Gartner

Defining AI and Setting Realistic Expectations

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Initiatives:Artificial Intelligence; Analytics and Artificial Intelligence

Superheated rhetoric surrounding the potential benefits of artificial intelligence is inflating related expectations. This research helps CIOs define AI, defuse the hype, promote AI engineering and AI literacy, and focus conversations on real business problems and achievable use cases.

Overview

Key Findings

- Marketing hyperbole is increasing confusion around artificial intelligence (AI). Consequently, many enterprises are struggling to put a realistic value on an important source of innovation and differentiation.

- Business leadership tends to overestimate the impact of AI and underestimate its complexity — requiring IT leaders to manage the business's expectations, or risk costly project failures.

- As evidenced in the 2024 Gartner CIO and Technology Executive Survey, 73% of surveyed CIOs and technology leaders are planning to increase their AI investments.

Recommendations

CIOs tasked with evaluating and implementing AI techniques should:

- Defuse the hype by adopting a common taxonomy for AI technologies, based on Gartner's AI Techniques Framework. Devise a multichannel education plan to communicate the taxonomy across the organization through an AI literacy program.

- Adopt critical AI disciplines, such as AI engineering and AI literacy, to strengthen the impact of AI techniques while sustainably improving their value to the organization.

- Introduce AI techniques by identifying specific, business-relevant use cases, appropriate skills and expertise, and pertinent data. Financial and business metrics should drive business cases to objectively secure their success.

Strategic Planning Assumption

By 2025, generative AI will be a workforce partner for 90% of companies globally.

Introduction

AI techniques solve a wide array of business problems and generate significant return on investment, ranging from about 20% to over 800% (see 5 Ways Artificial Intelligence and Machine Learning Deliver Business Impacts). However, unchecked hype generated by the industry, the press and overenthusiastic software vendors is creating confusion, making it difficult for CIOs to set the right expectations regarding business outcomes. This untamed hype drives unrealistic expectations, leading to projects with a lower chance of success.

Artificial intelligence applies advanced analysis and logic-based techniques, including machine learning (ML), to interpret events, support and automate decisions, and take actions.

Seventy-three percent of respondents to the 2024 Gartner CIO and Technology Executive Survey indicate that they will increase their investment in AI in 2024, while only 1% say they will decrease their investment. In addition, 34% of respondents have already deployed AI technologies. [1]

However, in Gartner client inquiries, end users have identified a wide range of reasons why AI deployments are not sustainable. These include lack of early financial assessment or rampant AI operationalization issues.

How can CIOs mitigate the negative aspects of AI hype while preserving the enthusiasm rightfully associated with AI's power to create real value?

This research offers approaches that CIOs can use to manage business leaders' expectations of AI, set realistic goals and increase the success rate of AI projects.

Analysis

Defuse the AI Hype

AI techniques go by a wide variety of names, including expert systems, data mining, predictive analytics and ML, neural networks, genetic algorithms, and deep learning. Because many clients find this complex terminology confusing, we created the Gartner AI Techniques Framework (discussed below).

The difference between AI techniques and AI practices is also a source of confusion. Generative AI (GenAI), decision intelligence and adaptive AI are AI practices, not AI techniques. GenAI, for example, is not a singular technology or technique, per se. It is a practice that uses many AI techniques to generate artifacts or learning methods. GenAI uses deep learning techniques at its core, along with other AI techniques, such as reinforcement learning, rule-based systems and knowledge graphs.

Another misnomer creating confusion is the acronym "AI/ML." AI/ML implies that AI is equivalent to ML, which is not true. ML is only one technique in the family of AI techniques (see Figure 1). So, instead, we suggest using either:

- "AI and ML" to emphasize ML among the various techniques
- Simply "AI," as ML is implied in the whole set

Adopt a Common Taxonomy for AI Techniques Based on Gartner's AI Techniques Framework

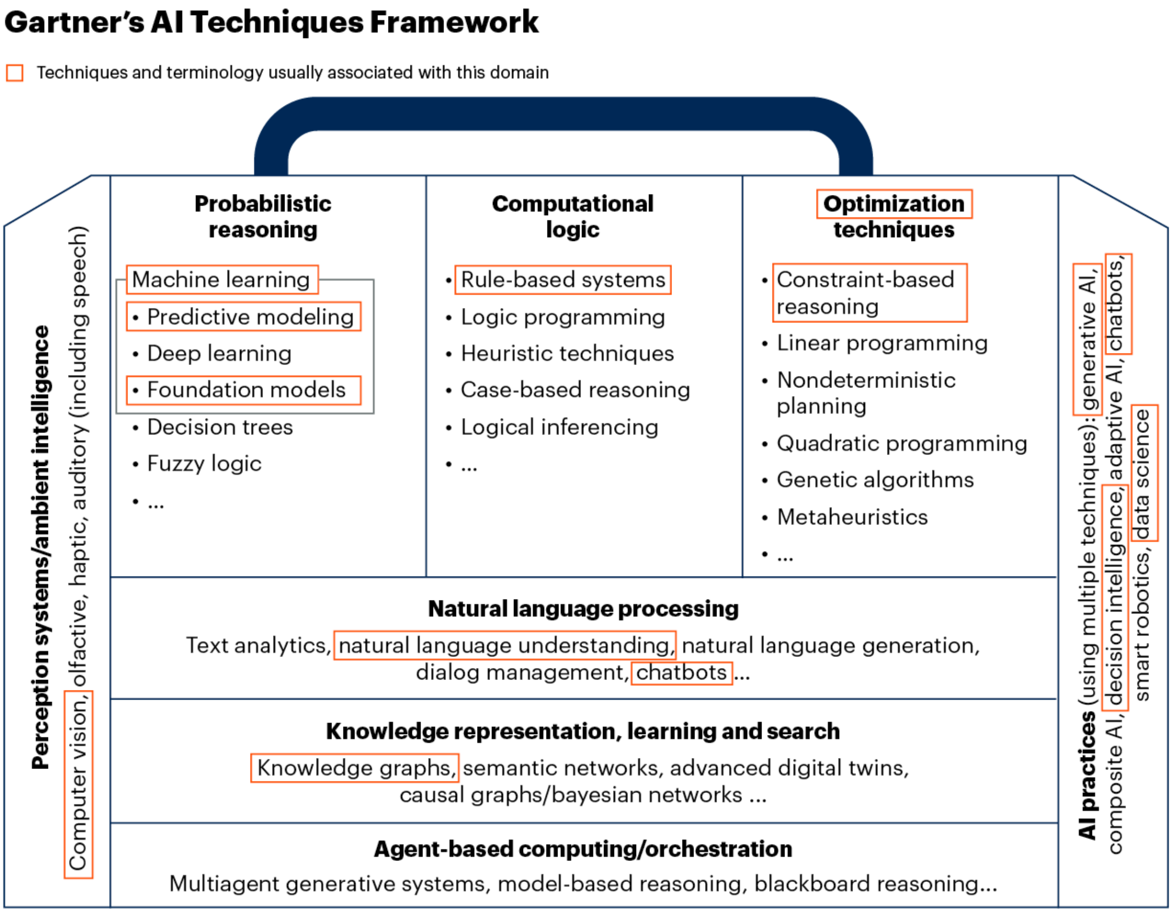
Gartner's AI Techniques Framework consists of a set of computing engineering techniques that fall into seven principal categories (see Figure 1). This framework is essentially use-case-driven, but respects the basic principles established in Stuart Russell and Peter Norvig's reference textbook "Artificial Intelligence: A Modern Approach." [2] It is an attempt to impose some order on the chaotic terminology related to AI. The list of techniques mentioned in Figure 1 is illustrative, not exhaustive. Also, for completeness, the box on the right lists AI practices (not AI techniques).

In short, AI is mainly a computer engineering discipline composed of software tools aimed at solving problems, not at replicating the human brain (let alone the mind). From that perspective, the AI discipline (and its toolbox) comprises a series of mathematical or logic-based techniques. These techniques not only uncover, capture and represent knowledge, but also use sophisticated and clever mechanisms to solve problems.

About half of AI techniques and practices rely on data, while the other half rely on logic, predicates and knowledge. In other words, AI is *not* all about data. Data plays a fundamental role in many AI techniques and practices (especially in data and analytics), but logic and knowledge play an equally fundamental role.

This framework breaks the AI concept down into tangible pieces and removes the philosophical element from the AI discussion, enabling CIOs to see through the hype. They can then show how each of these techniques can solve real-world problems. The following sections provide more detail on established AI techniques, advancing AI techniques, AI sensory systems and AI practices.

Figure 1: Gartner's AI Techniques Framework



Source: Gartner
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Established AI Techniques

Today, three main categories of techniques form the majority of use cases in AI. They are distinct and embody very different approaches that are robust and mature:

- **Probabilistic reasoning:** These techniques are often generalized as ML (see Note 1). They extract value from typically large amounts of data. This category includes techniques aimed at unveiling unknown knowledge held within a large amount of data (or dimensions). Such techniques reveal unknown knowledge by discovering interesting correlations linked to a particular goal or label within that data. For example, an ML technique may involve sifting through a large number of customer records, identifying certain factors and unveiling how the factors are correlated. This technique enables organizations to anticipate whether certain customers are potential churners.

- **Computational logic:** Often referred to as rule-based systems, these techniques use and extend the implicit and explicit know-how of the organization. These techniques aim to capture known knowledge in a structured manner, often in the form of rules. Business people can manipulate these rules, but the technology guarantees the coherence of the rule set. (That is, the technology makes sure that rules do not contradict each other or lead to circular reasoning — which is not that obvious when you are dealing with tens of thousands of rules.) A new series of compliance laws has brought rule-based approaches to the forefront.

- **Optimization techniques:** Traditionally used by operations research groups, optimization techniques maximize benefits while managing business trade-offs. They do so by finding optimal combinations of resources, given a number of constraints in a specified amount of time. Optimization solvers often generate executable plans of action and are sometimes described as "prescriptive analytics" techniques. Operational research groups in asset-centric industries (such as manufacturing and utilities) and functions (such as logistics and supply chain) have been using optimization techniques for decades.

Advancing AI Techniques

The bottom three layers in Figure 1 represent emerging techniques in descending order of maturity:

- **Natural language processing (NLP):** NLP provides intuitive forms of communication between humans and systems. NLP includes computational linguistic techniques (symbolic and subsymbolic) aimed at recognizing, parsing, interpreting, automatically tagging, translating and generating (or summarizing) natural languages. The phonetic part is often left to speech-processing technologies that are essentially signal-processing systems. That is why applications dealing with speech-to-text or text-to-speech functionalities are often delivered by different software solutions. Additional knowledge capabilities, such as dictionaries or ontologies, are also part of NLP systems.

- **Knowledge representation:** Capabilities such as knowledge graphs or semantic networks aim to facilitate and accelerate access to, and analysis of, data networks and graphs. Through their representations of knowledge, these mechanisms tend to be more intuitive for specific types of problems. For instance, such representations can map out specific relationships among entities for investigative research, process optimization or manufacturing asset management purposes. To do so, they employ techniques like graph traversal, memorization and hybrid learning (while using composite AI systems).

- **Agent-based computing:** This is the least mature of the AI techniques categorized in this framework, but it is quickly gaining popularity. AI agents are autonomous or semiautonomous software entities that use AI techniques to perceive, make decisions, take actions and achieve goals in their digital or physical environment. In increasing order of complexity, the five main types of agent systems are reflex-based agents, model-based agents, goal-based agents, utility-based agents and learning agents.Today, existing solutions commonly use two main classes of agent applications: task automation agents and autonomous object programs. Task automation agents can be generic, such as meeting scheduling assistants in email systems, or more specific, such as contract validation softbots for sales automation applications. Autonomous object programs can serve functions such as automatic temperature setting (found in car diagnostic systems or home thermostats, for example).Agent-based techniques also have to deal with particular orchestration principles, given the distributed and autonomous nature of their operations. This means they have the ability to manage the collective behavior of dispersed computing and self-organized systems, as well as the emerging properties of these systems. Game theory and other complex-systems-theory disciplines can provide techniques to address software agencies' orchestration problems.

AI Sensory Systems

The far-left column of the framework depicted in Figure 1 covers the following:

- **Perception and ambient intelligence systems:** These systems interpret sensory and streaming data from internal and external sources to detect events, objects, people or other entities. They then share their results with other AI techniques for further processing. Perception and ambient intelligence systems include a wide variety of advanced technologies, continuously capturing different types of data, including audio, visual, olfactory, haptic and chemical data. These technologies also capture environmental and geospatial inputs, thus providing context and precision to develop more effective analytical assets.

AI Practices

The far-right column of the framework depicted in Figure 1 covers AI practices. Those practices use AI techniques, either alone or in combination, to achieve specific goals and outcomes. Such practices include:

- **Generative AI:** GenAI can produce new derived versions of content, strategies, designs and methods by learning from large repositories of original source content. It is a prominent and currently very hyped AI practice, leveraging AI techniques in creative work. Foundation models, such as large language models (LLMs), are a core technique of this practice. GenAI is still in a very early phase of enterprise adoption, with the hype surrounding it leading to unrealistic expectations of short-term value. However, GenAI has much greater potential for the long and medium term once it is well-integrated into business processes.

- **Decision intelligence:** Decision intelligence is a practical discipline used to improve decision making by explicitly understanding and engineering how decisions are made and how outcomes are evaluated, managed and improved by feedback. AI intersects with data science and business process management. These three disciplines meet at the decision-modeling level, where users can describe how AI techniques will improve decision making through modeled know-how and data evidence. Decision intelligence is the discipline that enables the reengineering of such decisions to make them adaptable and resilient.

- **Adaptive AI:** Adaptive AI systems aim to continuously learn within runtime and development environments by continually retraining models or adapting them through other mechanisms. Such systems can adapt more quickly to changes in new, real-world circumstances that were not foreseen or available during initial development.

- **Composite AI:** Composite AI combines different AI techniques to improve the efficiency of learning, broaden the scope of knowledge representations and, ultimately, solve a wider range of business problems in a more efficient manner. Related terms include “hybrid AI,” “neuro-symbolic AI” and “causal AI.” As more organizations realize the limitations of GenAI, they are exploring composite AI to meet their needs.

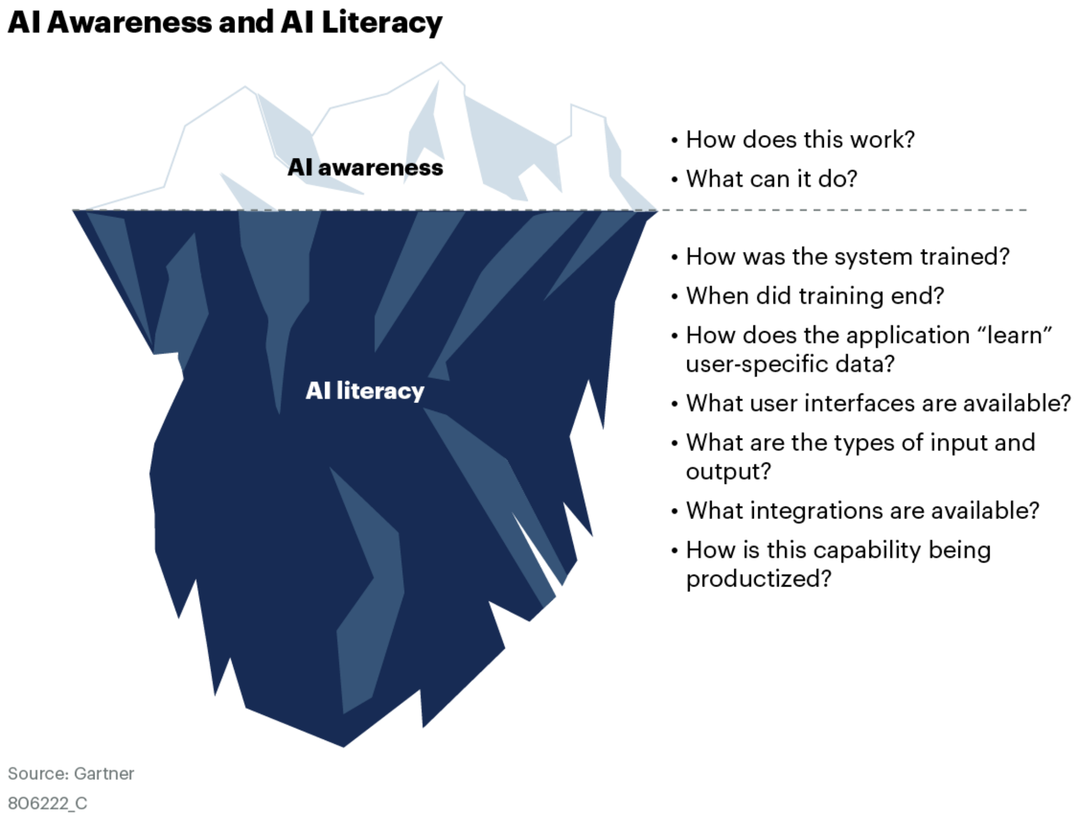
Adopt Critical AI Disciplines to Strengthen the Impact of AI Techniques

Without robust supporting disciplines, AI projects will struggle to scale and achieve their goals. To increase the success rate of these projects, CIOs should advance the following disciplines:

- **AI engineering:** Moving AI from exploration to sustainable production requires understanding and mastering not only the various AI techniques, but also the necessary infrastructures, the methodologies for getting started and the implementation best practices. AI techniques do not operate in a vacuum; they often represent a small part of a much larger system. Thus, AI practices and systems must align with a traditional software ecosystem to be effective and deliver business value. AI engineering is well-aligned with neighboring disciplines, such as data engineering and software engineering. It is critical to make AI an embedded and sustainable element in the organization's technology fabric.

- **AI literacy:** The democratization of AI will require organizations to educate their entire workforce — from the board to frontline workers — on the technical, value and ethical aspects of AI. AI literacy is the ability to effectively and responsibly utilize AI in context (business and societal). This discipline is necessary to identify relevant AI use cases, implement corresponding AI applications and operate them competently. AI literacy requires knowledge of the implications, risks, resulting business value and outcomes of AI projects. To be AI-literate, practitioners must understand the fundamental principles of AI, technology and applications, analytical and algorithmic methods, data and knowledge sources, and ethical considerations (see Figure 2). For further details, see the Gartner webinar Build an AI Literacy Program to Unleash the Power of AI.

Figure 2: AI Awareness and AI Literacy



Introduce AI Techniques by Identifying Business-Relevant Use Cases, Appropriate Skills and Pertinent Data

To paraphrase the chemical producer BASF's iconic tagline: [3] *AI does not make a lot of the software you buy; it makes a lot of the software you buy better.*

A clear understanding of AI's final business impact should be the start of every project that uses AI techniques. Line-of-business stakeholders should be able to clearly articulate the tangible business benefits they are expecting by asking:

- What is the problem the business is trying to tackle?
- Who is the primary consumer of the technology?
- What is the business process that will host that technique?
- How will the impact of implementing the technology be measured (compared to more traditional techniques)?

- How will the value provided by the technology be monitored and maintained? And by whom?
- Which of the subject matter experts from the lines of business can guide the development of the solution?

Any AI initiative must first focus on the organization's readiness. It must allow for learning and practical use before embarking on a grand AI program. Engaging in an AI initiative without first experimenting with its component techniques — if those are new to the organization — is like putting the cart before the horse.

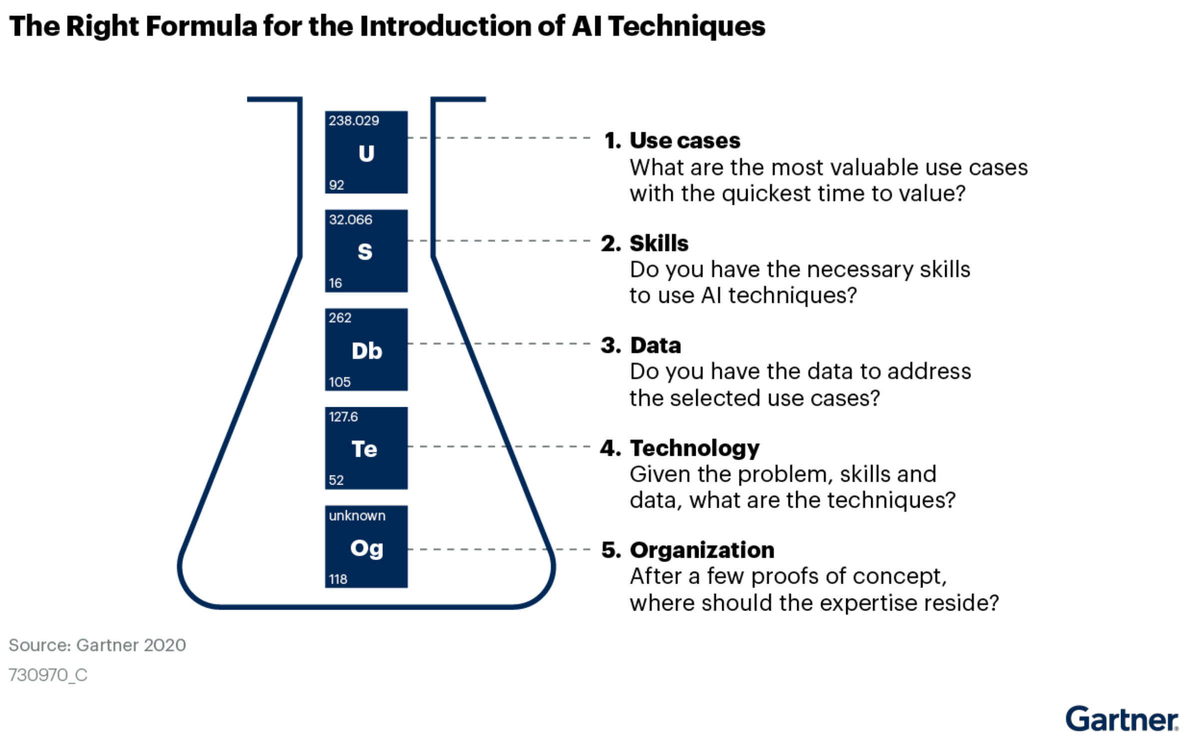
As shown in Figure 3, CIOs in organizations of all sizes can achieve the practical adoption of AI through five steps:

1. **Use cases (value):** Build a portfolio of impactful, measurable and quickly solvable use cases.
2. **Skills (literacy):** Assemble a set of talents pertinent to the use cases to be solved.
3. **Data:** Gather the appropriate data relevant to the selected use cases.
4. **Technology:** Select the AI techniques linked to the use cases, the skills and the data.
5. **Organization:** Structure the expertise and accumulated AI know-how.

This five-step formula is a tactical approach to the introduction of AI techniques, favoring a quick time-to-value perspective. It is not a strategic, longer-term outlook. A long-term strategy can be developed only after the organization has established its current strengths and weaknesses (both culturally and technologically) in terms of using these techniques. For further details, see:

- 5 Practical Steps to Implement AI Techniques
- AI Zodiac: Mapping AI Use Cases to Techniques
- Toolkit: Discover and Prioritize Your Best AI Use Cases With a Gartner Prism
- The Pillars of a Successful Artificial Intelligence Strategy

Figure 3: The Right Formula for the Introduction of AI Techniques



Evidence

[1] **2024 Gartner CIO and Technology Executive Survey:** This survey was conducted online from 2 May through 27 June 2023 to help CIOs determine how to distribute digital leadership across the enterprise and to identify technology adoption and functional performance trends. Ninety-seven percent of respondents led an information technology function. In total, 2,457 CIOs and technology executives participated, with representation from all geographies, revenue bands and industry sectors (public and private). Disclaimer: The results of this survey do not represent global findings or the market as a whole, but reflect the sentiments of the respondents and companies surveyed.

[2] S. Russell and P. Norvig, “Artificial Intelligence: A Modern Approach,” Prentice Hall, 2010.

[3] “A Campaign for BASF,” The New York Times, 26 October 2004. In almost every brand awareness test, BASF’s circa-1990 North American commercial tagline — “We don’t make a lot of the products you buy. We make a lot of the products you buy better.” — may be considered among the most recognized corporate slogans.

Acronym Key and Glossary Terms

AI	artificial intelligence
ML	machine learning
NLP	natural language processing
RPA	robotic process automation

Note 1: Machine Learning

Machine learning (ML) refers to a set of techniques and algorithms. Machines do not “learn”; they store and compute. People use anthropomorphisms to more intuitively convey complex mathematical mechanisms, but this comes at the expense of attributing qualities to these mechanisms that they do not possess. The concept of ML comes from a set of AI techniques known as probabilistic reasoning. Those ML techniques are different from traditional programming methods because — through supervised or unsupervised methods — they compute formulas from data to create “models” that operate as programs. Subsets of ML techniques can also be referred to as “predictive analytics” or “data mining.”

Document Revision History

What Is Artificial Intelligence? Ignore the Hype; Here’s Where to Start - 15 March 2022

What Is Artificial Intelligence? Seeing Through the Hype and Focusing on Business Value - 17 July 2020

Artificial Intelligence Hype: Managing Business Leadership Expectations - 5 June 2018

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How to Use Machine Learning, Business Rules and Optimization in Decision Management

Hype Cycle for Artificial Intelligence, 2023

Hype Cycle for Generative AI, 2023

AI Zodiac: Mapping AI Use Cases to Techniques
