



▶ **Leading the Way to an AI-driven Organization**

A practical guide for executives to navigate tectonic shifts and build an enduring competitive advantage with AI

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Introduction

Despite the sometimes exaggerated hype around Artificial Intelligence (AI), there is no doubt that AI is revolutionizing the way companies are doing business. Fueled by technological breakthroughs in recent years, we are observing a fast proliferation of AI across industries. So far, it may be the fastest paradigm shift in the history of technology. The increasing adoption should not obscure the growing divergence between leaders and laggards. While industry leaders have shifted their view on AI as a strategic business enabler and incorporated AI into their corporate strategy, the majority of companies are still caught in the “AI pilot trap” and are not generating the promised value of AI. While almost 93 percent expect to get some value from AI, only 35 percent have reported that they are seeing value from recent AI investments¹.

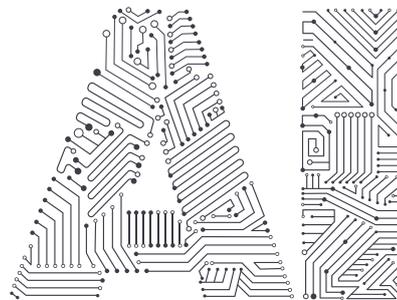
This publication serves as a realistic and practical guidebook on how companies can transform themselves into AI-driven organizations, leveraging the full potential of AI. Based on numerous Porsche Consulting initiatives and projects, the goal is to particularly shed light on the execution side of AI initiatives. The study also integrates practical experience from Porsche Consulting’s strategic partner appliedAI,² Europe’s leading initiative to accelerate the adoption of artificial intelligence in Germany and Europe and a consistent collaborator with over 50 large corporate partners on AI strategies, education, and AI implementations. Furthermore, an accompanying survey with 78 C-level and AI-expert participants³ provides an honest snapshot of the status-quo of AI implementations and the current challenges across industries.

Each chapter of this study is devoted to resolving the most common challenges companies face with the adoption of AI. We often observe insufficient understanding of what AI is and what potential it offers. This results in unrealistic and strongly divergent expectations within an organization.

Chapter 01 of this study therefore provides a strategic perspective on AI in terms of business value. **Chapter 02** highlights the transformative character of AI and why it is imperative to become an AI-driven organization. The journey to become an AI-driven organization requires a strong alignment and commitment among the entire leadership team to strategic directions and ambitions in order to avoid conflicts of interest or lack of focus. **Chapter 03** provides a framework for companies to define their AI agenda as a foundation for broad alignment. **Chapter 04** addresses the most critical aspects currently preventing the majority of companies from scaling AI across their organizations: the deployment of an AI operating model. The model consists of four building blocks: The portfolio block, a structured approach for the identification, selection, and execution of AI use cases, while matching required capabilities with strategic priorities and ambition levels. The organizational block focuses on the right structures and governance to drive use case implementation beyond the proof-of-concept stage into productive environments. The talents and culture block explains how to communicate AI’s relevance, how to build the required new skills using existing and new talent, and how to establish a culture that supports AI solutions. Lastly, the technology and data block illustrates how to design an architecture that supports the core team, developers, and everyone else in the organization to experiment, build, validate, and deploy AI solutions into production at scale. And finally, **chapter 05** summarizes success factors, or business imperatives, for companies embarking on the journey to become AI-driven organizations.

WHAT AI IS: A BRIEF EXPLANATION

Artificial Intelligence (AI) is the science and engineering of making intelligent machines. In other words, it describes the ability of computers to perform tasks normally associated with human intelligence. This includes intelligence that is programmed and rule-based, as well as more advanced techniques. Currently, the term AI mainly covers a range of computational machine learning (ML) techniques that turn low-level, "noisy" data (structured and unstructured) into abstract concepts to solve narrow tasks. The business value centers around eight capabilities:



//01 Vision

AI understands visual elements like pictures and videos (e.g., augments radiologists' diagnoses)

//02 Audition

AI detects patterns in sound signals and audio (e.g., assists root-cause sound anomalies)

//03 Conversation

AI mimics human communication (e.g., interacts on websites via chat bots)

//04 Expert system

AI extracts logical conclusions (e.g., derives next-best-action recommendations based on CRM data)

//05 Planning and optimization

AI optimizes resource allocation (e.g., optimizes production and logistics planning)

//06 Predictions

AI predicts certain events by using data (e.g., predicts consumer demand to optimize supply chain)

//07 Control and robotics

AI controls plants and machines (e.g., perceptive robots for human-machine interaction)

//08 Autonomous operation

AI monitors, controls, and optimizes the environment to make decisions and act autonomously (e.g., autonomous production lines)

01 | The Business Value of AI

AI is becoming progressively important, because it enables machines to perform a growing list of tasks hitherto reserved for humans. Machines can now see, hear, talk, walk, learn, and even drive cars. AI is becoming more efficient, effective, and low-cost. In most cases, its performance strongly exceeds human capabilities.

From an economic perspective, AI provides value in its ability to make cheap predictions. If we consider that predictions of any kind are associated with making decisions under uncertainty—and our lives are full of such decisions—and that AI can remove a great portion of uncertainty at incremental costs, the extraordinary potential of AI becomes apparent.

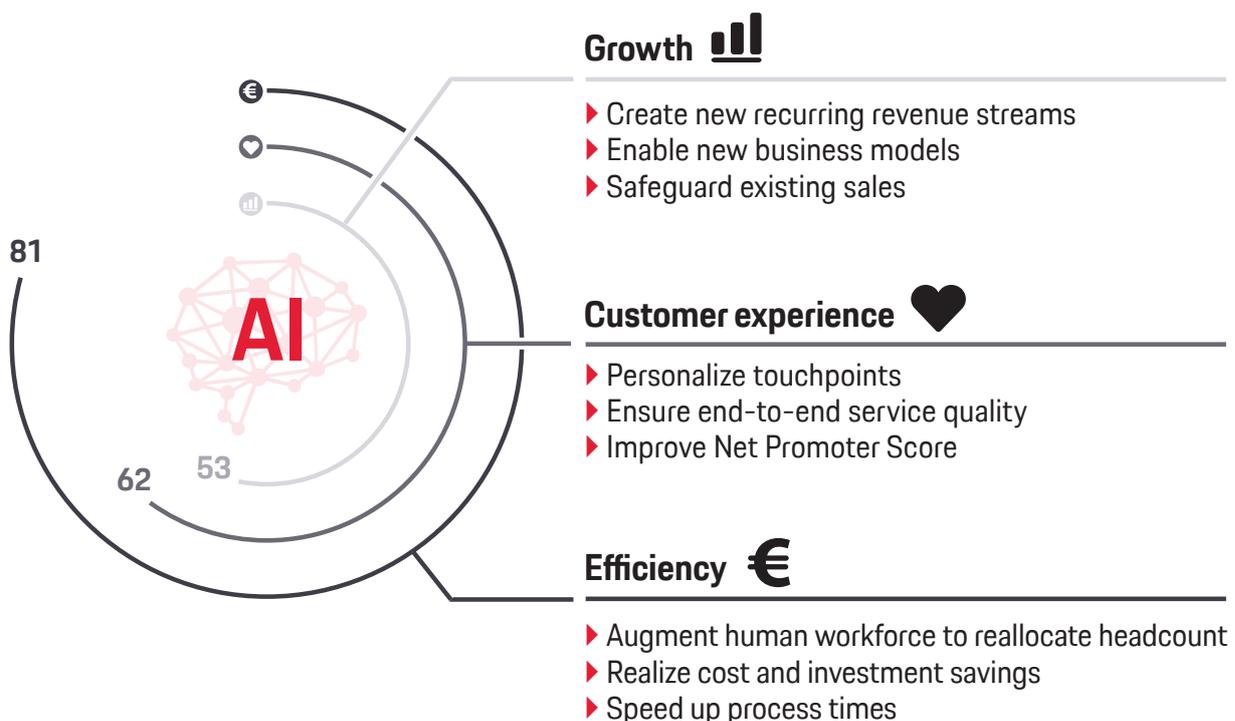
From a strategic perspective, companies of all industries can now generate substantial business value from AI while building a decisive and enduring competitive advantage for

the future. Some executives even expect larger value-pool shifts in entire industries such as healthcare and automotive. While studies differ in the exact value figure, the magnitude of AI's future business impact is in the range of trillions of euros. This value arises from three AI impact dimensions companies—and even entire ecosystems—benefit from:

- ▶ AI as a driver of top-line **growth** through new AI-driven or AI-enhanced products and services
- ▶ AI as a driver of improved **customer experience** through new personalized customer interactions
- ▶ AI as a driver of **efficiency** through automation and optimization of business processes or augmentation of human tasks

What is the biggest benefit you want to address with the adoption of AI?

% of respondents; multiple selections possible (n = 78)



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Fig 1. Survey results on the business value dimensions of AI

Growth | By incorporating AI into products and services, companies can level up their existing business and tap new revenue sources. They are now able to develop new business models or extend customer reach.

// KONE, the elevator company, has connected more than one million of its escalators and elevators to the cloud to offer predictive maintenance services to avoid unplanned downtimes for its customers. First results are encouraging with more than 25 percent decrease in breakdowns and 60 percent fewer customer reports of problems, compared to equipment on traditional maintenance schedules. AI also helps to predict demand and availability of the elevator system in larger buildings to optimize waytimes for users.⁴

// John Deere, the agriculture tech company, is a compelling example of leveraging AI for new growth opportunities. Back in 2017, John Deere acquired the machine-learning startup Blue River, which has provided the foundation for a new generation of smart agriculture solutions that help farmers to eliminate up to 90 percent of their herbicide volume, which directly translates into less costs and higher profits for farmers and additional business for John Deere.⁵

// Delta Air Lines is using AI-powered facial recognition to speed up security checks at airports. While the program (CLEAR) is designed to help travelers experience a more convenient journey through the airport, it is also a new revenue stream and an opportunity for Delta Air Lines to enter new sectors with similar challenges, such as stadium security gates.⁶

// MedTech giants such as Siemens Healthineers or GE Healthcare enhance their radiology equipment (CT or MRI scanners) with AI-driven software solutions for faster, more accurate diagnostics as well as automated and standardized workflows to meet the needs of the individual patient and radiologists. Siemens Healthineers, for example, has invested in a dedicated, structured reading team, building a database that potentially accesses more than 750 million curated images, reports, and clinical and operational data that is used to train their algorithms.⁷

Customer experience | A further specific advantage of AI is its ability to personalize any kind of business-to-human interaction, while at the same time automating its related processes. The resulting improved customer experience can propel higher interaction frequencies, average transaction volumes, retention rates, customer referrals, and consequently a higher customer lifetime value. The same principles apply to interactions with employees and business partners such as retailers or suppliers.

// The online clothing retailer ASOS developed an AI-based app that enables customers to upload a picture of their favorite celebrity, whereupon the service recommends similar but affordable clothes in ASOS's product portfolio. Based on this AI-enabled feature, 75 percent of its app users were more likely to return to the app, with ASOS increasing its orders by 9 percent.⁹

// The Royal Bank of Scotland provides individualized financial advice to its 17 million customers through AI-enabled customer intelligence, leading to increased trust and loyalty.

// Volkswagen developed a bot to streamline and partly automate the procurement of commodities and merchandise under €10,000 per order. Every year, the company spends hundreds of millions of euros in this price range. The bots collect pricing feedback from suppliers and provide pre-sorted overviews to the purchasing agents. Once the purchase decision has been made, the bots automatically migrate the data to the SAP system and create the order. In addition to direct savings of €1,000 (or more) per order, it dramatically increases the purchasers' productivity.¹⁰

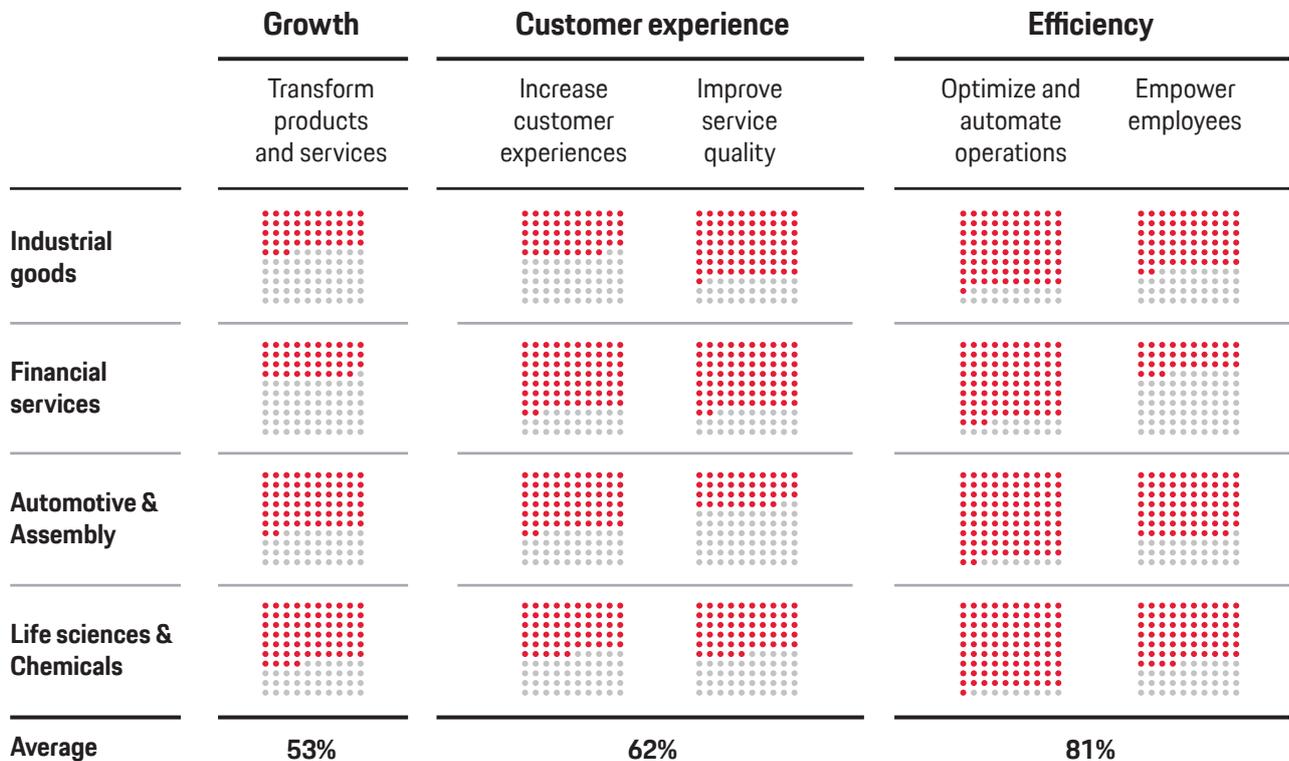
Efficiency | AI helps firms promote internal efficiency by optimizing operations, automating processes, and empowering employees. Business value is generated by leveraging AI to streamline or completely redesign internal processes. Porsche Consulting's strategy paper "The Path towards the Self-Driving Enterprise" highlights the significant potential in corporate supporting functions and showcases over 40 top use cases.¹¹ According to this experience, smart process automation through AI can help technically capture leapfrog efficiency gains, particularly in IT operations (60 percent) and procurement (around 50 percent), but also in finance and HR departments (40 percent each). AI solutions can automate or augment humans to achieve higher process speed with fewer resources required for more standardized workflows.

// The Swiss bank UBS is one enterprise that has been implementing Arago's AI-based problem-solving platform throughout its global IT department. Since 2016 the bank has been able to address 80 percent of all—hitherto manually processed—inquiries using AI and saw a 50 percent reduction in manual efforts.¹²

// Pentair, a water treatment company, is another great example of AI-driven efficiency gains in procurement. Their category managers typically spent more time compiling data from different data silos than deriving effective sourcing strategies. To rectify this, Pentair implemented an automated spend-analytics engine. This tool constantly monitors, analyzes, and scores category spend, supplier base, and supplier performance, thereby enabling category managers to make better-informed decisions. As a result, Pentair reduced spend-analysis cycle times from weeks to minutes and reduced its working capital by 15 million US dollars under new payment terms.¹³

What is the biggest benefit you want to address with the adoption of AI?

% of respondents; multiple selections possible (n = 78)



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Fig 2. Survey results on business value dimensions of AI (breakdown for selected industries)



WHERE TO START CAPTURING VALUE

Most executives of leading companies are concerned, even obsessed, about speed. “It’s not the big that eat the small; it’s the fast that eat the slow.” This title of a business publication from the early 2000s has become their mantra with regard to digital programs. While speed is essential for digital transformations in general, it is even more important to understand that companies who wait to adopt AI may never catch up. AI is not a plug-and-play technology that magically transports companies ahead their competitors. If a company’s culture does not embrace learning by experimentation, and testing is not an integral part of the managers’ KPIs, AI implementation will be long and difficult. Most companies are therefore better served by beginning with promising use cases, rather than waiting to identify the one case with the highest business value.

Porsche Consulting has queried 78 executives and AI experts on how their companies capture value from AI use case implementations. While the survey results (see figure 1) indicate that the majority of companies target more than one of these dimensions, the strongest emphasis is currently placed on applying AI to optimize operations and processes (81 percent).

Gains from process automation are relatively easy to achieve and have the potential to create visible lighthouse projects that demonstrate AI’s business value to the organization. Based on these lessons and with momentum developed in initial successful implementations, firms then approach more complex AI implementations (e.g., for products and services) or improve customer experience to generate a competitive advantage using AI.



02 | The Need for an AI-Driven Organization

AI: THE TIME IS NOW

//01 Data availability

The volume of available data has mushroomed, accessible in (near) real time, both from internal sources (e.g., machines) and external sources (e.g., weather).

//02 Advances in infrastructure

Storage capacity, processing power, as well as available bandwidth have continued to increase exponentially at decreasing costs.

//03 New data structures and algorithms

The creation of new data structures, dedicated to applied AI and significant progress in deep-learning core algorithms have opened the door to new, practical AI applications.

//04 Access to ready-to-use capabilities

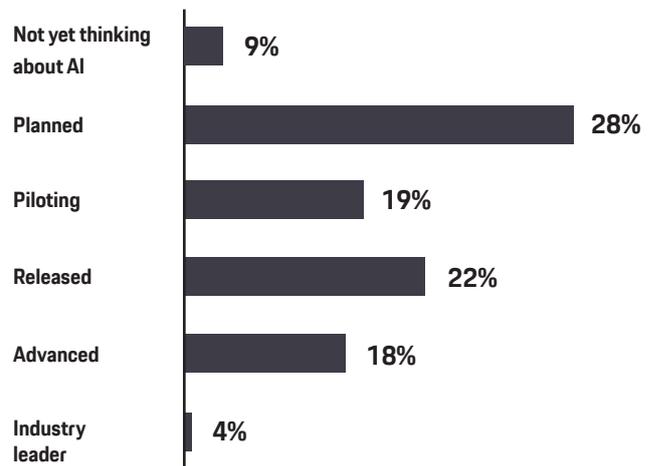
AI is also becoming more accessible to committed companies, thanks to open-source tools, libraries, and easy-to-integrate services. For the first time, it is possible to implement and deploy AI at scale without having to start from scratch and recruit a team of researchers and engineers.



While many incumbents have realized AI's potential value and its disruptive impact on their future business, about half of the surveyed companies report that AI activities are still in their infancy, or in the best-case scenario, stuck in the proof-of-concept or pilot phase with single use cases (figure 3).

How would you describe your company's general AI maturity?

% of respondents; multiple selections possible (n = 78)



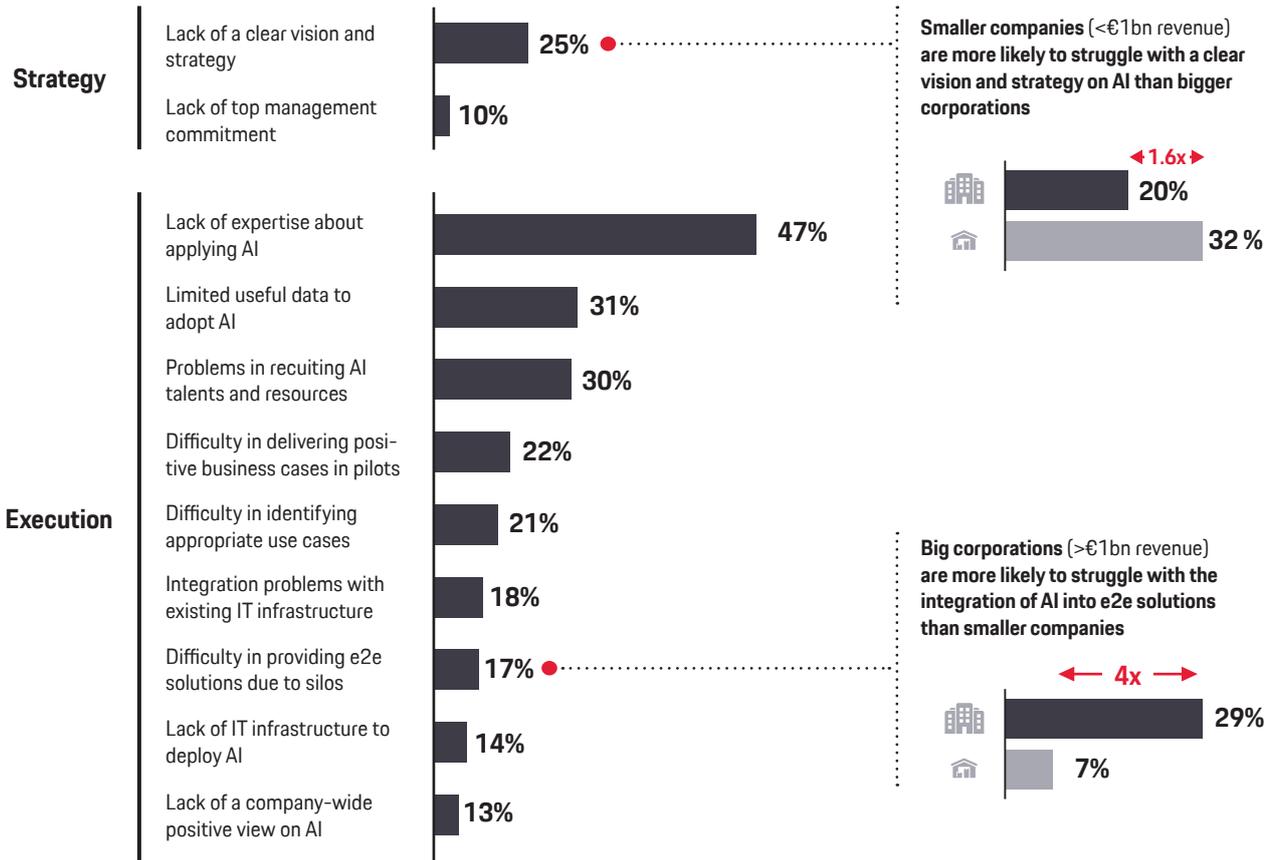
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Fig 3. Survey results on AI maturity levels

Why is it so difficult for companies to move beyond initial AI use case prototypes? When asked about the key challenges in implementing AI, 47% of survey participants pointed to the lack of expertise in applying AI; they lack both internal expertise and appropriate mechanisms to access external expertise (see figure 4). Limited access to useful data for AI ranks second (31 percent), followed by challenges regarding ROI for the first pilots. Not surprisingly, major corporations with revenue of more than a billion euros find it four times more difficult to integrate AI into end-to-end solutions than companies with less than a billion euro revenue.

What are the biggest challenges for your company in implementing AI?

% of respondents; multiple selections possible (n = 78)



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Fig 4. Survey results on biggest challenges in implementing AI

The development of an overarching vision or target picture for AI is crucial; however, most companies are struggling with AI's execution. The reasons for this are manifold. On a more general level, the focus—across firms and all industries—seems skewed to the what-question of AI (i.e., what should be realized?), rather than on the how-question (i.e., how can we facilitate AI's adoption, experimentation, and deployment in every corner of the company?). The democratization of AI technologies has fostered the paradox that AI pilots are deceptively easy to launch; companies tend to think too narrowly about AI as a plug-and-play technology with immediate returns and underestimate or ignore the transformative character of AI.

Many traditional companies seem to carry over misconceptions of digitalization success factors from the internet era into the AI era of today. Back then, some firms viewed their newly created websites as a sure-fire success factor for immediate digitalization benefits, without considering that successful digital value creation requires an entirely new culture and novel ways of working and culture, such as A/B testing, short cycle times based on trial-and-error principles, and decision-making by engineers and product managers. In today's AI era, many traditional players seem to consider the acquisition of machine-learning capabilities as the cornerstone for transition to an AI-driven company. In reality, however, global digital platform leaders such as Google, Facebook, Amazon, Uber, Alibaba, and Tencent have shown that an AI-driven company encompasses much more than that.



MACHINE LEARNING IS A CORE, TRANSFORMATIVE WAY BY WHICH WE'RE RETHINKING HOW WE'RE DOING EVERYTHING... AND WE'RE IN EARLY DAYS, BUT YOU WILL SEE US—IN A SYSTEMATIC WAY—APPLY MACHINE LEARNING IN ALL THESE AREAS.¹⁴

Sundar Pichai
CEO, Google

A couple of years ago, all of these players committed themselves to an “AI first” paradigm. In the meantime, AI is a key driver of any of their businesses. It would be too easy, however, to assume that these digital giants, with all their resources, would simply build on their existing technology stack, get the best talent, write the best algorithms—and leave it at that. A look behind the scenes reveals that successfully scaling AI requires much more than getting the technology right. To leverage the business value of AI at scale, these companies focus on building the right operating model, thereby enabling anyone in the company to harness AI to achieve aspired targets. A competitive advantage comes from access to a significant amount of relevant and consistent data, architecture that facilitates high-velocity data experimentation, automated workflows along the AI life cycle, and new ways of thinking about business challenges. Only a fraction of the overall value creation comes from algorithms, which is also reflected in the difficulty companies have protecting their algorithms, since most of them are open-source.

Understanding why and how digital platform leaders have fully embraced AI can help any organization that is ready to invest in its algorithmic future.

Comparable to the term “data-driven”, the imperative “AI-driven” is not only associated with a shift in mind-set that recognizes data as an asset, but also with a rewiring of the way organizations operate and decide. Such fundamental changes do not come easily. Leaders therefore need to prepare, motivate, train, and equip their workforce to make a change—but start with themselves. Several AI initiatives have failed due to senior executives' lack of understanding for AI.



JUST AS ELECTRICITY TRANSFORMED ALMOST EVERYTHING 100 YEARS AGO, TODAY I ACTUALLY HAVE A HARD TIME THINKING OF AN INDUSTRY THAT I DON'T THINK AI WILL TRANSFORM IN THE NEXT SEVERAL YEARS.¹⁵

Andrew Ng
Former VP & chief scientist, Baidu

03 | Defining an AI Agenda

To systematically reap AI's benefits throughout the organization, companies need to define an overarching AI agenda that is aligned with the corporate strategy. Since AI has the potential to affect the overall strategic direction, enterprises need to understand how AI might help them create a competitive advantage. In some cases, successful implementation of AI

projects have influenced the enterprise's overall objectives. The transformative nature of AI means this process needs to be CEO-driven. A solid understanding of AI—concerned less with its in-depth technology and more with its underlying principles and possibilities—is nevertheless crucial for the entire executive suite to kick-start a successful strategy process.

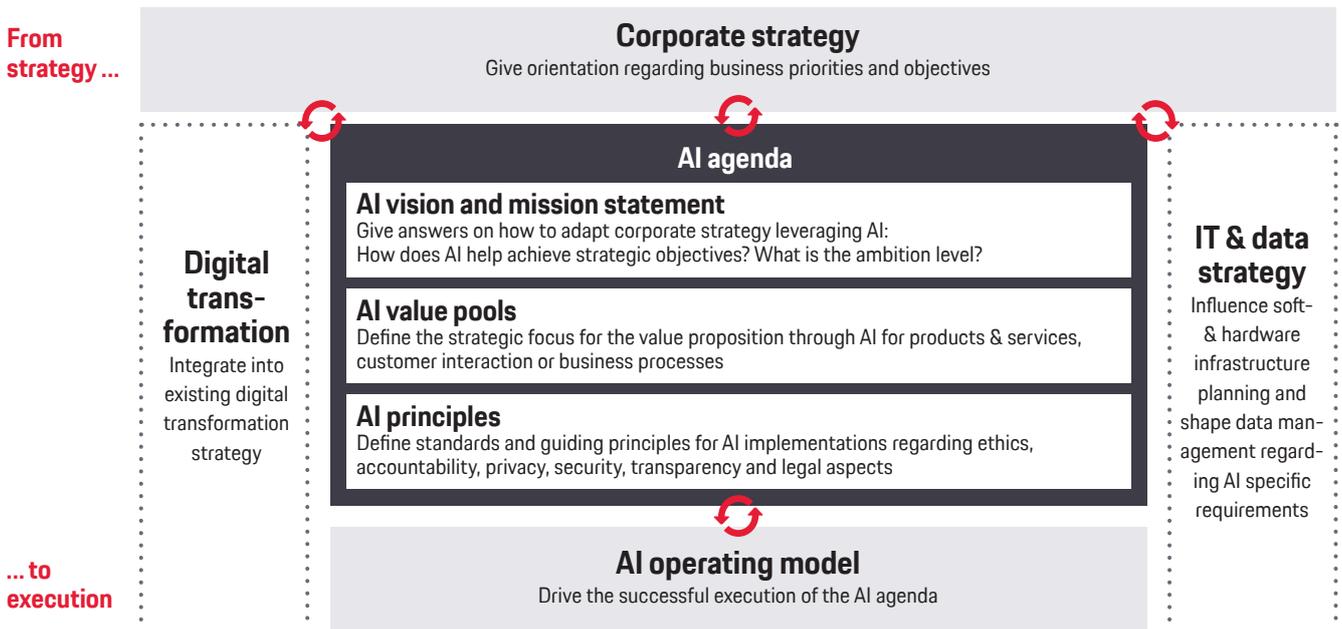


Fig 5. The AI agenda as a strategic foundation to build the AI operating model

A comprehensive AI agenda consists of three core elements (see figure 5):

First, a distinct AI vision and mission statement offer direction for AI to help achieve corporate strategy objectives. A clear “north star” definition sets concrete objectives for a particular time frame, such as the ambition level publicly stated by Bosch CEO Volkmar Denner.

Bold ambition levels are great for communication; however, firms should not underestimate the implications of an operating model for successful strategy execution in terms of attributed cost, focus, and effort. Positioning the firm in the continuum of AI-enabled players—from laggard to industry average to best-in-class and beyond—is ultimately a key strategic move that has the potential to change the business model.



TEN YEARS FROM NOW, SCARCELY ANY BOSCH PRODUCT WILL BE CONCEIVABLE WITHOUT ARTIFICIAL INTELLIGENCE. IT WILL EITHER POSSESS THAT INTELLIGENCE ITSELF, OR AI WILL HAVE PLAYED A KEY ROLE IN ITS DEVELOPMENT OR MANUFACTURE. 16

Volkmar Denner
CEO, Bosch

While some of the survey respondents (see figure 6) do not incorporate AI in their overall strategy (19 percent), the majority of the companies reported that AI—at least indirectly—impacts their corporate strategies (25 percent) or use AI as an enabler tool for strategy deployment (39 percent).

AI is currently a central pillar of corporate strategies for only 13 percent of the respondents, or will be so in the future (4 percent). Based on these findings, most companies still need to substantiate their position towards AI.

How well is your corporate strategy transformed to position your company appropriately to reap AI's potential benefits?

% of respondents (n = 77)

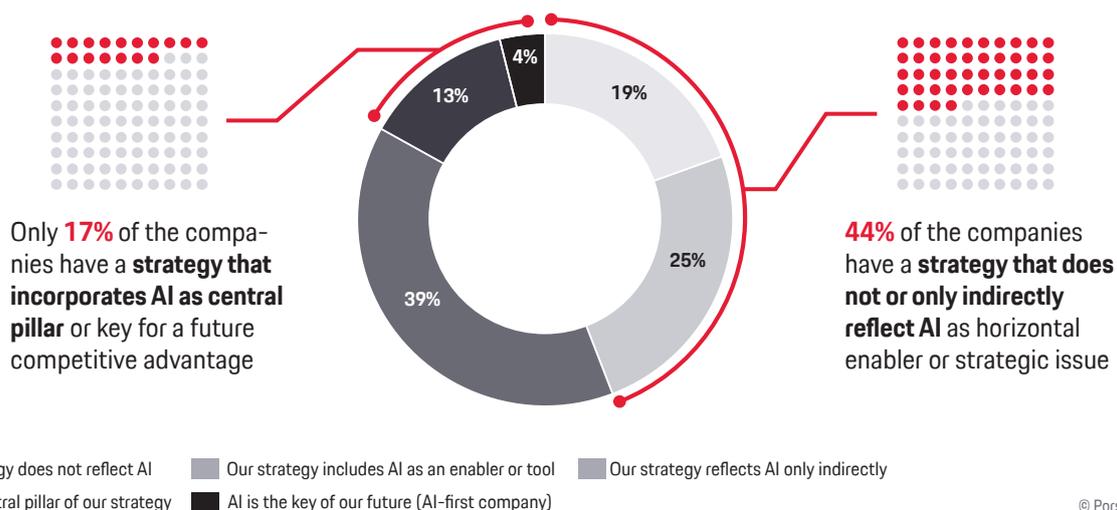


Fig 6. Survey results on the integration of AI into corporate strategy

Second, the strategic focus should be substantiated by defining AI value pools that reflect the strategic bets, as most promising areas of AI application for the company. These discussions on value pools help prioritize and define the focus for later use case identification and the management of a suitable use case pipeline. For instance, an automotive company might see its main AI value pools in the fields of autonomous driving, digital companions, and artificial engineers. The value pools for an agricultural company could be automated farm equipment via computer vision and demand prediction. A pharmaceutical company might place its bets on personalized smart drugs and intelligent drug design.

It sounds like an easy, rather not value-adding exercise. The reality is that a deep understanding of AI's capabilities and potential strategic implications is a fundamental prerequisite for achieving competitive advantages. Defined value pools are also beneficial to determine what the company is not going to do with AI.

Third, when AI becomes a new tool in the CEO repertoire to drive revenue and profitability, it becomes clear that deploying AI requires careful management to prevent unintentional but significant damage, not only to brand reputation, but more importantly, to employees, individuals, and society as

a whole. While company values can offer a compass for AI's appropriate application, top management must provide employees with more concrete AI principles, translating these values into practice when developing and using AI. As the third ingredient in an AI agenda, these principles serve as corporate-wide standards, particularly concerning ethics, accountability, transparency, privacy, and security aspects of AI. They support technology adaptation by creating trust in customer- or employee-focused AI applications by deliberately regulating self-determination of data or anti-bias standards. They also help developers or engineers make the right decisions on an operative level and thus foster pragmatic and speedy implementations in line with corporate values and customer expectations.¹⁷ With an exclusive mobility brand, for example, such principles provide actionable guidelines to manage the trade-off between desired personalization and required data privacy.

It is crucial when defining the AI agenda to anchor it in the overall strategic picture, including interfaces to digital transformation strategies and other domain strategies. In addition, the AI agenda must be closely aligned with the IT and data strategy, down to the operative level. Most companies have already recognized data's theoretical significance but often lack understanding what it means in practice.

CASE STUDY – AI@PORSCHÉ

ANJA HENDEL—DIRECTOR PORSCHÉ DIGITAL LAB AND HANNES FISCHER—MEMBER OF AI@PORSCHÉ PROGRAM TEAM

Anja and Hannes, you work together at Porsche. Could you give us a brief insight on how you started AI@Porsche, from use cases to setting up an organization that can actually scale?

We truly believe: If you want to shape your own future business, you have to understand its driving technologies. Building on this paradigm, Porsche operates its own innovation laboratory—the Porsche Digital Lab—in the middle of Berlin since 2016. The Lab identifies and tests deep-tech from its location right on the banks of the Spree. A team of technology and software experts as well as scientists focuses on the question of how Porsche can identify innovations, e.g. in the fields of Artificial Intelligence, and turn them into practical solutions. To do so, we adhere to two principles: First, we inspire the Porsche organization with the underlying potential of these technologies and second, we are building the capability to deliver deep-tech products. As an example, to inspire the Porsche organization, we took a Raspberry Pi and outfitted it with a standard USB microphone to monitor the only production machine directly accessible in the Porsche Digital Lab—our coffee machine. This way, we found an approach to investigate the sounds (and potential anomalies) of production machines. You could argue that a coffee machine is a hardly a production machine but think about it: It consumes input (coffee beans, water, and milk), executes processing steps on those inputs (grinding, brewing) and finally creates an output based on your choice and inputs. However, even more important: We were able to transfer the results of this experiment and applied to a wide variety of use cases. For example, we took the gained insights from this small-scale case to develop our acoustic anomaly analysis tool A³ that will soon help our engineers at the test benches in Weissach to detect unintended noises such as squeaking in our electric car side mirrors and thus will support the vehicle development.

All those products that kickoff in the Lab are introduced with a town hall meeting that we call the Brain Trust. Here, the product owners show what they would like to do and test in the upcoming months. The results are then presented in the same event format, giving everyone a chance to see what we are working on. Sometimes people fear new technology rather than see the possibilities, and we try to counterfeit that by having a very open and inviting approach to our activities.

In parallel, and in line with our vision “AI as an integral part of Porsche”, we initiated AI@Porsche as a dedicated AI program to coordinate and streamline our efforts to build and—specifically—to implement AI use cases. We formed a team of methodical, organizational and technical experts as our core AI team and implemented a holistic use case innovation funnel methodology that supports use case validation, incubation and scaling. Based on this, we have built a product-driven organization (with business owners fully integrated in the process) that is able to develop AND implement products for internal and external customers.

The above-mentioned A³ example demonstrates our own AI development capabilities, which become more and more important for Porsche, especially if required solutions are not available off the shelf. Furthermore, we are now even able to provide industry-independent solutions for use cases of other industries that are similar to our own. For us at Porsche Digital Lab, this successful expansion of our value proposition has been the most valuable learning on this journey so far. Everything is allowed in your dreams; it would have not been the first case of a successful expansion of Porsche into a seemingly untapped market, as the success of Porsche Consulting has shown, starting with lean management 25 years ago.

04 | Building the AI Operating Model

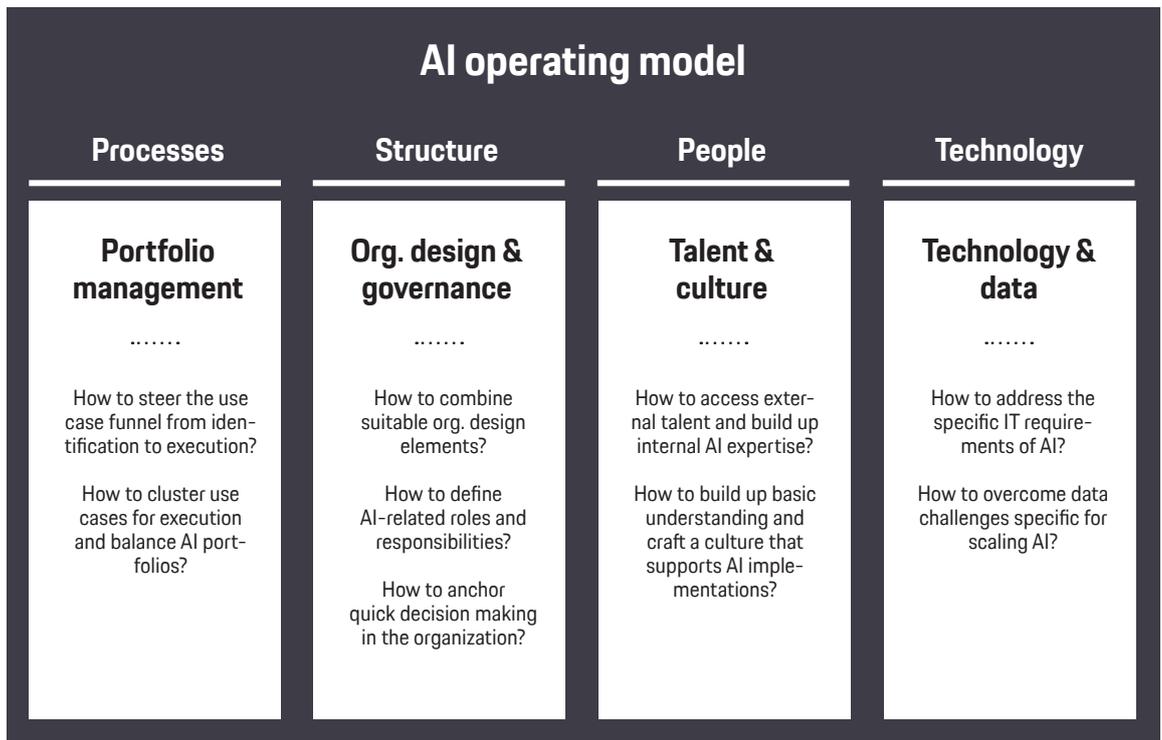
“Ideas are easy, execution is everything ...” According to John Doerr, an American venture capitalist at Kleiner Perkins, companies need to go beyond ideation to scale AI successfully.¹⁸ Execution requires clear structures and appropriate decision mechanisms to select the right use cases, forming strong product teams with sufficient talent, creating, end-to-end responsibility as well as building a flexible, supporting IT backbone. The AI operating model summarizes those

considerations along four central building blocks (see figure 7): portfolio management, organizational design and governance, talent and culture, as well as technology and data.

The following sections will run through the key considerations of these building blocks, each underlining their objective, addressed key challenges as well as actionable advice on how to execute them successfully.

**Design
levers**

**Building
blocks**



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Fig 7. The building blocks of an AI operating model along the HPO design levers¹⁹

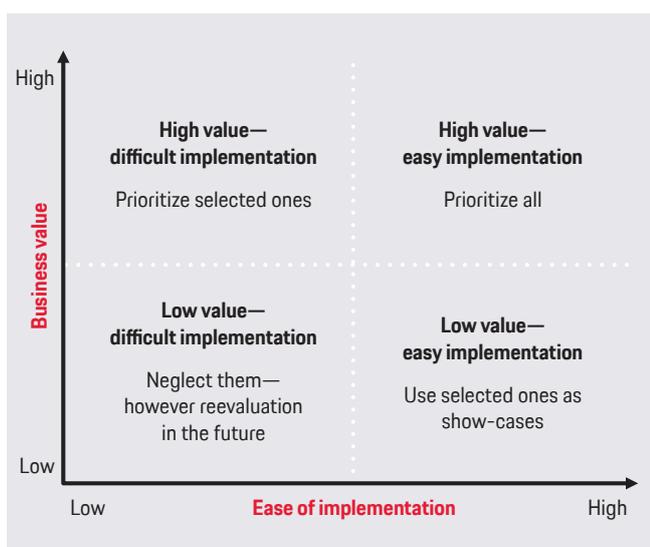
4.1 | Managing the AI Portfolio

Successful AI-driven organizations have set up a systematic and structured approach to identifying, assessing, prioritizing, and subsequently implementing use cases. Objectives may vary over time, such as creating initial lighthouse cases at the beginning of an organization's AI journey, but ultimately aim at fostering implementation. This process of strategically managing AI's use case funnel helps find the most promising bets, minimizing dangerous handovers when ownership changes. It also aids in balancing the scarce AI talent pool between quick wins (that deliver a return within months) and long-term challenges (that bind these talents but are more likely to pay off over time). Many companies still struggle, for instance, with clustering use cases to develop algorithms, capabilities, APIs, or even internal applications for company-wide reuse or deployment. For example,

vision- and audio-based quality controls represent the core of AI use cases in several production or logistics processes within automotive value creation. All related use cases leverage similar types of AI. Clustering these use cases can create common denominators so that one team, such as a computer audition team, could work on any machine-learning application for audio anomaly detection and make components available for reuse within the company. While most of these AI product teams start with a very specific use case, their scope will grow over time, adding more use cases that fit the same type of AI. Building reusable components is an especially important approach for companies that want to scale AI from a small core team to the broader organization. The portfolio management process follows three distinct phases along the use case funnel:

//01 Identification of use cases typically occurs in close cooperation of AI technology “champions” with domain experts. Exchange with external ecosystem partners, such as the appliedAI initiative, can help in the ideation process and provide best practices or impulses that serve as a starting point or continuous impulse for the use case funnel. Three perspectives that help to identify relevant use cases are as follows:

- ▶ **Strategy-driven:** How does AI contribute to the visions set out by the strategic AI value pools?
- ▶ **Asset-driven:** How can existing data and infrastructure within the organization be leveraged through AI?
- ▶ **Capability-driven:** How might commercially available, in-house, or easily built capabilities address problems in products or processes—from a customer's or employee's perspective?



Business value	Ease of implementation
Financial value considers the direct monetarization, such as savings and sales growth potentials.	Input data considers aspects, such as data quality, availability and complexity of the data source(s).
Customer & company value targets the direct value-add, such as increased service quality, improved product quality, process improvements and employee satisfaction.	Required know-how assesses the required knowledge, such as domain expertise and technical knowledge.
Strategic value contributes to strategic aspects, such as achieving the AI vision, sustainability, degree of innovation and differentiation.	Change impact considers organizational aspects, such as process changes, technical system adaptations and cultural changes.

© Porsche Consulting

Fig 8. AI use case assessment and prioritization

//02 The second phase concerns use case assessment and prioritization. Here it is crucial to find the right level of detail for an initial evaluation of a potential use case. The results of this assessment form the basis for the prioritization of use cases along the dimensions of business value and ease of implementation (see figure 8 for more details). Experience shows that an indicative assessment including financial impact, added customer- or user-focused value add, and an evaluation of the strategic fit is sufficient to describe the business value of a single use case. To assess the ease of implementation, it is sensible to have a rough look at the availability of input data and quality, evaluate the type of required expertise, and estimate the change impact including the complexity of affected systems or processes. An even more extensive assessment does not provide added value and would delay taking action.

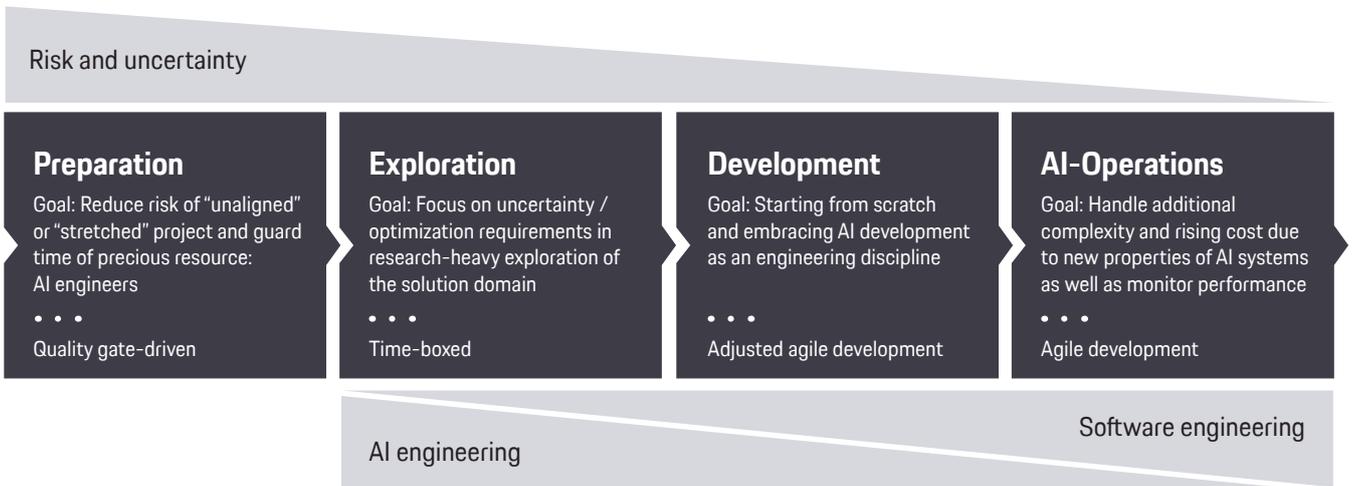
Balancing a portfolio implies management along time horizons. Certainly, the portfolio should include quick wins based on proven technology that can generate tangible results within a few months. This helps secure stakeholder buy-in and attract internal customers for further AI projects, especially during an AI journey's early phase. To successfully drive AI at scale, however, consider "bolder" use cases with high strategic relevance and a medium- to long-term implementation perspective. These larger experiments also attract new and retain existing AI talents.

The clustering of use cases according to required capabilities is a key to facilitating the make-buy-partner decision on a strategic level. The portfolio management should define guidelines on what to build in-house (strategic value for

the company), together with partners (faster implementation), or with commercially available solutions (only minor customizing activities required). Firms need to balance the competitive advantage achieved by an exclusive in-house AI solution against the benefits of commercially available third-party solutions, including a broader database to train AI solutions, access to a capable developer base, or interoperability with other solutions.

//03 AI use case execution follows different paradigms than traditional use case implementations, which require a specific process model for AI use case execution (see figure 9). A major difference between classic software development and AI engineering is that the latter involves data (vs. code) and must cope with an uncertain solution space (vs. changing customer requirements as the biggest uncertainty). AI engineering wants to better understand inputs and outputs, rather than the formation of a computational unit.

Data acquisition and data quality control, which can consume considerable amounts of time and entail a high degree of risk, must be integrated explicitly into the preparation phase, the first step of the execution process. Risk regarding data, suitable algorithms, and process embedding drives the high uncertainty entailed in the exploration phase of AI use case implementations. One successful result of the exploration is a working AI proof-of-concept that has demonstrated feasibility of the use case. For the subsequent development and operations phase, use case execution relies on the combination of various skill sets of AI engineering and software engineering—skills that are rarely found in a single person and hence require interdisciplinary collaboration, typically with the IT department.



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Fig 9. The appliedAI process model for AI use case execution ²⁰

4.2 | Designing the AI Organization and Governance

Many companies are stuck in the proof-of-concept or pilot phase of use cases when they try to implement them within their traditional structures. Those companies typically struggle to set up the required interdisciplinary teams with sufficient capacities, restrict flexibility with a rigid project setup, or encounter problems when integrating isolated use case implementations.

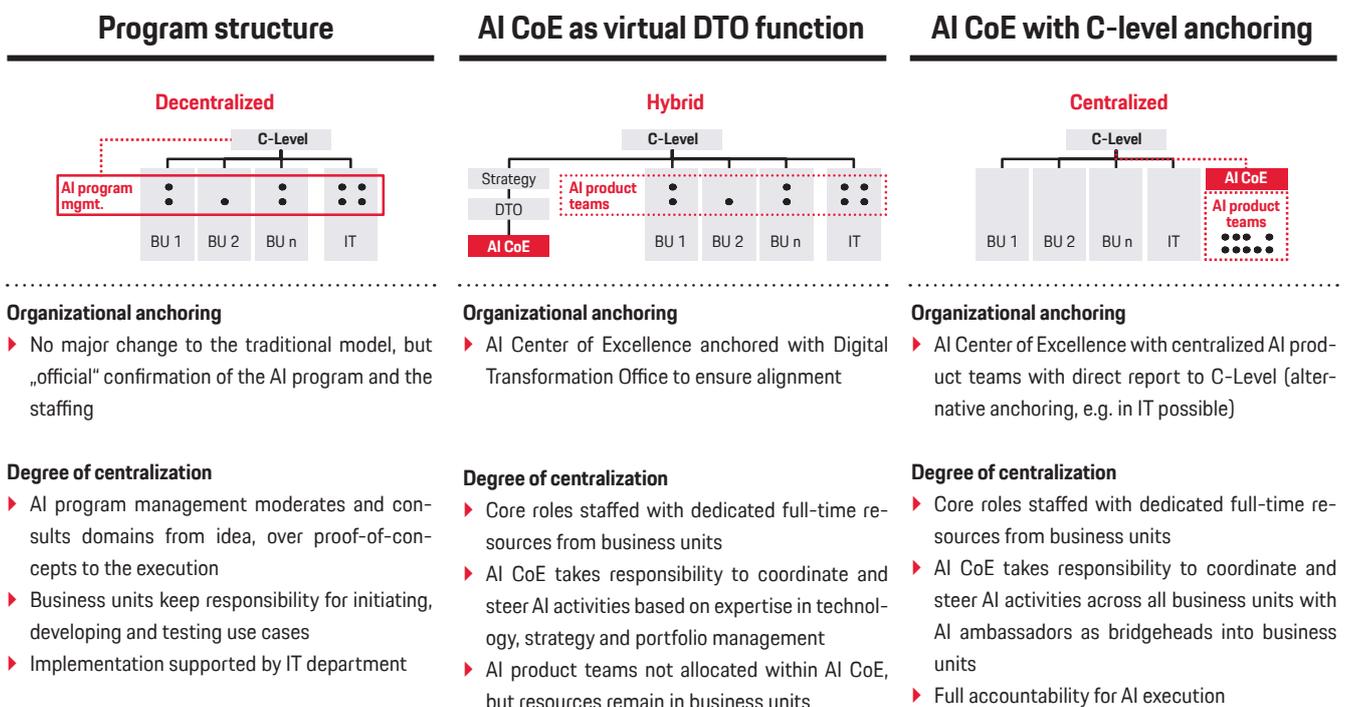
When looking at the organization and governance redesign within the AI operating model, companies must bear in mind that use cases are strongly interlinked with the businesses and its processes and require the input, expertise, and collaboration of domain owners. Hence, the model cannot be designed as a greenfield or standalone version. The concrete organizational design depends to a large degree on company specifics and varies according to maturity level and (pre-)existing structures of the company at hand. Figure 10 illustrates three general, but not universally valid, design options to drive AI adoption.²¹

An AI program structure is a reasonable starting point for organizing activities, since a central AI program management is easy to install and can integrate existing AI efforts throughout the company. Experience indicates, however, that it is not the

optimal format to further scale AI adoptions, as interfaces and inflicted politics can easily result in deadlocks.

The bundling of relevant skills into an AI Center of Excellence (CoE) is the most common way to organize AI deployment at scale. Porsche Consulting survey respondents reported that setting up a CoE has proven to be the most relevant contributor to fostering AI implementations within their organizations (see figure 11).

A central CoE, with dedicated resources, functions as an overall coordinating mechanism: supporting the definition and refinement of the AI agenda, driving the AI portfolio management process, coordinating capability building with external partners, and providing a clear interface for the mandatory collaboration with other departments. Particularly companies that have just embarked on their journey must create a central skill pool to commence AI-related activities beyond isolated use cases. The CoE should be in the driver seat regarding enablers such as communication, training and knowledge exchange, (technology) research, and scouting in order to spread a common understanding throughout the enterprise and counteract AI-ignited fears with a suitable change management.



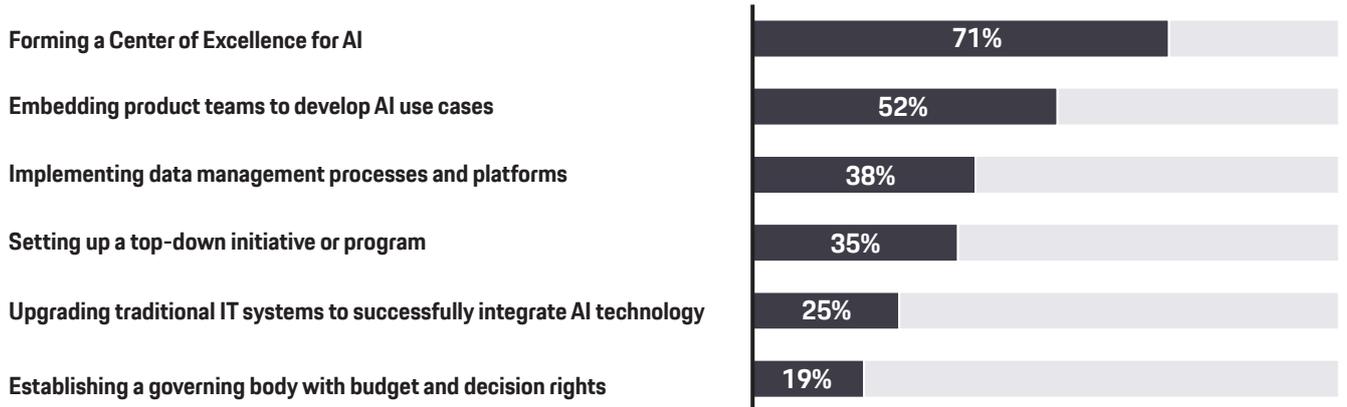
■ Anchoring of AI organization

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Fig 10. Organizational design options for anchoring AI within an organization

Which factors have contributed best to foster the implementation of AI solutions in your organization?

% of respondents; multiple selections possible (n = 48)



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Fig 11. Survey results on success factors for AI implementation

// The pharmaceutical company Pfizer established its AI Center of Excellence in order to develop and drive data analytics and AI strategies to generate insights across all areas of Pfizer's business. To achieve this, Pfizer's IT team grouped their so far scattered in-house AI talent and hired AI developers who understood the pharmaceutical business and could rapidly apply AI techniques in a business context. They also employed a wide range of tools ranging from natural-language processing and neural networks to statistical models and more. The CoE assesses and selectively implements new AI use cases and leverages analytics, visualization, and technical capabilities that accelerate Pfizer's ability to discover new medicines, bring them to market, and positively influence patient outcomes.²²

In course of their transformation journey, many companies have implemented a Digital Transformation Office (DTO) or similar structure for centrally steering digitalization activities. These could be a good anchoring point for the AI CoE to align the AI agenda with other digitalization activities. The proximity to the business development or strategy department allows direct access to the C-level in case of escalations. As these typically lean structures focus on strategy and portfolio management, it is not an appropriate place to allocate the required AI product teams as an execution organization.

AI product teams, comprised of 100 percent dedicated and interdisciplinary members, usually work autonomously and are fully financed. Their focus is on creating customer and business value and they continuously release increments²³ of their solutions. The CoE typically oversees all product teams without disciplinary lead, supports where needed,

delegates AI experts into the teams, resolves potential conflicts among all departments involved, and delegates experts.

// For instance, Rolls-Royce launched their R² Data Labs to create an organizational base for their product teams and to accelerate data-driven innovation in general. Their so-called data innovation cells consist of interdisciplinary teams of data experts who collaborate with teams throughout the organization. Their aim is to identify, validate, develop, and operate data applications that unlock efficiencies within Rolls-Royce or realize value for customers and new business opportunities for Rolls-Royce.²⁴

Anchoring both CoE and product teams within a C-level department (e.g., CIO, CTO, CSO) is another wide-ranging design option for AI organization. According to a recent survey by MIT Sloan, companies with CIOs in charge of AI are only half as likely to obtain value from AI as companies with AI initiatives managed or led by a different C-level executive.²⁵ This does not mean CIOs are less capable of steering AI initiatives than other leaders. Indeed, many CIOs are strategic business partners, empowered to develop new talent and pioneer new ways of working. These executives enable their companies to create meaningful value from AI. But companies that view AI from a narrow technological standpoint, which can occur when mapping AI initiatives to IT, tend to ignore the transformational character of AI. Whether companies choose the CIO department or other board members as AI's sponsor and organizational anchor point, the CoE needs to discuss AI's effects on the existing IT backbone and systems jointly with the IT organization. Experience shows that a specially assigned IT collaborator, who takes on respon-

sibility for resolving potential IT-related roadblocks, can facilitate AI deployment to a great degree. To steer the use case identification and assessment phase within the portfolio management, the CoE should ensure suitable bridgeheads within the business units. Figure 13 provides a summary of the responsibility shared among the AI CoE, the AI product teams, and business units as concerns the most important task clusters for AI proliferation at scale.

// Anthem, an American health insurance provider, serves as an example of AI adoption driven by a CIO department. The firm established an AI Center of Excellence, known as the Cognitive Capability Office, led by CIO Tom Miller. Its objective is to centralize cognitive capabilities, skills, and talent in order to build the capacity to develop and scale AI pilot projects. In this case, the CIO department has taken a leadership role in driving early AI developments, because IT's involvement before or during the pilot phase is critical to scaling the project.²⁶

// In 2017 the Bosch Center for Artificial Intelligence (BCAI) was created from existing Bosch competence centers to develop innovative AI technologies for the company. Using data from various business divisions, BCAI not only conducts research on AI, but also designs and implements AI for smart, connected, and autonomous technologies across Bosch's business sectors.

Currently, BCAI has five locations including Bengaluru (India), Palo Alto (USA), Pittsburgh (USA), Amsterdam (the Netherlands), and Renningen (Germany).²⁷ This year Bosch unveiled its plan to invest an additional 35 million euros in a new campus for applied artificial intelligence in Tübingen's Cyber Valley, with workplaces for up to 700 AI experts.

But which roles and responsibilities are required to become an AI-driven organization. Figure 12 summarizes the allocation of responsibilities for successfully driving the transformation to an AI-driven organization, while figure 13 details the required roles.

AI product owners have a pivotal role within AI product teams. They have an end-to-end responsibility for the assigned product. AI brings in requirements beyond those of a traditional product owner: the product owner must understand both machine learning and the domain. The management of uncertainty throughout the development phase becomes an important task for the product owner. In contrast to agile software development, AI use case implementations are much more experimental and cannot be broken down into story points. Product owners have revert to other forms of planning and must have a high tolerance for frustration and an aptitude for changing plans.

	Responsibilities	AI CoE	AI product team	Business units
Strategy	Development of AI agenda and AI operating model	✓		
	Definition and review of AI value pools & investment areas	✓		✓
Portfolio management	Consulting for idea development, substantiation & piloting	✓	✓	✓
	Coordination of AI use case funnel	✓		
Technology & infrastructure	Identification, testing and enablement of new technologies & tools	✓		
	Provision of AI platforms & tool stacks	✓		✓
	Extension of tool stacks along new requirements	✓	✓	
Execution & scaling	Execution of proof-of-concepts	✓	✓	✓
	Implementation and scaling of AI use cases		✓	✓
	Operations, lifecycle management and continuous improvement		✓	✓
Enablement & communication	Provision of trainings and basic knowledge	✓		
	Provision and development of an AI playbook	✓		
	Driving of change management & communication measures	✓		✓
Ecosystem management	Strategy, development & nurturing of ecosystem partner relations	✓		
	Selection of supplier & integration of partners	✓	✓	✓
	Development of (internal & external) AI community	✓		

✓ Responsible ✓ Support © Porsche Consulting

Fig 12. Allocation of responsibilities within AI organizational design

Beyond individual product teams, AI portfolio managers are responsible for use case clusters. They are the driving force behind the centralized portfolio management process. They steer the development of AI capabilities, resolve resource conflicts across AI product teams, and manage other stakeholders, working closely with AI ambassadors across the domains.

These AI ambassadors function as so-called bridgeheads for the CoE within the business units since AI use cases require significant domain expertise. Based on more advanced expertise about AI's potential, AI ambassadors promote AI in their domains and support the identification and assessment of relevant use cases. While AI ambassadors keep their disciplinary anchoring in their original business unit, they have a "dotted line" to the CoE for technical guidance.

In terms of AI governance, companies require fast decision-making and escalation paths up to the C-level to scale AI across the organization. The CoE and otherwise autonomous AI product teams require a mechanism to promptly address and resolve conflicts, as AI solutions can easily lead to cultural clashes or political infighting. Such situation occur frequently with AI, with middle managers apparently losing "power" due to AI solutions directed at process automation intended to free up significant personnel resources. Setting up separate structures for AI is usually unnecessary, but existing committee structures must be adapted. Particularly strong ties to digital transformation activities and existing IT-related decision or escalation paths are required to ensure alignment—either via integrating AI topics into those committees or by integrating respective key stakeholders in dedicated AI committees.

	Roles	Structure
Central	 AI portfolio manager Challenges the AI product owner and manages AI use case cluster vision as strategist	AI CoE
	 AI tech lead Keeps AI team informed about new AI solutions and methods	
	 Agile coach Coaches the AI product teams regarding agile workflows	
	 AI product owner Is a domain expert and takes typical product owner function	
	 Data scientist Cleanses & analyzes data, sets up prediction models and visualizes results	
	 AI engineer Develops the solution to a production-ready application	
	 Data engineer Sets up the architecture and pipelines for data management	
Decentral	 Software engineer Manages the IT infrastructure and deployment of continuously developed code releases	AI product team
	 IT collaborator Removes all IT barriers and ensures an optimal working environment	
	 AI ambassador Functions as bridgehead to business units, promotes AI and identifies use cases	
	 AI trained expert for law and compliance Understands the legal and compliance side of AI and can assess implications	
		Enabling roles in business units

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Fig 13. Allocation of key roles within the AI organizational design

4.3 | Developing AI Talent and Culture

Now more than ever, harnessing AI opportunities requires the interplay of various disciplines: from data engineers who build the architecture around the data, to data scientists who provide meaningful insights into data, to AI engineers who transform the work of their colleagues into deployable solutions. All these roles are new to most traditional companies, and related competencies are rarely found in-house. External hiring of new talents is mandatory and should go hand in hand with an upgrade of the existing workforce's skills.

Companies often take an ad hoc approach in their efforts to develop talent, either through external hiring or by relying on online learning platforms, universities, and executive-level programs for the education of existing employees. We believe that these quick-fix tactics are not sufficient for the transformation into an AI-driven

organization. While hiring new talent can address immediate resource needs, such as rapidly building a nucleus AI practice, it is equally crucial to develop competencies across all hierarchical levels.

Porsche Consulting has identified three areas of action for people enablement that deserve special attention:

//01 Development of the core team

A successful AI core team requires a combination of technical, sector-specific, engineering, and commercial competencies (see figure 14), ideally all combined in one person. According to Kaggle, the leading community of data scientists and machine learners, the demand for AI talents has doubled over the last 24 months.²⁸ In contrast, the number of highly skilled AI experts is between 20,000 and 25,000 globally.²⁹

Engineering experience,
to develop solutions that work in the labs as well as in the real world

Business acumen,
to develop and manage AI teams towards realized business values



Technical skills,
to analyze data, set-up models and visualize results

Domain knowledge,
to interpret data appropriately and provide relevant recommendations

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Fig 14. Required competencies within the AI organization

Governments of various countries—such as France, Finland, and most recently, Germany—have become aware of the increasing demand for talent and initiated new university education programs to cope with the AI talent shortage. The proliferation of AI courses and resources from universities and technology companies will further boost the talent supply. In addition, AI will follow the pattern of most IT skills toward higher levels of abstraction and therefore become accessible to less specialized developers over time.

While it is challenging for traditional companies to hire talents from the outside, the useful integration of such talents is equally difficult. Only a powerful alliance of AI specialists and in-house domain experts (e.g., R&D engineers, machine operators, and IT systems engineers) has the potential to leverage the promises of AI. This in turn requires a common language and skill upgrade of the existing workforce.

A reasonable starting point to acquire new, external competencies is the collaboration with external partners. A total of 63 percent of survey respondents reported that they began their AI endeavor with external partnerships. Such collaborations can range from contractual work to strategic partnerships or even joint ventures. Regardless of the type of partnership, collaborations can act as an enabler for building implementation capabilities from scratch and allow access to a bigger talent pool.

Fruitful partners can come from different spheres: technology vendors, academia, startups, or complementary companies. appliedAI, for example, has built a sizable network of AI talent, offers a profound knowledge base, fosters the exchange of lessons learned among their more than 50 partners, and hosts AI-related hackathons. Platforms such as Kaggle enable companies to host interesting data challenges tackled by the international data science community. The best solution is awarded a cash reward. Firms can leverage such platforms to generate solutions and simultaneously attract talent. Companies can also find candidates at crowd-sourcing platforms such as Crowd AI and Crowd Analytix. Beyond typical recruiting approaches, strategies like “key-hires” or “acqui-hires” offer faster access to relevant exper-

tise. The acquisition of startups, as a seemingly attractive approach for quickly internalizing new competencies, tends to be costly, and the startup's integration is just as challenging as retaining its talent.

There is no one-size-fits-all approach. Companies with high AI business relevance and ambitions might prefer to develop in-house AI capabilities, while others might consider the establishment of (strategic) partnerships a better sourcing option. Regardless of the approach, companies need to ensure continuous support for implementing AI applications in all departments.

//02 Reskilling employees

As noted in the introduction to this chapter, the acquisition of AI competencies needs to come hand in hand with the development of internal talents by reskilling or upskilling the existing workforce. Companies that report difficulties in hiring or retaining AI talent but who are actively helping their existing workforces to gain AI skills are more likely, by 40 percentage points, to have generated value from AI, compared with companies that are not focused on reskilling.³⁰ Companies typically define a suitable education strategy for their internal target groups using a blended learning concept. This modularized learning program comprises defined learning paths for each of the required roles of AI implementations (see figure 13) and usually consists of the following four components:

- ▶ Digital learning modules are advantageous by being easily conveyed to and flexibly timed for a broad audience. They also promote integration with existing jobs. External AI knowledge may be more accessible than most companies imagine. Online learning platforms like Coursera, Udacity, and Udemy provide a multitude of online courses in most AI fields.
- ▶ Classroom training modules are important as a platform for discussion and access to the topic of AI. Trainings sessions should foster practical transfer of conveyed content into the company's specific context (e.g., via the assignment of real projects as “homework” between sessions).

- ▶ Internal communities are powerful for fostering knowledge exchange and providing fresh impulses. If these communities are partly open to the public, they can also help build links to external parties and support hiring activities, a visible signal to outside talent. For the CoE, the active promotion of communities is a strong accelerator for AI proliferation across departments.
- ▶ Ambassador programs train people that translate business problems into analytical questions. Deploying translators is especially important during a company's early efforts to use AI, when analytics expertise tends to be scattered across the organization or only covers a small part of the organization. Ambassadors are not only productive translators, but serve as teaching assistants or facilitators of internal AI marketplaces.

// Boeing has recently announced investments of US\$300 million, including US\$100 million for workforce development. The investments support training, education, and other capability development to meet the scale needed for rapidly evolving technologies and expanding markets. The company has also earmarked another US\$100 million for the "workplace of the future" and other infrastructure enhancements for Boeing employees.³¹

// Schneider Electric has fully integrated its AI initiative into the overall digital program, with AI as a platform for each of the four key themes: digital offering, customer experience, operations, and cybersecurity. As part of this effort, Schneider Electric installed capability owners who are not AI specialists but sufficiently savvy AI ambassadors who will support business units and practice leaders to prioritize and deploy AI projects where they make the most sense.³²

//03 Change management and cultural transformation

As AI requires profound changes in a company's way of thinking and working, they should proactively steer the transformative effect of AI on their respective organization. The effects are manifold:

For executives, changes are specifically associated with a shift in decision-making—from experience-based and/or leadership-driven to data-based. They have to cope with a high degree of uncertainty attributed to AI implementation. The required agility, expertise, and tolerance for experimenting and coping with possible failure is a difficult learning for traditional enterprises. Employers and employees do not have a common view of AI's impact on their organization. More than 85 percent of employees do not think AI increases coworker collaboration, according to a recent Gartner survey of 2,639 employees from 848 companies.³³ At the same time, Hollywood-ignited fears of AI replacing humans as well as a lack of knowledge of and access to AI in the early stage of the transformation journey can create anxiety and even resistance among the workforce of any organization.

The need for an AI culture is fundamental, even to technology giants. Apple analyst Gene Munster explained that the relative failure of Siri compared to rival products, such as Amazon's Alexa, is crucial because "Artificial Intelligence is not in Apple's DNA".³⁴ A veteran of the hardware era, Apple has developed a corporate culture based on commercializing physical products and the software applications that support them. Succeeding today, however, requires a culture built around "AI first". Apple also fosters a culture of privacy, which has clashed in the past with the need to harvest and exploit the quantities of data. Today this has changed, with new algorithms and frameworks performing on smaller data sets while respecting users' privacy.³⁵

These examples highlight the "softer side" of AI implementations that needs serious attention. Obviously, some homework must be done: Organizations will first have to build their business practices for harnessing data across all departments and businesses, replacing a culture of no-transparency with a one of complete transparency. Corporate data can no longer be sealed in traditional silos. Instead, a company will have to become a closely interconnected organism, with information continuously shared among all individual cells. Allocate as much budget and resources to the change and training as for the actual implementation and architecture.

4.4 | Building the Technology and Data Backbone

Realizing AI at scale calls for new technological designs, as currently no reference architecture exists. Even thought leaders, such as Nvidia, Facebook, Uber, or Google, are still in a trial phase of testing frameworks and building platforms, workflows, new infrastructures, and hardware to enable AI deployment at scale. Most of their lessons so far are either published or made accessible to the public as open-source. In the following, this publication will cover the general challenges of establishing appropriate AI technologies in companies and elaborate design principles that will help navigate the iterative path toward a technology backbone that works well for scaling AI. Even leading companies that have solved many of those challenges are aware that this is a never-ending process.

In general, a required AI technology backbone can be structured along the following pillars: frameworks, infrastructure, and platforms. Only a small fraction (about 5 percent)³⁶ of real-world AI systems are composed of the actual AI/ML algorithm. Most companies will not invest in framework or infrastructure innovations. This chapter therefore focuses on the platform-building pillar that address the remaining 95 percent, as this is the most impactful aspect for operationalizing AI.

//01 Frameworks

Most organizations dream of standardization based on a single framework. That idea has proven impractical in large organizations, as different data scientists and AI engineers are likely to use different frameworks to conduct their experiments. Companies are well advised to let scientists and developers use the tools they want. As a general principle, however, frameworks should be split into development and deployment (production) environments, as they each have

different priorities. While flexibility is important for the developer's ability to iterate fast in the development environment, framework stability and scalability of thousands of network nodes matter the most in production environments. To facilitate the "translation" of models among various frameworks and their transfer from development to production, companies can use tools like ONNX (Open Neural Network Exchange).³⁷ For deployment, ONNX includes hardware optimizations and guarantees model comparability with vendors like Nvidia, Intel, Qualcomm, and Apple.

//02 Infrastructure

The three main infrastructure challenges for building an AI backbone are storage, networking, and computational power. One of the key decisions companies must make concerns the question of cloud versus on premise infrastructure. On-premise refers to a delivery model where the infrastructure (e.g., data center, CPU clusters) is installed and operated by the company itself.

For general IT and applications, running one's own infrastructure does not provide any competitive advantages for most companies, and the shift to (public) clouds is associated with significantly lower costs, higher speed, and improved flexibility. The overall trend across industries is a migration of classic IT infrastructure to the cloud.

The answer is not that simple with AI. In industrial automation and IoT networks, latency and bandwidth constraints may prevent the cloud from serving as a complete solution. On-premise infrastructure might offer AI several advantages. Most companies, however, should start local deployment on decentralized laptops to speed up initial results with less investment, using cloud infrastructure only where needed.

//03 Platforms

Compared to most disciplines of software development, AI relies on experimentation and validation, rather than on empiric tests, to assess the behavior of a specific model. Without the right architecture, however, experimentations on data can become the greatest impediment for large-scale machine learning solutions. Streamlined experimentation architecture will allow data scientists to develop, test, and evaluate various machine learning models for a specific scenario and capture “knowledge elements” that can be reused in future models.

It has become evident that AI development is still evolving to become as robust, predictable, and widespread as traditional software development. To cope with this circumstance, many of the global digital platform leaders have started to build internal machine learning platforms to manage the AI life cycle. For example, Facebook, Google, and Uber have built FBLeaRner Flow,³⁸ TFX,³⁹ and Michelangelo⁴⁰ to man-

age data preparation, experimentation, model training, deployment, and monitoring. Figure 15 highlights how Uber has solved some of the AI scaling challenges. Because other companies cannot use these internal platforms for their purposes, a multitude of solutions is currently entering the market, including:

- ▶ Commercial platforms and services (e.g., SageMaker by Amazon, Azure ML by Microsoft, Cloud ML by Google)
- ▶ Commercialized open-source projects (e.g., Driverless AI by H2O)
- ▶ True open-source solutions, such as comprehensive platforms that cover nearly all aspects of the workflow (e.g., MLFlow⁴¹ by DataBricks) and solutions for specific parts of the AI workflow (e.g., Airflow⁴² by Airbnb)

Technical problems with AI scalability

Diffuse data workflows

Individual teams work on problems—all with different approaches

Unstructured modelling approach

Every team has their own way of building their models, leading to non-reproducible solutions

Repetitive processes

Consume time by having to solve the same problems (e.g. data cleansing) again and again

Complexity Trade-off

One-serves-all AI platform vs. customization potential for special problems

How UBER tackles those problems

Single end-to-end workflow

Structured, centralized workflow from data management to prediction monitoring. The progress of different teams is bundled

AI as software engineering

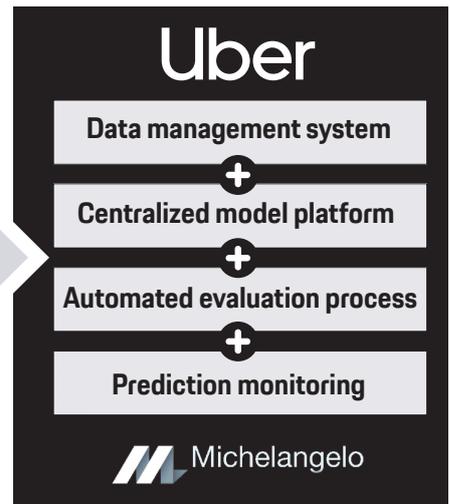
Apply software engineering techniques (e.g. version-control or testing) also to AI problems

Model developer velocity

Automating and speeding up repetitive tasks leaves time for the model optimization bottleneck

Modularity

Build the platform in a modular and tiered way, that allow single modules to be addressed directly



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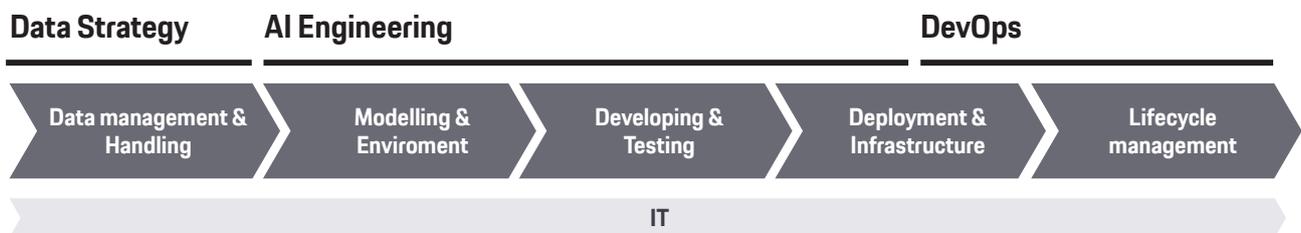
Fig 15. How to set up a scalable AI platform along Uber’s Michelangelo

The following general design principles can help to design the company-specific AI technology backbone:

- ▶ Treat AI as software engineering, including versioning of data and models.
- ▶ Aim for high cohesion inside any phase of your workflow and the overall pipeline design.
- ▶ Decouple the interface between the process steps, technically and workflow-wise.
- ▶ Automate the set up and running of experiments to increase model developers' velocity.
- ▶ Ensure reusability of algorithm and models and make past experiment results easily searchable.
- ▶ Follow architectural patterns, continuous integration and test automation.

Whether organizations buy one of these emerging platforms from a vendor or build their own, companies that want to deploy AI at scale need a rigorous and consistent system to manage, document, and monitor workflow from data input to final action.

With regard to the overall AI workflow (see figure 16), this publication has mainly focused on the engineering and DevOps/MLOps. Given that availability and accessibility of relevant, high-quality data is key to the performance of any AI solution, the following section will illustrate what companies need to do to build the right data strategy.



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Fig 16. AI implementation workflow

Data strategy

When it comes to data, most companies have already recognized the value potential of data and have implemented a data strategy with respective data management standards. However, AI imposes some additional requirements on how to identify, access, store, qualify, and prepare data in productive real-time environments. The key implications to be addressed across the AI funnel are the following:

- ▶ **Data identification:** create transparency about the relevant data and related meta-information.
- ▶ **Data sourcing:** make data accessible to teams across the company based on clear governance principles.
- ▶ **Data storage:** assure systems meet the requirements of continuous data in/output and versioning.
- ▶ **Data quality:** create a data preparation pipeline and data management with defined levels of quality.

Depending on the selected AI use cases, solutions will require access to and the integration of various data sources from a variety of different systems and environments. Linked to data storage, infrastructures have to meet high bandwidth requirements and guarantee the retrieval of AI metadata, for example, for versioning models and training data, or for tracking model hyper-parameters. Data quality is key to ensuring high model performance, as data characteristics that change over time often result

in downgraded model quality. A stringent monitoring of data quality (and the data pipeline in general) becomes particularly mandatory when use cases migrate from the proof-of-concept phase into productive environments.

Most businesses are simply not yet equipped to manage and mine data. If your data or algorithms are inaccurate or biased, the results will be ineffective or erroneous. For example, if companies intend to automate their hiring process and simply use data that reflect relations of historical input (CVs) and output (human hiring decisions), the AI algorithm is biased and will perpetuate hiring practices of the past.

It is therefore crucial to make data part of the corporate culture, from the C-suite to the front lines. With this as a focus, your data science, AI engineering, and business teams will work together more fluidly and, as a data-forward business, you will attract and retain top talent.

To summarize, hardware and software are just emerging and as yet lack clear reference designs or best practices. Hence, companies need an agile setup and “shadow IT” for testing. The standard (and AI-ready) IT will establish over time. Accordingly, an AI Center of Excellence needs freedom to develop automated pipelines based on initial successes, and later on, platforms that aim at scalability, reproducibility, and traceability. Without these platforms, AI solutions are not maintainable in the application and remain stuck in proof-of-concept stages.

05 | Conclusion: Critical Success Factors for Scaling AI

Neural networks have to learn, as do enterprises when applying AI; it is about the learning curve. Starting early by elaborating proof-of-concepts and gradually working on both the AI agenda and the AI operating model—this is essential for scaling AI successfully. But what are the ingredients to avoid common pitfalls when implementing AI and going beyond the pilot stage? Let ten core imperatives guide your way from understanding to scaling AI.

Understanding AI

//01 Make AI a CEO topic. A basic, shared understanding in the C-level suite about AI avoids misleading expectations and guarantees commitment. AI implementations at scale will affect the entire company and can have disruptive power that will need to be managed. This definitely means AI belongs on the CEO agenda.

//02 Understand AI as transformational change. Invest in not only technology but also enabling factors such as continuous communication, training sessions, and suitable implementation workflows. In the context of AI, education is key, not only for skilled AI talent but for the whole organization, particularly those end users affected by it. Transport a compelling change story explaining the why and communicate, communicate, communicate.

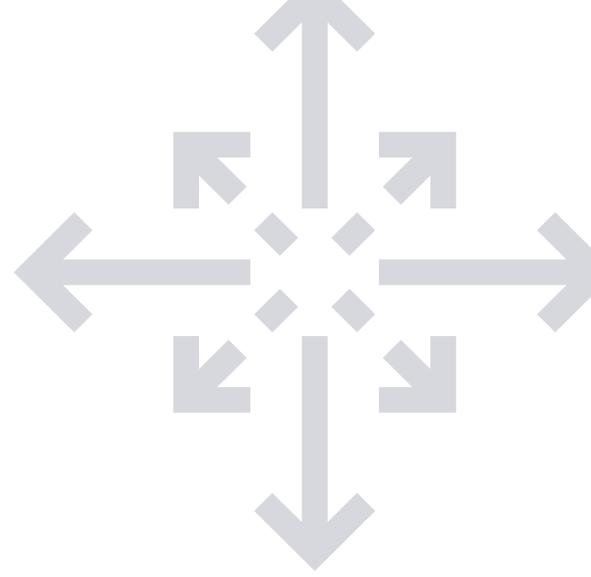
//03 Set your AI agenda. Define a coherent vision, mission, and ambition level, which is further broken down into actionable value pools. This sets the stage for successful implementation. AI principles provide orientation during the journey.

Kick-starting AI

//04 Build an AI nucleus. Bundle existing AI talent around your top profile(s) to gain momentum and drive initial implementation with an internal team. A Center of Excellence provides the punch you need and enables interdisciplinary project work.

//05 Start with first pilots. Select use cases that have the potential to become visible lighthouse cases and collect first-hand experience with AI. Initial measurable outcome not only illustrates the potential executed by a specific organization but also offers important lessons that form the basis for strategic directions.

//06 Build coalitions with IT and business. Integrate key stakeholders across the company to anticipate roadblocks and make business owners responsible for AI implementation. By involving and enabling these stakeholders early on, it becomes easier to create common objectives with tangible results that go beyond lab-style “gimmicks”.



Scaling AI

//07 Scale your AI operating model design. Build structures around the AI nucleus team. Provide sufficient budget and degrees of freedom. Interlink the structure to decentral bridgeheads across the enterprise.

//08 Think AI—Think ecosystem. During the entire AI transformation, partners and collaborators are key to success. Engage in networks like appliedAI or formats like AI Mondays that offer expertise, access to talent, technology, and fresh impulses outside of the company.

//09 Keep the pace of your AI transformation. Be active in leading the transformation, and be proactive in recognizing and resolving problems. Keep a finger on the pulse of the firm: involve stakeholders who know the organization well, talk to employees, or even conduct panels to discuss AI adoption. Stay one step ahead.

//10 Keep fine-tuning the AI operating model. As with any transformation, scaling AI requires adaptability. AI product teams provide such flexibility for execution. Give the Center of Excellence a coordinating role in the portfolio management and allow it to continuously foster strong ties to the domains.

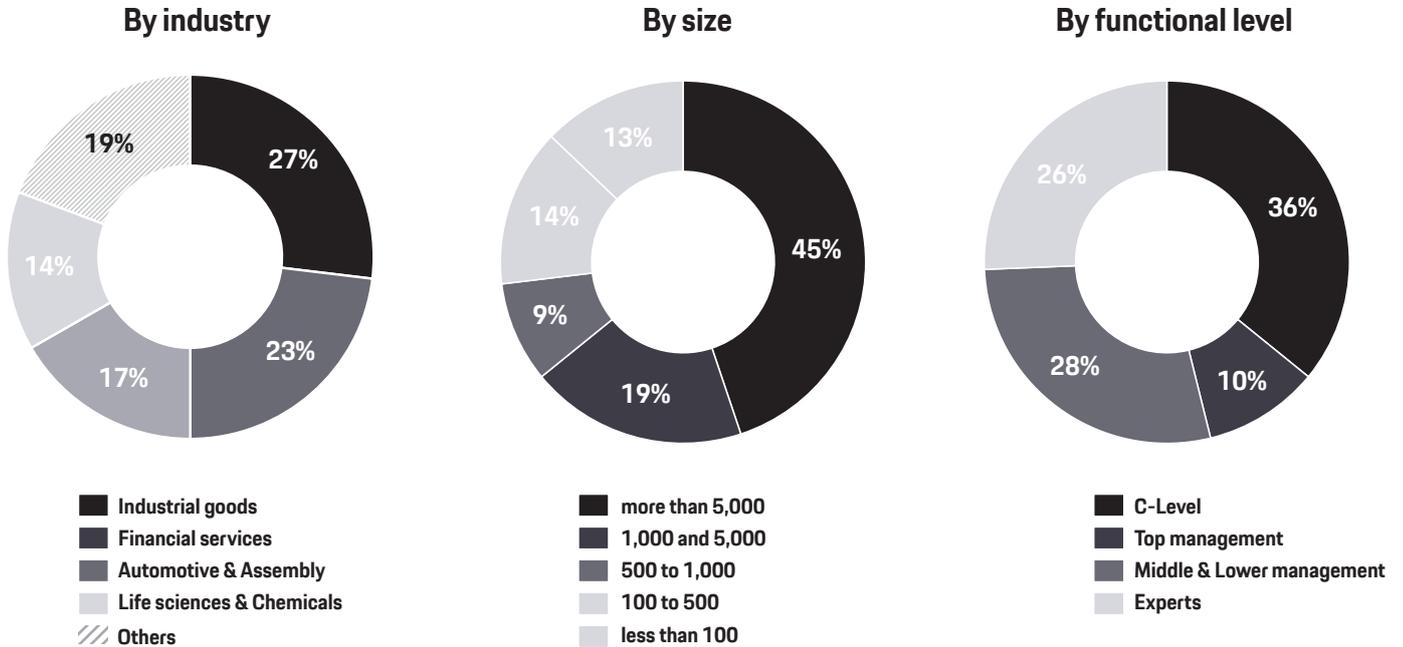
Transforming a company into an AI-driven organization means engaging it in a continuous learning process, characterized by not only success but also failure. A realistic set of objectives and a holistically involved organization are essential to mastering this challenge. Keep in mind: the opportunities of AI are only realized in that terms that your organization allows to use it. Manage uncertainties and ensure the organization is guided through the entire learning process. Not all approaches will have the desired results, but starting with initial use cases creates valuable insights and often reveals opportunities that an organization did not foresee.

It is time to get moving and unlock AI's potential!

Survey Results

Survey participant demographics

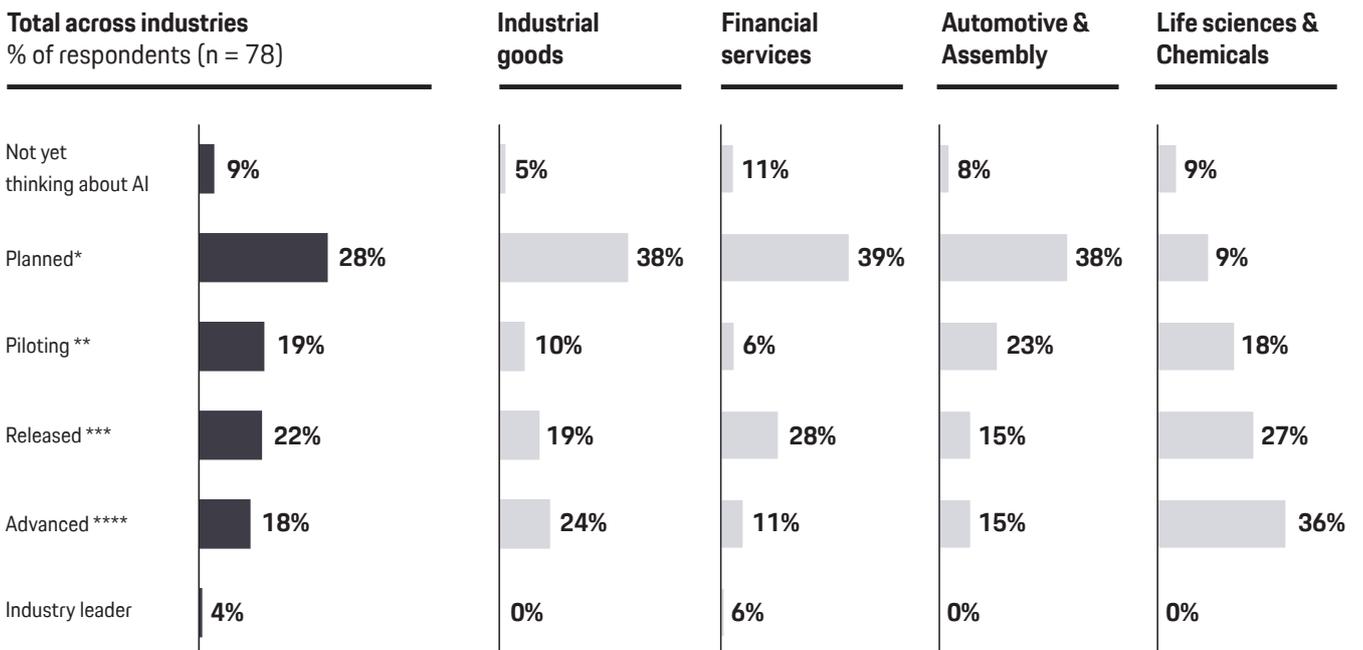
% of respondents (n = 78)



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How would you describe your company's general AI maturity?

Total across industries
% of respondents (n = 78)



* AI is being planned, but not yet put to active use, not even in early stage pilots

** AI is put to active use, but still only in early stage pilots

*** AI is put to active use in one or a few processes in the company, but still quite selectively, and/or not enabling very advanced tasks

**** AI is actively contributing to many processes in the company and is enabling quite advanced tasks

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How important are the following organizational capabilities for your success with AI at scale? And how competent is your company today?

Average of respondents value from 1 (least) to 5 (most) possible (n = 77)

Biggest gap
between stated
and revealed

Data Strategy: Organization has a clear strategy for acquiring, managing and governing data to enable AI and digital solutions.

Skills: Mechanism for specialized AI skills by educating employees, attracting talent and working with externals.

AI Strategy: Organization has a clear AI strategy including a map of strategic value pools incl. required level of investments.

Data Management: Organization has the infrastructure for capturing, storing, structuring, labeling, accessing and governing data.

AI Leadership: Senior leaders demonstrate true ownership of and commitment to AI initiatives.

Smallest gap
between stated
and revealed

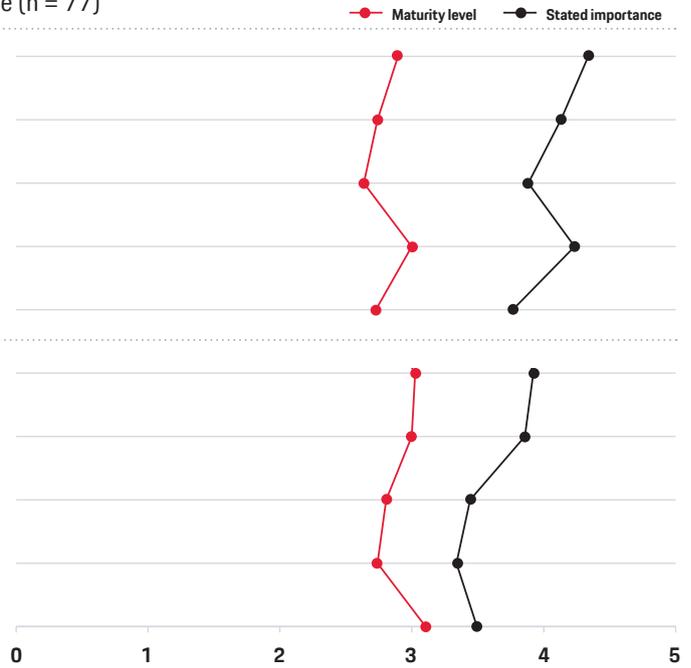
Open Culture: Organization has an open culture to embrace change, break down silos, and collaborate across and with externals.

IT Infrastructure: Organization has tools to enable and support teams along the entire lifecycle/ workflow of AI implementations.

Portfolio Management: Organization runs a process for developing and selecting portfolio of most valuable AI opportunities.

External Alliances: Organization has collaborative alliances with extern partners for technical capabilities, best practices and talent.

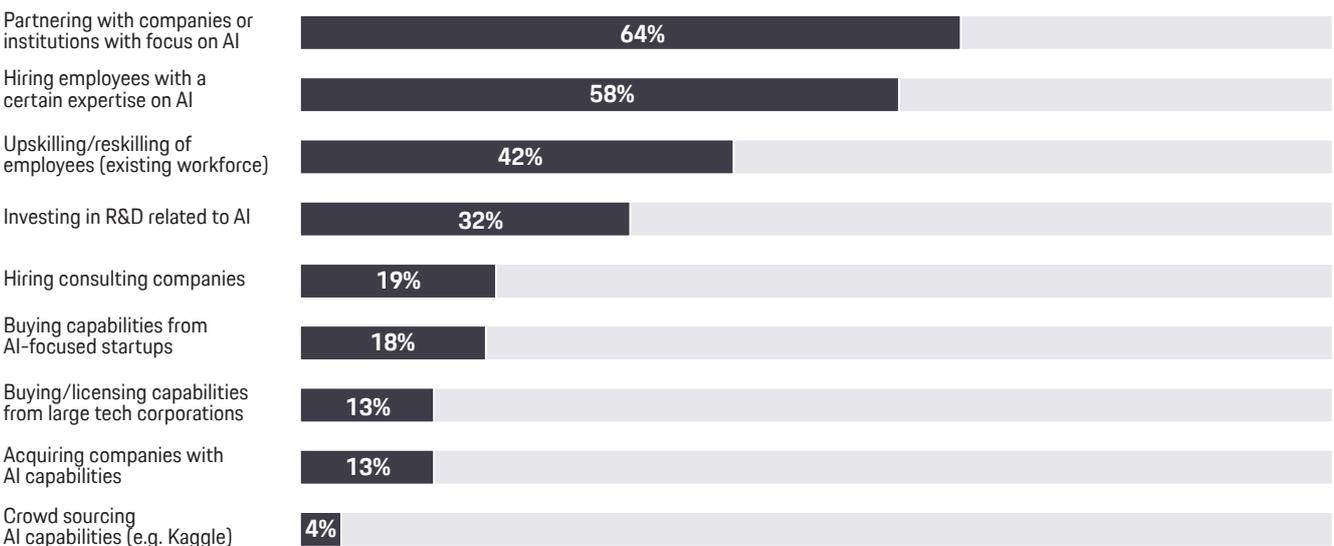
Agile Development: Organization has cross-functional teams to effectively run AI experiments, lift PoC and enhance solutions.



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What is your strategy for obtaining and deploying AI skills across your organization?

% of respondents (n = 77)



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Appendix

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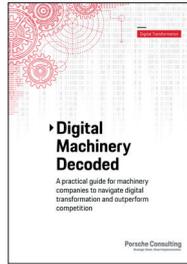
Further reading



The Path towards the Self-Driving Enterprise



Automation of Production Planning Enhanced by AI



Digital Machinery Decoded

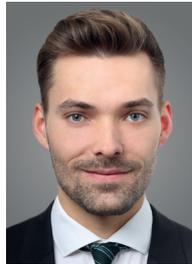


The success formula of winning corporate transformations

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