Achieving business impact with data

A comprehensive perspective on the insights value chain

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There has never been a better time to achieve impact with (your) data. More and more data is available, computing power is ever increasing, and mathematical techniques and the so-called data science are getting more and more advanced. What's more, "digital" and "data" have become the talk of the town. Yet while talking about data as the "new oil" or the "new gold" is fairly widespread these days, several technology- and business-related difficulties make understanding data's importance and realizing its potential a persistent challenge.

Against this backdrop, in this article we 1) outline the scope of data's growing importance and impact potential, 2) describe the fundamentals of the insights value chain's upstream and downstream processes, and 3) introduce key practice perspectives on creating insights-based value and making an impact with it.

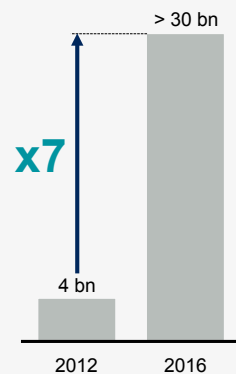### 1. Data's skyrocketing importance in value creation

Not only has the sheer volume of available data – mainly driven by the IoT – grown exponentially over the past five years and is expected to continue to do so (Exhibit 1), but also have new tools been developed for turning this flood of raw data into insights and eventually into action. Machine learning, a term that encompasses a range of algorithmic approaches from statistical methods like regressions to neural networks, has rapidly advanced to the forefront of analytics.

Underpinning this progress in its entirety has been steady improvement in computational power from better processors and graphics processing units, increased investment in massive computing clusters often accessed as cloud services, improvements in storage, and strong price decreases for all relevant parts (Exhibit 1).
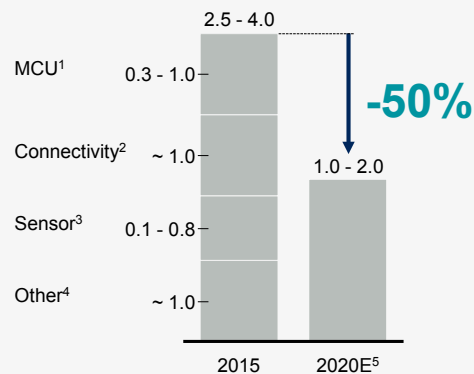
Exhibit 1

Falling IoT prices related to sensors and wireless device will drive the growth of available data

Increase in available data volume
Number of delivered sensors, globally

> 30 bn

x7

4 bn

2012   2016

Expected development of cost for IoT nodes, 2016 - 20
Unit price, USD

2.5 - 4.0

MCU[1]   0.3 - 1.0

-50%

Connectivity[2]   ~ 1.0

1.0 - 2.0

Sensor[3]   0.1 - 0.8

Other[4]   ~ 1.0

2015   2020E[5]

1 Current prices range from USD 0.3 (e.g., Cypress 32-bit) to USD 1.2 (e.g., TI 16-bit), dependent on speed, quality, and integrated memory size (ranges for larger order volumes)
2 Combination of filter transceiver and antenna – additional costs for switches and amplifiers not included
3 E.g., temperature, position, pressure, gyroscope
4 Additional components such as ADC converters, power management converters, capacitors, resistors, fuses, PCB (list not exhaustive)
5 2020 prices estimated by inflating current prices with a CAGR of -15% p.a.

SOURCE: Federal Statistical Office; Deutsche Bundesbank; Prognos; Digital Society Study; Thomas Nipperday; digikey.com; expert interviews; McKinsey
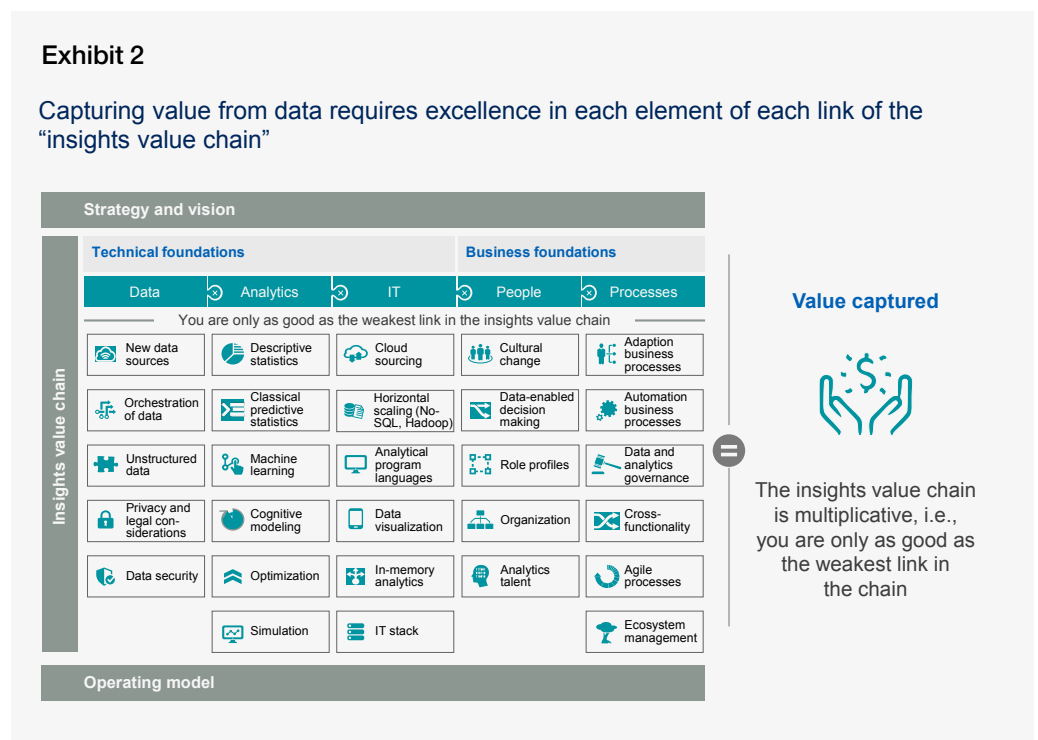
Each of these trends – more data, more tools for analyzing the data, and an increase in the firepower needed to do so – constitutes a break-through in its own right. Together these developments reinforce each other, and the broader field of Big Data and Advanced Analytics is making rapid advances as they converge. Vast increases in the amount and complexity of data require greater computational power and infrastructure to analyze and access it. Both data and computational power enable next-generation machine learning methods such as deep learning. The confluence of data, storage, algorithms, and computational power today has set the stage for a wave of creative disruption.

However, data has not only increased in volume; it has also gained tremendous richness and diversity. We have entered a new era in which the physical world has become increasingly connected to the digital world. Data is generated by everything from cameras and traffic sensors to heart rate monitors, enabling richer insights into human and "thing" behavior.

As a consequence, data has become the new corporate asset class – and the best way for companies to generate and access is to digitize everything they do. Digitizing customer interactions provides a wealth of information for marketing, sales, and product development, while digitizing internal processes generates data that can be used to optimize operations and improve productivity.

2. A "link-by-link" look at the insights value chain

Data in its raw and most basic form is virtually worthless until we give it a voice by gleaning valuable insights from it. But how do we make data speak? Today everyone talks about Big Data and Advanced Analytics and even machine learning and artificial intelligence (AI). The tendency we observe is that people are so excited about the new technology that they focus too much on single technical components of the "insights value chain," as we call it. Taking this one step further illustrates how important a series of components is in capturing the full value (or any value at all) from relevant (smart) data (Exhibit 2).

Exhibit 2

Capturing value from data requires excellence in each element of each link of the "insights value chain"

We can already say that the insights value chain is multiplicative, meaning that if one single link in that chain is zero, your impact will be zero. In other words: the entire data ecosystem is only as good as its weakest component. This illustrates the critical importance of understanding and working on all components and steps of the insights value chain – not focusing on only one piece and forgetting about the others.

In this chapter, besides briefly explaining the function of each of the insights value chain's core components (see Text box 1) we shed light on its upstream as well as its downstream steps and processes.

Text box 1: The insights value chain – definitions and considerations

First, the insights value chain consists of the technical components of data, analytics (algorithms and technical talent), and IT. In practice, this means that value is possible when data scientists use smart algorithms to extract meaningful information from high-quality data. In today's world of Big Data, you also need an IT environment capable of processing large amounts of data fast.

Second, the insights value chain consists of the business components of people (nontechnical talent) and processes, both of which are required to turn the insights distilled from data into (business) action.

Here are some key considerations concerning the components of the insights value chain:
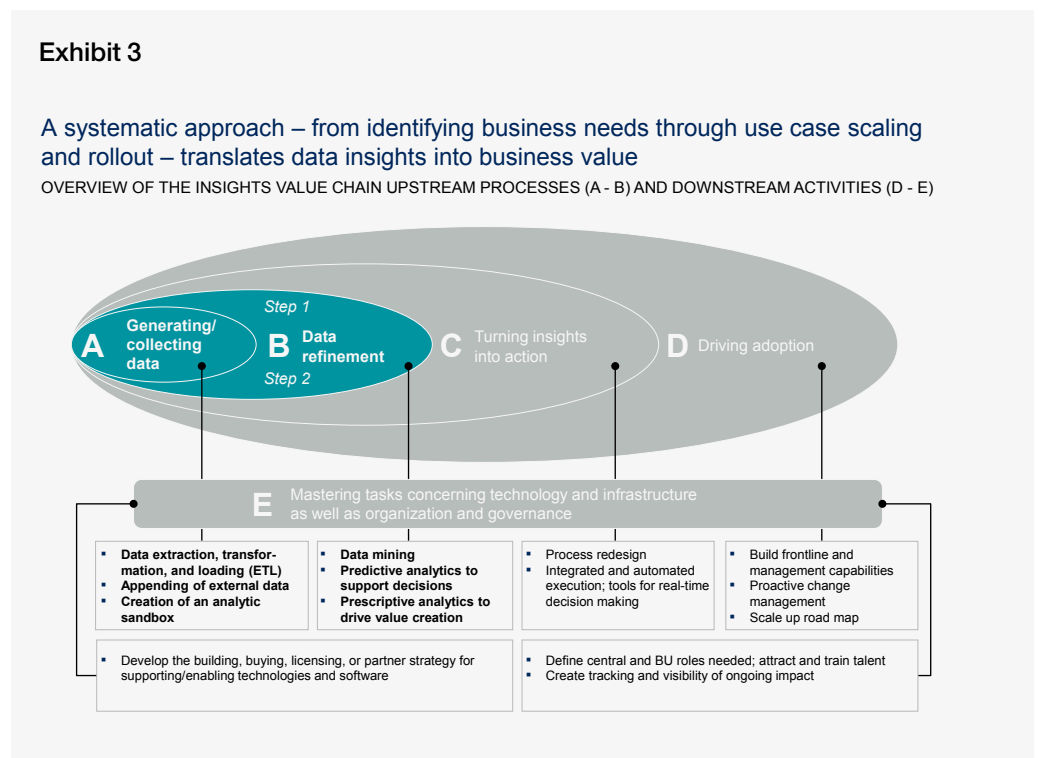
- **Data** must be thought of as the entire process of collecting, linking, cleaning, enriching, and augmenting internal information (potentially with additional external data sources). In addition, the security and privacy (e.g., GDPR) of the data throughout the process are fundamental.

- **Analytics** describes the set of digital methodologies (e.g., software) deployed to extract insights from data as well as the talent (e.g., data engineers and data scientists) capable of developing and applying these methods.

- **IT** is the technical layer enabling the storing and processing of data, e.g., data lakes, two-speed IT architecture.

- **People** from the front lines of sales to deep within the business – not just "geeks" – are needed to run an analytics operation that turns data into insights and successfully implements those insights in the business. The crucial capability in today's Big Data world is being able to "translate" analytics- and data-driven insights into business implications and actions.

- **Processes** must be assessed for their ability to deliver at scale. Some old processes might need to be adapted, some might need to be fully automated, and others might need to be made more agile.

In addition, there is an overarching frame and an underlying governance in which the insights value chain is operating:

- **Strategy and vision** are the overarching frame in which the insights value chain is meant to operate. Data Analytics shouldn't be "done" for the sake of Data Analytics but in fulfillment of the organization's vision and in support of its overall business strategy. "Think business backwards, not data forward."

- **Operating model** is the underlying governance in which the insights value chain lives. Core matters to be addressed include deciding where the analytics unit will sit within the organization and how it will function and interact with BUs (e.g., centralized, decentralized, hybrid).

2.1 From dull data to invaluable insights: the upstream processes

The insights value chain's upstream processes comprise two steps (Exhibit 3).

Exhibit 3

A systematic approach – from identifying business needs through use case scaling and rollout – translates data insights into business value

OVERVIEW OF THE INSIGHTS VALUE CHAIN UPSTREAM PROCESSES (A - B) AND DOWNSTREAM ACTIVITIES (D - E)

| A Generating/collecting data | Step 1 / Step 2 — B Data refinement | C Turning insights into action | D Driving adoption |

E Mastering tasks concerning technology and infrastructure as well as organization and governance

- Data extraction, transformation, and loading (ETL)
- Appending of external data
- Creation of an analytic sandbox

- Data mining
- Predictive analytics to support decisions
- Prescriptive analytics to drive value creation

- Process redesign
- Integrated and automated execution; tools for real-time decision making

- Build frontline and management capabilities
- Proactive change management
- Scale up road map

- Develop the building, buying, licensing, or partner strategy for supporting/enabling technologies and software

- Define central and BU roles needed; attract and train talent
- Create tracking and visibility of ongoing impact

A. Generating and collecting relevant data

When watching what companies in the field of analytics are doing, we observe two trends. First, algorithms seem to be commoditizing; Google and Amazon, for instance, are providing free access to their analytics libraries. Second, these companies are holding on tightly to the data itself and not granting outsiders access, as their bet is that the value is all in the data.

Collecting massive amounts of data is not solely the domain of tech giants. Data's value is being recognized even in more traditional sectors, where new types of data ecosystems –

e.g., joint ventures between telecoms and retailers – are being built to enable data collection on an increasingly bigger scale. This enhanced data capture ability is not only relevant in B2C environments. It is becoming even critical in B2B as well, as the IoT with its sensors everywhere will take the amount of data being generated to new dimensions.

As data generation and collection grow in volume – given, e.g., the massive increase in e-commerce and sensor-generated data – data relevance will become even more important. It is simply impractical (and perhaps impossible) to collect and save every bit of the tera- and petabytes of data that will be generated every second. Defining certain requirements based on particular use cases will help ensure that only relevant data is captured. The data requirements for some use cases will be very concrete, while the requirements for others will be fuzzy. Some use cases will require significant time series of data (sometimes making up for lack of data quality). Other use cases depend on the timeliness and "freshness" of data, e.g., when analyzing social media data that is affected by frequent changes in trends. As data can become "stale" quickly, these use cases may require that only relatively recent data will need to be stored. The situation requires a thoughtful approach to which data to store in its original granularity and which to aggregate or preanalyze. In the case of relevance, the more classical "hypothesis-driven" or "use case backwards" approach often delivers better results than the often praised "Big Data, brute force" approach.

Another important aspect of the generation and collection of data is data layering. Instead of "throwing" all unconnected data into the analytics layer all at once, carefully organizing it into several logical layers and then employing a logic by which to stack these layers can help generate more meaningful data.

B. Data refinement is a two-step iteration

Once the organization has successfully captured all relevant raw data, it must begin the process of turning vast amounts of unrefined raw data into actionable insights. The two-step process is comprised of enrichment and extraction.

Step 1: Enriching data with additional information and/or domain knowledge. Once raw data is collected, cleaned, and combined, one of the most important refinement steps begins: data needs to be transformed and enriched with additional and domain knowledge – which is a somewhat more complex process. All of this means, however, that human expertise is as important to making data useful as is the power of analytics and algorithms.

Our experience has proven multiple times that, in today's world, "man + machine" is still the optimal approach to data enrichment (see Text box 2) – although this may well change one day due to further developments in the AI space. So, before we even start with machine learning, we need to involve human experts who use their expertise to explain their hypotheses. The task of a data scientist (or sometimes a data engineer at this stage) is now to translate, i.e., codify, additional information and/or this domain knowledge into variables (Exhibit 4). Concretely, this means transforming existing data into new variables – often also called feature engineering.

Textbox 2: "Man + machine = actionable insights"

When the domain expertise of data scientists and business knowledge is used to enrich the data collected by machines, very specific performance-enhancing actions can be taken. The additional knowledge and human expertise of this enrichment step is what allows the creation of ratios of variables, trends or derivatives (e.g., changes in customer behavior), and categories from numerical variables (e.g., low, medium, high income instead of the actual number) that then enable powerful action.
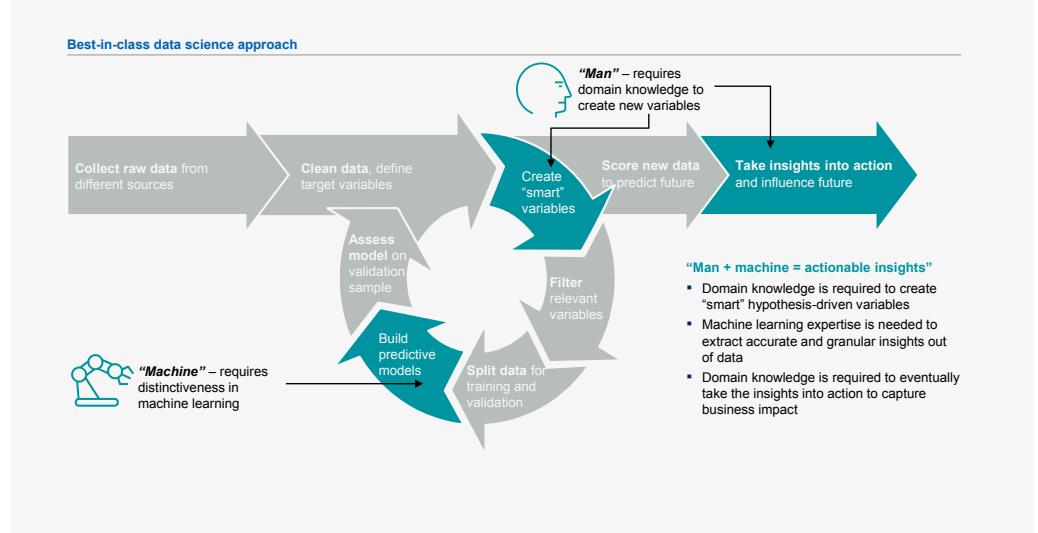
Man + machine example 1: Customer churn in banking. Instead of having 12 variables – each of which describes the average account balance of one of the previous 12 months – a data scientist would create one new variable showing the trend of average balances. The underlying business hypothesis in this case would be that churn in banking happens slowly, and customers pulling out assets over time should trigger an early warning.

Man + machine example 2: Predictive maintenance in telecoms. Deep knowledge in the data science field is important in the development of the right methodology and in fine-tuning models in a way that best predicts machine/component failure in telecoms. What's more, business knowledge can further optimize these models by providing additional ideas for drivers of failures that can be used in the predictive model to further improve the predictive power. Business knowledge can also help interpret the results and derive concrete business-based solutions to prevent failures in the future. Finally, business knowledge is critical in implementing the recommendations, so that processes can be appropriately aligned, e.g., training call center agents using the outputs of the predictive maintenance model in their daily work.

Man + machine example 3: Predictive maintenance for turbines. A predictive maintenance approach for turbines would use a mathematical model very similar to the one used in the telecoms example above. However, engineering domain knowledge specific to turbines will make a big difference since the root causes of turbine failures are completely different from those behind telecoms failures. Also, the approach to changing business processes in turbines to, e.g., optimize maintenance, will be completely different from any process transformation related to maintenance in B2C.

Exhibit 4

Best-in-class data science is an iterative process that leverages both human domain expertise and advanced machine learning techniques

Best-in-class data science approach

"Man" – requires domain knowledge to create new variables

Collect raw data from different sources

Clean data, define target variables

Create "smart" variables

Score new data to predict future

Take insights into action and influence future

Assess model on validation sample

Filter relevant variables

Build predictive models

Split data for training and validation

"Machine" – requires distinctiveness in machine learning

"Man + machine = actionable insights"
- Domain knowledge is required to create "smart" hypothesis-driven variables
- Machine learning expertise is needed to extract accurate and granular insights out of data
- Domain knowledge is required to eventually take the insights into action to capture business impact

Step 2: Extracting insights using machine learning. The second step in making the raw data usable involves the actual math and number crunching – the part that data scientists are most excited about. One could argue that the human component isn't even necessary because the most sophisticated algorithms can find any and all patterns. The truth, however, is that the combination of human hypothesis-driven input and new surprising patterns that machines reveal is the winning combination. Creating new features just helps the machine find patterns better and also helps humans better describe and act on these patterns.

The core of this step is using various methods to identify these patterns. Typically, one can distinguish among descriptive analytics (what happened in the past and why?), predictive analytics (what will happen in the future?), and prescriptive analytics (how can we change the future?). In all these steps, simple but also quite sophisticated methods can be used. More and more advanced techniques in AI and machine learning are being used given the increased amount of available data and computing power.
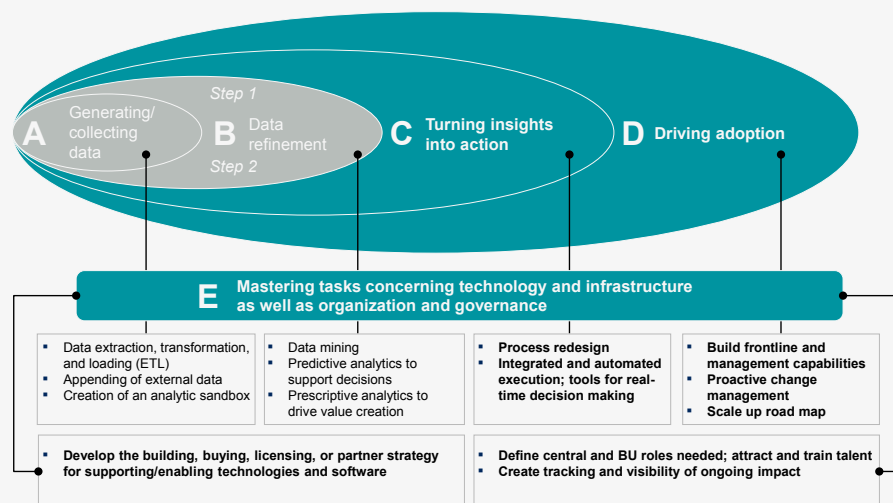
2.2 From valuable Data Analytics results to achieving business impact: the downstream activities

The downstream part of the insights value chain is comprised of nontechnical components. It includes people, processes, and business understanding that – through a systematic approach – can operationalize these new data-driven insights via an overall strategy and operating model (Exhibit 5).

Exhibit 5

A systematic approach – from identifying business needs through use case scaling and rollout – translates data insights into business value

OVERVIEW OF THE INSIGHTS VALUE CHAIN UPSTREAM PROCESSES (A - B) AND DOWNSTREAM ACTIVITIES (D - E)

A Generating/collecting data · *Step 1*	**B** Data refinement · *Step 2*	**C** Turning insights into action	**D** Driving adoption

E Mastering tasks concerning technology and infrastructure as well as organization and governance

• Data extraction, transformation, and loading (ETL) • Appending of external data • Creation of an analytic sandbox	• Data mining • Predictive analytics to support decisions • Prescriptive analytics to drive value creation	• **Process redesign** • **Integrated and automated execution; tools for real-time decision making**	• **Build frontline and management capabilities** • **Proactive change management** • **Scale up road map**
• **Develop the building, buying, licensing, or partner strategy for supporting/enabling technologies and software**		• **Define central and BU roles needed; attract and train talent** • **Create tracking and visibility of ongoing impact**	

C. Turning insights into action

Once we have extracted important insights from the models, the next crucial step starts: turning these insights into action in order to generate business impact. A churn model, e.g., typically predicts churn but doesn't prevent it. It is also clear that domain knowledge and business understanding play an important role in being able to act on insights. Continuing with the same example, a deep understanding of the customer and the sector is fundamental to a company's ability to prevent a customer from churning.

Similarly, a predictive maintenance model gives you warning as to when a machine or some asset might break down, but maintenance is still required. As with churn, just knowing the probability of a breakdown isn't sufficient; prevention, not prediction, is the key to business impact. Turning insights into action thus requires two things: first, domain knowledge is critical in this case. For although the mathematics of predictive maintenance for pumps on oil platforms might be similar to that of networks in telecoms, the actions that need to be taken afterwards will be very different. Second, even once it becomes clear what action needs to be taken, success can depend on how that action is taken. This means that a look at processes and structures will be key. E.g., on the structure side, call centers might be reorganized, and save desks might be implemented in order to support the action of hiring specialized agents for customer retention. Beyond this organizational structuring, incentive schemes will need to be developed to encourage the success of these specific agents, as retention rates and not average handling times are among their measures of success. On the process side, automation might be introduced to activities such as making pricing decisions on online platforms.

D. Driving adoption

When talking about data and analytics, a common mistake is to focus too much on the new technical talent required. While this is indeed a crucially important and highly scarce resource on the market, the true change has to happen with your "regular" employees – the majority of the workforce for whom "all things data" is neither their expertise nor focus. These employees need to increase their analytics quotient (AQ) and become more Data-Analytics-proficient if data-enabled insights are going to be implemented in the business and yield real value.

To this end, we have offered some of our clients the chance to participate in analytics academies that focus on translator skills for employees for whom data science hasn't been central to their job descriptions on relevant technical matters. These "translator trainings" as the ability to translate between the technical and business worlds is becoming more and more important. Business will be enabled in order to frame challenges and define analytical tasks to tech people as well as challenge, interpret, and implement the results. Marketing, retention, and maintenance employees (among others) need to understand which questions can be asked of data and analytics, and they need to be able to translate the answers, i.e., turn the insights into actions they can take in their day-to-day work activities.

E. Mastering tasks concerning technology and infrastructure as well as organization and governance

Technology and infrastructure and organization and governance are the enablers that help organizations take action on the insights from Advanced Analytics and create impact. An organization needs the right set of easy-to-use tools – e.g., dashboards or recommendation engines – to enable personnel to extract the relevant insights and a working environment that facilitates the integration of those insights, e.g., governance that enables and manages the necessary change within the organization.

One design question often asked is how close the new data science departments should be linked to the business units. The clear answer is "as close as possible to the target state." Often, however, incubating this new skill in the form of a centralized and pooled center of excellence (CoE) is the best way to start. Then, over time, skills and people can be gradually transitioned into business units. The CoE would still exist but transition its role more into an innovation center responsible for recruiting and ongoing training. The BUs will, over time, increase their AQs by training the "regular" employees. In addition, heavy users of data will even hire more specialized data scientists to complement the skill set of the generalists already staffed to the CoE.

3. Key practice perspectives on creating insights-based value and capturing impact with it

Now that we've explored the environment in which data is gaining importance (context) and looked closely at the steps that comprise the up- and downstream processes of the insights value chain (framework), let us look at how concrete insights-based value can be created and business impact with it can actually be captured (practice).

We thus begin this chapter with an overview of insights-based value creation models and their impact, including deep dives into two real-world use cases of these models in

consumer-facing industries. Then we look at what still tends to stand between organizations and the successful implementation of these models. Finally, we offer a set of guiding principles as well as a series of strategic actions to help organizations address structural challenges and get the ball rolling on their journeys toward capturing (and then scaling) value from data-driven insights.

3.1 Overview of typical use cases and their impact potential

Insights-based value creation models in the evolving spaces of the connected world can be grouped into one of three overarching categories and can be explored individually or in combination:

- Top-line use cases typically help companies improve customer-facing activities. These use cases can enhance activities in the areas of pricing, churn prevention, cross- and upselling, and promotion optimization to drive growth.

- Bottom-line use cases employ data-driven insights to optimize internal processes. Predictive maintenance, supply chain optimization, and fraud prevention are among the processes that can be improved with the benefit of data. These use cases are becoming increasingly relevant due to the growing number of IoT applications and the collection of massive amounts of data that can be used in order to improve business processes.

- New business models is the category of data-enabled use cases that moves beyond processes and brings value by expanding a company's portfolio of offerings. This can include the rather rare case of straightforward selling of the data itself, selling of insights gleaned from data, offering new products or delivering analytics as a service.

In all categories, there are different levers to be engaged, and the potential impact that one might observe by implementing these use cases is wide ranging (see Exhibit 6 for some reference numbers as well as Text box 3).

Exhibit 6

Insight-driven use cases create value by either supporting growth (top line) or reducing costs (bottom line)

Top line			Bottom line	
Use cases	**Reference impact[1]**		**Use cases**	**Reference impact[1]**
	Sales impact	Margin impact		Cost reduction
Assortment optimization	2.0%	1.0 ppt	Predictive maintenance	20 - 50% of call center costs
Cross- and upsell	2.0%		Marketing spend effectiveness	5 - 10% of marketing costs
Churn prevention	1.5%		Demand planning	20 - 30% of warehousing costs
Pricing	2.0%	1.0 ppt	Fraud prevention	1 - 5% of fraud loss
Stock and replenishment optimization	2.0%	0.5 ppt	Bad debt management	10 - 20% of bad debt loss
Promotion optimization	1.5%	1.0 ppt	Workforce planning	10 - 20% of service costs
Space and shelf optimization	1.5%		Supply chain optimization	10 - 30% of logistics costs

Impact values not additive and only achieved in case of investment and change management!

1 Based upon 100+ reference cases; realization over 1 - 3 years

SOURCE: McKinsey Advanced Analytics

Text box 3: Deep dive on the application and impact of two top-line use cases

"Churn prevention" in contract-based businesses

In banks and other contract-based businesses, such as telecoms or utilities, it is important to prevent churn, as a consistently strong and loyal customer base is essential to succeed in this business model. Machine learning can support sophisticated, amazingly accurate churn prediction methods; however, the most valuable business task is not to predict churn but to prevent it.

In recent cases where we have implemented churn prevention the impact has been a 10% decrease in churn, which was equivalent to 1 to 2% of annual customer value. Successful churn prevention also has a broader impact on internal processes and organizational structures. When churn models identify particular pain points, businesses have an opportunity to optimize their customer journeys accordingly and address issues long before they lead to an increased risk of churn. Specifically, triggers have been implemented to quickly react to events known to drive churn, such as network failures in telecoms, billing errors in utilities, or customer complaints more broadly. Organizational structures are sometimes rebuilt to organize marketing teams differently. For instance, instead of the traditional split by channel, teams might be organized by customer segment and lever, e.g., a high-value customer retention team and call center "save desks."

Personalization at scale in consumer-facing industries

Cross-selling is another customer-facing use case that we all know from e-commerce recommender engines such as Amazon's famous "People that buy A also buy B" feature. Beyond e-commerce, this use case is crucial in other industries such as banking, retail, and telecoms as well. The business question at hand is how to increase the value of existing customers over time. The answer to this goes beyond cross-selling and classical campaigning: personalization at scale. It involves multiple channels across multiple customer touch points during the entire journey. All cross- and upselling activities must be informed by deep customer knowledge in order to offer personalized content at precisely the right time.

In recent cases where we implemented personalization at scale, the impact has been an increase of more than 100% in campaign conversion rates, which was equivalent to 2 to 5% of annual customer value. Again, a major impact was achieved in terms of changing organizational structures and processes as well as the organizational culture around action and innovation. Specifically, cultivating a "fail fast" and "test and learn" mentality that is based on a new agile way of working encourages the development of successful customer personalization efforts and supports their continuous improvement. Traditional organizational structures were broken down and cross-functional agile teams have been set up. These teams were again organized around customers, e.g., segments or touch points. The working mode has been completely changed from quarterly push campaign planning into weekly stand-ups to plan the next learning sprint.

3.2 Main challenges in capturing the value of data-enabled insights for today's organizations

If the value of Data Analytics is so substantial and clear, why is it that not everyone is already monetizing and achieving impact with it? One clear observation in the market is that while companies are becoming more and more mature in the technical parts of the value chain, most of them are still significantly lagging behind when it comes to the "structural" parts such as, e.g., getting the link or the "translation" between the technical and business worlds right, or managing the cultural shift away from gut-feeling-based decision making towards decision processes driven by data. At the end of the day, however, the technical part is always the easier one to solve.

Given these realities, we see above all three structural challenges that block our clients from achieving maximum business impact from data:

■ **The separation of data and business.** In many companies, data science and business execution are totally separate. This leads to a lack of understanding from the business side of what is possible and to the development of data science "solutions" that business doesn't actually need.

■ **The gap between insight and impact.** In many cases, the crucial step of moving "from insight to insight-based value creation" is never fully and properly taken. Often our clients already believe in the importance of analytics and have even conducted one or more proofs of concepts (PoCs). However, these PoCs are often isolated from each other and hardly ever turned into successful use cases, let alone scaled.

■ **No proper anchoring of the Data Analytics competence at a high corporate level.** Business impact from data-derived insights only happens when data analytics is implemented deep within and consistently throughout the organization. This requires the commitment and direction of a leader with the authority to drive this type of insights-oriented transformation, and many companies have yet to see that level of organizational commitment.

There is certainly no singular, standardized approach to overcoming these barriers in an organization. Companies looking for guiding principles and strategic actions recommendations as they intend to (re)build an organizational environment that facilitates the effective use of data, however, can start in the following chapter.

3.3 Best practices for implementing and scaling Data Analytics

Our observations of the most successful data-driven enterprises reveal clear beliefs and effective approaches that aspiring companies might adopt.

Five guiding principles

■ **Analytics is not a tool but a new language.** Acting on analytics outputs requires business to understand the implications of those outputs.

■ **Translators are crucial.** Focus on hiring and training talent to serve as the interface between Data Analytics and business.

■ **Change management is crucial.** Business users need to trust analytics results, and they need to be enabled to act on them.

- **IT cannot be held up or allowed to stagnate.** You might need to initially "bypass" corporate IT to start quickly and prove the concept early, but you will need to ultimately involve IT timely and heavily in order to scale.

- **Agility must be lived and breathed.** A "risk to fail small, to win big," a test-and-learn approach, and an "experimental mindset" should be woven into the organizational fabric. Cross-functional teams are essential to keeping pace with rapid test-and-learn cycles.

Five medium- to long-term strategic actions

- **Work "business backwards" not "data forward"** – first identify business use cases you believe in and then think about the models and data you need to operationalize them, not vice versa.

- **Focus and prioritize the top-3 use cases** that are the easiest or fastest to implement or the ones that generate significant business impact.

- **Rapidly and pragmatically build the basic IT in an agile way,** i.e., "build the plane while you fly it".

- **Hire a few data scientists** and link them to business teams to quickly prove the concept.

- **Set yourself up for scale** – build a central analytics unit and set up an analytics academy to boost the AQ of the overall company ("hire 50 data scientists and train 5,000 translators").

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The value in data is its potential to generate insights that lead to better business. Stepping back from the process steps described above, a couple of macro-level principles can help companies turn vast amounts of data into insights-based use cases that boost performance.

First, companies can further develop the use cases they've come up with by identifying ways of gathering even more data. This could take the form of, e.g., installing additional sensors, identifying other external data sources, or incentivizing customers to provide more data. They might also get more out of existing data by making a bigger investment in feature engineering, i.e., creating smart variables based on business insights and domain knowledge and leveraging faster IT and better algorithms.

In addition to more fully exploiting data, organizations should commit to moving strategically and boldly into the implementation of use cases. This means that not only should implementation focus on impact, it should not be limited to a single use case. Rolling out multiple use cases simultaneously and orchestrating them to achieve impact at scale requires a full tech-enabled transformation of the business. Getting the technical foundations right is one task, typically the easier one. What is likely to be the bigger challenge is aligning the organization to the goal of successfully implementing new insights-based use cases. Enabling an organization to manage use cases across organizational siloes, to automate processes, and to teach almost all employees the basics of data and analytics often requires a complex but necessary shift of organizational structure and culture.

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