5 Practical Steps to Implement AI Techniques

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Moving from "I want to use AI" to a tactical approach aimed at practically and sustainably solving business problems, while managing expectations, does not require superpowers. Data and analytics leaders can follow the five steps in this research to pursue an AI strategy in a pragmatic fashion.

Overview

Key Findings

- Creating an AI strategy has become a distraction for many organizations and data and analytics (D&A) leaders. It is obscuring the focus that is needed on business outcomes.
- When it comes to AI, the first question many data and analytics leaders, and even line of business (LOB) leaders, ask is, "Which platform should I use?" But asking about technology options before focusing on business problems is simply the wrong order.
- When implementing AI techniques, AI skills and good data engineering practices should be front and center, but many organizations only make these second-order considerations.
- Organizational issues (such as syndicating AI talent, creating an AI lab, maintaining an AI framework) are important for the sustainability of AI efforts, but they are often promoted at the expense of a rigorous business use-case selection process.

Recommendations

To start applying AI in the enterprise, organizations should:

- Define the criteria and key performance indicators that make use cases impactful and invest in those measurable business use cases that are achievable in a limited time frame.
- Hire the right analytics, IT and business skills necessary for those business use cases.
- Organize AI use case delivery based on cross-functional teams with the right mix of competencies, seeking individuals with expertise in AI, IT and the relevant subject matter.
- Assign data experts to select, secure and prepare the appropriate data linked to the selected use cases.
- Determine the most appropriate AI techniques depending on the problem to be solved and the skills at your disposal — keeping in mind that those techniques can be combined to address the selected use case.
- Keep the AI technical debt at a minimum and keep the learning within the organization by building an AI expertise organizational structure designed for knowledge transfer and problem solving.

Strategic Planning Assumption

By 2023, 80% of all digital business industry visions will be powered by AI selected from AI industry use cases.

Introduction

The 2021 Gartner AI in Organizations Survey shows a marked increase in AI adoption. [1] Forty-seven percent of respondents said their organizations are using AI — that's up from 35% in the 2019 survey. In the same survey, 33% also reported they had been deploying models by the thousands. However, respondents also stated their main concern was the difficulty of measuring the business value of the deployment of AI techniques.

Furthermore, in the 2023 Gartner CIO and Technology Executive Survey, 32% of respondents said their organizations had deployed AI and machine learning, with an additional 17% indicating they would follow suit within the next 12 months. [2]

Establishing an artificial intelligence strategy before first testing the organization's readiness to adopt AI techniques is much like this backward military battle analogy:

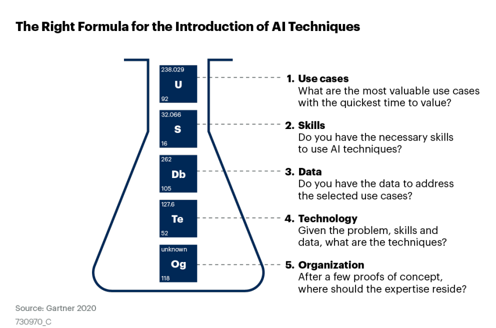
1. Establishing a battle strategy without knowing if troops are trained and prepared (unknown skills)
2. Heading into the battle zone with no intelligence regarding enemy movements and capabilities (unknown data)
3. Possessing zero knowledge about the weapon systems at your disposal (unknown technology)
4. Having no understanding of the objectives (unknown goals)

The practical introduction of AI techniques within an organization of any size can be achieved through the five steps listed in Figure 1:

- **Use cases:** Build a portfolio of impactful, measurable and quickly solvable use cases.
- **Skills:** Assemble a set of talents pertinent to the use cases to be solved.
- **Data:** Gather the appropriate data relevant to the selected use cases.
- **Technology:** Select the AI techniques linked to the use cases, the skills and the data.
- **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, which can be developed but only after the organization has established its current strengths and weaknesses, culturally and technologically, in terms of leveraging those techniques. An AI strategy comes after a few learning experiences.

Figure 1. The Right Formula for the Introduction of AI Techniques



Analysis

Step 1. Build a Portfolio of Impactful, Measurable and Quickly Solvable Use Cases

Measurable outcomes should be the foremost goal of this first step. As with most successful AI and machine learning (ML) initiatives, the idea is to start with the answer — one that is as complete as possible. A clear understanding of its final business impact should be the start of every project leveraging AI techniques. Line-of-business stakeholders, for example, should be able to clearly articulate the tangible business benefits they expect to see from AI. Those expectations may change or evolve as the project progresses, but firmly establishing them at the outset is important.

Three principles are important for this foundational first step:

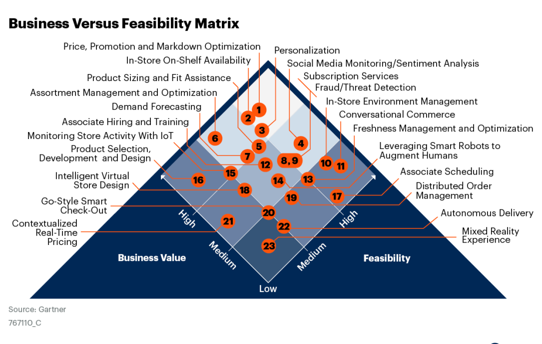
- Select the right use cases (i.e., measurable, impactful, feasible).
- Describe their value propositions as clearly as possible.
- Do not compromise on metrics expectations, and watch their evolution closely.

Selecting Use Cases

Many techniques are possible to establish a small portfolio of use cases. Gartner provides guiding principles and practical examples for organizations to select and prioritize the most promising areas for AI techniques to be leveraged with sample domains and industry use cases.

Simple instruments such as the business value versus feasibility prism (the Retail example is shown in Figure 2) can help in quickly and clearly prioritizing use cases. For more AI industry Prisms examples, see Uncovering Artificial Intelligence Business Opportunities in Over 20 Industries and Business Domains.

Figure 2. Business Versus Feasibility Matrix



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> Think big, start small, act fast ... and deliver results in nine weeks!

To investigate the top use cases in a wide number of industries, Gartner has created "AI Prisms" that map those use cases, by industries, along two axes: feasibility and business value. (See Uncovering Artificial Intelligence Business Opportunities in Over 20 Industries and Business Domains.) Leaders can also create their own AI use case using the AI Prism Toolkit: Discover and Prioritize Your Best AI Use Cases With a Gartner Prism.

In selecting use cases, another important criterion is time. Despite the very large number of combinatory factors, a simple rule-of-thumb, nine-week sequence has shown merit in a large number of proofs of concepts (POCs): Think big, start small, act fast. The point is to pick a critical problem for the organization, one that other techniques have not been able to tackle (think big). But scope the problem to fit it into the nine weeks mandate (start small). Finally, start iterating around its execution as quickly as possible to rapidly uncover any issues and rescope as necessary (act fast).

Describe Use Cases as Clearly as Possible

Even for small and rapid POCs, and especially when it comes to AI techniques, value propositions need to be articulated as clearly as possible. A value proposition canvas such as that shown in Figure 3 can be a powerful tool for data and analytics leaders to transparently assess business outcomes and potential barriers.

Figure 3. Value Proposition Canvas

Value Proposition Canvas

Problem	Key Activities	Value Proposition	Differentiated Advantages	Customer Segments/ User Types
• What user problems are we focusing on solving?	• What key activities does our value proposition require?	• What value do we deliver to the user/ customer? • What value do we bring to the organization? • What does the minimal viable product look like?	• What unique value can be derived from solving the problem?	• What type of users should the solution be focused on?
	Key Resources		**Channels**	
	• What key resources does our value proposition require?		• How is the solution best integrated into existing processes?	
Key Metrics (Which metrics are indicators of success?)				
Cost Structure		**Revenue Streams**		
Estimated Return on Investment				

Source: Gartner
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Do Not Compromise on Established Metrics

The Gartner Business Value Model can help you to establish an appropriate set of metrics. This model is a structured framework and definition of nonaccounting metrics that can be applied generically to help organizations identify how their business activities will impact financial performance.

Creating concrete, measurable metrics can also help organizations apply three types of value to the AI techniques they wish to implement:

- Information value (improving the information management process itself)
- Business value (improving business processes)
- Stakeholder value (what the data and analytics mean for stakeholders such as customers, partners, shareholders and society at large)

See Data and Analytics Strategies Need More-Concrete Metrics of Success.

However, as mentioned earlier, given the unconventional approach that AI techniques represent, early adopters should keep an open mind because metrics may change or evolve as their exploration advances.

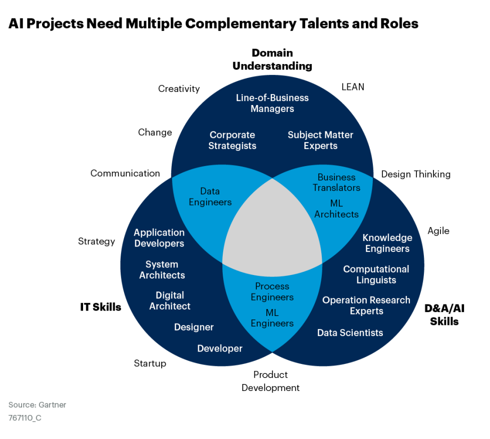
Step 2. Assemble a Set of Talents Pertinent to the Use Cases to Be Solved

Three personas provide an ideal balance to initiate AI efforts, depending on the use cases that have been prioritized:

- An AI specialist who, for example, could specialize in ML (data scientists), rule-based systems (logistician) or natural language processing (NLP) systems (computational linguists).
- An IT professional who understands the current state of IT capabilities, potential integration points and source systems, and their potential limitations.
- A subject matter expert (SME) who understands the business requirements and metrics.

These personas will form a complementary triumvirate of AI, IT and domain expertise. But in each area of expertise, a host of skilled personas will be central to solving the proposed use cases (see Figure 4).

Figure 4. AI Projects Need Multiple Complementary Talents and Roles



Despite the hype, it turns out that AI skills are not necessarily extremely scarce, expensive or mysterious. Curious database administrators or mathematically inclined data engineers can become great data scientists; they do not need a Ph.D. or even Python skills. The latter might sound iconoclastic in today's fashionable ML world, but it is possible to build valuable predictive analytics models without writing one line of code. What is required, however, is a combination of sound ML knowledge, a strong understanding of statistics principles, and a passionate curiosity for data exploration and manipulation.

Of equal importance are collaboration skills. From the three areas of expertise mentioned above, people working in tight collaboration mode create a surer path to success than a single person's deep knowledge in one of those areas mired with unrealistic expectations. Motivated, open-minded, competent and focused champions, often coming from the organization's ranks rather than from outside, make a better recipe for successful POCs.

Step 3. Gather the Appropriate Data Relevant to the Selected Use Cases

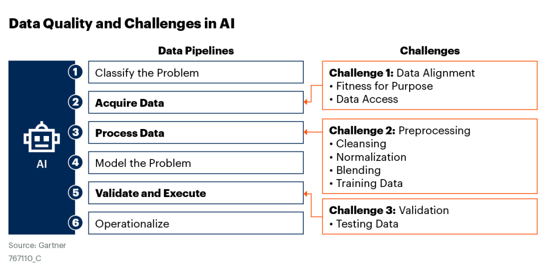
The quality and relevance of your data should preside over volume.

A myth plaguing early AI exploration is that you need massive amounts of data to build successful AI models. In fact, many successful use cases can be achieved using a reasonable amount of data, as long as that dataset is of sufficient quality (i.e., normalized, complete, diversified). The lack of volume can always be compensated for through a reduction in project scope, but a lack of data quality invariably leads to POC failure. Probabilistic reasoning techniques such as ML rely heavily on data to deliver insights. Therefore, this is where data quality problems are most acute — throughout the ML life cycle. Another approach is to consider minimum viable datasets (see 4 Machine Learning Best Practices to Achieve Project Success).

In addition to the data quality challenges outlined in Figure 5, it is important to remember that the processes in place to ensure the quality of the data will be iterative.

However, a "reasonable amount of data" could mean different things depending on the AI techniques that are selected. ML techniques will require significantly more data than logic-based or optimization techniques. The same is true for NLP systems, whether they leverage subsymbolic (ML techniques) or traditional symbolic (linguistics) techniques. The skills identified in Step 2 are critical in making that determination.

Figure 5. Data Quality and Challenges in AI



Explore the Sustainability of Your Data Pipelines

While gathering the data relevant to the business problems selected in Step 1, and in addition to quality and completeness, it is also important for data and analytics leaders to understand the sustainability of that data. The questions to ask here are:

- Are the data sources anecdotal or systematic?
- Are they partial, complete, discrete or continuous?
- Can the data be obtained on a subsecond basis, daily, weekly, etc.?

This exploration is crucial for the potential scalability of the POC, and it could be instrumented through the implementation of data pipelines. This practice encompasses initiatives that are described in detail in Enabling IoT Data Pipelines for Machine Learning Inference.

Step 4. Select the AI Techniques That Are Linked to Use Cases, Skills and Data

The majority of AI techniques are mature and have been around for decades (see Figure 6). Many are suited to specific problems, data and talents. For example, probabilistic reasoning techniques (like ML) are particularly good for uncovering hidden patterns in a large amount of data, like fraud patterns, churn issues or risk variables. But ML techniques require a sufficient amount of very high-quality data, along with analysts who are conversant in analytical mechanisms and algorithms.

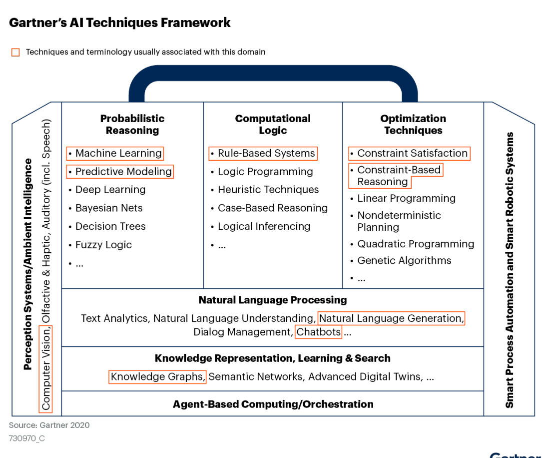
At the other end of the AI spectrum, is, for example, finding a perfect balance in inventories, perfecting routes within a supply chain, and generating a workable plan under multiple hard constraints in a limited amount of time. Think about, for instance, what is needed to manage landing and gate and crew assignments at an international airport during a snowstorm. This situation will most certainly require the use of optimization techniques. Such techniques require talents in operations research and the ability to appropriately gather data, especially while considering the operationalization of those models in production.

Again, there are multiple AI techniques (see Figure 6) that might already be integrated in certain scenarios, such as:

- Within enterprise solutions (e.g., Oracle, SAP, SalesForce)
- Decision-modeling solutions (e.g., Aera Technology, Xpertrule, FICO, Peak.ai, Merlynn, Airin)
- Pure-play techniques (e.g., Attivio, Decisions, Deepomatic, FlexRule, Frontline Systems, Grakn, Gurobi, KNIME, Matroid, Narrative Science, PROPHESEE, RapidMiner, Swarm Technology)

It is also possible to leverage these techniques via many open-source libraries and platforms.

Figure 6. AI Techniques



However, when it comes to the "technology step," a successful POC does not exclusively focus on AI techniques. The surrounding technology fabric into which the techniques will be woven is equally important. Other technology considerations, such as those below, should be discussed at this stage as well:

- **IT infrastructure:** For example, resources available to train algorithms and integrate with target systems
- **Existing process automation software:** Where AI models will be integrated
- **Adequate user interfaces:** To interact with those models

Step 5. Structure the Expertise and the Accumulated AI Know-How

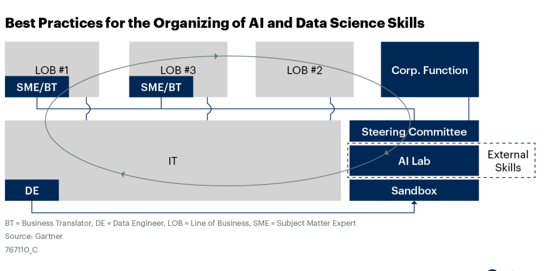
AI techniques are still "shiny objects," and CEOs are growing wary of the money invested and the lack of ROI that too often follows, even when POCs are successful. Executing a few POCs on various business problems enterprisewide should allow organizations to identify not only gaps in skills, data and technology, but also gaps in culture, readiness and general education about the AI discipline. The various levels at which AI techniques can be leveraged and complement human tasks should also be taken into consideration. The appetite can vary widely from one department to another.

AI competence can reside in many areas of the business. From LOBs to the IT department or other specific functional areas, enterprises tend to have pockets of skills that they consolidate into competency centers.

Nonetheless, organizations tend to evolve toward a certain model (with a few variations) once they have gone through a number of experiments leveraging AI techniques. That organizational model is based on a separate "AI lab" or "AI center of excellence" (see Quick Answer: How to Organize Your AI Center of Excellence). The lab is independent of both the LOBs and the IT department, usually reporting to a neutral corporate function. The idea is to nurture intimate ties to the business, stay abreast of the organization's technical capabilities and investments and stay in sync with the overall strategy.

While still reporting to the lab, AI experts can perform "tours" within lines of business, working closely with subject matter experts (SMEs) and IT professionals on the various ongoing projects, favoring a technical cross-pollination of the AI capabilities. That proximity also allows them to entertain serendipitous ideas from technical and business stakeholders (see Figure 7).

Figure 7. Best Practices for the Organizing of AI and Data Science Skills



After the five steps described in this research have been worked through a few iterations, the organization should consider a larger and more ambitious vision on AI strategy.

Evidence

[1] **2021 Gartner AI in Organizations Survey:** This study was conducted to understand the keys to successful AI implementations and the barriers to the operationalization of AI. The research was conducted online from October through December 2021 among 698 respondents from organizations in the U.S., Germany and the U.K. Quotas were established for company size and for industries to ensure a good representation across the sample. Organizations were required to have developed AI or intended to deploy AI within the next three years.

Respondents were required to be part of the organization's corporate leadership or report into corporate leadership roles, and have a high level of involvement with at least one AI initiative. Respondents were also required to have one of the following roles when related to AI in their organizations:

- Determine AI business objectives
- Measure the value derived from AI initiatives
- Manage AI initiatives development and implementation

A team of Gartner analysts developed the survey, and Gartner's Research Data, Analytics and Tools team reviewed, tested and administered it. Disclaimer: Results do not represent global findings or the market as a whole, but reflect the sentiments of the respondents and companies surveyed.

[2] **2023 Gartner CIO and Technology Executive Survey:** This survey was conducted to help CIOs and technology executives overcome digital execution gaps by empowering and enabling an ecosystem of internal and external digital technology producers. It was conducted online from 2 May through 25 June 2022 among Gartner Executive Programs members and other CIOs. Qualified respondents are each the most senior IT leader (e.g., CIO) for their overall organization or some part of their organization (for example, a business unit or region). The total sample is 2,203 respondents, with representation from all geographies and industry sectors (public and private). Disclaimer: 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.

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