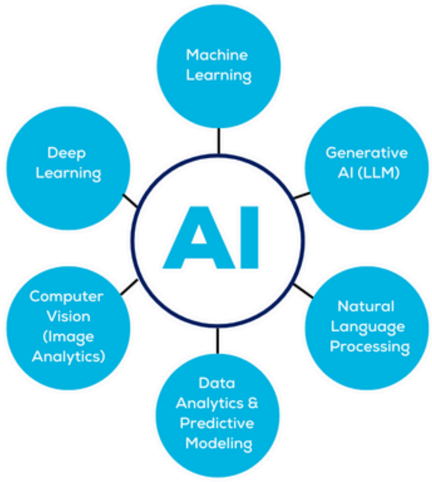
The purpose of this White Paper is to explain how AI benefits manufacturers. It includes:

- An explanation of Industrial AI,
- The history of Industrial AI,
- The Digitalization Journey,
- An introduction to Generative AI,
- Use cases along the journey,
- Benefits along the journey to AI, and
- How to get started.

1.1 WHAT IS INDUSTRIAL AI?

AI performs human-like tasks by learning and adapting from various data sources. AI can even outperform its human counterparts when processing large amounts of data quickly.

In the context of industrial operations, AI refers to the application of data-driven systems to optimize production processes, improve efficiency, and reduce costs. It uses algorithms and models to analyze vast amounts of operational data, predict maintenance needs, enhance quality control, and adapt to changing conditions in real-time.



1.2 THE MAIN CATEGORIES OF AI SOLUTIONS

At its core, AI refers to machines or systems that mimic human intelligence to perform tasks. They can improve themselves based on the information they collect.

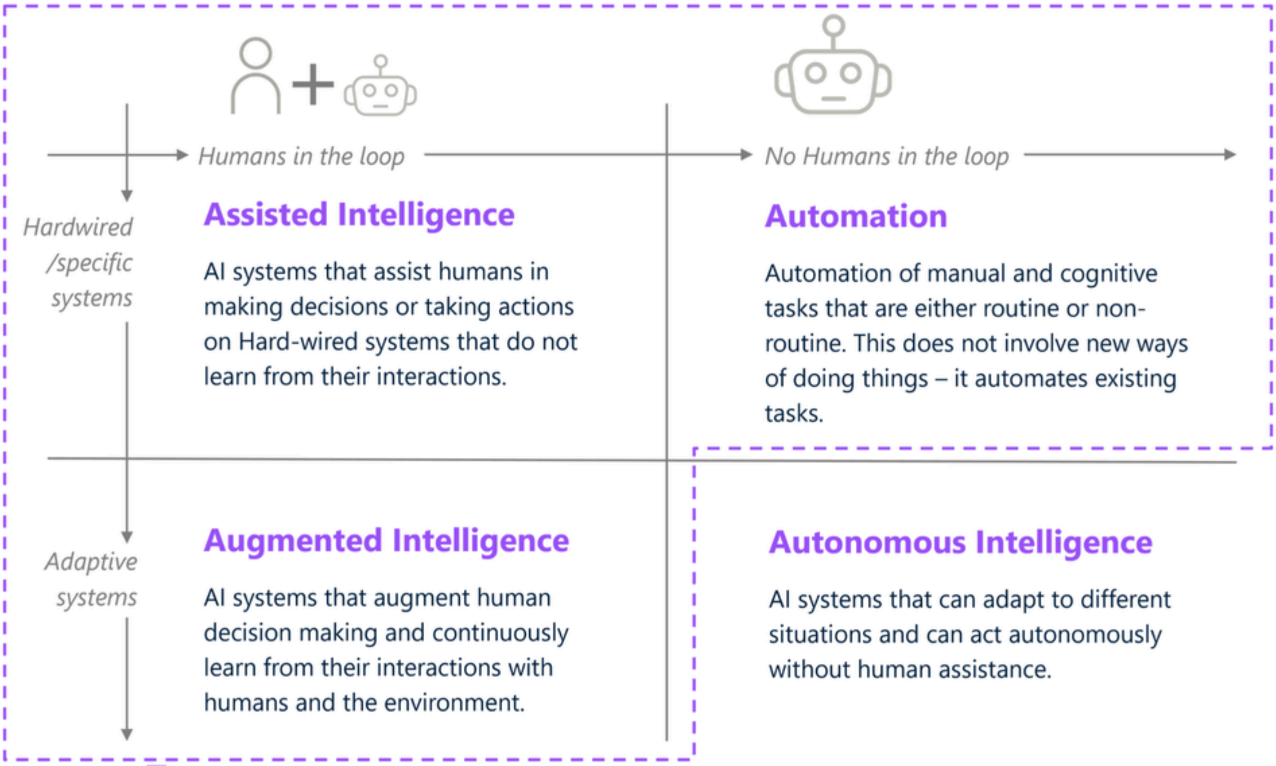


Figure 1. AI generally can be broken down into four categories. Assisted, Automation, and Augmented intelligence show the most promise for the process manufacturing industry right now.

There are generally four categories that represent Industrial AI, as shown in Figure 1.

- Assisted Intelligence systems are the most basic form of AI. They help engineers by making their tasks easier. For instance, an Assistive Intelligence system might use operational data to suggest an improvement. However, the final choice is up to the engineer. Assistive Intelligence devices cannot make decisions on their own.

- Automation Intelligence systems, on the other hand, are suitable for repetitive tasks that do not require much human interaction. An example is a machine that sorts products on a conveyor belt.

- Augmented Intelligence systems work with humans to perform tasks better than either could alone. An Augmented Intelligence system could analyze sensor-generated data to help engineers make better and quicker decisions.

- Autonomous Intelligence systems are the most advanced form of AI. They can make decisions and act on their own without human help. A self-driving vehicle in a warehouse uses Autonomous AI.

Autonomous systems, however, are not yet suitable for managing manufacturing processes because they can act on their own without human assistance. The level of trust in autonomous systems is too low to allow them to make changes on the factory floor. The three remaining categories are a set of services, functions, models, and techniques that, when put together, emulate human intelligence. The most useful of these categories for operations are Deep Learning, Machine Learning (ML), and Large Language Models (LLM).

1.3 THE PROMISES OF INDUSTRIAL AI

AI has immense promises and significant challenges. It also has received a lot of hype in the past year, as shown in Figure 2. On the one hand, it is praised for its potential to drive considerable benefits by enhancing productivity and spurring innovation. With advancements in ML, deep learning, and reinforcement learning, AI applications are becoming increasingly well known throughout the process manufacturing industry. These technological achievements are contributing to a more efficient and productive manufacturing landscape that promises to provide a new way of working.

However, the journey toward fully harnessing AI's potential has many challenges. They include bias, privacy, and security, as well as trust in the decisions that AI makes. As manufacturers begin to adopt AI solutions, they also must have a realistic expectation of how these new technologies will achieve business goals.

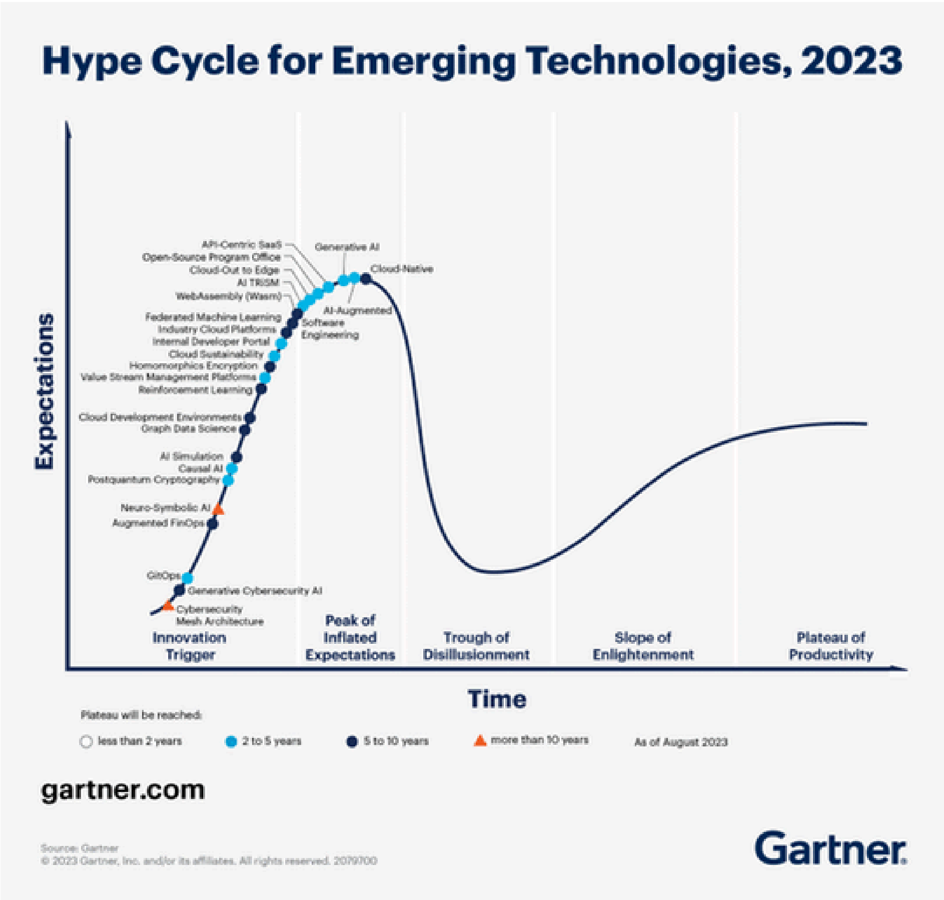


Figure 2. The 2023 Gartner Hype Cycle for Emerging Technologies shows Generative AI was at the peak of its inflated expectations within the past year.

02 THE HISTORY OF INDUSTRIAL AI

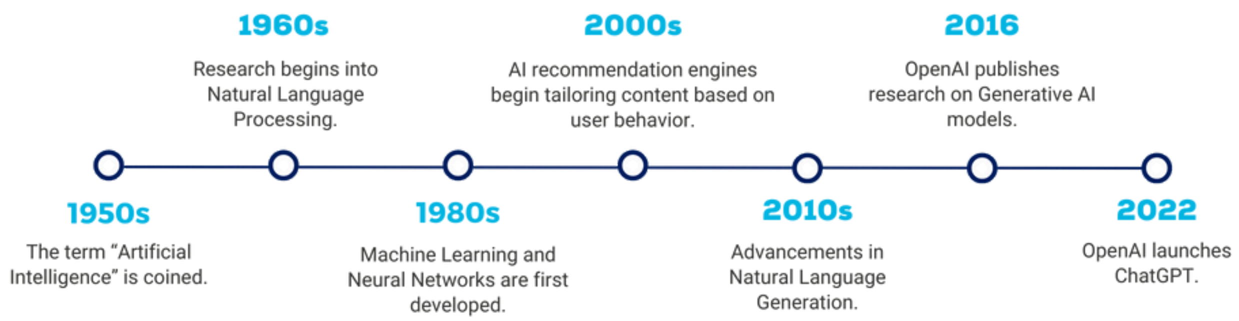
The journey to industrial AI from its early concepts has included an evolution of ideas, breakthroughs, and applications over many years. AI first came to being in the mid-20th century. Its roots are in the works of Alan Turing, whose Turing Test proposed the idea that a machine could simulate human intelligence. This was the beginning of computational thinking and the theory of AI.

2.1 EARLY CONCEPTS OF AI

In the 1950s and 1960s, AI witnessed its first milestones with the development of programs such as the Logic Theorist and ELIZA. They demonstrated the potential for machines to perform reasoning tasks and engage in human-like dialogue. These early achievements generated enthusiasm and funding for research followed.

Since then, high expectations often have been met with technological hurdles. However, there have been a number of advancements. The development of machine learning algorithms in the 1980s and the ability for neural networks to adjust to complex patterns laid the groundwork for deep learning. These technologies enabled computers to improve their capabilities over time without explicit programming for each task.

SIGNIFICANT EVENTS IN THE FIELD OF ARTIFICIAL INTELLIGENCE



2.2 MILESTONES AND INDUSTRIAL APPLICATIONS

The turn of the millennium marked a renaissance in AI research and development. It was fueled by exponential increases in computational power and data availability. AI systems became capable of defeating human champions in complex games such as chess and Go, which symbolized its growing proficiency and potential.

In the past 25 years, Industrial AI has witnessed the following advancements:

- Integration of AI in Industrial Automation: In the early 2000s, systems such as programmable logic controllers began to incorporate more sophisticated AI algorithms to optimize processes and reduce human intervention.

- Predictive Maintenance: AI started to play an important role in predictive maintenance by using machine learning models to predict equipment failures before they happen.

- The IIoT: The advancements of IoT technology in the 2010s led to a vast network of connected devices within industrial settings that allowed for real-time collection of operational data for analysis.

- Deep Learning: Especially in image and speech recognition, predictive analytics, and autonomous systems, deep learning has taken off within the past 10 years. It has been used for quality control, safety monitoring, and fully automated systems.

- Industry 4.0: The concept of the smart factory became a central part of the Industry 4.0 revolution. This involves everything from supply chain logistics to production lines, which are being optimized with operational data and systems powered by AI.

- Expansion of Robotics: AI has significantly advanced the capabilities of industrial robots, which are now capable of handling complex tasks and adapting to new environments in certain manufacturing settings.

Recently, the development of Generative AI and LLMs has again brought artificial intelligence into the spotlight. While AI techniques, including machine learning, have been used in the industry for many years, Generative AI is experiencing its peak of rapid advancement. A breakthrough in transformers has paved the way for innovations and new releases, including Open AI’s ChatGPT in 2023. In just over a year since the announcement of the breakthrough, several major tech companies have launched their own LLMs. These include Google’s Palm 2 and Meta’s Llama 2.

03

THE JOURNEY TO OPERATIONALIZING INDUSTRIAL AI

Manufacturers have been on a Digitalization Journey, which is the path to successful adoption of Industrial AI, since the early days of Industry 4.0. Factories are constantly adapting to an ever-changing digital landscape in pursuit of a smart factory. Those that continue to make digital improvements also go through a series of phases. Each of these represents growing digital and analytics maturity.

In the earlier phases of the journey, manufacturers learn that they can optimize process behavior with help from operational data. As they see success from their efforts, they also want to find more opportunities. The goal of the Digitalization Journey is to help manufacturers manage change more effectively so they can find those opportunities. It also provides a roadmap for greater agility when rolling out industrial AI applications.

There are four phases in the Digitalization Journey, and each provides new opportunities to find improvements. But they also have challenges—or gaps between them—that manufacturers must address before they can move to the next phase.

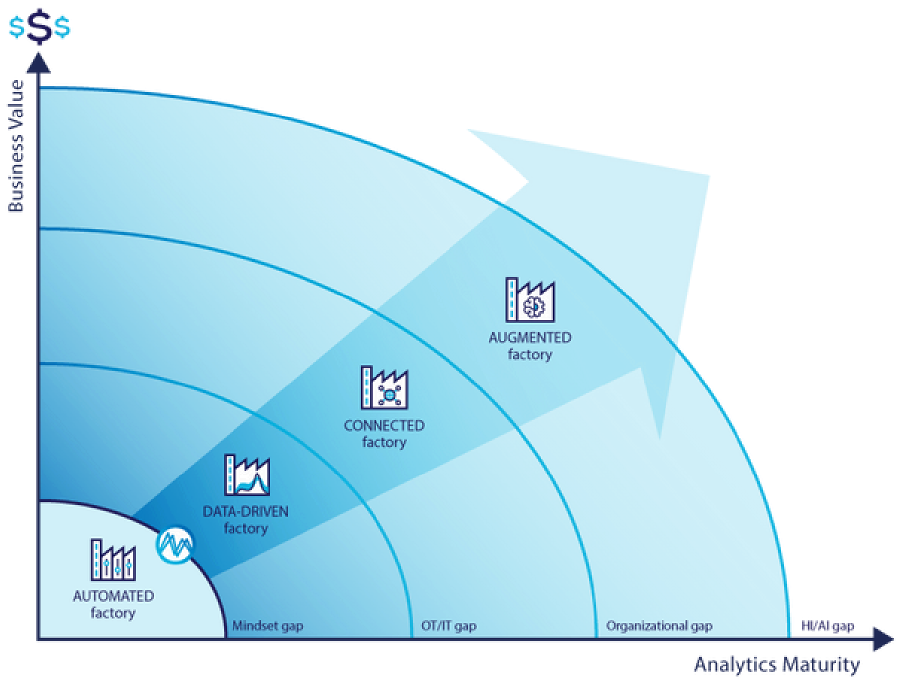


Figure 3. This model of the Digitalization Journey for the process manufacturing industry also shows the phases and challenges during a digital transformation.

Figure 3 illustrates the maturity model for the Digitalization Journey within the process manufacturing industry. During the journey, factories move from a state of simply collecting operational data to enhancing data-driven insights with AI and ML. The figure also shows the anticipated challenges between the various phases.

3.1 PRE-DIGITALIZATION: UNDERSTANDING TRADITIONAL METHODS

New factories are delivered as Automated Factories, and most manufacturers have been in this phase for years. Industrial software, such as Supervisory Control and Data Acquisition (SCADA) systems, help control complex production processes. SCADA systems were designed to collect data and monitor processes. Eventually, historians were added to SCADA systems to store the enormous amount of data they were collecting. They originally were used to fulfill regulatory requirements but have proven to be more valuable. Manufacturers began to realize that the industrial data in their historians could provide information on process behavior. However, accessing and using the data was very difficult.

Factories began using Manufacturing Execution Systems (MES) in the early 1990s to bridge the gap between SCADA systems and Enterprise Resource Planning (ERP) software. They also promised to provide analytics, such as KPI data, to improve plant operations. These systems have been able to provide advanced capabilities, but they are expensive and sometimes require extensive engineering.

Instead, operational experts began using spreadsheets to search through sensor-generated data. This helped them find the root cause of some issues. However, spreadsheets are not designed to analyze large datasets. Spreadsheet files also become large and hard to manage, so there is a greater risk of human error. For the 2-5% most critical systems, operational experts would plot trend lines on paper and overlay them against a window to analyze timeframes with similar behavior. However, this required multidisciplinary teams, so it could take months before engineers had actionable information.

3.2 WHY MANUFACTURERS MUST ADAPT

By themselves, these systems have proven to be impractical for getting insights quickly. Companies realized that they needed a user-friendly platform that provides a collaborative environment for engineers and data-scientists to gain actionable insights from sensor-generated data. Advanced industrial analytics software became the solution.

The journey toward Industrial AI is just one reason that manufacturers need to make data-driven decisions about production. Other reasons include:

1. Greater operational efficiency. Engineers must be able to quickly search through a specific period of sensor-generated, time-series data for answers to their everyday questions. They then must be able to visualize all of the related plant events that occurred during that period of time so that they see these events within their operational context. The contextual data for these events comes from various systems throughout the plant.

2. Better quality and batch control. Engineers need to accurately predict the outcome of a batch process. From a combination of time-series and contextual data, they can create a golden fingerprint of ideal batch parameters. It makes

batches that are more efficient, more consistent, and achieve the desired quality.

3. Rigid environmental and safety regulations. Through analysis, manufacturers identify areas where they have the most significant environmental impact and prioritize actions to reduce their environmental footprint. At the same time, they improve asset performance and increase the bottom line.

The digital era has provided the opportunity to transcend the limitations of traditional methods by harnessing the power of operational data, cloud computing, and advanced industrial analytics. This transformation includes the addition of technology, but it also represents a fundamental shift in how industries view their operational environment. To be successful in a Digitalization Journey, manufacturers need to take a holistic approach that integrates digital tools into the fabric of industrial operations.

3.3 OVERCOMING CHALLENGES ALONG THE WAY

Many new changes occur during the Digitalization Journey, and some people will resist them. Resistance to change is a natural response to the disruptive nature of digital transformation, but it becomes a significant barrier when it prevents progress along a Digitalization Journey.

The path from an Automated Factory to an Augmented Factory is marked by several gaps that must be bridged on the journey toward Industrial AI. They are:

- The Mindset Gap: Many people resist change and believe that the “old way” of doing things is better. This is the Mindset Gap. Overcoming this gap requires cultural change initiatives and change management approaches.

- The IT/OT Gap: The IT/OT Gap is a traditional divide between Information Technology and Operational Technology domains. This separation can create data silos and prevent data from being available for analysis. In newer business models, these systems are managed by a unified team.

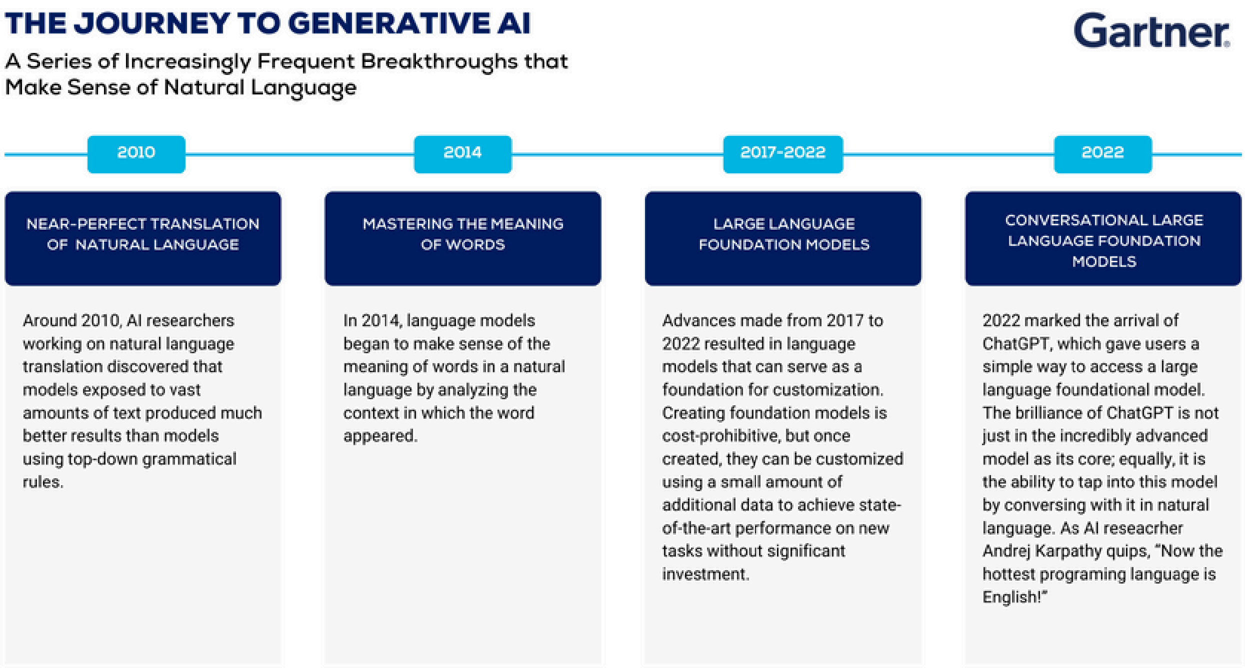
- The Organizational Gap: To close the Organizational Gap, manufacturers must align people, processes, and technology. Collaboration is essential to achieve higher efficiency in solving complex use cases.

- The AI/HI Gap: This gap represents the divide between engineers and their digital counterparts. Once a manufacturer has reached the Augmented Factory phase, it must achieve greater collaboration between operational experts and AI systems before advancing to Industry 5.0.

- Each of these gaps can be a source of resistance because of fear of the unknown, perceived threats to job security, or a lack of understanding of the benefits of becoming data driven. Overcoming this resistance requires a well-structured approach that includes leadership, training, change management practices, and ongoing support.

04 GENERATIVE AI: THE NEW FRONTIER

Generative AI is arguably the most exciting technology ever developed. By late winter of 2023, OpenAI's ChatGPT already had broken a record for the fastest-growing user base of any computer application in history. More than 100 million people were using the app weekly when OpenAI announced in early November that it was giving its ChatGPT Plus subscribers the ability to create their own GPTs, and the use cases—including those for industrial applications—are growing.



4.1 WHAT IS GENERATIVE AI?

The rapid advancements in Generative AI are the result of research breakthroughs since 2010 in transformers, which is the "T" in GPT (Generative Pretrained Transformer). A transformer is a type of neural network regression model, as shown in Figure 4, that takes an input sequence and turns it into an output sequence. These transformers allow for parallel processing of unlabeled datasets, which means they can be trained quickly with relatively few resources. Transformers are designed to process sequential material. This could be a sentence used in natural language or a collection of observations, such as time-series data.

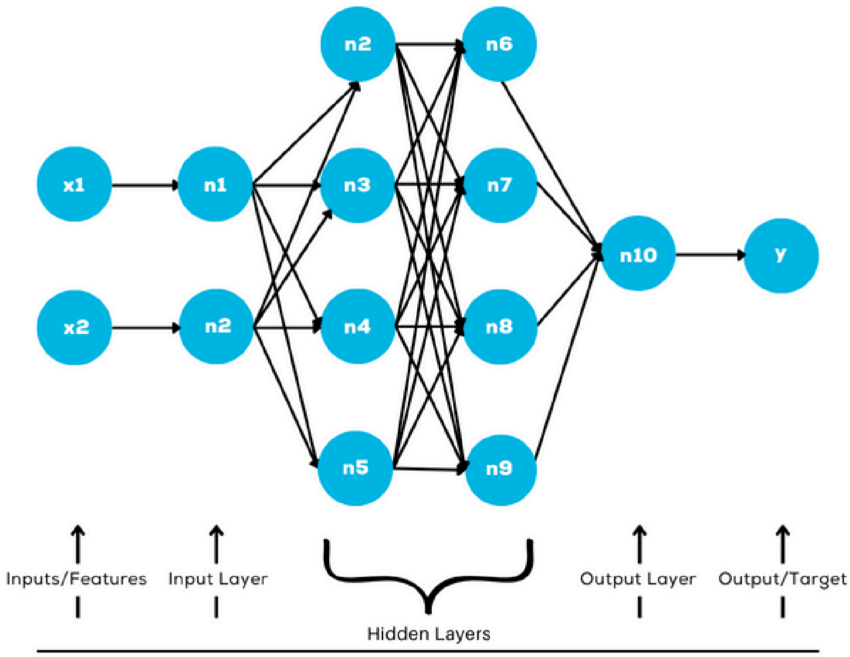


Figure 4. The most basic type of neural network is a Multilayer Perceptron (MLP). Here, it shows multiple input layers, hidden layers, an output layer, and a target variable.

The transformers used in Generative AI associate patterns and relationships between the sequential components. This means they learn these patterns and can repeat them, in context, at query. To get the desired result, they are trained on massive amounts of data. This gives them the name Large Language Models. Essentially, LLMs are trained on all available written data in the world at the time of their creation, or roughly all the information available on the internet.

4.2 NEW IDEAS WITH GENERATIVE AI

The use of natural language means that coding knowledge is not required to use a GPT. It also means that natural languages are processed well. This makes a GPT ideal for changing the tone of text to make it softer or sound more professional. It also creates tangible drafts of text tailored to the requested style and length.

But the use cases for Generative AI are more than just text generation.
They include:

- Discovery: Asking questions in a GPT search field, which leads to the discovery of answers that might not otherwise have been found.
- Summarization/simplification: Quickly generating abbreviated versions of lengthy articles and web pages, as well as creating outlines and extracting key points from content.
- Classification: Sorting topics for specific use cases.
- Code generation: Creating portions of code or generating entire software programs.
- Product design: Meeting the demands of creating new product ideas.

This new technology is also useful for helping operational experts make improvements throughout the plant.

4.3 ETHICAL CONSIDERATIONS AND MANAGING EXPECTATIONS

As industries increasingly use Generative AI, they need to address a number of growing ethical concerns. According to an article by McKinsey & Co., concerns include a lack of transparency in how Generative AI systems function as well as:

- Their training data,
- Bias and fairness in generation,
- Intellectual property infringement,
- Privacy issues,
- Risks associated with third-party tools, and
- Security.

The reliance on datasets that contain sensitive operational information requires safeguarding measures to prevent unauthorized access and breaches. The protection of such data is not only a matter of maintaining competitive advantage but also of upholding the confidentiality of potentially sensitive information that could affect a stakeholders' privacy and security. Various privacy and data protection laws also must be considered before using such data.

The advent of Generative AI also prompts a reevaluation of workforce dynamics. The potential for AI-driven automation to replace human roles raises many concerns. Manufacturers should take the initiative to emphasize the importance of human-AI collaboration. By fostering an ecosystem where AI augments human capabilities rather than replaces them, manufacturers prioritize the reskilling and upskilling of their workforce to ensure that the integration of AI contributes positively to the job market.

Furthermore, the transparency and explainability of AI-driven decisions holds ethical significance. The decisions made by AI systems in industrial applications can have far-reaching implications, from affecting production quality to influencing environmental sustainability. Transparency is important for building trust among users and ensures that AI-driven decisions are subject to scrutiny, validation, and accountability.

The issue of bias in Generative AI outputs also warrants careful consideration. Because AI systems learn from historical data, there is a risk of perpetuating existing biases or inefficiencies that are already within that data. Ethical deployment of AI in industrial settings requires measures to detect and mitigate biases so that output is fair and correct.

Despite these concerns, early use cases of Generative AI in industrial settings shows great potential.

05 PRACTICAL APPLICATIONS ALONG THE JOURNEY

Manufacturers at every phase of the Digitalization Journey find a tangible use for the insights that are made available by leveraging operational data. In solution areas such as anomaly detection, predictive maintenance, or classification, the addition of artificial intelligence or machine learning simply makes the task easier or provides more efficient options.

For example, anomaly detection is frequently mentioned as a use case for AI and ML. However, there are many ways to detect anomalies that do not require more advanced types of analysis. The following demonstrates how a manufacturer can detect anomalies at every phase of the Digitalization Journey.

5.1 EARLY ANOMALY DETECTION TECHNIQUES

Anomaly detection can identify unusual patterns or deviations from normal operation in real-time. Early detection allows manufacturers to address issues before they become serious failures, which prevents costly downtime and potential damage to machinery. It also helps with planning for predictive maintenance schedules. Use cases at different phases of the Digitalization Journey are shown in Figure 5.

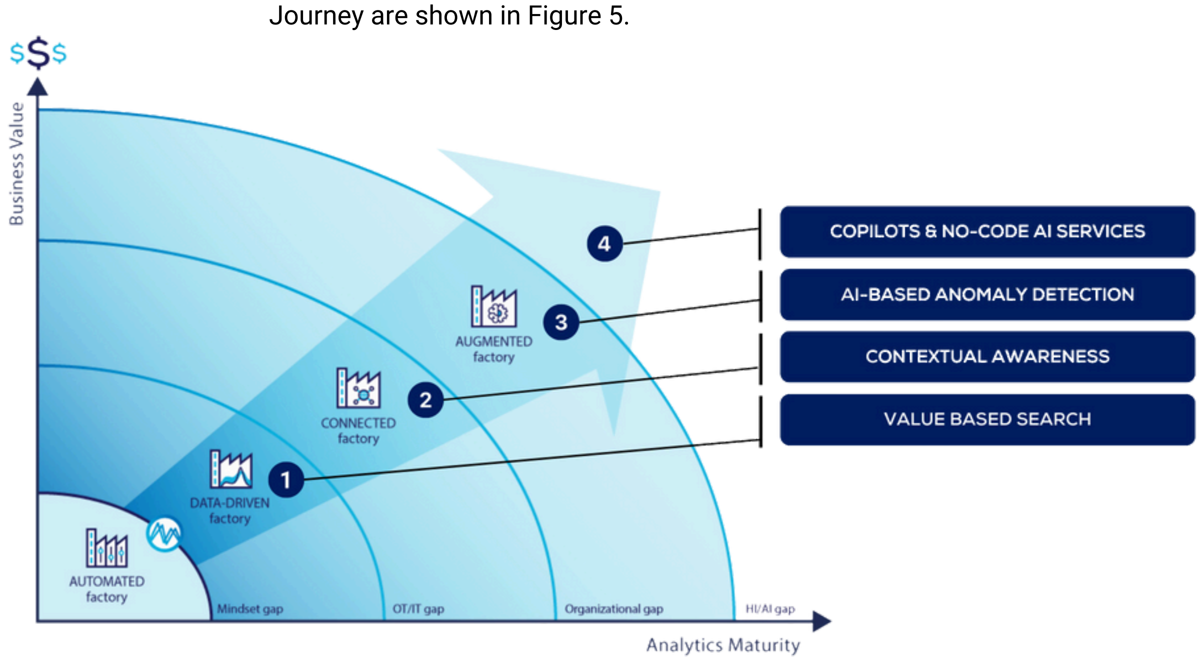


Figure 5. Companies can find use cases for operational data at every point along the Digitalization Journey.

In the Data-Driven Factory phase, anomaly detection is limited to the information contained within time-series data. However, it is still possible to find the root cause of anomalies and prevent them. One way is to conduct a value-based search of time-series data to find outliers from expected patterns. These outliers are presented using visualizations that help operational experts quickly see the problem and understand it. They can take this a step further by creating a dashboard monitor that will alert them when an anomaly occurs so that they can correct the problem before it leads to a complete shutdown.

More opportunities become available for advanced anomaly detection at the Connected Factory phase. Here, operational experts use data from various systems to strengthen the understanding of the anomalies within their operational context. For example, planned shutdowns for maintenance or shift changes can be filtered from the results, which allows for a cleaner analysis. It also helps operational experts create a golden fingerprint from the ideal batch parameters, which further aids in the detection of anomalies that are outside the ideal profile.

5.2 APPLYING ML TO ANOMALY DETECTION

At the Augmented Factory level, the insights gathered through the early phases of the Digitalization Journey become a trusted data source for developing and training AI and ML models. Generally, these fall into two categories, as shown in Figure 6. Self-service AI models are available off the shelf. They are premade for a specific purpose and can be deployed quickly into operations with minimal changes. They provide opportunities for a wide range of use cases and are especially helpful for those just starting with systems powered by AI or ML models.

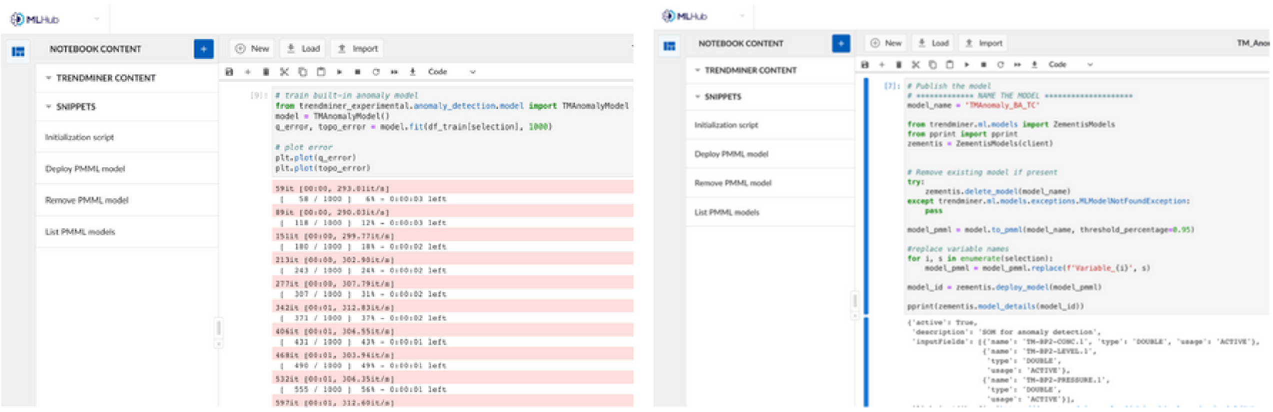


Figure 6. Manufacturers have a choice of using a self-service ML model or creating a custom model in a Python notebooks environment.

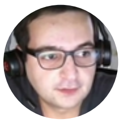
The second type is a custom-built model. These are generally developed in Python and require extensive knowledge of the programming language as well as statistics. Using anomaly detection as an example, the application of a Self-Organizing Map (SOM) uses self-service models that are capable of finding both global and local outliers within a multivariate context. These models are trained using time-series data from a normal operating period. They are then combined with ML techniques to create models that detect anomalies on new, incoming data.

These models already are providing benefits in the industry. For example, specialty chemical company Clariant has developed models that include soft sensors, anomaly detection scoring, and predictive maintenance alerts.

The integration of these machine learning capabilities has helped Clariant achieve substantial operational improvements. Notably, the manufacturer recorded a 10% reduction in batch processing time, or the equivalent of one batch a day. Moreover, the enhancements in operational efficiency led to a 9% reduction in energy consumption.

> ***"What we do is get the data from the cloud and import it into TrendMiner. We then gather the time-series data from there and use our own algorithms and our own data science platform, where we then derive analytics from it, discuss the results and get opinions for the next steps."***

Nimet Sterneberg,
Data Scientist, Clariant



5.3 USING GENERATIVE AI TO FIND ANOMALIES

In an even more advanced situation, operational experts could use the power of Generative AI to detect anomalies. Because Generative AI solutions and LLMs are great at generating natural language text, they are also good at structuring natural and programming languages. They also can query a database or assist with problem-solving. In fact, they make good copilots for engineers and data scientists.

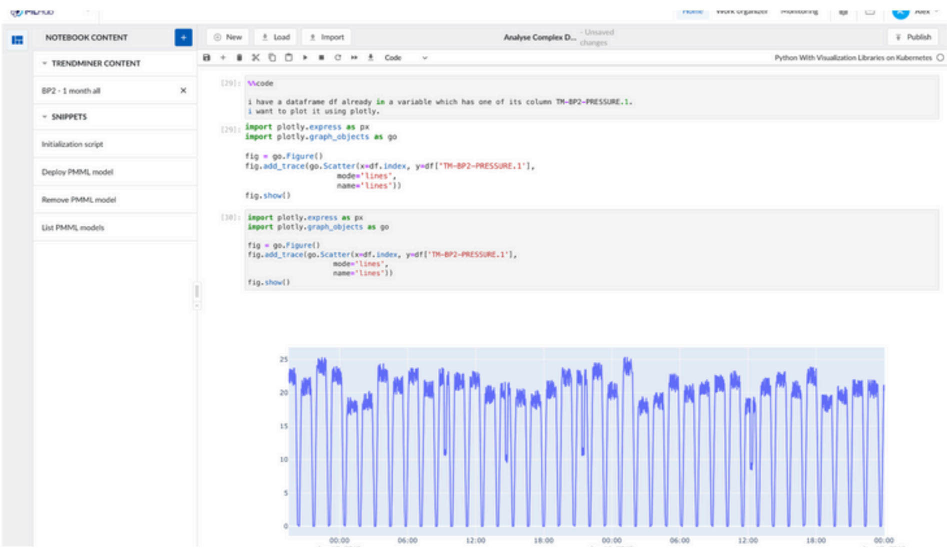


Figure 7. By combining known insights with Generative AI, engineers and data scientists could produce snippets of Python code or even complete machine learning models.

For example, a data scientist could use Generative AI to create the Python code needed to develop a machine learning model, as shown in Figure 7. When combined with operational insights, they can quickly train an anomaly detection model or soft sensor. This method speeds up a time-consuming task and creates models with the right technical functions in place. It also splits up datasets and generates the code for model deployment.

5.4 THE FUTURE OF ANOMALY DETECTION

In the future, the trust of autonomous systems may lead to the development of automations for detecting maintenance, finding anomalies, and other areas. For now, the best way to detect an anomaly in a manufacturing setting with the help of AI also requires the decision-making skills of an engineer.

Research is ongoing for a way to chain LLMs together to work on a bigger singular outcome, where one set of LLMs could ask questions to other LLMs that are trained on something different. That second set of LLMs then could request a specific AI function to classify or to forecast another piece of information. It then could feed that back to a whole chain of events that eventually lead to an outcome. In theory, these outcomes could mimic human intelligence or even surpass the job a human could do.

06 THE BENEFITS OF AI

The benefits of adopting AI solutions are seen long before its technology is available in the factory. Manufacturers begin to realize these benefits when they make the decision to embrace all operational data. From democratizing its availability to harnessing its insights, each step of the Digitalization Journey also provides value on the road toward AI.

6.1 IMPROVEMENTS ALONG THE JOURNEY

To ensure accuracy and reliability, the right data is necessary for training AI and ML systems. As shown in Figure 8, quality data leads to precise predictions, operational efficiency, and cost reductions. It also enables AI adaptability to new trends, which fosters innovation and sustained growth.

In a manufacturing environment, this data includes but is not limited to:

- Machine sensor time-series data,
- Quality metrics,
- ERP data,
- MES data,
- Labeled human input, and
- Maintenance data.

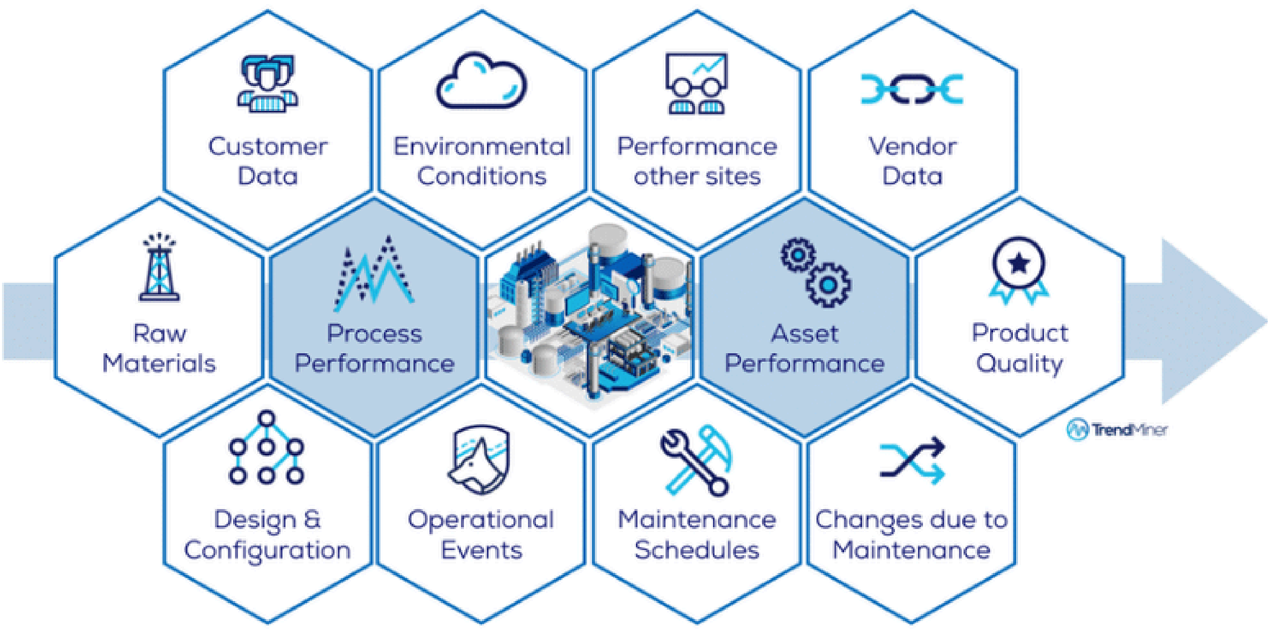


Figure 8. As raw materials are turned into products, many types of data from different systems are leveraged to make a higher quality product

Each of these data sources provides valuable input for AI and ML models to enhance their capability to predict and optimize processes as well as automate tasks within the manufacturing environment. In exchange, the systems create models for anomaly detection, classification, and forecasting. They also are derived from improvements made on the road to AI success. These more advanced insights into operational behavior were obtained after leveraging other operational data sources, such as time-series and contextual data, and generating insights from that information. Those insights then can be saved and used to train AI and ML models.

6.2 SOLUTION AREAS IN FOCUS TODAY

In general, there are four areas where Industrial AI shows the most potential to provide benefits.

ANOMALY DETECTION

Anomaly detection models made with AI and ML techniques keep multiple operating parameters in check and indicate different failure modes to explore. Knowing when failures occur also helps plan predictive maintenance schedules.

CLASSIFICATION

Classification algorithms can be used to identify and organize information based on multivariate inputs. For example, algorithms can tell if a batch meets its quality expectations or the type of product grade it could be used for. This could even be forecast while production is still running to give engineers time to adjust the process so it meets expectations before the end of the run.

FORECASTING

Industrial AI aids in forecasting with the help of time-series data. It predicts equipment statuses and product quality with high accuracy, facilitates prescriptive maintenance, and minimizes downtime. Predictive quality analytics help maintain standards and reduce waste, while AI-enhanced demand forecasting optimizes production schedules and inventory.

SUMMARIZATION

Summarization uses AI assistants and production reporting tools to automatically analyze and condense vast amounts of production data. This provides succinct, actionable reports and helps monitor compliance.

6.3 QUANTIFYING THE BENEFITS

Furthermore, manufacturers can begin seeing the results of these improvements immediately. During the journey, it is important to periodically measure how far an organization has come since it began to adopt AI strategies.

BASELINE MEASUREMENT AND KPI IDENTIFICATION

Begin by assessing operational efficiencies, output levels, and quality rates to establish a clear baseline. Clearly define Key Performance Indicators (KPIs) relevant to the company's goals and AI's potential areas for improvement, such as Overall Equipment Effectiveness (OEE), yield rates, downtime, and maintenance costs.

OPERATIONAL IMPROVEMENTS

By integrating AI, manufacturers can expect a number of improvements that can be measured. These include increased throughput, reduced cycle times, and higher resource use. Also, AI's ability to improve product quality by reducing defect rates and rework leads to significant cost savings.

STRATEGIC BENEFITS

The strategic advantages of AI extend beyond immediate operational gains. Technology powered by AI facilitates quicker product development cycles. It also enables product customization and a provides competitive edge by improving responsiveness to market changes. Furthermore, by upskilling employees and enhancing their decision-making capabilities, the journey to AI adoption contributes to a more engaged and efficient workforce.

FINANCIAL METRICS

A comprehensive financial analysis includes calculating ROI and determining the payback period. Compare the costs associated with AI implementation and ongoing operations against the financial gains. Understanding the financial benefits helps to justify the investment and future expansions.

LONG-TERM STRATEGIC VALUE

AI's scalability is the cornerstone of long-term strategic planning. Its ability to adapt to evolving business needs ensures its continued relevance and value. Moreover, capitalizing on the wealth of data generated and analyzed by AI provides invaluable insights for strategic decision-making and positions the company for sustained success in an increasingly competitive landscape.

07 THE ROAD AHEAD FOR INDUSTRIAL AI

7.1 SKILLS FOR AN AI-ENHANCED WORKFORCE

Operational experts and data scientists do not have to start out as data engineers to use industrial AI systems. Yet, as they become more comfortable with making data-driven decisions, they will find that they become citizen data engineers in their own right. Skills such as programming and statistics are helpful for some jobs, but they are not expected—nor required—of most end users.

Instead, soft skills are becoming increasingly critical for process engineers. Adaptability is important. Engineers need to be able to embrace new technologies and methodologies. Equally important are creative problem-solving skills. As data-driven insights reveal new opportunities and challenges, operational experts need to come up with new solutions to meet them. Collaboration and communication skills are also essential for cross-functional teamwork with stakeholders across the organization. A strategic mindset also encourages a focus on scalability, sustainability, and the potential for technological advancements to drive competitive advantage and customer value.

The integration of industrial AI also requires a change in management skills. Management must champion the adoption of Industrial AI and mitigate resistance to change. The role involves managing not just technical adjustments but also a transformation in organizational culture and mindset. As they work with process engineers to foster a data-driven environment, they become pivotal in building a resilient, forward-looking workforce that is equipped to harness the full potential of Industrial AI.

7.2 MAKING TRENDMINER YOUR PARTNER

The journey toward Industrial AI is an exciting adventure, and it requires a partner that is well equipped to meet the needs of the evolving landscape. By choosing TrendMiner's advanced industrial analytics platform, manufacturers ensure that their own unique needs and challenges will be met along the way.

TrendMiner's capacity to leverage time-series, contextual, and asset data empowers process engineers and data scientists to optimize operations in real-time and anticipate future process behaviors. It provides operational experts with the insights they need at any level of analytics maturity, from diagnostic analysis and monitoring capabilities in a real-time environment to MLHub for collaboration on a data science exercise.

Powered by AI, TrendMiner's flexible deployment options fit with the varied IT landscapes and security requirements of manufacturers at all phases along their AI journey.

7.3 PREDICTIONS FOR THE FUTURE

In the early days of Industry 4.0, data analytics was still a mystery to most companies in the process manufacturing industry. Today, many companies rely on operational data for daily decision making. Engineers already using a state-of-the-art advanced industrial analytics platform such as TrendMiner also find that they are well on their journey toward Industry 5.0.

Industry 5.0 is the ongoing digital transformation of traditional manufacturing and industrial practices. It represents a shift toward newer technologies, such as systems powered by AI. As an extension of the digital transformation started during Industry 4.0, Industry 5.0 adds Human Intelligence (HI) to those new technologies. It aims to improve communication and collaboration between humans and their automated counterparts. Like its predecessor, Industry 5.0 also seeks to optimize manufacturing processes. The skill and experience of a process engineer are necessary to make operations decisions that are in the organization's best interest.

An Augmented Factory allows engineers to manage their processes by exception. This lays the foundation for the first phase of Industry 5.0. However, because Industry 5.0 is conceptual, these phases have not been defined yet. When they are, each will add an additional layer of Human Intelligence to the AI systems developed and integrated during Industry 4.0. With the development of systems such as coding co-pilots in AI environments, engineers will use advanced industrial analytics to collaborate with data scientists, other experts at various local sites, and with their digital counterparts.

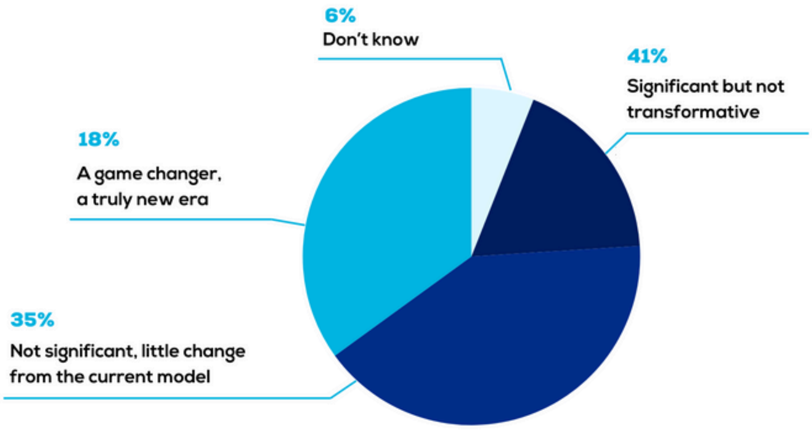


Figure 9. This chart based on information from the Manufacturing Leadership Council shows that many believe Industrial AI will be a significant change for the process manufacturing industry.

In fact, The Manufacturing Leadership Council, through its Manufacturing in 2030 Project, fielded a survey on AI to its members and others in the manufacturing community to assess their perceptions, plans, expected benefits and challenges in using Industrial AI, as shown in Figure 9. Almost all respondents said their companies expected to increase funding for Industrial AI initiatives. Furthermore, 57% are piloting and experimenting with AI systems to identify how they can use Industrial AI in future business models.

ABOUT AUTHORS

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Julian Pereira has a background in chemical engineering with extensive experience as a process engineer leading improvement projects onsite and later driving analytics solutions for the process manufacturing industry. Julian is passionate about transforming challenges into valuable solutions through consistent technology innovation and currently leads the TrendMiner Product team.

ROB AZEVEDO
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Rob Azevedo has a background in Computer Science by education and years of experience in building software platforms, which include B2B business applications and high performant B2C ticketing and entertainment experiences that were viewed by millions. Rob has always been passionate about new user experiences driven by technology. It’s that knowledge and drive that he now uses to bring Digital Transformation, Artificial Intelligence, Industry 4.0, and data analytics initiatives to market.

08 GLOSSARY OF TERMS

ANOMALY DETECTION
The identification of items, events, or observations that deviate significantly from the standard or expected pattern in a dataset. Vital for monitoring industrial processes to quickly identify and rectify deviations.

ARTIFICIAL INTELLIGENCE (AI)
The simulation of human intelligence processes by computer systems, including learning, reasoning, and self-correction.

ASSISTED INTELLIGENCE
Refers to AI systems that assist humans in making decisions or taking actions by providing support and enhancements to existing processes without autonomously operating.

AUGMENTED INTELLIGENCE
A collaboration model in which AI systems enhance human intelligence, provide advanced insights, and support decisions.

AUTOMATION INTELLIGENCE
Involves the use of AI to automate routine tasks, which improves efficiency and productivity. It often applies to repetitive and predictable tasks where it can reduce the need for human intervention.

AUTONOMOUS INTELLIGENCE
Describes AI systems that can operate independently without human intervention. They make decisions and perform tasks in a self-governing manner based on programmed algorithms.

GENERATIVE AI
A branch of AI focused on creating new content by leveraging models such as GPTs and variational autoencoders to generate outputs that can mimic human-generated content.

GENERATIVE PRE-TRAINED TRANSFORMER (GPT)
A type of Artificial Intelligence model that uses Deep Learning techniques to produce human-like text. It is pre-trained on a large amount of text and then fine-tuned for specific tasks.

INDUSTRY 4.0
The current trend of automation and data exchange in manufacturing technologies. It includes cyber-physical systems, the Internet of Things, cloud computing, and cognitive computing. Also known as the Fourth Industrial Revolution, Industry 4.0 uses interconnectivity, automation, machine learning, and real-time data.

INDUSTRY 5.0
A forward-looking vision beyond Industry 4.0 that emphasizes the collaboration between humans and smart systems. It highlights personalization, sustainability, and enhancing human capabilities in the workplace through advanced technologies such as AI.

LARGE LANGUAGE MODEL (LLM)
A type of machine learning model designed to understand, generate, and interpret human language. These models are trained on vast datasets of text that allow them to perform a variety of natural language tasks including translation, summarization, and content generation.

Machine Learning (ML) — A subset of AI involving algorithms that learn and make predictions or decisions based on data, improving performance on tasks over time.

MULTILAYER PERCEPTRON (MLP) — A class of feedforward artificial Neural Network that consists of at least three layers of nodes: an input layer, one or more hidden layers, and an output layer. MLP uses a backpropagation technique for training that is suitable for complex pattern recognition tasks.

NATURAL LANGUAGE PROCESSING (NLP) — Gives computers the ability to understand, interpret, and produce human language and speech, used in industrial analytics for analyzing maintenance logs.

NEURAL NETWORK — A computational model inspired by the human brain's network of neurons. It consists of layers of interconnected nodes that process inputs and can learn to perform complex tasks by adjusting the connections based on the input and desired output.

PREDICTIVE ANALYTICS — Uses data, statistical algorithms, and machine learning to predict future outcomes based on historical data, aiding in process behavior anticipation.

PROCESS ANALYTICS — Examines and analyzes operational data to improve production process efficiency and effectiveness by identifying data patterns, trends, and relationships.

PYTHON — A high-level, interpreted programming language known for its clear syntax and readability. It is widely used in data analytics and statistics.

REINFORCEMENT LEARNING — A machine learning type where an algorithm learns decision-making by taking actions to achieve a goal, learning from action consequences.

SUPERVISED LEARNING — Machine learning where the algorithm is trained on a labeled dataset, with each training set example paired with the correct output.

UNSUPERVISED LEARNING — Trains algorithms on datasets without pre-existing labels, allowing it to identify data patterns and relationships independently.

LEARN MORE

At Trendminer, we are dedicated to helping companies leverage the power of data to drive transformation and growth. We hope this White Paper has given you new insights and ideas for how you can achieve your goals. If you have any questions or would like to learn more about our solutions, please don't hesitate to reach out. We look forward to working with you on your journey to success.

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