



Artificial intelligence: how leading companies define use cases, scale-up utilization, and realize value

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Abstract

Artificial intelligence (AI) is one of the most transformative information technologies of our century. Despite high expectations across all industries and corporate functions, companies have difficulties to realize the full potential of AI and struggle to move beyond AI pilots. This article provides empirical evidence from survey data and three case studies to better understand the value drivers of AI. Leading companies specify use cases from a business perspective and leverage domain expertise to tap into value pools by combining technology with human capabilities. They provide fundamental enablers for AI like digital and data platforms, a data-centric organization with solid governance, and a dedicated human resource base to facilitate AI value creation. Moreover, these firms assess the financial and business impact of AI initiatives and reprioritize projects if the expected value does not materialize. Based on these insights, recommendations to better scale and derive value from AI projects will be offered.

Beyond experimentation: scaling AI to create tangible value

With annual growth rates of over 25% since 2018, global investments in artificial intelligence (AI) are likely to pass the \$100 billion threshold in the coming 5 years¹. Across all sectors and functions, there are high expectations for AI, e.g., higher efficiency, strengthened resilience, increased revenues. However, as our research shows, many companies that invest significantly in AI have difficulties leveraging the full potential AI has to offer.

In a survey covering 1817 companies in Q1/2019, executives in the US, Europe, and Asia responded to which degree they adopted digital technologies, particularly AI. This study was based on the same methodology as the study from

2020 on which the main findings in this article are based (see Sect. “Research methodology and conceptual framework”). Only 8% of companies have answered that they can fully leverage AI’s potential (Fig. 1). At least 24% of companies stated that AI is currently being rolled out across their organization. In contrast, the remaining 58% of firms had not proceeded beyond strategizing, rollout planning, or AI pilot projects. One in 10 executives admitted that AI is not even a discussion topic in their company yet.

Experimenting with AI is not very demanding, but it is challenging to scale-up the numbers of transactions of AI-related information systems (AI systems) that create tangible value. Having enablers like technology, data, and people ready is essential to scale, but most companies have not yet proceeded beyond pilots, which is the apparent reason why they realize little value. Only those who excel in data and AI can positively impact, for instance, higher organizational performance.

The fact that AI use is often not transformed into business value is even more concerning given AI’s ability to accelerate companies out of the current Covid-19 crisis. For example, AI can help to detect new consumer patterns while demand patterns are shifting during the pandemic. With higher personalization and real-time product customization, companies can even boost sales and gain market share during a crisis [4]. Furthermore, as AI can improve workforce allocation to supply requirements, it can help to lower the cost base and free up scarce financial resources to facili-

¹ IDC Worldwide Artificial Intelligence Systems Spending Guide, www.idc.com, Document US45481219.

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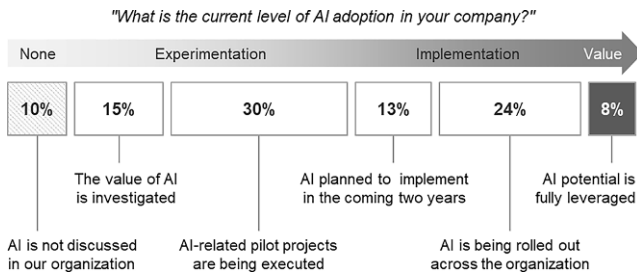


Fig. 1 Levels of corporate artificial intelligence (AI) adoption

tate innovation where it is required to gain advantage in adversity and come out of the crisis stronger than peers. By considering this potential, two questions emerge: “Why are only a few companies able to extract tangible value from advanced analytics, and how can companies transform AI expenditures into valuable outcomes?”

This article will present empirical evidence from a global survey and three case studies to better understand the value drivers of AI. Based on these insights, we will formulate actionable recommendations to better scale and derive value from AI projects in the future.

How leading companies scale AI utilization: insights and case studies

Overview of results

Our results indicate that effective companies approach AI differently compared to those who fail to achieve economies of scale. In particular, leading firms rely on three activities:

1. They specify use cases from a business perspective and leverage domain expertise to tap into value pools, e.g., digital business opportunities, also by combining technology with human capabilities.
2. They provide fundamental enablers for AI like digital and data platforms, a data-centric organization with solid governance, and dedicated human resources to these enablers, especially AI.
3. They assess AI's financial and business impact and re-prioritize projects if the expected value does not materialize.

Research methodology and conceptual framework

Our quantitative findings are based on a global survey of 2296 managers from 28 countries across Asia, Europe, and the US. The data was collected between October 2019 and January 2020. Respondents were general managers (35%), senior executives like business unit heads (32%), and CxO-level managers including chief executives (33%) from nine industries: consumer and retail goods, energy, financial

institutions, health care, insurance, industrial manufacturing (including automotive), public sector, technology, and telecommunications.

The respondents provided their perception about their organization's current digital capabilities based on 36 individual dimensions of digital maturity (Fig. 2). Each dimension is captured with a measurement item on a four-stage ordinal scale, with the lowest stage being “starter,” second “literate,” third “performer,” and the highest “leaders” (see Appendix for domain-related examples). The dimensions cluster into four domains that encompass the following blocks [9]:

- Purpose and strategy: digital-first strategy, organizational alignment, digital priorities, and roadmap
- Outcomes: personalized customer experiences, improved operations processes, and new offers built
- Technology: modular technology stack fueled by liberated data, available for AI to generate insights
- Human: digital talent, upskilling, a platform organization with small autonomous teams

High levels of digital maturity across those domains characterize organizations as leading digital firms that can mainly intertwine humans' and technology's capabilities to achieve superior customer experiences and relationships, more productive operations, and increased innovation rate.

The 36 items have been amalgamated with equal weights into a maturity figure on a scale from 0 to 100, which denotes the Digital Acceleration Index (DAI)². Companies that score over 67 qualify as digital champions, while those with a score lower than 43 classify as digital laggards. Companies that respondents evaluated in the highest maturity level (stage 4) regarding the item “Artificial intelligence” are classified as “AI leaders.” The study covered further questions about investment priorities, the degree to which talent is hired and upskilled, the perceived performance compared to peers, and a set of key performance

² For every item, each respondent provided an answer whether its organization has capabilities that represent stage 1 (digital starters), stage 2 (digital literates), stage 3 (digital performers), or stage 4 (digital leaders) of a maturity model. Measurement examples can be found in the Appendix. To normalize the scores on a scale from 0 to 100, the selection of a stage is converted into a DAI score by the formula $DAI = 100 / 3 * (stage - 1)$. Following this conversion per dimension, digital starters have a DAI of 0, literates of 33.3, performers of 66.7, and leaders of 100. The DAI is calculated as the average over all dimensions. In a subsequent step, we differentiate underperformer against overperformer. The underperformer (laggards) have a DAI of 0 to 43. They rank on average and at best only in the digital literate stage in up to two thirds of the dimensions, and can, again at best, rank in the digital performer stage only in the remaining third of the dimensions. On the contrary, the overperformers (champions) score on average in the digital performer stage across all assessed dimensions and, consequently, have a DAI of 67 or above ($DAI = 100 / 3 * (performer = 3 - 1) = 100 * 2 / 2 = 66.7$).

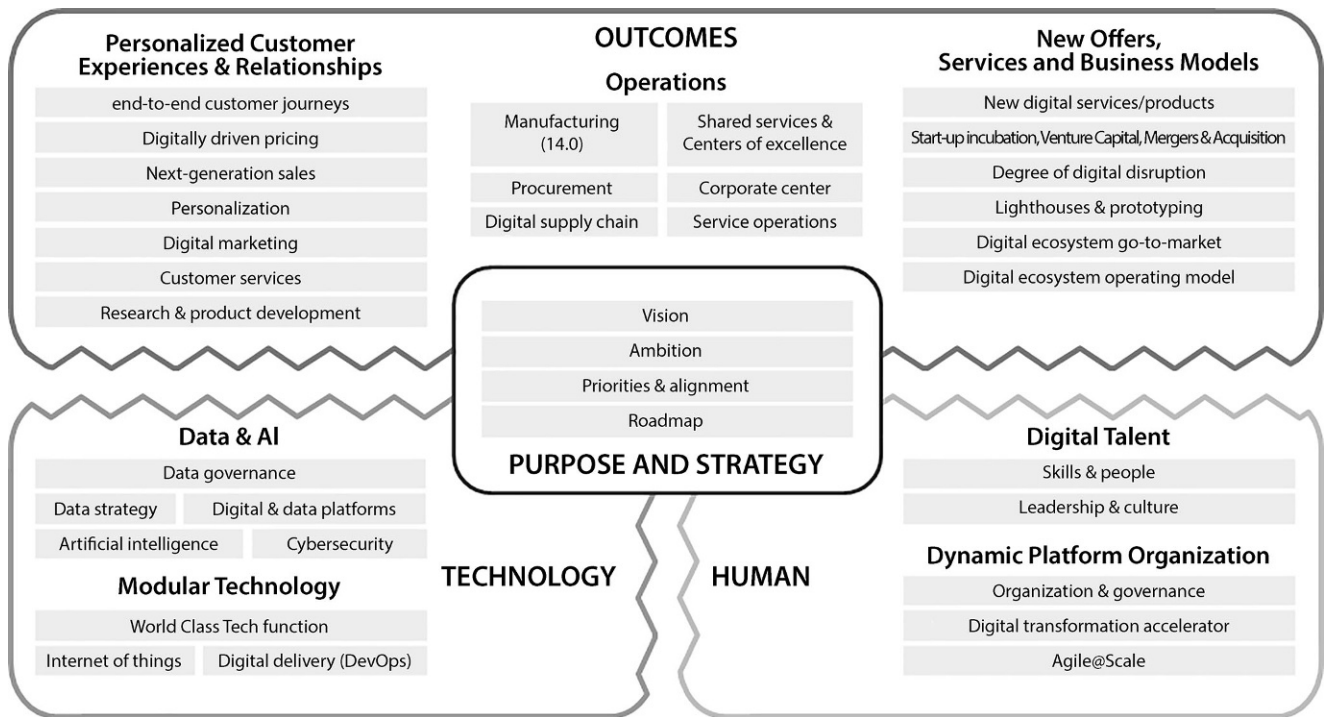


Fig. 2 Conceptual framework for investigating artificial intelligence value creation

indicators to complement the maturity assessments. This outcome-related data will be used to assess the impact of AI investments.

Our quantitative findings will be complemented and deepened with three selected cases, which exemplify the characteristics and impact of ongoing AI initiatives. Our first case study reveals how an Airline Carrier has improved operations worldwide by specifying and prioritizing AI use cases to solve pressuring pain points. Second, we present how a Chemical Firm provided intelligent solutions for the mining industry. This case serves as an example of how the combination of enabling factors like humans and technology can help to achieve remarkable outcomes. Finally, the importance of turning AI into value is exemplified by an Energy Utility deploying an AI-enabled Integrated Operations Center.

Approach AI from a business perspective and specify use cases

To create value, organizations strive to build AI systems that address major pain points and tap into value pools instead of focusing on areas where data is readily available. AI is pivotal for solving business problems and hence deserves a top spot on the CEO agenda. In this spirit, data must underlie every aspect of a business model that is elevated and renewed with AI. Business leaders should think from an angle of AI capabilities to identify use cases and envision outcomes. AI can not only increase automation, but leaders

are well advised to look for use cases that generate insights and create innovative solutions rather than looking at the technological core and focusing on new computational methods only.

First, with respect to the value potential from process automation, AI can handle customer requests more efficiently, e.g., filing complaints or extending credit lines that cut costs at the front office while speeding up transaction handling. According to our survey results, digital champions have automated 25% of their core processes using AI 2.3 times more than digital laggards, including customer processes, operations and manufacturing, and support processes in the human resources and finance function.

Second, AI algorithms are often executing tasks without human supervision (= task automation). They can uncover meaningful patterns in unstructured data with two benefits: they can guide the response to a process event and direct a business decision. Moreover, AI algorithms can scrutinize and challenge the process itself. Therefore, next to supporting preexisting workflows, decisions, and legacy platforms, organizations need to deploy AI with the objective to fundamentally change the process or solution itself, as an implication of the algorithm’s learning and insights. A means to foster radical redesign is to adapt processes and routines to incorporate AI tools directly into employee’s daily jobs to provide short feedback loops. To accelerate learning, employees need to actively instruct algorithm developers with their strong domain expertise and process know-how.

Third, as AI is capable of creating content, it can transform business models and provide novel AI services itself. Recent examples relate to artificial computational creativity, where AI can create new music based on an artists' previous work, supposedly indistinguishable from its original plays for the human ear.³ Leading AI companies pursue innovation with AI vigorously, driven by the inherent risk of lagging behind their competitors and the fact that revenue uplift can outweigh cost-saving potentials [6].

Fourth, ideating use cases can also start by envisioning how the roles and contributions of people shift. Beyond automation, human actors and decision-makers are often enriched with process or decision augmentation techniques (e.g., virtual assistants, conversational agents). On the other hand, humans complement AI to become trainers, which contextualize knowledge and apply judgment or moral values [10]. Finally, humans and AI can act as cohesive tandems in more advanced use cases, such as wearables-enabled factory workers or remote surgeons [5].

No matter whether the value of an AI use case lies in automation, insight generation, decision augmentation, or business model creation, organizations must define a vision, form an AI initiative portfolio, and deduct a strategy for building the required enabling capabilities [8]. Business leaders should prioritize use cases based on value and ease of implementation. The latter includes data availability, existing know-how, systems readiness, ethical aspects, cyber risk, and the future potential for scale, which depends on the resilience of an AI solution to changing dynamics and the required degree of maintenance.

Case 1: Airline Carrier enhancing operations worldwide

One of the largest Airline Carriers worldwide took a deliberate approach to reap AI benefits. Airline operations are complex and expensive, often consisting of more than 150 aircraft to coordinate, over 700 departures to organize per day, and more than 30 million passengers to transport per annum. A companies' success largely depends on creating and synchronizing plane and crew schedules, maintaining aircrafts, and reacting to disruptions such as unforeseen extreme weather, which may cause passenger delays and require flight schedule and booking changes [11]. Costs increase with the number of flights that have to be rescheduled or canceled due to unexpected disturbances. Hence, the carrier investigated how AI can help reduce high operations complexity and costs.

Step one for the airline carrier was to identify the most relevant pain points for the business. Consequently, leader-

ship teams of each business area involved were interviewed. Step two was to assess the expected value AI may unlock and the time required to implement the AI solution per pain point. For instance, the value potential and needed time to optimize the schedule adaptation with AI were assessed. The implementation time is determined by the availability and quality of necessary data and skills, technological maturity, and ease of implementation.

After step two, three priority projects were identified and endorsed by top management: (i) optimizing flight scheduling dynamically, (ii) crew scheduling optimization to deal with disruptions, and (iii) dynamically handling day-to-day disruptions on the day of operations. Cross-functional teams then developed and implemented solution concepts leveraging AI for each priority topic.

As a result, the airline could reduce its non-performance costs, i.e., costs accruing from service delivery failures, by more than 25% compared to before. Moreover, unexpected delays impacted approximately 30% fewer passengers due to intelligent handling of disruptions. These results were obtained by ensuring that frontline professionals used the new AI solution as part of their daily working routines and provided ongoing feedback on new releases and features. Additionally, based on its own experience, the carrier identified a growing demand for optimizing flight scheduling and operations in the industry. Since there were no previous offerings available in the market, the airline expanded its service portfolio by launching and marketing a new business line for improving other airlines' operations.

Key learnings and recommendations for specifying and prioritizing use cases

- Identify, specify, prioritize, and develop solutions to address critical business pain points and create value pools. Go beyond exploring and deploying solutions only where data is readily available.
- Incorporate AI systems into the work routines of professionals and adapt processes to new technologies and tools. Then train professionals to use them, which ensures that the organization uses AI systematically and effectively.
- Be open to new business opportunities based on AI that may allow companies to expand their core business functions, for instance, by offering new service-based or data-enabled business models.
- Track the benefits of AI with quantitative key performance indicators that allow executives to measure objectively and monitor and communicate the unlocked value to create further buy-in.

³ For example, Time magazine (time.com/5774723/ai-music), Google Magenta project (magenta.tensorflow.org), Sony Flow machines (www.sonycs.jp/paris/2811), Amper (www.ampermusic.com).

Provide fundamental enablers to scale-up pilot use across the organization

As explained above, the DAI measures maturity along strategy, outcomes, technology, and human domains. While the domain “Purpose and Strategy” focuses on translating a vision into a roadmap, “Outcomes” aim to digitize the core along the value chain and innovate, with the target to increase value, market performance, and financial returns. The domains “Technology” and “Human” are complementary enablers. Since all organizations captured scored the highest for Purpose and Strategy ($\varnothing\text{DAI}_{\text{Purpose-and-Strategy}} = 57$) and lowest for Outcomes ($\varnothing\text{DAI}_{\text{Outcomes}} = 51$), we conclude that many organizations struggle to convert their strategy into measurable impact and fail to achieve significant outcomes from leveraging the potential that digital technologies including AI can offer.

A comparison between digital champions versus laggards reveals that the gap between strategy and outcomes amounts to only 4% for champions ($\varnothing\text{DAI}_{\text{Purpose-and-Strategy}} = 79$, $\varnothing\text{DAI}_{\text{Outcomes}} = 76$). In contrast, laggards show a 28% lower digital maturity score for outcomes than for strategy ($\varnothing\text{DAI}_{\text{Purpose-and-Strategy}} = 40$, $\varnothing\text{DAI}_{\text{Outcomes}} = 29$). Furthermore, digital champions report significantly higher scores in both enabling dimensions: Technology ($\varnothing\text{DAI}_{\text{Technology}} = 78$ for champions and 29 for laggards) and Human ($\varnothing\text{DAI}_{\text{Human}} = 78$ for champions and 31 for laggards).

It is essential to differentiate between a “what” and a “how” for enablers. The “what” describes which resources organizations acquire and build from investments. The “how” describes how these resources are organized and allocated effectively and how obstacles for operating effectively can be removed.

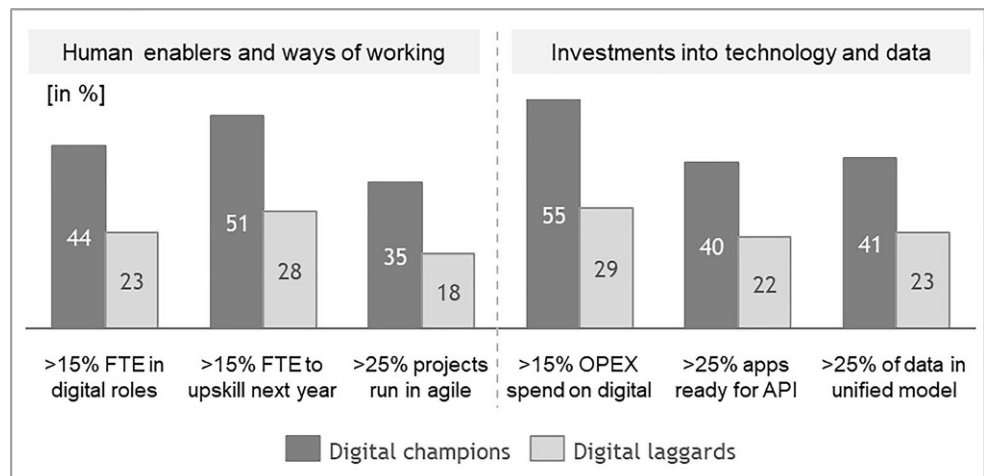
Enhance workforce capabilities and establish agile ways of collaboration

Employees need an enriched skill set to work in organizations enabled or supported by AI. As AI is likely to overtake standardized automatable tasks, humans need to contribute “people skills” like judgment, creativity, or communication ability [2]. Due to the specificity and complexity of AI, Beck et al. [3] emphasize the importance of dedicated AI-related roles to exploit its potential. The authors provide examples such as an “AI engineer” who develops AI products, is savvy in enterprise architecture, and integrates AI into existing systems. Another example relates to complementary data capabilities that “fuel” AI systems. The “Data Czar” offers sophisticated business expertise to source, clean, and transform the data needed to run the system and overcome the particular business problems involved.

As research shows, these capabilities are often not available. According to Brock and Wangenheim [1], more than 3500 answers across over 1200 companies have described three key challenges in implementing digital technologies and AI. “Lack of skilled staff and knowledge in digital technologies” was mentioned in 54% of cases, which is twice as frequent as the following challenges “lack of organizational agility” (27%), “lack of sufficient funding” (26%), or less relevant technology inhibitors.

According to our study, organizations differ enormously concerning the digital capabilities of their workforce. Almost twice as many digital champions as laggards (44% vs. 23%) already dedicate a significant proportion (over 15%) of their full-time equivalents (FTE) to digital roles and responsibilities. When asked how many people in the entire workforce shall undergo re- or upskilling in the coming year, 51% of the champions reported “over 15%.” In comparison, only 28% of the laggards provided the same response (Fig. 3). Besides, firms across Asia report far higher

Fig. 3 Digital champions focus on human enablers and investments more intensively to scale-up artificial intelligence. *FTE* full-time equivalents, *OPEX* operating expenses



ambitions for hiring and upskilling digital talent than comparable organizations in Europe and the US.

Next to the “what,” i.e., the available workforce to deliver digital projects, the “how” can be considered equally important. Successful companies employ agile ways of effectively developing minimum viable products jointly in cross-functional business and IT teams and converting them into operative solutions. As indicated in Fig. 3, 35% of the champions state that more than 25% of joint business-IT projects apply agile techniques of working, a factor of almost two compared to laggards who apply agile techniques in 18% of all cases on the respective level.

To conclude, people dedication and hiring, up- and reskilling the entire workforce, and working in agile ways are key success factors to scale-up AI to achieve better outcomes and realize value benefits.

Invest in technology and data

Technology is the second enabler for scaling the utilization of AI successfully. It includes an advanced technology function, state-of-the-art cybersecurity capabilities, and a digital and data platform⁴ as the data-centric organization’s foundation. The latter is described in more detail later in this section.

Companies classified as digital champions invest a significant share of their operating expenses (OPEX) into digital initiatives. More than half of the firms in this category (55%) state they invest more than 15% into such initiatives compared to only 29% of digital laggards (Fig. 3). Of this spending ratio, champions spend on average 50% of the digital budget on technology and data, compared to only 38% of the laggards. Thus, champions invest more into digital initiatives, mainly digital technology and data.

Higher investments provide the basis for faster innovation in technology and data. Nearly twice as many digital champions report that 25% or more of their applications are application programming interface (API)-ready in comparison to the laggards (40% vs. 22%). Similarly, almost twice as many champions as laggards have been able to organize at least 25% of their data under the architecture of a unified data model, which increases consistency, improves reusability, and speeds up access to all data in one place. Such a data model unifies data from different sources and platforms in one location to be considered when conducting analyses and making decisions. Champions seem to be striving more intensively towards becoming a data-centric organization.

⁴ Digital and data platforms are defined in the DAI as “A coherent set of applications, data & technologies, with ready-to-use and reusable components, answering business needs and enabling the delivery of business use cases rapidly and at scale.”

Becoming a data-centric organization

To understand what differentiates AI leaders (stage 4) from AI starters (stage 1), we further analyzed the group of organizations that show the highest level of maturity in AI and that have been able to generate substantial value from AI, measured by the dimension “Artificial intelligence” in the DAI framework (See Appendix, item “DAI dimension Artificial intelligence”). AI leaders agreed to the statement: “AI is successfully adopted in core offerings and processes, providing competitive advantage. AI is rolled out across the whole value chain and shapes new business models. AI is key to decision-making in the organization.” In comparison, AI starters chose the lowest maturity stage: “Basic understanding of AI in parts of the organization but neither larger adoption nor use case prioritization. No AI job profiles exist, and the common perception is that existing analytics experts like statisticians could cover AI.”

AI leaders have successfully set up a data-centric organization and use data analytics to rationalize and improve decisions. In line with the DAI framework, three dimensions compose a data-centric organization: data strategy, data governance, and digital and data platforms. Between 77% and 79% of AI leaders are already in the two highest maturity stages for the three respective dimensions. In comparison, and to take an extreme view, of those organizations that chose either of the lower two stages in the question to measure their AI maturity, i.e., digital starter or digital literate, only 48% reached the highest maturity in data strategy and only 39% in data governance. In particular, the infrastructure, a digital and data platform, is a challenge for these organizations as only 6% have reported that they have reached the highest maturity stage here.

So how do AI leaders differ from AI starters? First, AI leaders pursue a formulated data strategy. They recognize data as a critical corporate asset and have various automated, scaled, and commercialized analytical solutions. They regularly measure how to exploit value from the existing data assets and have defined performance targets to reach from commercializing data. A transparent operating model covers all data-related issues [7].

Second, AI leaders have established data governance. They have assigned essential data and analytics roles, implemented data quality policies, perform master data management, and provide methods and tools to harmonize and link data from distinct sources. Everything operates in a hub-and-spoke model [14]), fueling the entire organization with the help of data warehouses and data lakes.

Third, AI leaders have also built-up the necessary technology infrastructure to enable data integration and support focused development of analytics upon required data [13]. In the DAI methodology, this capability is named “digital and data platform,” and AI leaders have implemented such

Data Strategy	Data governance	Digital & Data Platform
Data is a key corporate asset, and a value map was developed. Our organization implements a roadmap with sufficient funding and people and the realization of data value is measured regularly	Key data governance roles, policies and tools have been implemented. The topic "Data" is a top management priority. Since data domain are defined, the data quality has significantly improved	Fully optimized infrastructure, based on best-in-class technologies (e.g., Hadoop). Data lakes exist and some are fully functional in production, supporting advanced analytics tools
79% of AI leaders defined a data strategy, cascaded throughout the organization	78% of AI leaders agreed on data governance, roles, tools, and principles	77% of AI leaders have built a digital and data platform, and operate data lakes
vs 48% or AI starter/literate	vs 39% or AI starter/literate	vs 6% or AI starter/literate

Fig. 4 Companies that lead in artificial intelligence (AI) have built a data-centric organization

a fully optimized platform based on best-in-class technologies, e.g., a Hadoop ecosystem [12] and using one or more data lakes in full production. An overview of these three differentiators is provided in Fig. 4.

Case 2: Chemical Firm providing intelligent solutions for the mining industry

Pioneering companies aim for AI systems that are fully integrated into day-to-day operations, i.e., in the production environment, instead of small pilots. For instance, a leading supplier for gold mining operators faced saturated customer demand in a consolidated market. The business’s core was to manufacture and provide cyanide, a special chemical in a market segment with few growth opportunities. Therefore, the company’s ambition was to build a new business model enabled by AI to support clients beyond a chemical substance’s mere offering.

The companies’ strategy was to look for new opportunities that help mining operators improve in gold recovery. First, the company started by gathering data from historic production cycles for relevant process parameters (e.g., oxygen in the tank, throughput per hour, leach feed grade, and cyanide concentration) and the resulting gold recovery. Data scientists then analyzed the data to identify potential gold recovery improvement levers. Various machine learning algorithms were deployed and tested. However, despite sophisticated algorithms and the breadth of data, no significant improvement levers were identified initially. Hence, the chemicals supplier started to involve metallurgical experts to refine the analyses and account for the gold recovery process’s key steps and corresponding variables. Combining chemical and metallurgical process know-how with collected data allowed the company to build a “digital twin,” meaning a virtual model, of the gold recovery process. This new model used the data for the process parameters to explain, predict, and control the resulting gold recovery. In fact, it explained 60% of the overall variance of the selected input parameters.

With the help of the “digital twin,” the company was able to identify four key improvement levers. Gold mining operators can improve their operations by optimizing (i) dissolved oxygen, (ii) throughput levels, (iii) feed blend approach, and (iv) cyanide concentration. As a result, miners’ earnings before interests, taxes, depreciation and amortization (EBITDA) has been able to increase by 10–15%. Of this effect, 80% accrued from a higher recovery rate and translated into top-line growth, whereas 20% came from cost savings. This value creation evidence was obtained in less than one month, including developing the “digital twin,” simulating the process variables, and deriving the business insights. Afterward, the chemicals provider prepared a comprehensive business model to actively market the value proposition of AI technology for gold recovery processes, including the required operating model. In other words, the developed capabilities and agile collaboration between chemical, metallurgic, and data experts empowered the Chemical Firm to transform from a chemical commodity provider into a digitally enabled operator of highly specific processes.

Key learnings and recommendations for providing fundamental enablers

- Intertwine human and technological capabilities around AI through forming one team with business domain know-how and advanced analytics capabilities. A cross-functional team of business and data analytics experts is necessary to unlock the value of data.
- Aim for rapid AI value proof with a test-driven approach. Fast iterations and short sprints facilitate early adjustments for process parameters, particularly in case of unsatisfactory results. Quick learnings from failures offer a basis for leaps forward. Establish a failure culture for digital innovation.
- The value potential for revenue increases from AI may be higher than cost savings opportunities. As AI often changes industries’ value drivers, AI leaders tend to address new business opportunities as a first try before optimizing their operations.

Quantify how to measure AI impact and turn AI into tangible value

In our survey, we asked companies about their primary focus during their digital transformation (See Appendix, item “Digital transformation focus”). Unsurprisingly, laggards prioritize “digitizing organizations” and “improving cost and efficiency” (39%) over “looking for innovation” and “managing data at scale” (21%). In contrast, both priorities were reported respectively by 34% of digital champions, so

they have a similar focus. Consequently, more digital champions invest significantly more time and money in data and innovation and have shifted their focus away from just “digitizing operations” and “improving cost and efficiency.”

Consequently, organizations balance their priorities between making the core more efficient and significantly fostering innovation. They should further prioritize their project portfolio based on value and measure the business and financial impact of AI—competencies we have seen at digital champions who score highest for purpose and strategy. Often, companies define short-term objectives and key results (OKR) to operationalize their journey and monitor AI’s impact realization more closely. In the case of insignificant results, they change the targets as well as the direction of AI support as they follow a hypothesis-driven approach with rapid value proof.

Digital maturity and AI focus offer positive returns

Organizations that take on a business lens, build fundamental enablers, and measure AI, achieve tangible impact, which is notably higher than those that do not. We included indicators to analyze how digital champions perform against laggards (Fig. 5). Some measures report shareholder value from external sources⁵, e.g., market capitalization, total enterprise value. Others offer self-reported indicators, e.g., earnings before interests and taxes (EBIT) from digital, the magnitude of scale (Appendix, item “Scale”). To assess a firm’s competitiveness, the respondent evaluated the perception of where the organization stands compared to industry peers over the past 3 years (Appendix, item “Competitiveness”). It is not surprising that both digital champions and AI leaders outperform other organizations in our sample, but the magnitude strikes. About twice as many champions as laggards (64% vs. 34%) consider their firm to be more competitive than industry peers, i.e., better in cost-efficiency, product quality, time-to-market, and customer satisfaction. Digital champions are growing stronger in total enterprise value every year and experience higher EBIT impact from digital investments. Furthermore, they are better at scaling-up their digital pilot projects into operating solutions that deliver the full potential of the technologies behind them.

Moreover, the Covid-19 crisis has accelerated many companies’ digital transformation as the value of digital capabilities in responding to and recovering from the crisis became evident. A closer look into the total shareholder return of champions vs. laggards from February 2020 to January 2021 shows that digital drives resilience. Champions’ market capitalization is not only back to its pre-crisis

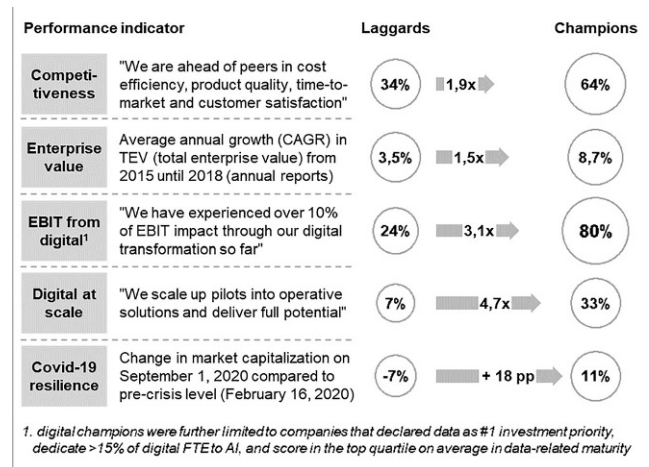


Fig. 5 Digital and artificial intelligence (AI) advantages enhance competitiveness, value, scaling, and resilience. *EBIT* earnings before interests and taxes, *FTE* full-time equivalents

level but has grown by 23%. In contrast, laggards stood at plus 7%, so 16 percentage points lower (Fig. 6).

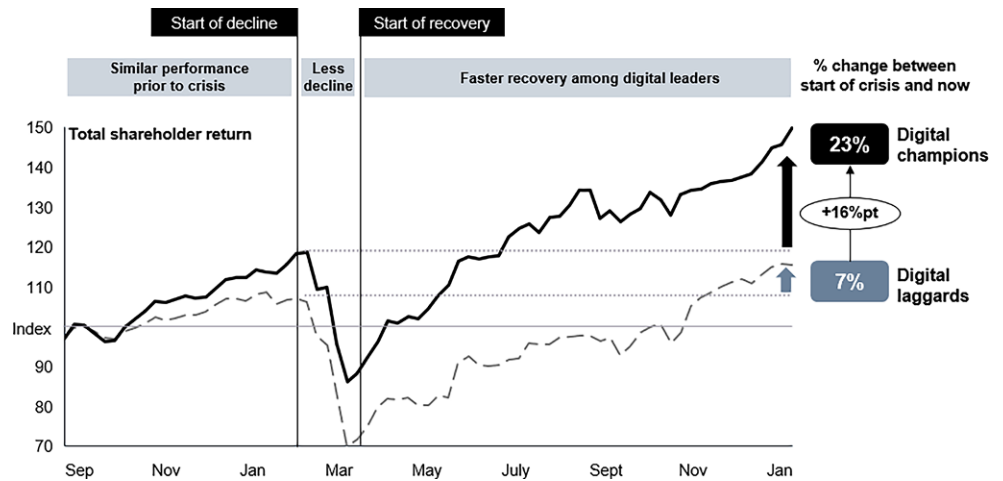
Case 3: An energy utility company innovating integrated operations through AI

Companies invest in AI to generate tangible value. An example is a European energy firm with business activities in natural gas supply, petroleum products exploration, combined heat and power (CHP), and renewable energies. The company aimed at reaping the potential by moving from efficiency-centric operations to innovation-centric operations enabled by AI. The ambition was to deliver on the value promise of AI by building use cases, changing the firm’s operating model, and setting up new forms of data governance and comprehensive digital and data platforms. For instance, digital collaboration tools and agile collaboration processes were introduced to foster upstream coordination and joint innovation with suppliers. Energy production was advanced by more sophisticated ways of asset management for improving safety and field productivity, as well as advanced practices for energy trading. Downstream activities were innovated through personalized sales approaches, non-fuel sales improvements, renewables production forecasting, cross-selling identification, and digitally enabled energy services.

The company identified and prioritized potential AI use cases by expected value and speed. For selected use cases such as predictive maintenance, safety, and turbine productivity, cross-functional teams were formed combining business experts, data scientists, and IT architects. These teams worked agile and started to collect the required data from existing and newly deployed Internet-of-Things devices and sensors (e.g., process data on turbine lube oil temperatures

⁵ Source: S&P Capital IQ Platform.

Fig. 6 Digitally mature companies show stronger resilience during Covid-19 crisis



and performance). To implement the use cases, the company followed a four-step approach.

First, machine learning algorithms were trained with existing data to develop “local” models of lube oil temperature for each turbine. Second, differences between modeled and actual lube oil temperatures were identified, indicating potential anomalies, i.e., potential upcoming problems. Third, early maintenance was performed on turbines with abnormalities to preempt possible shutdowns and system downtimes. Last, the maintenance findings and root causes, such as faulty compressor units, were fed back to the machine learning prediction model to further refine the identification of abnormality causes. To accelerate the scaling of this value-generating use case, the company pushed the data from legacy systems into a cloud-based data lake, implemented a shared, quality-assured data repository, and defined clear data governance roles.

As a result, the energy utility company successfully set up a new Integrated Operations Center, which fully enabled AI activities with over 100 employees. These employees combine their expertise and leverage AI tools in their day-to-day work. Production volumes have increased through higher capacity utilization by 3–4% based on innovation and redesign of upstream activities, energy production, and downstream activities. AI has enabled the energy utility to preempt breakdowns before their occurrence, increase daily production, and proactively reduce bottlenecks regarding installations.

Key learnings and recommendations for measuring AI impact and delivering AI value

- Set clear expectations on goals, define OKR, and measure business and financial impact. Continuous AI impact measurement enables organizational learning for exploiting AI toward its full potential.

- Redesign business processes to incorporate AI tools. AI can only deliver its full value potential if employees leverage new tools in their work routines, as digitizing legacy processes will likely not yield positive outcomes.
- Make data accessible and utilizable with the innovative technology and provide governance that facilitates experimentation, continuous improvement, and data-enabled learning. Cloud-based data infrastructure are prerequisites for facilitating data access. Defined data governance roles foster data quality which enables data analytics centrality.
- Employ agile ways of working to develop minimum viable products for use cases efficiently. Cross-functional teams are needed to build an AI use case, and agile approaches enable quick iterations to accelerate development cycles.
- Utilize AI innovation, process redesign, data centrality, and agile working practices to permeate all the operating model’s significant elements. Become a digital innovator who is not solely focusing on isolated use cases but advances the organization’s operating model in an integrated logic.

Three steps towards accelerating AI to achieve business transformation

This article focused on why many companies’ struggle to scale AI beyond pilot use cases and why firms do not realize tangible value from AI projects. Based on the presented empirical data and three case studies, we outline three actions that business leaders can pursue to overcome this problem.

1. *Identify AI business opportunities:* Leaders need to establish a concrete vision for AI, so stakeholders recognize its potential for the organization. It is essential that top management from the CxO level actively support AI ini-

tiatives and integrate them into the overall business strategy. Second, leaders need to identify and prioritize the use cases to operationalize this vision and rapidly prove AI's value to the organization. Use cases will leverage the potential of AI for automation and decision augmentation. Champions push AI beyond and design business processes, enhance customer journeys, and build new offers that are genuinely differentiating and lead to tangible outcomes.

2. *Promote the interplay of humans with technology and establish a data-centric organization:* Leaders need to promote the interplay of “man and machine.” AI can automate digitized manufacturing processes or augment human decisions that affect the well-being of firms and individuals. As we were able to demonstrate, data-enabled analytics and learning are essential drivers for companies as they increase the odds of realizing AI's financial benefits. Irrespective of whether the human or the AI judges a problem while the other party executes the decision, it is important to foster learning through continuous feedback loops and act on the learnings.

Data plays a pivotal role as a complementary asset to fuel AI algorithms. The quality of input data is a prerequisite for valuable analytical insights. First, companies need to adopt an up-to-date digital infrastructure, including a data platform that allows organizing data as a resource pool as well to access it via micro-services through pre-defined APIs and makes it easily accessible from microservices using APIs. Second, companies need to establish a data-centric organization with dedicated employees to focus on data and AI and build a robust data strategy and governance. This will also enable leaders to move towards the paradigms of (big) data analytics and data-enabled learning. Contemporary data governance modes will assure the quality of input and output data required for meaningful and reliable analyses.

3. *Assess how AI turns into value:* Control mechanisms are indispensable in successfully navigating companies towards more mature AI capabilities. Leaders need to set clear objectives, deduct key results that help to achieve them, and adjust AI-related initiatives to these results. By defining how to measure the impact of AI, the initiatives get operationalized, and leaders can take corrective actions, e.g., a portfolio adaptation, if projects miss targets or if the context changes. Measuring AI's impact typically implies that initiatives are stopped if they do not create sufficient tangible value.

Transforming from an AI starter to an AI leader is neither a one-time activity nor can it be achieved over a few months. Companies that succeed in this journey approach AI from a business lens provide the fundamental enablers and specify how to measure the value from AI. As companies with a higher maturity in AI can

demonstrate a stronger financial performance and more resilience during the prevailing pandemic, embarking on and accelerating the AI journey is a no-regret move for companies.

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Appendix

Table 1 Additional survey questions

Item	Question
FTE in digital roles	How many FTEs (full-time equivalents) of your organization’s workforce are currently dedicated to digital? (five ranges from less than 5% [min] to 20% or more [max])
FTE to upskill	Which percentage of your organization’s FTEs (full-time equivalents) are planned for re- and upskilling in the topic of digital within the next year? (Same ranges)
Projects in agile	What percentage of business and IT capacity operates in agile for joint business/IT projects?
Investments	Approximately what percentage of your organization’s operational expenses are dedicated to digital?
Investment priorities	In which areas does your organization primarily invest? (eight choices)
Target of digital transformation	Where does your organization focus on in its digital transformation?
API-ready application	What percentage of applications is digital-ready with API layer, data separated from functionality, running in private/public cloud?
Unified data model	What percentage of total company data is already mapped to a unified data model with clear definitions and a single-source-of-truth?
Digitized processes	What percentage of processes have been transformed using digital technologies, i.e., RPA (robotics process automation), ML (machine learning), AI, Manufacturing 4.0, Big data analytics?
Scale	Where does your organization overall stand in the process of digitizing the core business towards full-scale? 1. We assess our organization and define digital action areas 2. We design use cases into solutions and launch quick wins 3. We refine pilots into full-scale solutions across operations 4. We scale up operative solutions and deliver full potential
Digital transformation focus	Where does your organization primarily focus on in its digital transformation? 1. Looking for innovation 2. Driving customer centricity 3. Managing data at scale 4. Improving cost and efficiency 5. Digitizing operations 6. Renovating technology stack 7. New ways of working 8. Accelerating digital programs
EBIT impact	What size of impact (as % of EBIT, earnings before interest and tax) have you experienced through your digital transformation so far? (six ranges)
Digital revenue	What percentage of the organization’s revenues comes from adjacent digital businesses/products/services, which are not part of the core business?
Competitiveness	Over the last 3 years, how was your organization’s position in your industry with regard to: 1) cost efficiency, 2) product quality, 3) time-to-market, 4) customer satisfaction?
DAI dimension “Artificial intelligence”	Do you leverage AI to improve your offerings and business processes and achieve significant business value? 1. <i>Starter</i> : Basic understanding of AI in parts of the organization but neither larger adoption nor use case prioritization. No AI job profiles exist, and the common perception is that AI could be covered by existing analytics experts like statisticians. 2. <i>Literate</i> : Awareness of major use cases enabled by AI on management level, with first pilot project(s) to assess their impact, e.g., NLP (natural language processing) or deep learning. Job profiles (e.g., data scientists) are being defined with explicit AI, and machine learning skills demand. 3. <i>Performer</i> : Major AI use cases are defined and prioritized with first value-generating lighthouse implementation and clear responsibilities to drive adoption and experimentation. The current focus is just on parts of the value chain, but here AI becomes key for decision-making and to create new value pools. 4. <i>Leader</i> : AI is successfully adopted in core offerings and processes, providing a competitive advantage. AI is rolled out across the whole value chain and shapes new business models. AI is key to decision-making in the organization

Table 1 (Continued)

Item	Question
DAI dimension “Data strategy”	<p>Do you fully understand the value that data can create, also from use cases, and have you implemented a structured plan to realize this value?</p> <ol style="list-style-type: none"> <i>Starter</i>: The organization has started experimenting with use cases and POCs (proof of concepts) but data is not part of the top-management agenda. The potential of data has not been assessed. <i>Literate</i>: Selected BUs have started assessing the value that can be generated from data. Several successful POCs (proof of concepts) are in the process of industrialization and receive funding, but no long-term agenda is defined. <i>Performer</i>: A clear data strategy is part of the top-management agenda. A data value map (i.e., structured collection of use cases) is developed, and a comprehensive roadmap for implementation is built. A structured POC (proof of concept) pipeline is starting to be developed. Funding is available at the enterprise level for infrastructure and HR data. <i>Leader</i>: Data is clearly recognized as a critical corporate asset. Several applications and data-driven business models have been industrialized. Data value realization has spread throughout the company, and data value contribution gets measured regularly. Our company highly invests in data projects and respective resources
DAI dimension “Data governance”	<p>Do you have the organizational structures necessary to effectively and efficiently govern data and analytics?</p> <ol style="list-style-type: none"> <i>Starter</i>: Data is still managed by IT with limited input from business. No central function or C-level appointed to assure cross-company data management. <i>Literate</i>: A CDO (Chief Digital Officer) has been appointed and started implementing a structured data governance approach (including on regulation). First global data governance policies and procedures are planned. <i>Performer</i>: A fully functional data organization exists under a CDO (Chief Digital Officer) reporting to top management. The CDO (Chief Digital Officer) organization includes design authorities for data platforms and data architecture. A governance charter for data is defined, including policies and tools. Data quality has significantly improved. <i>Leader</i>: All key data and analytics governance roles have been implemented and fully functional in a hub-and-spoke operational model covering the entire organization, where all data domains are defined. Data and analytics leadership is included in all corporate governance processes
DAI dimension “Digital & data platform”	<p>Do you have an efficient data platform in place to deliver significant business value from data?</p> <ol style="list-style-type: none"> <i>Starter</i>: Traditional data warehouse systems for historical data in place, but often lacking efficient MDM (master data management) functionalities and clear referential. Analytics are mainly descriptive and run primarily through packaged BI and database tools via batch feeds. Analytical resources are disseminated across the organization. <i>Literate</i>: Fit-for-purpose systems using a mix of traditional technologies and an efficient but small Hadoop/Apache big-data platform. Most MDM (master data management) issues are addressed. Data lakes are in advanced testing. New ways to improve analytics with dashboards, interfaces, or high-performance data platforms are investigated. <i>Performer</i>: Fit-for-purpose enterprise-level platform based primarily on Hadoop/Apache ecosystem or cloud resources for batch-processing solutions. Predictive analytics has become a key input in most operational and strategic decision-making, using modern visualization and geospatial analyses. MDM (master data management) issues are being fully addressed at an enterprise level. Data lakes exist and offer new <i>Leader</i>: Fully optimized batch and streamlined big-data infrastructure, based on best-in-class technologies originating primarily from the Hadoop/Apache ecosystem or cloud resources. One or more data lakes are fully functional and in production, supporting advanced-analytics tools (real-time capability). This technology has become a key enabler to offers, new business models. There is also an enterprise-wide analytics resources strategy

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