



# ARTIFICIAL INTELLIGENCE IN INDUSTRIAL MARKETS

## WHY ARTIFICIAL INTELLIGENCE MATTERS TO INDUSTRIAL MARKETS

Industries like manufacturing, mining and construction are sometimes characterized as digital Luddites, with an odd attachment to business relics like fax machines, paper catalogs, clipboards and Post-it Notes.

In reality, of course, industrial companies have been at the forefront of technological innovation for decades, with sophisticated robots and other complex, highly-automated machinery widely deployed on the shop floor and in the field.

Nonetheless, it is true that there is a real, widely-acknowledged gap between this operational technology and business-centered information technology (IT). Industrial markets have long trailed others in their level of IT investment. This, however, is about to change.

Industrial companies are now expected to outspend their B2C counterparts on digital transformation solutions. Will this investment yield the same kind of disruption and transformation seen in industries like retail, banking, insurance and health care? This remains to be seen.

### Digital Transformation is More Than Simple Digitalization

Global market intelligence firm IDC has found that most manufacturers' digital transformation investments will not yield the results they seek. Why? For some, it will be because their efforts are not really geared toward "digital transformation" but rather "digitalization", which is focused primarily on improving efficiency.

While efficiencies are desirable (who doesn't want to save time, lower costs, or reduce waste?), the changes resulting from digitalization are not transformational, and the yields are likely to be minimal: industrial companies have already spent years using dozens of strategies to squeeze out every ounce of production and supply chain efficiency they can.

Digital transformation, on the other hand, goes far beyond efficiency. It is a strategy that encompasses digitalization, yes; but it also enables continuous and substantive process improvement, increased agility and, most importantly, breakthrough innovation.

### What is Digital Transformation?

IT analyst firm Gartner, Inc., defines "digital **business** transformation" as "the process of exploiting digital technologies and supporting capabilities to create a robust new digital business model." It's an important definition in that it places "business" literally in the middle of "digital transformation," and it foregrounds the development of a new business model that is data-centered ("a new **digital** business model").

It is the kind of definition Jeffrey Immelt, former Chairman and CEO of General Electric, had in mind as he mused on the impact of the Internet of Things (IoT) on industrial companies. His advice to his peers? Digital transformation is going to reshape your market more profoundly and more rapidly than you can imagine: "If you went to bed last night as an industrial company, you're going to wake up today as a software and analytics company."

"If you went to bed last night as an industrial company, you're going to wake up today as a software and analytics company."

Jeffrey Immelt, former Chairman & CEO  
General Electric

Specifically, digital transformation involves using data, analytics, and connectivity to rethink everything you do from the perspective of your customer, and using these same tools as the backbone of new products and services for a compelling, personalized customer experience. Let's see how this kind of deep transformation can be achieved via advanced technologies like artificial intelligence and machine learning.

---

# US\$690B

Approximate amount IDC forecasts discrete and process manufacturing will spend on digital transformation solutions in 2023, representing nearly 30% of total global DX spending.  
[IDC Worldwide Semiannual Digital Transformation Spending Guide](#)

---

## INDUSTRIAL APPLICATIONS OF ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

The use cases for artificial intelligence (AI) and machine learning (ML) in industrial markets (see Appendix) are quite broad and diverse, but behaviorally they are somewhat similar. Like a valued butler, a good AI or ML application is a helpmate, anticipating needs, managing tasks, and providing trusted advice (recommendations). Below are some examples of the kind of valuable assistance AI and ML can provide throughout a product's or an asset's lifecycle.

### Predictive Maintenance and Field Operations

The most commonly cited industrial application of AI is predictive maintenance, e.g. the ability to predict when an equipment failure will happen to avoid expensive downtime costs. Few people realize how much AI can be used upstream, downstream, and beyond these specific AI-powered predictive models in order to design and scale the benefits of AI to all field operations.

ML-enabled field support can assist with:

- Maintenance, Repair and Operations planning;
- Generation of preventive and predictive maintenance recommendations;
- Analysis of quality issues;
- Automation of routine operations and maintenance tasks using automation software, robots, autonomous vehicles and drones;
- Interpreting and funneling operational data back to teams working on service design; and
- Interpreting and sharing performance data, along with other quality-related data like customer feedback and warranty information, to manufacturing teams.

### BENEFITS OF PREVENTIVE MAINTENANCE



Improved reliability and life of equipment

Fewer costly repairs and downtimes associated with unexpected equipment failure



Fewer errors in operations as a result of equipment working incorrectly

Reduced health and safety risks



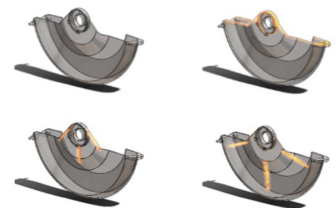
### Design

In the conceptual phase of product development, ML is applied in combination with virtual engineering models and simulation for iterative design.

With these technologies, millions of design options can be cycled through in an instant, with recommendations automatically generated for optimal solutions based on multiple criteria (cost, sustainability, time, regulatory requirements, etc.).

AI and ML are also valuable in the earliest ideation stages. They are being used in cognitive search systems to help designers explore existing design concepts via both text and image searches. And they can help designers understand customer demand through analysis of sources like social media or internal customer feedback systems.

Which Design is Better?

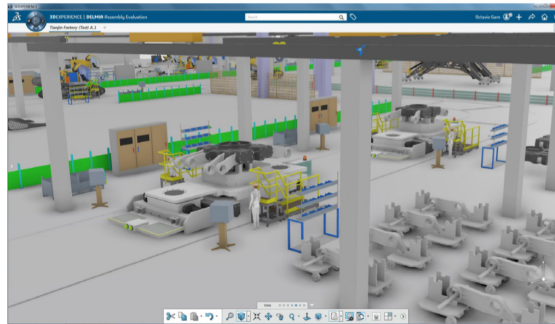


## Testing

ML can also be used to develop highly accurate digital models of both physical objects and systems. This enables the development of realistic behavioral models that can be used to run performance simulations. This use case is so well-established that physical prototyping has been all but eliminated in some industries (architecture, automotive, aerospace).

## Manufacturing

ML-powered digital modeling and simulation (including virtual reality systems) are also being used to 1) plan production lines and systems, 2) develop and integrate smart equipment, smart robots and production-line drones, 3) recommend and execute proactive maintenance (preventive/predictive maintenance), and 4) funnel important production data back to teams working on product design and specifications.

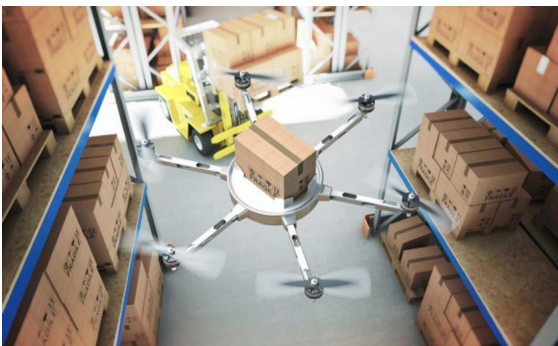


**Factory Flow Simulation**

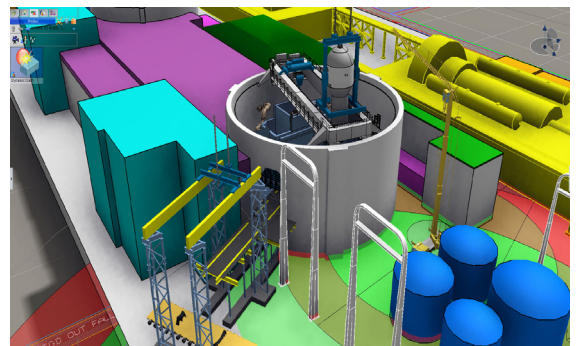
## Sales & Marketing

In commercialization phases, AI and ML applications are being used to:

- Predict demand trends,
- Deliver highly personalized/micro-targeted marketing,
- Create intelligent, multi-lingual bot assistants for self-service ordering and support,
- Power sales- and marketing-related virtual and augmented reality applications, and
- Customize products and services.



**Drones are being integrated into logistics systems**



**A 3D plant model can be used for training**

## Summary Benefits of Machine Learning in Industrial Contexts

The most significant payoffs of using ML in industrial sectors include greater innovation, process optimization and industrialization, automation, and improved quality, with the latter often yielding the quickest returns.

Real-time monitoring systems for early detection of issues, advanced cognitive systems for issue investigation, predictive maintenance systems, and feedback loops for design teams have proven to be helpful aids in enhancing quality and reducing direct and indirect costs related to rework, waste, warranty claims, and recalls.

When solutions like these and other ML applications share common digital models of products and assets, and are deployed via a common collaborative platform, they can also provide the consistent digital thread (digital continuity) needed for continuous product and process innovation. This makes immediate wins in quality improvement an important lever for exponential gains through accelerated innovation.

## KEY CHALLENGES OF ARTIFICIAL INTELLIGENCE IN INDUSTRIAL SECTORS

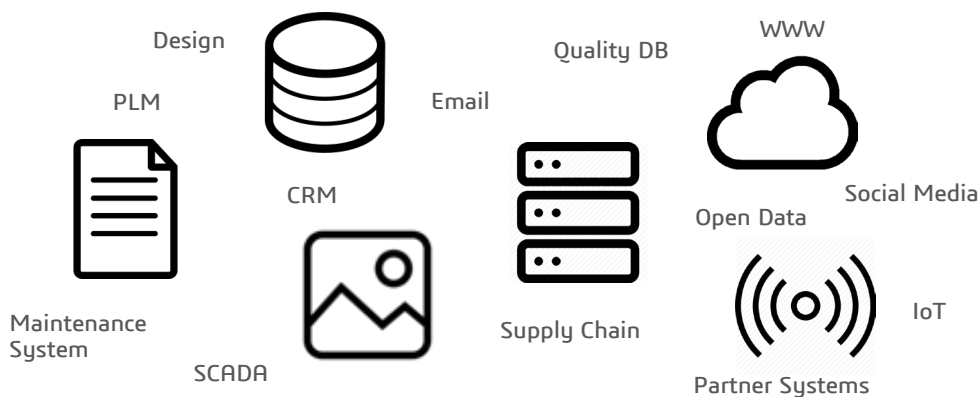
To reap the full value of quality improvements and other potential AI and ML benefits, several important challenges will need to be overcome. Scaling AI and ML to the organization requires more than just the right amount of data and the right infrastructure. Scaling ML requires collaboration.

### Collaboration vs. Data Silos - In-Context Information is Still Stuck in Silos

One of the core challenges of ML is providing it with the proper fuel, that is to say the right data. Getting the right data usually requires tackling enterprise silos, including data silos and silos of analysts and analytical products.

On the data side, this means combining disparate types of internal and external data (sound, images, text, 3D files, structured data, etc.) in order to provide the full context for design, production or field operations issues. This context is valuable not only because it enables smarter, better-informed analyses and recommendations, but because it gives human beings greater confidence in relying on machine-generated answers.

## ANALYTICS CHALLENGE: INFORMATION SILOS



### **Collaboration for Trust in Data - Black Box/White Box Balance**

This issue of confidence is important in ML for business. Executives and operations teams often demand to understand the recommendations and algorithms used to produce results, but this too often forces data scientists to sacrifice model efficacy in order to boost legibility. A better option is to allow specialists to craft optimal algorithms and to share their work and data with peers, and to “whitebox” only the context for non-specialists, providing visibility and drill down into the parameters and data used, but not the algorithms themselves.

### **Collaboration to Scale the Benefits to the Broader Organization**

Likewise, it is important to industrialize ML outputs that prove to be of value. This means packaging and integrating them in a platform to make them accessible to all enterprise applications, across all teams and lifecycle processes. Using a platform strategy to break down analytical silos also enables critical governance for ML products, supporting standardization, certification, IP protection, personnel training (a perennial challenge), and traceability.

Without such governance and industrialization, ML cannot truly support continuous process or product innovation and improvement.

But with the right discipline and technology choices, these challenges are all addressable. What’s most important now is to define the right digital business platform for your business in order to enable the right collaboration capabilities across your organization, and set your company on the path to leveraging AI and ML for your digital transformation. An evaluation should be performed to identify the internal capabilities and talents required in each of these collaboration areas, and a blueprint developed for leveraging these internal and external resources. With competition tight for data science professionals, a more efficient collaboration will be mandatory.

## **REALIZING THE VALUE OF ARTIFICIAL INTELLIGENCE IN INDUSTRIAL SECTORS**

### **Digital Continuity & Digital Twins**

Digital continuity is about creating an environment where all information from every phase of a product or asset’s lifecycle - from concept to disposal or reuse - is captured in real time and transformed into actionable insights.

Manufacturers have long wanted this kind of full lifecycle visibility, but they have been frustrated by either siloed data, or data deserts (nonexistent data for certain objects and events). Now, enhanced data access technologies and sensor-based IoT connectivity can deliver the comprehensive data and data views needed.

What’s more, a “digital twin” of a physical process, product, asset or environment can provide a unique, authoritative and consistent referential for this lifecycle data. For instance, a 3D CAD model of a product can provide a referential to which data can be linked from conception through to design, engineering, manufacturing and post-sales service.

Going a step further, a simulation-capable twin, like Dassault Systèmes’ virtual twin experience, provides more than just a consistent, “single-version-of-the-truth” referential. It is an extremely powerful tool for iterating through scenarios and options for everything from design to fabrication to maintenance and repair, for continuous improvement and innovation. And the more real-world data the digital model is fed, the more accurate and valuable are the simulations it supports.

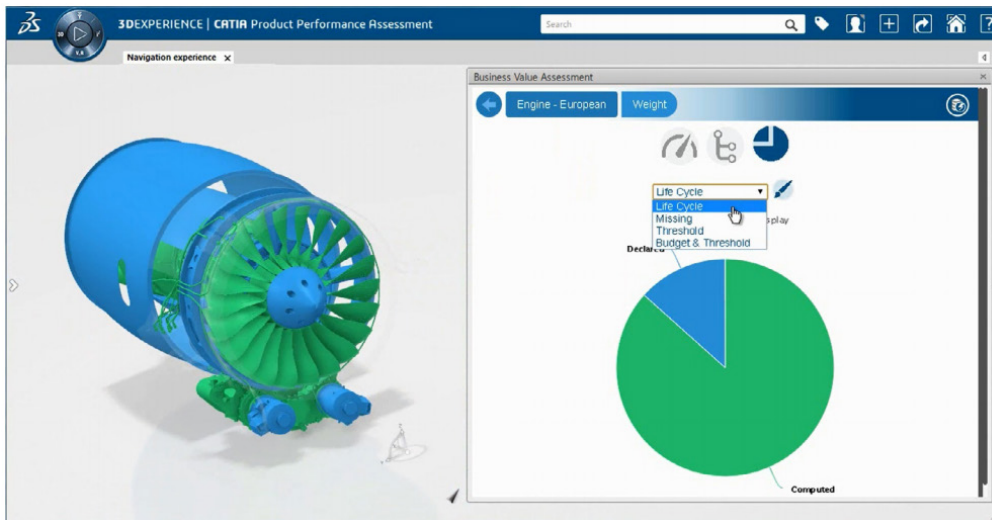
### **The Right Digital Collaboration Infrastructure**

Digital transformation requires a general foundation of social, mobile, cloud and Internet technologies. Connecting people, places, and objects, and enabling anywhere, anytime collaboration, is at the heart of the digital age.

For digital continuity and the proper functioning of digital twins, a business platform with integrated search capabilities is a requirement. This type of platform can connect to or crawl all relevant internal and external resources, and provide unified views of both structured and unstructured information across these silos. With the right platform, these views can include dashboard metrics and recommendations based on advanced analytics.

“Digital continuity is the core characteristic that we need for the 21st century digital world.”

[Michael Grieves, Executive Director, Center for Advanced Manufacturing and Innovative Design Florida Institute of Technology](#)



And if that platform is 3D-based like the **3DEXPERIENCE** platform, decision makers can view and drill down on KPIs that are integrated into 3D renderings of products, assets, or environments. This provides an intuitive visual means of reviewing performance for all stakeholders, as well as providing designers with immediate, in-context feedback on the performance impacts of their design choices. As with recommendations, these performance simulations are powered by advanced analytics.

#### Advanced Analytics for Informed Decisions in Context

Traditional business analytics are descriptive in nature. They provide summary or detailed views of a current state of affairs (e.g., project progress or spending reports) or an analysis of historical events (e.g., lifecycle cost or revenue for a product line). They are “what is” and “what has been” analytics.

Advanced analytics go further. They enrich such descriptions with critical context, helping decision makers to not only better understand “what is,” but to make more accurate “what will be” predictions, and wiser “what should be” decisions.

Advanced analytics can be performed using traditional mathematical or statistical techniques, or newer, big data-enabled ML strategies. It is these newer strategies which are key to digital transformation in industrial markets.

Industrial companies already have masses of under-utilized structured and unstructured data scattered across active and legacy systems, and the Industrial IoT (IIoT) is adding enormous new streams of valuable real-time data. And according to McKinsey & Co., the IIoT is especially valuable during challenging times (see below).

To sift through and make sense of this big data, transforming it into business insights and new products and services, discipline is required. Organizations need to enrich it with context and enable digital continuity. This will facilitate more efficient collaboration and, as a result, it will be much easier to develop AI strategies in general, and ML techniques in particular.

Advanced analytics seek to answer “what will be” or “what should be” questions though predictive and prescriptive analytics.

## The Industrial IoT is an important improvement lever during challenging times.

Theme	Lever	IIoT use-case example	Full potential
Resolve	Ensuring employee safety and security	Remote employee collaboration Workforce tracking Vision-based control systems Remote asset control	Safeguarding operations
	Improving liquidity	IIoT-enabled inventory management Waste reduction Maintenance-cycle increase	-10 to -35% inventory -20% waste -10 to -15% maintenance costs
	Lowering costs in short term	Digital performance management Remote assistance	20 to 40% labor productivity -10 to -40% service costs
Return and resilience	Connectivity and cybersecurity	Large-scale connectivity rollout Cybersecurity	Strategic enabler
	Mid-term cost improvement and flexibility	IIoT-enabled asset optimization Real-time procurement transparency	Up to five-percentage-point overall equipment effectiveness -2 to -5% spend
	Revenue stability	Next best action for sales and service Dynamic pricing optimization	Case dependent 5 to 8% revenue
Reimagination and reform	Increasing operational flexibility	Supply-chain integration across value chain In-line process optimization	Strategic enabler

McKinsey  
& Company

### ARTIFICIAL INTELLIGENCE & MACHINE LEARNING AT DASSAULT SYSTEMES

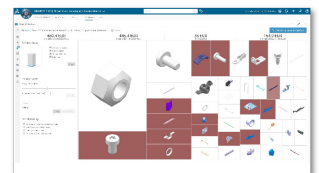
The NETVIBES brand reveals Information Intelligence on the Dassault Systèmes **3DEXPERIENCE** platform. It enables organizations to gather, align and enrich big data - whether internal or external, structured or unstructured, simple or complex, real-time or archived - and to deliver that information to users within high-value applications. The brand's portfolio of solutions has incorporated big data management technologies and advanced analytics, including ML tools and techniques, since its inception. Specifically, its first product was a Web-scale search platform designed for enterprise use. It used ML to enrich data by surfacing hidden information and relationships, and successfully integrated advanced analytics into its sub-second query processing framework. As such, NETVIBES provided an ideal foundation for the development of ML technologies on the **3DEXPERIENCE** platform, and its big data processing framework remains the core engine powering the brand's suite of enterprise applications.

#### Sourcing & Standardization Intelligence

Sourcing & Standardization Intelligence solutions address four common and costly problems about how to: define product part standards and share them across projects; choose whether to reuse an existing part from a previous project, buy it from a supplier, or create a new one; equip purchasing departments with the right level of knowledge to improve cost efficiency; and drive reuse in engineering in accordance with the company's sourcing and standardization policy.

These problems are solved by AI and ML techniques that automatically group parts together based on their shape similarity and semantic characteristics, as well as aggregating technological and business information to break down the silos between engineering and procurement. The result is a pre-identified classification of parts that complexity and sourcing managers can review and use to launch appropriate actions to either de-duplicate the part references or renegotiate with suppliers.

In addition, the PartSupply service on the **3DEXPERIENCE Marketplace** makes comparative data available on tens of millions of catalogued parts from more than 1,000 suppliers. Users can search to evaluate technical characteristics, performance and quality, and quickly secure vendors in their area able to deliver.



## ONE-THIRD

Amount of time engineers report they waste on non-value-added work

[How to Reduce Non-Value-Added Work in Engineering.](#)  
[Tech-Clarity](#)



## THE HIGH COST OF A NEW PART

The U.S. DoD estimates the average lifecycle cost of a new part for a weapons system is \$27,500

ACTIVITY	COST (\$)	% OF TOTAL COST	CUMULATIVE COST (\$)
Engineering & Design	12,600	45%	12,600
Testing	1,000	4%	13,600
Purchasing	5,200	19%	18,800
Manufacturing	2,400	9%	21,200
Inventory	1,200	4%	22,400
Logistics Support	5,100	19%	27,500
<b>TOTAL</b>	<b>27,500</b>	-	-

Source: SD-19 Parts Management Guide U.S. Dept. of Defense

### PLM Analytics

Aimed at bridging the gap between virtual and real worlds, the PLM Analytics portfolio allows customers to fully leverage advanced analytics around product data along with related projects, issues, changes and quality processes. Uncovering such metrics is especially challenging because related data is heterogeneous, ranging from technical notes, 2D drawings and 3D models to multiple bills of materials stored in various formats.

To overcome this challenge, NETVIBES uses specific search and aggregation mechanisms and ML algorithms to produce mathematical representations of these diverse objects, allowing them to be integrated in relevant context for analytics purposes.

One solution using this strategy is Asset Quality Intelligence (AQI). Dedicated to improving the quality and reliability of assets in their operation phase, the AQI cognitive search engine uses internal and/or external data to detect anomalies and emerging trends, while automatically classifying and clustering multi-source field issues.

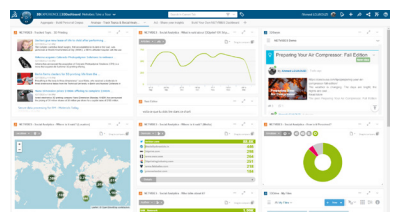
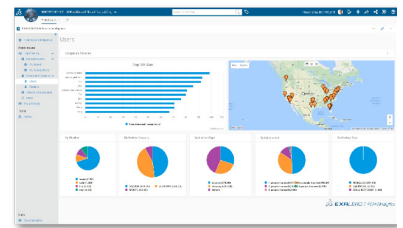
The use of ML in this context provides a full 360° view of similar issues. It also enables valuable discovery with deep learning techniques used (when data volumes are sufficient) to surface and qualify issues. The solution is also designed to satisfy the need for transparency with sufficient visibility into the data used to aid comprehension, confidence, and certification - while avoiding over-simplifying and weakening algorithms - in order to expose them in a way that is comprehensible to non-specialists (for example, all the parameters and filters used during indexation are exposed, even if complete indexation algorithms are not).

Additional solutions also apply ML techniques to solve custom analytics challenges. Developed with customers, they cover many use cases around 360° fleet views, 360° customer views, analysis of customer churn risk, sales prospect scoring, customer targeting, discovery of adverse effects in FDA data and manufacturing procedures, regulation discovery and matching for individual specifications or change requests, and new supplier discovery.

### Social Business

NETVIBES Social Business solutions equip enterprises to listen, learn, and act on all the social Web data that matters to their business. ML-enabled algorithms allow users to analyze these data and extract relevant insights on all-in-one dashboards for informed decision-making.

Available on the Dassault Systèmes 3DEXPERIENCE platform, Information Intelligence solutions support continuous product improvement and integration, and enable essential analytics governance and traceability (history/versioning), ultimately helping customers improve innovation, operational excellence and business performance.



## APPENDIX: DEFINITIONS

### Artificial Intelligence

Artificial intelligence (AI) is conceptual in nature. It is a term that is used in a general way to describe the capacity of machines to imitate some aspect of human intelligence. Accordingly, AI is a label often applied to software programs that perform cognitive tasks that humans can also do, like filtering junk email, interpreting handwriting, detecting fraud, translating speech, and recommending products.

But these types of applications can perform their functions with or without the aid of advanced analytics and behavioral models. They can execute their functions with or without any capacity to “learn,” that is to say, to independently improve their performance over time.

Certainly, however, their performance can be greatly enhanced with such attributes. Moreover, many would argue that the use of models and the capacity to “learn” are defining characteristics of “true” AI.

### COMMON USES OF AI



#### Robotics

- Factory Automation
- Exoskeletons
- Autonomous Vehicles
- Security Systems
- Environmental Monitoring
- Remote Exploration



#### Natural Interfaces

- Speech Recognition
- Natural Language
- Eye & Hand Gestures
- Brain-Computer Interfaces
- Touch Surfaces
- Virtual Reality



#### Cognitive Systems

- Smart Agents/Bots
- Expert Systems
- Recommendation Engines
- Adaptive Learning Systems
- Translation Systems

Regardless of the level of precision one wishes to attach to AI, however, machine learning is inarguably a core - if not the core - technology used to implement AI strategies today for all types of tasks. But what, precisely, is machine learning?

### Machine Learning

Machine learning (ML) is a body of techniques that enables computers to learn how to execute tasks without having every step and every possible option scripted via software programs (i.e., without relying on rules-based programming). This is accomplished by processing data using ML algorithms.

An algorithm is simply a discrete, step-by-step set of procedures, like a recipe, that enables a computer to solve a specific problem or perform a particular task. While algorithms are used for both traditional software programming and ML, the “task” a ML algorithm performs is to build a (reusable) model that describes or predicts something about the world.

Inherent in the “learning” part of the definition is the idea that the models will improve over time with exposure to new data or feedback about the accuracy of predictions or descriptions.

A baseline ML model can be developed using training sets of real or simulated data prepared under the supervision of a human being (hence it is called “supervised learning”).

For example, in the case of specific types of equipment malfunctions, a scientist may feed a computer a set of carefully annotated documents detailing past malfunctions. These documents are used to train the computer to identify patterns associated with various types of malfunctions, thereby enabling it to detect possible future instances of these malfunctions.

An algorithm is simply a discrete, step-by-step set of procedures, like a recipe, that enables a computer to solve a specific problem or perform a particular task.

Alternatively, a scientist may use simulation software to generate a very large number of simulated malfunction scenarios (alone or in tandem with real, historic data) to help train a malfunction-detection algorithm.

In unsupervised learning, the emphasis shifts from training a computer with the types of real or synthetic examples, to equipping it to sift through mountains of data and detect meaningful signals on its own (for example, identifying clusters of performance anomalies for a piece of equipment without being trained to look for specific malfunctions).

Unsupervised learning works best with very large data sets, and therefore computer-generated virtual data – which can be produced in massive quantities – is particularly useful. Virtual data is also valuable for a particular type of ML framework known as deep learning, which can be unsupervised, supervised, or semi-supervised, but always requires an extremely large data set.

### Deep Learning

Deep learning is a ML framework patterned after the neural networks of the brain. It involves processing extremely large amounts of data in steps, or layers, with the results of each layer passed to the next layer to cumulatively build a complex and (hopefully) accurate digital model of a real-world behavior, like playing a game of chess or driving an autonomous car.

[Capgemini](#) estimates “that by 2020, 125 billion devices could be connected through IoT.” With the rise of the IoT/IIoT, millions of new sensors are being deployed daily to help gather the big data that deep learning thrives on, like periodic or streaming measures of pressure, volume, temperature, direction, etc. This sensor data - especially when combined with virtual data and with other types of real data like images, audio files and text documents - can fuel high-value AI applications.

---

# 125B

Estimated number of devices connected through IoT by 2030

[Capgemini](#)

---

**LEARN HOW TO PUT ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING  
TO WORK FOR YOUR COMPANY AT: [www.3ds.com/netvibes](http://www.3ds.com/netvibes)**

**Our 3DEXPERIENCE® platform powers our brand applications, serving 11 industries, and provides a rich portfolio of industry solution experiences.**

Dassault Systèmes, the 3DEXPERIENCE Company, is a catalyst for human progress. We provide business and people with collaborative virtual environments to imagine sustainable innovations. By creating 'virtual experience twins' of the real world with our 3DEXPERIENCE platform and applications, our customers push the boundaries of innovation, learning and production.

Dassault Systèmes' 20,000 employees are bringing value to more than 290,000 customers of all sizes, in all industries, in more than 140 countries. For more information, visit [www.3ds.com](http://www.3ds.com)



**3DEXPERIENCE®**

**DS DASSAULT SYSTEMES** | The **3DEXPERIENCE®** Company

**Americas**  
Dassault Systèmes  
175 Wyman Street  
Waltham, Massachusetts  
02451-1223  
USA

**Europe/Middle East/Africa**  
Dassault Systèmes  
10, rue Marcel Dassault  
CS 40501  
78946 Vélizy-Villacoublay Cedex  
France

**Asia-Pacific**  
Dassault Systèmes K.K.  
ThinkPark Tower  
2-1-1 Osaki, Shinagawa-ku,  
Tokyo 141-6020  
Japan

©2021 Dassault Systèmes. All rights reserved. 3DEXPERIENCE®, the Compass icon, the 3DS logo, CATIA, SOLIDWORKS, ENOVIA, DELMIA, SIMULIA, GEOVIA, EXPLEAD, 3DVIA, 3DSWYM, BOWIA, NETVIBES, IPWE and 3DEXCITE are commercial trademarks or registered trademarks of Dassault Systèmes, a French "société européenne" (Versailles Commercial Register # B.322.306.440), or its subsidiaries in the United States and/or other countries. All other trademarks are owned by their respective owners. Use of any Dassault Systèmes or its subsidiaries trademarks is subject to their express written approval.