Generating Impact with AI

How data analytics and AI change the way industrial assets are managed

Porsche Consulting
Strategic Vision. Smart Implementation.

INSIGHTS

//01

To unfold the full potential of data analytics and AI, a strategic and target-oriented approach geared towards gaining competitive advantage is required. Corporate investments in data analytics and AI are rising at a 24 percent CAGR.[1] Geared towards gaining competitive advantage, they do not always show the desired effects.

//02

Four guiding principles improve business impact by focusing on what is required, applying crystal box algorithms, setting realistic expectations, and making AI a process topic.

//03

The experience of several industries outlines tailored approaches and demonstrates the positive business impact—like more than a 20 percent output increase or up to a 15 percent cost reduction.

4 principles to generate impact with AI

HOW DATA ANALYTICS AND AI CHANGE THE WAY INDUSTRIAL ASSETS ARE MANAGED

People make decisions every day. Some of them are more important or more costly than others. For those important decisions, managers typically rely on a holistic picture based on facts and figures. To cut through today's complexity with countless influencing factors, dependencies, and cross-links, companies increasingly turn to data analytics and AI to reveal decision-supporting facts and causalities. As a result, worldwide spending in 2021 on data analytics and AI sums up to over $85 billion.[2] Unfortunately, many of these investments do not deliver the expected benefits: around 70 percent of all AI initiatives deliver little to no business impact.[3] Reasons for failure are manifold and reach from unclear business objectives,[4] poor data availability and quality[5] to insufficient organizational capabilities and team setups.[6]

This white paper shows four guiding principles to successfully establish data analytics and AI as an effective business decision support and improvement engine. It provides pragmatic guidance to elevate data analytics from a typical initial IT pilot stage into a usable daily management tool—for top management as well as for operational staff. The experience from partners and clients reveals smart implementation strategies on how to adapt and apply the guiding principles. In addition, examples from various industries describe tangible business benefits, demonstrate cross-transfer potential, and outline how to avoid the most common pitfalls.

> Information is the oil of the 21st century, and data analytics is the combustion engine.

Peter Sondergaard
Chairman of the Board for 2021 AI[7]

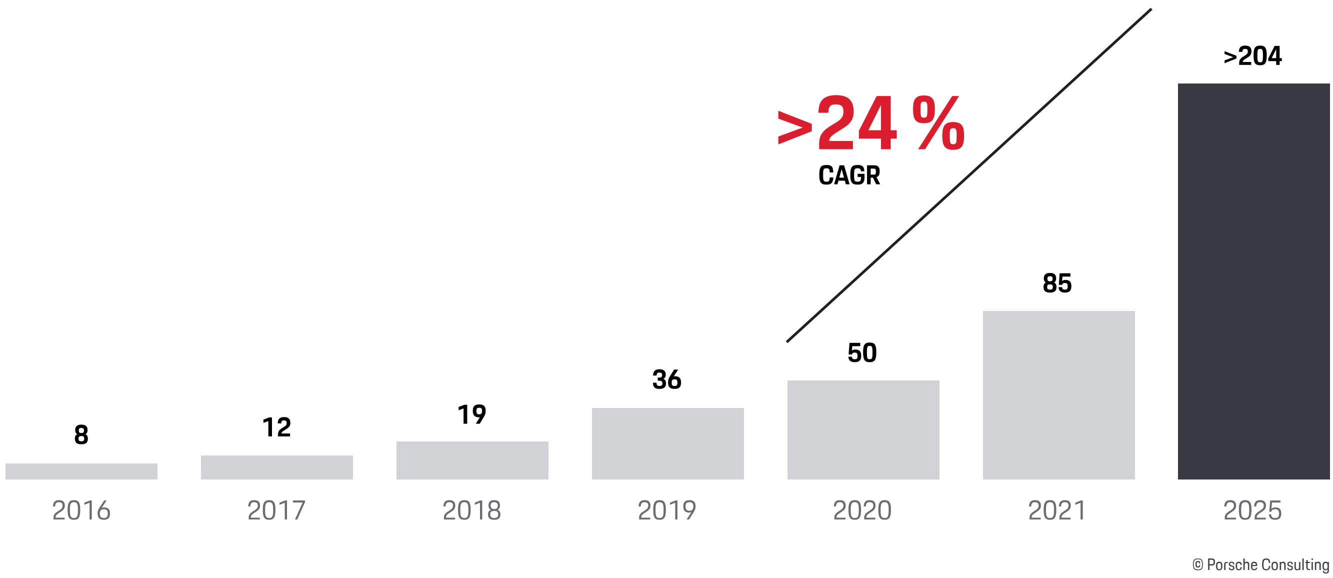


Fig. 1. Worldwide spending on artificial intelligence (AI) in billions of US dollars[8]

What Peter Sondergaard highlighted in October 2011 is about to become reality.[9] For the past decade, data analytics and artificial intelligence (AI) have become important topics in the context of digital transformation—and will become even more important. According to the International Data Corporation, spending for data analytics and AI will grow with an estimated compound annual growth rate (CAGR) of more than 24 percent for the 2020–2025 period, reaching an all-time high of >$204 billion (see Fig. 1).[10]

Increasing complexity and interconnection of products, services, and business processes as well as global competitive pressure propel a constant demand to innovate, expand, and improve. Successful companies utilize data analytics and AI to master today's business complexity by converting available data into useful information. Their business decisions are underpinned by real-time data, discovered relevant correlations, and a thorough understanding of cause and effect based on identifying and forecasting interdependency patterns.[11] Using the latest analytics technology and AI has become an integral part of managing their daily business and related decision processes.

Reality in the industrial world, however, looks different. Many data analytics and AI initiatives do not deliver the expected business impact. In a recent study among 85 Fortune 1000 companies, around 70 percent of the executives confirm that their AI projects deliver no business impact.[12] The first question that arises is surely "Why do AI projects fail to deliver." Partners and clients from various industries like automotive, aviation and aerospace, industrial goods, construction, consumer goods, retail, service, and banking confirm that failing data analytics and AI projects often have one or more of the following pitfalls in common (see Fig. 2). In the following, the four guiding principles are explained, using different industry examples with a clear recommendation on how to avoid these pitfalls. Finally, real-life project insights highlight how their application can positively influence the business impact of data analytics and AI initiatives.

Why AI projects often fail to deliver business impact

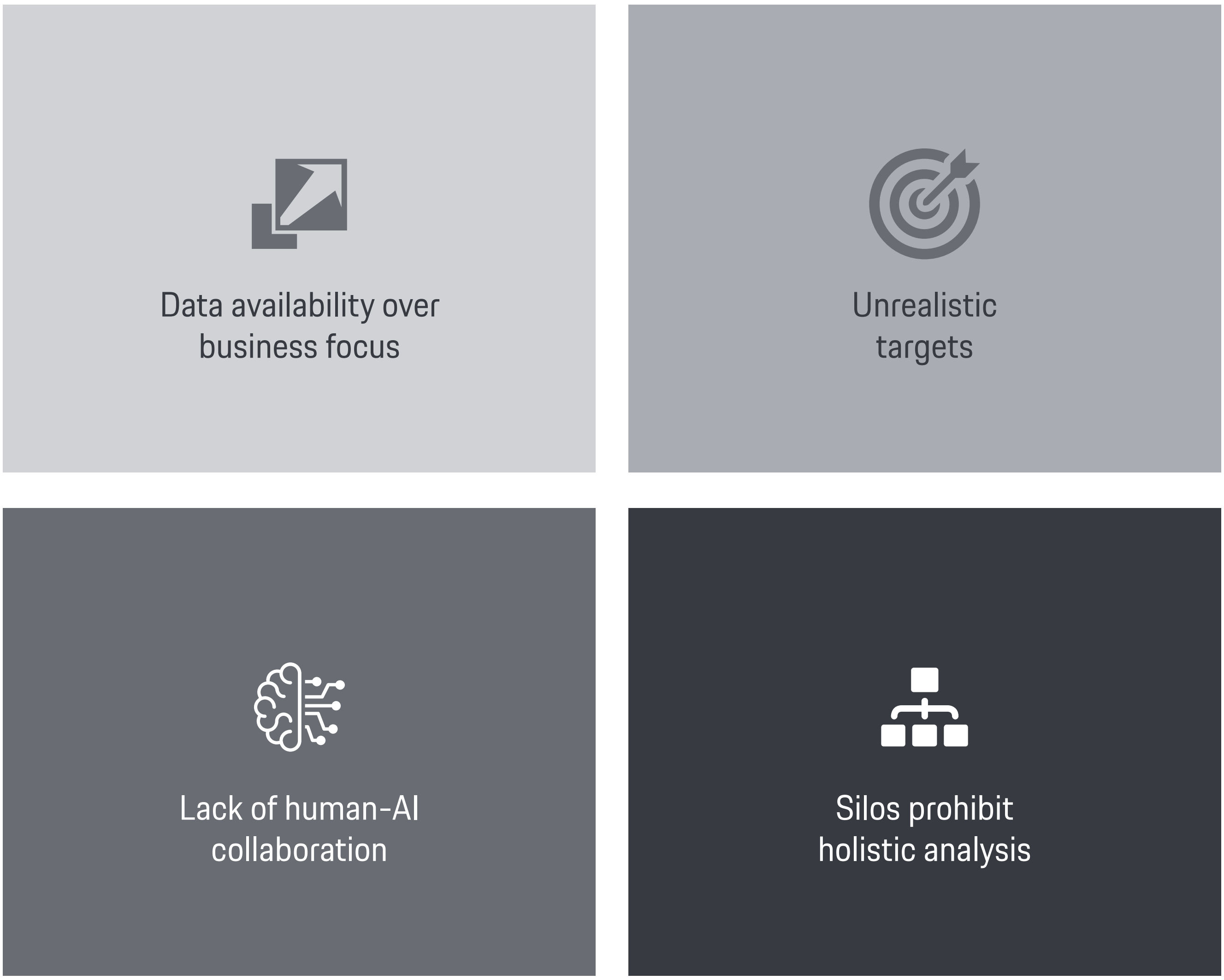


Fig. 2. Common reasons why AI projects fail to deliver business impact

How to successfully set up and manage data analytics and AI projects

To avoid these common pitfalls, Porsche Consulting has developed four guiding principles based on project experience as well as expert knowledge (see Fig. 3). They stand for a pragmatic approach that has proved itself in various industries. Specifically, they help to provide a business-oriented focus, select an effective analytics approach, support in setting achievable expectations, as well as providing the necessary cross-functional setup.

GUIDING PRINCIPLES

01	Focus on business impact instead of data availability
02	Apply crystal box instead of black box algorithms
03	Set realistic expectations instead of chasing science fiction
04	Make AI a process topic instead of an IT topic

Fig. 3. Guiding principles to set up and manage data analytics and AI projects

01

Focus on business impact instead of data availability

For everyone who wants to introduce data analytics and AI effectively, "What is your most expensive decision?" should be the first question. It sets the business decision focus as a clear goal, moving it away from the typical use case thought "We know there is data available, let's use it to see what analytics can do with it". This focus makes it possible to define exactly what is required: for example, which data points in what quality, with what frequency and in what structure, and what type of analytics approach is best suited to support the business decision.

Solution approach

When defining what is required, a scope covering the complete value chain related to the business problem is recommended. A value chain focus exposes interdependencies between different working steps, machines, parts or part categories, materials, processes, performance indicators, or even environmental parameters. Analytics on these interdependencies reveal why certain results are achieved and which effects influence the outcome. Capable tools can even tell you which effect influences the result by how much and simulate what-if scenarios. Furthermore, the value chain focus precisely highlights the most critical process steps or assets, influencing parameters, and determining settings in the process. Therefore, it is important not to just focus on a single asset like a production cell, a standalone robot, or—even more granular—on a component of an asset like its motor or gearbox. The goal is to learn and understand how the scoped value chain or business area reacts to defined scenarios or challenges and which element contributes to the reaction by how much—respecting all relevant influencing factors.

Common pitfall

Furthermore, selecting a business decision focus avoids the pitfall of "scattered and disconnected showcases" (see Fig. 4). Arguments for choosing these showcases are manifold and typically reach from data availability for an industrial asset or a critical value chain step to assigned responsibility to find reasons for process or product deviations. But also the presence of analytical knowledge that employees have acquired or simply individual or management preferences play a role. In addition, proper change management requires involving a critical mass of employees to support the analytics initiative. Consequently, companies often launch several showcases in different business processes or areas lacking an overarching concept or common business objective.

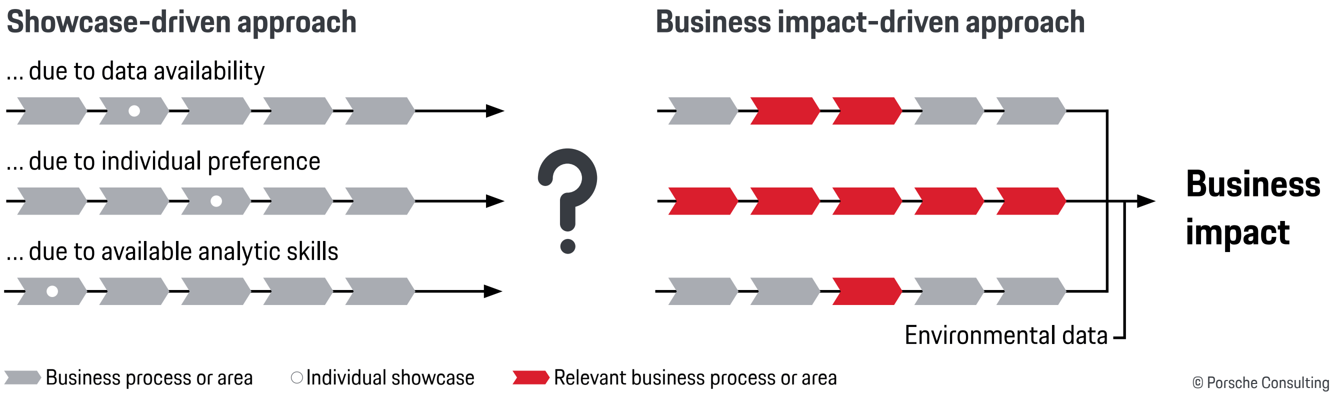


Fig. 4. Common reasons why AI projects fail to deliver business impact

Disconnected showcases then typically dig deep into the analysis of massive amounts of data stored in separate silos rather than to optimize an end-to-end process chain or value stream. As a natural consequence, different methods and approaches are applied, reveal data in different levels of granularity, and give indications of patterns in various directions. Results, which individually might all make sense, are subsequently hard to interlink towards understanding interdependencies and effects on a process chain or value stream level.

Therefore, it is important to start with a desired result: what business impact should be achieved? Once the desired business impact is defined, all business processes and areas contributing to that goal should be involved in the initiative. By building up this end-to-end process view, an environment is created where interdependencies are understood and actions can be prioritized and aligned according to an overarching concept and goal.

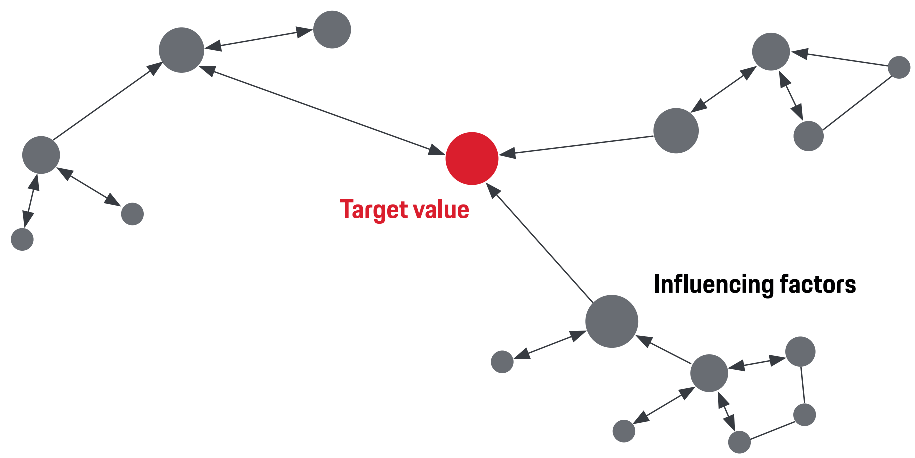
Practical example

The following case gives a good idea of the benefits a complete value stream scope is able to deliver. The challenge for an electronic engine manufacturer was its brand new greenfield production plant—packed with the latest assembly and logistics technology—which did not deliver the desired output quantity. To accelerate production ramp-up, the manufacturer launched multiple showcases scattered along the production process, aiming to leverage the power of data analytics and AI. They extended from route optimization of automated guided vehicles (AGVs) all the way to predictive maintenance solutions for essential machines to increase their overall equipment effectiveness (OEE). Six months into showcase implementation, 90 percent of them still were not able to show their dedicated impact on the overall production output increase or even detect which element plays which role on the critical path for ramp-up. An external analysis revealed that the cases were selected predominantly according to data availability, known good practices transferred from other industrial goods manufacturers, or supplier recommendations. Following a scope review, the focus was expanded to analyze the entire value stream from parts receiving all the way to finished goods with an overarching clear goal to find main levers for the required output increase. Data from all functions involved such as planning, manufacturing, logistics, and operational staff all the way to environmental data like temperature, humidity, packing material, etc. were collected into one model as the analytic basis. Causal analytics provided a transparent cause-and-effect overview of all value chain elements, their contribution towards output increase as well as improvement scenarios. Following resolute action implementation and tracking helped to boost production output consistently by more than 30 percent with analytics still providing a data treasure for future improvement ideas. As the example shows, it is key to direct all analytic efforts to solve the most important business challenges in order to generate large-scale impact.

02

Apply crystal box instead of black box algorithms

It is self-evident that no business leader would make an important decision blindfolded. Top managers usually want to oversee a situation end-to-end as well as understand and verify each step that leads to a conclusion. Crystal box algorithms offer the right solution for this way of working: all background calculations are visualized, they can be challenged at any step of the decision process, and—most importantly—they can be modified and adapted as the team learns. This enables human beings, algorithms, and computers to interact and complement skills and experience as well as analytical and processing power. Process expert knowledge gained over decades can therefore be integrated into the analytic model. In addition, more information can be processed in parallel, such as longer time series or vast amounts of external or environmental data. As a result, hidden root causes can be unraveled more detailed, better insights can be generated, and additional scenarios simulated to better understand the cause and effect of complex problems.



Causal AI—understanding the whys

Causal AI supports holistic decision-making by identifying complex dependencies and root causes. For Causal AI, Bayesian networks are used—an analytical approach often used in cybersecurity. The clear focus of this analytical direction is to connect relevant parameters to find clear dependencies and patterns of how the parameters influence each other towards a set system goal. Relevant parameters are identified in close collaboration of analytic experts and process experts.

Subsequently, the analytics tells which parameter has an impact on the overall system goal, whereas the process experts contribute with many years of experience and cognitive intelligence. All calculations can be visualized, challenged by physical subject matter experts, and, most importantly, they can be adapted. A quantum leap forward from blindly trusting correlations calculated by machines like the later described example of ice cream sales vs. shark attacks.

Solution approach

With the Causal AI approach, based on crystal box algorithms (see Fig. 5), value streams and processes with underlying causalities are completely visualized. Cross-influencing system effects thus become clear and criticalities of each element towards a desired result are understood. Physical subject matter experts are able to follow the analytic logic and challenge it. These experts with specific process and business knowledge can bridge missing information and logically connect data points, correct interdependencies between parameters, or identify causal relations that machines are unable to recognize.

Common pitfall

In contrast, commonly known algorithms such as neural networks work like an analytical "black box". What happens inside these "black boxes" is very hard to trace (see Fig. 5). The setup of neural networks makes it almost impossible to spot what influences what and hardly allows the user to interfere with the way it works. Human input to verify, challenge, or complement results along the way is not possible. Moreover, neural networks typically require large amounts of training data and time to learn in order to provide high-quality output.

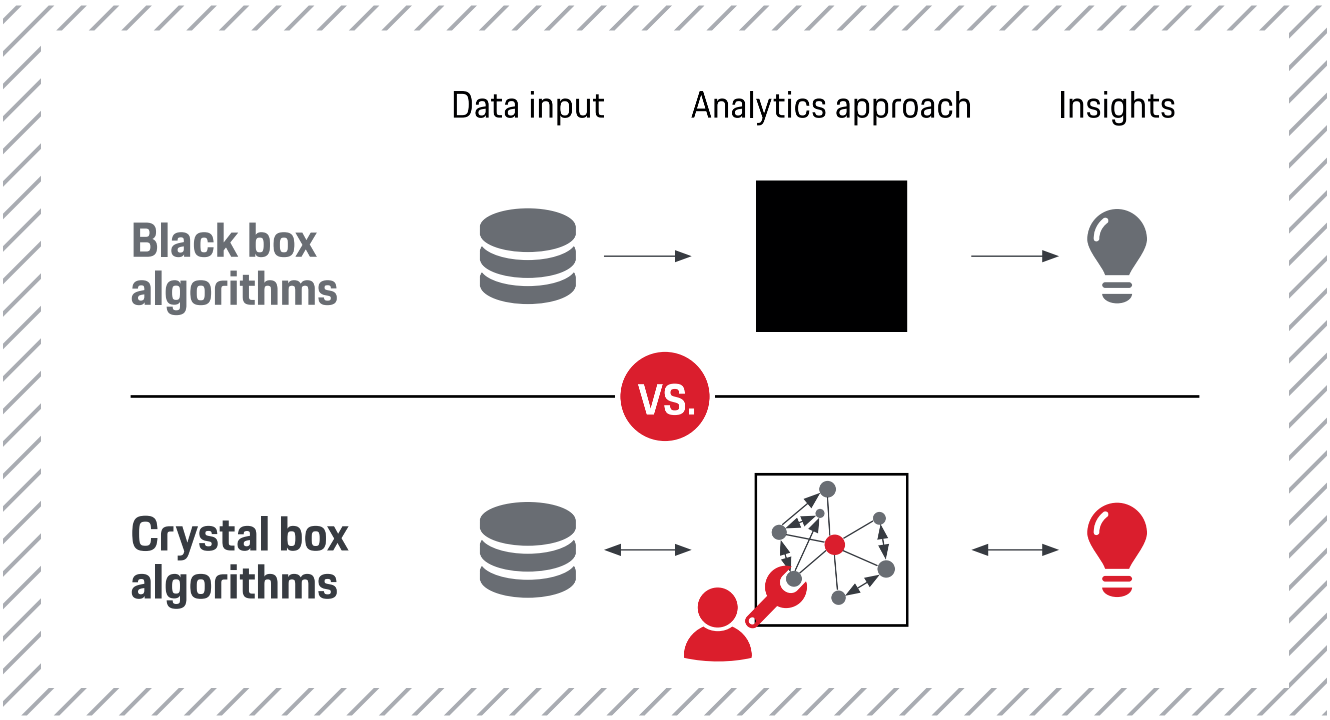


Fig. 5. Black box algorithm versus crystal box algorithms

In addition, in many companies algorithms are expected to solve business problems by themselves. The bitter truth is: that simply does not work. It is a fact that AI is great in analyzing or handling complexity far beyond our human capabilities. However, AI does not have the longstanding expertise of human beings in identifying causal relations. When AI is applied without any human involvement—especially without the knowledge of business and process experts—true causality and statistical correlation are often confused. A good and often cited analogy that explains this is to feed ice cream sales and shark attack numbers into an AI model. Algorithms will probably detect a perfect correlation between ice cream sales and shark attacks. However, even though the correlation is correct, ice cream sales are not the underlying root cause for shark attacks. For human beings, it is obvious that a third parameter needs to be added to the calculation to detect true causality for both figures—in this case, "seasonality" (see Fig. 6).

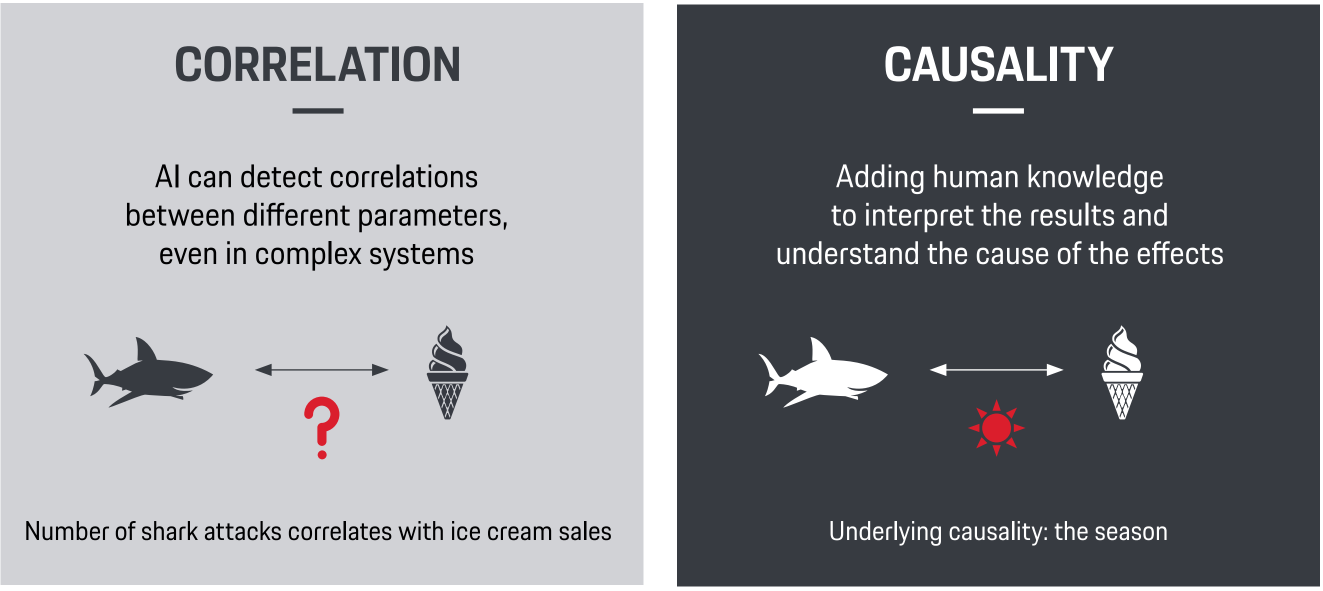


Fig. 6. Correlation versus causality

Practical example

What does that mean for industrial practice? Blindly trusting correlations detected by an AI algorithm can easily misguide you and potentially lead to the adjustment of the wrong process parameters. In a real-life example, an AI initiative was set up to increase the output of a body shop supported by an external group of data analytic specialists. Looking at the result, the specialists first interpreted open security cage doors of the robot cells as the main contributing factor for low output numbers. The process owners were neither impressed nor convinced by this result. It was mandatory to check the robot status after every interruption—which required opening the cage doors. A typical pitfall: the digital model doesn't sufficiently mirror the physical world due to lack of human-AI collaboration. The path to the actual root cause of the breakdowns was paved when production process and data analytic experts joined forces. Guided by a consultant, they identified numerous parameters that potentially also played a role, such as shift crews, their training patterns, material information, and environmental data. Combining these parameters with "classical" data from production planning, maintenance, and product variants led to the true causality: the lack of maintenance training for a particular night shift crew. A causality that no one had on the radar in this complex and deadline-driven industrial ramp up environment. As the example shows, it is key to use crystal box algorithms to generate a "supermind" combining years of human know-how with the AI's ability to manage complexity. By that, it is possible to derive the right insights on the one hand and to get the buy-in by all relevant stakeholders on the other hand, which is crucial for success.

03

Set realistic expectations instead of chasing science fiction

Looking at the success of tech companies such as Google and Amazon, data analytics and AI are often praised for previously unknown insights and realistic prediction capabilities. However, they are certainly not a cure-all for everything, as it is known from science fiction. The ability to understand, forecast, optimize patterns, find correlations, or influence parameters within all kinds of business processes and related decisions with such tools is undisputed.

Constantly increasing computation power is a supporting advantage behind it (see Fig. 7). Furthermore, AI helps to strengthen competitiveness by automating process steps of—up to now—mainly routine tasks. Current opportunities range from material sourcing, processing insurance claims, alerting, and organizing required maintenance work all the way to planning highly interlinked and dynamic projects such as the teardown of nuclear power plants. As customers, we are surrounded by AI technology advancements, like virtual assistants allowing us to order online, select music, or control home appliances. Who thought five to ten years ago that we could talk to our car and get a meaningful response? In their customer role, most people never notice that they have a conversation with an AI when using a modern customer hotline service. To add to the competitive benefits, AI-supported systems learn and become better with every transaction or call. Based on day-to-day experiences like that and not knowing what is required to deliver such solutions, expectations of AI can easily skyrocket.

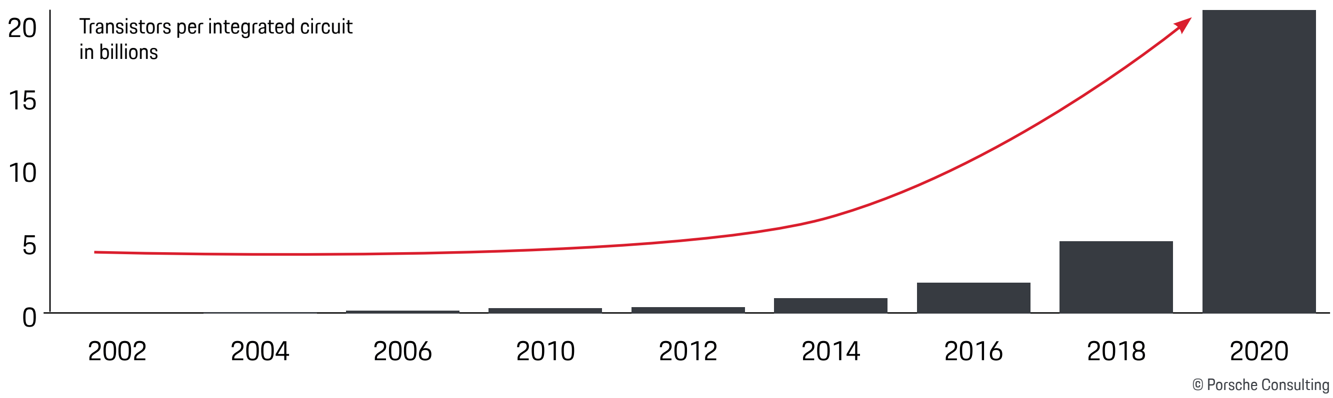


Fig. 7. Increasing computation power, represented by the number of transistors on integrated circuits (Moore's law)[13]

Solution approach

Several aspects need to be considered when setting expectations and targets for data analytics and AI initiatives. The first and foremost topic: the problem needs to be solvable with mathematical methods. Otherwise, there is no point in applying analytical methods. In addition, it is recommended that the following three dimensions are considered.

First, proven problem-related analytic application and implementation experience are an absolute requirement, as for most transformation processes. Second, the analytics skill levels of the people involved have to match the needs of the challenge ahead. However, this is not an easy task, as the data analytics and AI market is growing at a rapid pace, as are knowledge and tools in that field.[14] To keep up with the fast-paced growth, it is recommended to set up an AI center of excellence with a clear competence profile and development strategy. Assuming that skills and implementation experience match, knowledge of the physical process is essential to supplement and verify the findings from data analytics.

Common pitfall

Availability, granularity, and quality of data are always a challenge. Until the point where all data for an industrial process are stored and processed in a structured way and at a similar quality level in a common data platform like an industrial cloud, this will probably remain a challenge in the near future. Often, there is not enough attention to create the prerequisites, like sufficient data quality and data consistency or appropriate data analytic and AI application skills among staff involved. As a result, the business problem or challenge is tackled with the wrong data analytics methods and AI algorithms.

Practical example

The following abstract shows what is possible if existing data is managed correctly and if gaps in data are bridged with process knowledge. In the example, a leading manufacturer in the agriculture industry was able to increase its corn seed yield significantly along the overall production process using Causal AI. To build up a reliable analytic model, a vast range of process parameters, environmental conditions and settings were used to cover the entire value chain. Data points ranging from the plants on the fields through harvesting, and further to receiving and conditioning, were utilized to feed the analytic model (see Fig. 8).

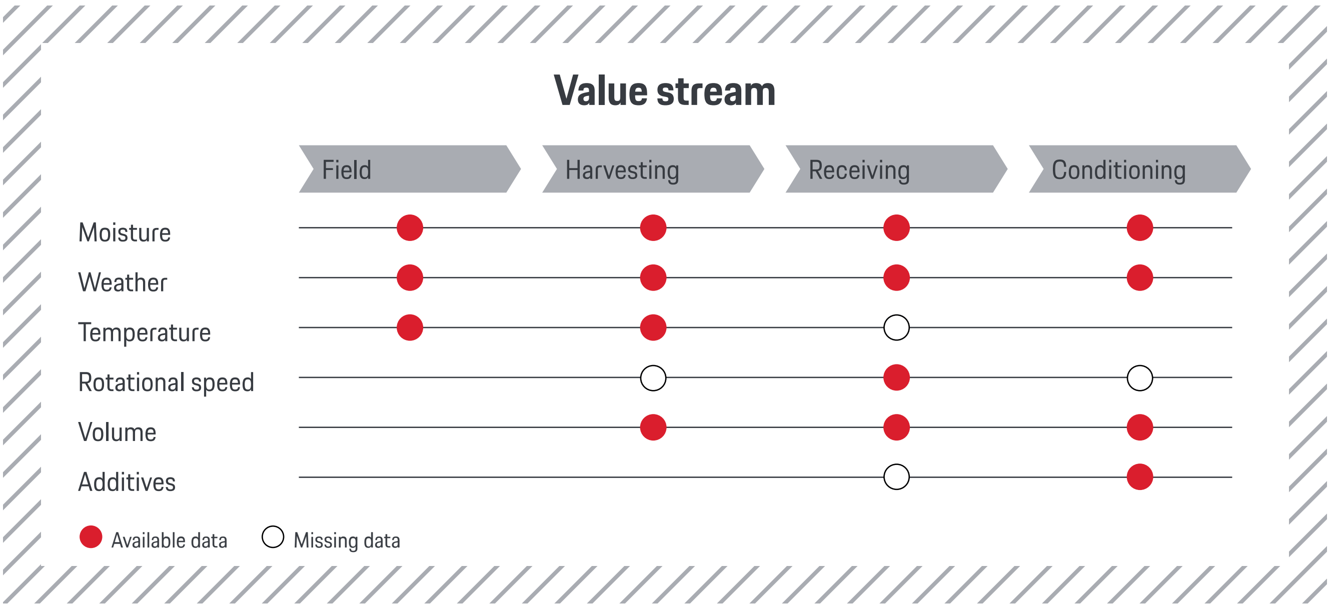


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Fig. 8. Black box algorithm versus crystal box algorithms

However, some necessary data were not available or accessible, especially in remote locations. With the help of Causal AI, it was possible to bridge those data gaps and verify the effects building on the knowledge and experience of process experts. In the end, approximately 10,000 heterogeneous—but high-quality—data points verified by subject matter experts mirroring the entire system covering two years were enough to build the analytic model and gain the necessary insights. Combining computational strength with human experience and logic means a quantum leap forward from blindly trusting machines towards finding "real-life" causalities. AI cannot change the basic rule that the output is highly dependent on the input. Therefore, it is key to manage the data flow within companies effectively, to be able to feed the analytics engine with high-quality data in a machine-readable format.

04

Make AI a process topic instead of an IT topic

When it comes to data analytics and AI deployment, two organizational recommendations are essential learnings to succeed:

01

Overall project responsibility should remain with the process owner

02

Data analytics and AI need to be integrated in daily management routines

Solution Approach

01

Overall project responsibility with process owner

First, the need to apply data analytics and AI has to come from the process owner and not the IT expert or data scientist. In line with this logic, the overall responsibility for an analytics project should remain with the process owner (see Fig. 9). This ensures that managers, subject matter experts, and data analytics specialists work closely together and drive the topic with joint forces. All parties involved need to be on the same page to execute implementation smoothly and efficiently. Process owners—from operators to managers—need to gain basic knowledge on how the analytics approach works. IT experts and data scientists, on the other hand, have to understand the basic business process, including the owner's experience and the needs of daily management routines required to steer. Only in conjunction with profound knowledge about affected processes, parameters, or machines can AI generate a real business impact. On top of that, by involving business and process experts and explaining data analytics and AI mechanisms to them at an early stage, employees will start gaining trust in the tools applied and the results generated.

02

Data analytics and AI integrated in daily management routines

Like in any well-managed project, clearly defined targets, aligned timelines, consistent status tracking as well as the right amount of management attention are vital to get data analytics and AI up and running. Ideally, applied AI reveals numbers and indicators that are understood, trusted, and utilized as a basis for decisions by process owners and management. In other words, data analytics and AI need to be integrated into daily operational management routines to be anchored in the organization. This transforms the topic from carrying out showcases to achieving sustainable business impact based on reliable data.

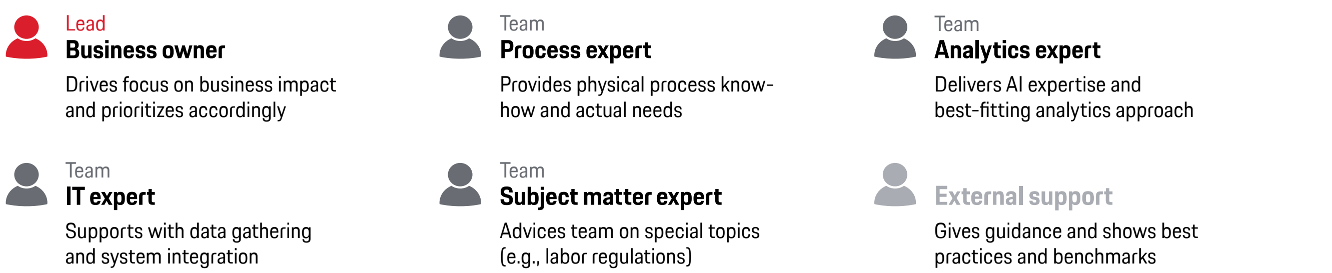


Fig. 9. Recommended team setup for data analytics and AI projects

Common pitfall

Both organizational recommendations in parallel help to tear down organizational, process, and data silos. They often prohibit successful data analytics if they are not properly connected. What are typical silo phenomena? Organizational silos typically represent different business functions, governed by different owners, budgets, targets, etc. Process silos are characterized by a wide and diverse process landscape with numerous interfaces between the executing staff, driven by their owners. Finally, data silos describe the fact that data is typically spread across multiple IT systems and databases, in machine control units—and, as we all well know—in countless spreadsheets on local storage drives.

Practical example

Take a company, which is offering maintenance services for renewable energy systems in remote locations, like an offshore windfarm as an example. With an established 24/7 online access to hundreds of sensors for operations and environment data, the analytics team in the IT department was able to perform calculations and correlation analysis remotely. However, it took weeks until the generated insights were processed from the analytics team to the responsible service department to be translated into executable actions. As a result, the insights became nearly useless, as the most forecasted problem alerts had already hit regular operation, while it took over a month to plan and execute the necessary actions. A clear example of organizational silos prohibiting the utilization of an existing data treasure. Imagine the possibilities if the head of operations had been in the driving seat to guide the business units for service planning and execution, data analytics, and logistics towards a common goal. And thinking beyond, future product development teams would have had a perfect launch pad of past performance and service data to build an even stronger new product generation. As the example shows, it is key to integrate solutions into daily management routines with clearly defined responsibilities in order to translate insights into tangible results!

Most leaders and experts can relate to one or more of the pitfalls described. Yet there are some companies that demonstrate how to take great advantage out of data analytics and AI. Caterpillar and Amazon are two of these lighthouses. Both companies are very different in what they do but both were able to boost their business significantly by integrating data analytics and AI into their business model and in their daily decision-making processes. Caterpillar achieves up to 90 percent asset availability for 850,000 of their heavy machinery assets through establishing and marketing their Cat Connect® condition monitoring system.[15] Using its AI and analytics capabilities, Amazon is able to create customized shopping recommendations for more than 300 million customers around the globe, yielding yearly revenues of $280 billion.[16]

Four guiding principles—selected examples showcasing successful impact

The following examples highlight tangible improvements through data analytics and AI for a variety of business challenges and industries. They clearly demonstrate that data analytics and AI implementation with a high business impact rate is possible. Avoiding the 70–90 percent failure category is not a lucky strike but the result of consequently addressing the guiding principles described. Answering the question "What is the most expensive decision?" was the common starting point for all of the examples. Giving priority to business relevance, the other guiding principles ensured that an effective analytics approach was chosen, achievable expectations were set, and the necessary cross-functional setup was in place. Insights in projects from various industries provide real-life experience, show the implementation potential, and help to level expectations on data analytics and AI. Nevertheless, it also provides options to what is possible—especially when using unconventional approaches.

In that regard, exploiting the potential of Causal AI helped to detect interdependencies in a medtech equipment company no one ever thought of: malfunctioning devices were predominantly used in areas of unstable power supply. The following example outlines the business value of stepwise widening the analytical scope. The original focus on product, production, and failure data revealed little useful information for the product and quality teams. Expanding the scope to all relevant phases of the product life cycle including usage patterns from customers and their environment helped to stabilize product quality and free up much-needed production capacity.

Product quality increase in the medtech industry

Business problem	**How can product quality be increased in order to reduce refurbishments and free up production capacities?**	A leading medtech company had been facing quality issues with one of their products. As a result, the malfunctioning products had to be sent back for refurbishment. In consequence, more than 50 percent of the production capacity was blocked for refurbishment, leaving the company behind with insufficient capacity to meet the demand for new products.
Solution	**Conduct data-driven root cause analysis of defects and definition of improvement potentials for R&D by applying Causal AI**	A holistic picture of the overall product life cycle was generated in a pragmatic way using Causal AI. The model included all relevant processes, parameters, and conditions: for example, supply chain, production, customer, and environmental data such as usage location, temperature, and humidity. After expanding the search scope and evaluating different scenarios together with subject matter experts, the hidden root cause was traced back to specific characteristics of power supply instability in certain areas the devices were used.
Impact	**> $ 2.5 m** **cost savings p. a.**	The newly generated insights were fed back to the R&D department in the form of specific recommendations in order to adapt the electrical power system of the device. All in all, malfunctioning was reduced almost to zero with yearly cost savings of more than $2.5m due to avoided re-work.

To gain acceptance from process and business owners when applying data analytics and AI, they need to be part of the journey. Knowing what happens at each step of the way, comprehending the underlying logic, and being able to follow how algorithms come to results, builds trust. Therefore, crystal box algorithms are recommended over black box algorithms.

In the following aerospace example, this was one of the tipping points to win the commitment of very experienced yet critical process owners. When employees come up with their own ideas or options to further investigate a business problem, requests to use additional data sources, or discussing interdependencies and intermediate results typically amplifies interest and acceptance.

Output increase in the aerospace industry

Business problem	**Can existing assets deliver future increasing volume or do we need to invest in a new chemical facility?**	Reacting to growing customer demand, an expensive decision for an aerospace manufacturer was whether to invest in a new facility for a critical chemical treatment process. Alternative: save the budget and optimize the existing environment based on new knowledge gained from data analytics and AI.
Solution	**Establish a data-driven process control in the chemical testing area to increase output quantity and quality applying Causal AI**	A data model mirroring all essential process steps of the complex chemical testing delivered the basis for applying Causal AI. Experienced staff together with data experts confirmed causalities, interpreted anomalies and developed scenarios. Dynamic alternative solutions were calculated from targeting ideal acid concentration of the etching baths all the way to line feeding logic of the installed robots.
Impact	**20%** **output increase** **(and no investment in new facility)**	In the end, feasible output increase outweighed investment in a new facility for this process bottleneck. Derived action steps were put into practice within less than a year. In addition, the robot manufacturer received suggestions to correct functional irregularities. Result: a 20 percent output increase, avoided spending for a new facility that offered options to invest in other areas of the business—and improved quality consistency came in as a positive "side effect."

Sparking broad and interdisciplinary interest in data analytics and AI initiatives marks a first step. Making it a viable and sustainable tool that helps to drive and underpin business decisions is key. This is where companies harvest the full benefit. Therefore, specialists covering the areas from IT, analytics, and all the way to process specialists need to work as one cross-functional team. In many cases, the first impulse for applying data analytics and AI comes from corporate IT departments or headquarters. To embed data analytics and AI into the DNA of an organization, the process owners need to drive the initiative—supported by management commitment. In the example from the chemical industry, increasing knowledge about physical processes and analytics capabilities initiated even more ideas for further Causal AI applications among owners, the analytics team, and management.

Cost reduction in the chemical industry

Business problem	**How can product quality in a complex chemical process be stabilized in order to reduce cost?**	A major manufacturer in the chemical industry was facing the challenge to stabilize product quality and increase output without major investments. In order to gain the required insights, the team needed to comb through data input from 1000+ sensors and develop solutions in a pragmatic way.
Solution	**Set up a customized analytics model to handle data input efficiently and develop ideal production parameter sets and product-to-line allocation**	To work efficiently, the team needed to tailor the data model to the targets of increasing output while decreasing chemical reaction variations. In that way, the cross-functional team of operators, process and analytics experts identified hidden causalities and developed a solution even though the model covered several processes at different production sites and multiple product families.
Impact	**>$4 m** **profit increase p. a.**	In addition to an ideal set of production parameters to decrease chemical reaction variations, the cross-functional team identified even more applications. Catalyst consumption—one of the main cost drivers—was reduced significantly. AI also helped to automate and optimize production planning based on the production targets, resulting in an ideal product-to-line allocation. All measures together stabilized product quality and increased output, resulting in >$4m of yearly profit increase—all within the existing production environment.

CONCLUSION

Substantial corporate investment,[17] technological advancements, and an increasing amount of powerful cases showing remarkable effects will boost the deployment of data analytics and AI in the modern business environment. With increasing functionality and user friendliness of related IT tools, more and more people will acquire knowledge and get in touch with this topic. Finally, competitive pressure will accelerate the corporate need to apply data analytics and AI in order to further optimize existing processes, craft new products and services, and improve decision-making quality. Ten years from now, data analytic capabilities will surely be a core competence in most business areas.

The outlined guiding principles have proved to be essential building blocks for successful and sustainable application of data analytics and AI in daily business. The vital starting point for all examples described is a clear business-oriented decision and optimization focus. Favoring explainable analytic approaches—like Causal AI—over black box algorithms provides process owners and analytic experts the chance to understand the "mechanism" of the business process and its underlying data. Setting achievable and problem-oriented expectation levels subsequently helped to select the most suitable analytic tools, algorithms, and to define the required skill sets of the people involved. Finally, deployment initiatives need to be driven by process owners rather than making them an IT topic. Nevertheless, process and business experts are required to closely collaborate with their analytic and IT counterparts to ensure sustainable implementation. Following those principles is key to generating impact with data analytics and AI in a business environment.

The guiding principles have demonstrated efficacy in various industries and business areas, e.g., in transactional, operational, financial, or support environments. No matter what the improvement focus is, when applied correctly, data analytics and AI drive fact-based decision-making and improve business performance. Finally, all those tangible results have been achieved without spending years on gathering data and investing large amounts of money in new corporate IT infrastructure like data lakes or new systems.

In Brief

01 Successful leadership applies data analytics and AI to gather necessary insights for profound decisions in today's increasingly complex business world. Several studies and surveys, however, reveal that 70 percent of all AI projects deliver little to no business impact.[18]

02 Four guiding principles are essential to make the application of data analytics and AI successful and provide the best real-time information for important decisions and create measurable results: a business impact focus, a transparent and explainable analytics approach, realistic expectations, and a process-oriented business setup.

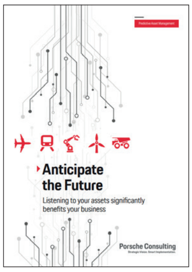
03 Setting a relevant business-oriented focus is essential when defining the scope and target of data analytics and AI projects. Connecting business requirements with data analytics gives direction and the right level of thrust for everybody involved.

04 Using crystal box algorithms like Causal AI as a target-oriented analytic approach helps business and process experts understand the AI calculations. Pragmatic opportunities to optimize the mathematical model ensure it sufficiently mirrors the physical world and allow what-if scenarios.

05 Given the hype around data analytics and AI, setting realistic expectations is required. They should consider the skill level and experience of the people involved, knowledge of the physical process as well as availability and quality of data.

06 By making process owners responsible for data analytic and AI projects, a close collaboration between business, process, and IT experts is fostered. Moreover, integrating data analytics and AI in daily management routines helps to anchor the topic in the organization.

Further readings



White Paper
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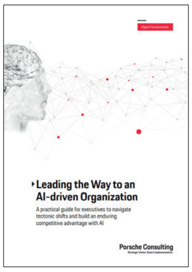
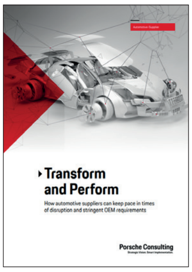


Study
Way to an AI-Driven Organization



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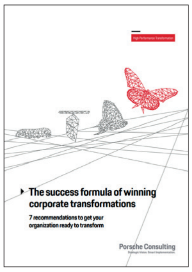

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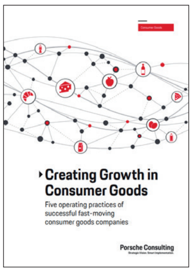

White Paper
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White Paper
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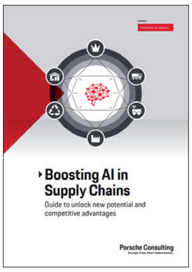

White Paper
Boosting AI in Supply Chains

Authors

Joachim
Kirsch
Senior Partner

Claus
Lintz
Partner

Fabian
Schmidt
Co-lead Data Analytics & AI

Kevin
Lin
Co-lead Data Analytics & AI

Henrik
Roß
Senior Consultant

Contact

Joachim Kirsch
+49 170 911 3600
joachim.kirsch@porsche-consulting.com

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Appendix

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