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INDUSTRIAL ANALYTICS 2016/2017

The current state of data analytics usage in industrial companies

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INDUSTRIAL ANALYTICS 2016/2017

The current state of data analytics usage in industrial companies

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December 2016

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“*Data is the new oil. It's valuable, but if unrefined it cannot really be used. It has to be changed into gas, plastic, or chemicals to create a valuable entity that drives profitable activity; so must data be broken down, analyzed for it to have value.*

Clive Humby, Mathematician and architect of Tesco's Clubcard, 2006”

Foreword

Industrial Analytics is evolving from an isolated business function towards a strategic capability that impacts the future competitiveness in any industrial business.

Today, we are facing a data-driven world that is changing faster than ever before. A large number of new methods, tools and technologies are finding their way into management circles, often accompanied by a variety of abstract buzzwords. For now, the world of data analytics seems to be dominated by visions rather than large-scale implementations. Reality shows that Industrial Analytics still has a long way to go before it is finally becoming that strategic and scalable business capability that it is promising to be.

Therefore, the Digital Analytics Association Germany set out to better understand the current status of data analytics in industrial settings and its role within today's discussions on the Internet of Things and other initiatives such as "*Industrie 4.0*".

This study was initiated and governed by the **Digital Analytics Association e.V. Germany (DAAG)**, which runs a professional working group on the topic of Industrial Analytics. Research firm **IoT Analytics GmbH** has been selected to conduct the study and assure professional methods and standards are applied as part of the research effort.

Such a study would not have been possible without the support of three sponsors. A special thanks to **Hewlett Packard Enterprise**, as well as to the data science service companies **Comma Soft**, and **Kiana Systems** for supporting and financing this study. All research and analysis related steps required for the study, such as interviewing, data gathering, data analysis and interpretation, were conducted solely by the authors and are not externally influenced. The case studies provided by the sponsors are clearly marked as sponsor-provided content.

The goal of the study is to paint an accurate picture on the current state of data analytics in industrial settings, thereby bridging the existing information gap on this topic. Furthermore, this study also represents a cornerstone for the **Digital Analytics Association e.V.** in its mission to support both decision makers as well as data analysts to further develop those skills and capabilities that are in demand and have been identified as being crucial.

For a detailed description of the methodology, please refer to the Appendix.

THIS REPORT INCLUDES:

- Results from an in-depth **industry survey** of 151 analytics professionals and decision-makers in industrial companies
- Introductions to Industrial Analytics, its relation to the **Internet of Things and Industry 4.0**, how analytics has evolved over time, what Machine Learning is and what value and paradigm shifts Industrial Analytics brings to the industry
- **3 prime case studies** of actual Industrial Analytics projects (in the areas of energy, healthcare, and automotive)
- **Further insights** into aspects such as how to organize for Industrial Analytics, which skills to build up and how to approach these projects.

We hope you enjoy the read, gain insights for your Industrial Analytics projects or your personal skill development as a data analyst, and become inspired to expand the art of the possible through industrial data analytics.

The **Digital Analytics Association e.V.** welcomes any interested supporters who are motivated to further develop related insights or want to contribute to making the vision of Industrial Analytics a reality over the coming years.

Frank Pörschmann

Member of the Board

Digital Analytics Association e.V.

Knud Lasse Lueth

Managing Director

IoT Analytics GmbH

Executive Summary

Findings per Chapter:

CHAPTER 2: INDUSTRIAL ANALYTICS - MAKING SENSE OF IT

1. **Status quo – Firms acknowledge the huge importance but are not yet completely set-up**

    - The importance of analytics for decision-making is increasing: Analytics started as mere operational support in the 1960s and 1970s. Today, it is increasingly **used to drive decision-making**. In the future, it will be used to automate decisions.
    - 15% of respondents surveyed view industrial data analytics as a crucial factor for business success today, while 69% think **it will be crucial in 5 years**.
    - Today, 68% of survey participants say they have a company-wide data analytics strategy, 46% have a **dedicated organizational unit** and only 30% have completed actual projects.

2. **Value drivers – Increasing revenue seen as the main driver; predictive maintenance as the leading application**

    - People see **increased revenue as the main value driver** for Industrial Analytics (33% weighted score). Increased revenue can be achieved in three possible ways: Upgrading existing products, changing the business model of existing products, or creating new business models.
    - Despite the fact that one can witness a number of efficiency-related projects today, **cost cutting is seen as less important** at only 3% (weighted score).
    - The three main applications of Industrial Analytics in the coming 1-3 years are related to **predictive and prescriptive maintenance** of machines (79% of respondents view it as important), **customer/marketing-related analytics** (77%) as well as the analysis of **product usage in the field** (76%).

3. **Analytics – Slowly shifting to more sophisticated types of analytics**

    - The type of analytics deployed on various projects are moving from descriptive analytics to applications of **real-time analytics, predictive analytics and even prescriptive analytics**.
    - The importance of **spreadsheets will decline** (from 54% to 27% in 5 years) while the **importance of Business Intelligence** (39% to 77%) and **advanced analytics tools** (50% to 79%) **will increase** sharply

- **IoT brings additional challenges to Industrial Analytics**, including real-time data streaming, management of enormously large data sets, time-stamp data storage and completely new use cases –Most companies feel they are good or excellent at collecting IoT-related sensor data (60% of survey respondents) but only **few say they are good or excellent at getting the right insights** from the sensor data (32%).

4. **Paradigm shifts – Industrial Analytics changes long-held manufacturing principles**

- **Agile project development** is replacing waterfall-based project planning. 58% of survey respondents indicate that they employ the agile (and often also "scrum") methodology for their data analytics projects today.

- Other paradigm shifts include the **creation of platforms and open ecosystems** (e.g., companies are building B2B marketplaces and app stores"), **the reshaping of the** well-established **5-layer automation pyramid** (software architecture), as well as an increasing flexibility and specialization of manufacturing through manufacturing-as-a-service.

CHAPTER 4: INDUSTRIAL ANALYTICS - MAKING IT HAPPEN

1. **Starting the project – Often in an explorative approach and using open source tools**

- In their quest to embrace digital business models and build on the power of data, companies **start projects increasingly in an explorative manner** (34% use an explorative approach) – still, **the majority (66%) of projects are approached with clear hypotheses in mind** (hypotheses driven approach)

- 4 areas need to be addressed, when structuring Industrial Analytics project: **Data sources, necessary infrastructure, analytics tools and applications**

- **Using open-source analytics tools are increasingly the norm**: Nearly two thirds of all survey respondents (64%) are using open-source tools for some aspects of their data analytics projects.

- Most costs in Industrial Analytics projects incur in the initial phase of getting **data access** (21%), **aggregating the data** (17%), and performing the **data analysis** (14%) – the costliest individual item, however, is related to **software and application development** (26%).

2. **Organizing and Staffing – Top management-driven, externally implemented – bridging the Data Science Skill Gap**

- Industrial Analytics is increasingly initiated by senior management - 34% of survey respondents indicate that it is the CEO who drives Industrial Analytics projects.

- Large corporations **have not centralized data analytics in one specific department** (Only 33%). Instead, many large industrial companies are **outsourcing some of their data analytics activities in an external Data lab, Digital lab, incubator or accelerator** (55% of respondents)

- The biggest **skill gap is currently in Data Science**. (92% of respondents say it is important or very important but only 22% of respondents have all necessary skills on board). **Machine Learning**, as an integral part of Data Science also represents a large gap (83% vs 33%) – Another significant deficiency can be identified around **IoT/M2M infrastructure** (68% vs 17%).

- Data Science Teams are diverse and typically include an overall manager, **an industrial expert, a data engineer, a data developer, a Machine Learning expert and a data analyst**.

3. Challenges & further Recommendations – Focus on interoperability issues, data accuracy and shaping the digital mindset

- **Overlapping tasks with departments** (60%) and **difficulties in building the business case** (60%) represent the most important business challenges for IA Projects

- **Interoperability between different** components of the data analytics IT/OT stack (78%), **data accuracy** (62%) and **gaining insights from data** (62%) represent the biggest technical challenges

- **Further leadership recommendations**: Shape the digital mindset, define strategic roles, start small, define a capability roadmap, embrace a data governance strategy, and enable supporting functions

1 Introduction to Industrial Analytics

"Data is the new oil": A highly valuable resource that is becoming more and more critical to worldwide business operations and the source of tremendous wealth if handled correctly. Analytics is to data what refining is to oil: The process that turns the resource into a valuable product.

The rise of Industrial Analytics: The value of data analytics is becoming increasingly important in industrial companies. This trend is supported by 3 main enablers:

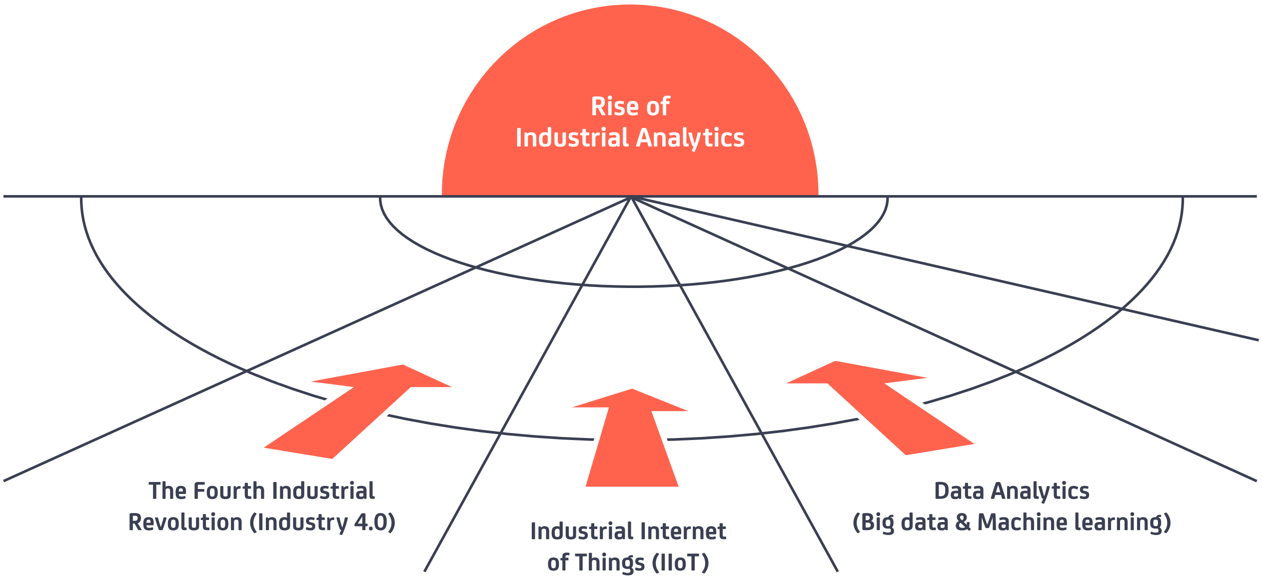
1. Next-generation industrial infrastructure (**Industry 4.0**)
2. Connected machines and products (**Internet of Things**)
3. Advanced data analytics techniques (**Data Analytics**)

1.1 Industry 4.0: The new industrial advancement

In the last 200+ years there have been three industrial revolutions and we are on the verge of the fourth one.

- **Industry 1.0**: Two centuries ago, James Watt's **vapor powered technology** created novel mechanical manufacturing techniques. This led to the First Industrial Revolution, characterized by machine-supported production. The result was a step-change in productivity as well as the emergence of completely new industry segments, like textile production, chemicals, metallurgy, and so forth.

EXHIBIT 1: 3 Enablers for the Next Wave of Industrial Analytics



- **Industry 2.0**: The Second Industrial Revolution followed at the beginning of the 20th century. It was Henry Ford's invention of the **production/ assembly line** that enabled a new kind of mass production and a division of labor. A key driver of this revolution was the widespread availability of electrical energy.

- **Industry 3.0**: The Third Industrial Revolution, which began in the early 1970s, is characterized by the increasing use of electronics, integrated circuits and IT systems to achieve a new kind of **automated production** (e.g., through the use of automated robots).

- **Industry 4.0**: As many leaders, scientists and engineers point out the world is currently in the early stages of the **Fourth Industrial Revolution** which is about to bring yet another major change to economies and societies.

INDUSTRY 4.0 IS CHARACTERIZED BY THE CONNECTION BETWEEN PHYSICAL AND DIGITAL SYSTEMS

This fourth revolution is characterized by the **connection between physical and digital systems**. The convergence of information technology and industrial automation is creating completely new technology architectures that allow yet another wave of productivity increases as well as new data-driven business models. Another central theme of Industry 4.0 is increased product individualization moving toward batch-size one.

Unlike the three previous revolutions, Industry 4.0 is not triggered by one single invention, like steam power or integrated circuits, but by a **fusion of technological advancements**. Cyber Physical Systems are often mentioned as a core technology of Industry 4.0. It describes how hardware and software components interact in a complicated network with physical inputs and outputs. Other technologies include advanced 3D Printing, Augmented Reality, and Cloud Computing.

1.2 Internet of Things (IoT): Bringing billions of products and machines online

The Internet itself was originally designed to connect computers. Over time it has expanded to connect mobile phones and tablets. With **the Internet of Things it will also connect any other physical device** used in everyday life, like cars, machines, industrial products and much more.

Whether there will be 20 or 50 billion connected Internet of Things devices by 2020, the fact remains there will be a significantly large number of devices, much more than the current number of computers or smart phones. McKinsey Global Institute predicts that by 2025 the Internet of Things will generate up to $11trillion in value to the global economy.

The Internet of Things (IoT) is seen by some as an integral part of Industry 4.0. Sometimes the two are used interchangeably. The industrial Internet of Things describes the network of machines and products that are able to communicate and share intelligence with each other within the industrial environment in order to optimize the related industrial operations.

While Industrial IoT connectivity leverages connections via IP-based networks and the cloud, other types of industrial communication aren't so novel. **On-premise industrial automation systems** (e.g., PLC/DCS and SCADA systems), for example, have been around for years. Some industries like automotive have been working with **Machine to Machine communication** (M2M) that allows cellular connectivity of devices (e.g., cars). With other types of communication emerging, M2M can now be seen as one potential connectivity module for the overall IoT architecture.

Compared to system architectures that were built on top of on-premise or M2M type of connectivity, IoT promises a cheaper, more flexible and less rigid architecture that enables completely new use cases. The backend architectures for IoT are not solely on-premise and the connection is not restricted to cellular networks. Therefore, the silo-like, closed solutions of the past are replaced by more modular concepts that connect building blocks from multiple, specialized service providers. New cloud architectures (e.g., IoT Platforms) and new communication methods are emerging (e.g., Low-Power Wide Area Networks) with the effect that the costs and energy requirements for connecting devices and machines continue to decrease quickly.

1.3 Data Analytics: The new intelligence frontier

Data Analytics describes processes and methods to examine data with the goal to extract useful insights, optimize processes and make better decisions.

Recent technological advancements are enabling data analytics to be used in broader settings and in more sophisticated ways. The two important drivers are:

1. Big Data architectures: The collection of huge and complex, often unstructured datasets, has been perfected. Today, there are a number of first-class NoSQL databases and data administration tools with the required processing power and server infrastructure.

2. Artificial Intelligence/Machine Learning: A number of Artificial Intelligence Tools and Machine Learning Algorithms are available to perform all kinds of analyses. These tools are often open-source and freely available to be used by anyone for their data analytics projects.

INDUSTRIAL ANALYTICS LEADS INDUSTRIAL FIRMS TOWARDS SMART DATA-DRIVEN ORGANIZATIONS

1.4 Bringing it all together: Industrial Analytics

Combining the advancements in **data analytics** with other **Industry 4.0** technologies and **the Internet of Things** means a significant stride forward for industrial companies. The unique combination allows for new business streams and higher efficiency levels:

- Processes across all business areas can achieve higher levels of automation
- Real-time analysis allows for increased equipment uptime and transparency
- Offerings can be quickly adjusted to individual customer demand
- New products, services and data-driven insights can be created and sold

Industrial Analytics plays a central role in all related activities.

As a result, Industrial Analytics is a key facilitator for the next wave of industrial optimization, turning firms into smart **data-driven companies**. Mastering it will be essential for every company that wants to take advantage of the next industrial revolution.

Defining Industrial Analytics

Industrial Analytics (IA) describes the collection, analysis and usage of data generated in industrial operations and throughout the entire product life cycle, applicable to any company that is manufacturing and/or selling physical products.

Industrial Analytics involves traditional methods of data capture and statistical modelling. However most of its future value will be enabled by advancements in connectivity (IoT) and improved methods for analyzing and interpreting data (Machine Learning).

Adjacencies: Industrial Analytics is sometimes mentioned in conjunction with consumer-facing and service industries (e.g., airlines, insurances) as well as with other operations of companies (sales, marketing, human resources). This study does not focus on these adjacencies – even though they are sometimes mentioned.

2 Industrial Analytics: Making sense of it

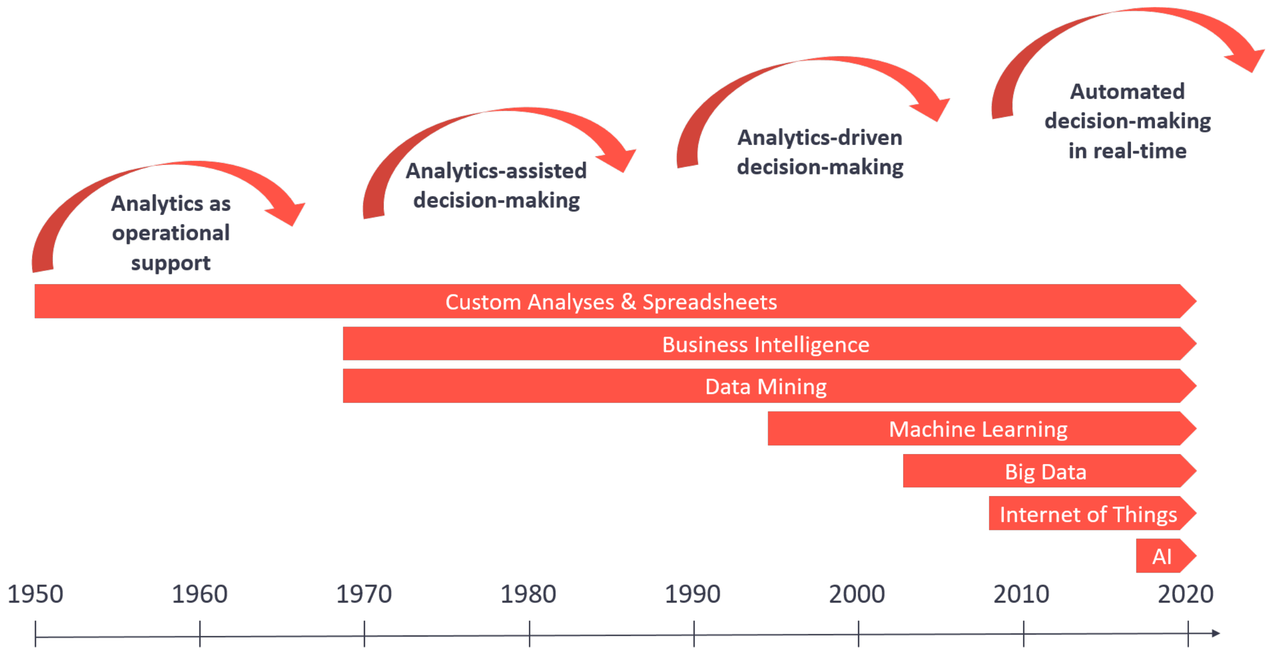
2.1 History - How analytics evolved towards automated decision-making

The mathematical foundations of data analytics were established in the 18th, 19th, and early 20th century but analytics was born in the 1950s and 60s when the first computers were used for **operational decision support**. The work involved small teams of experts responsible for descriptive analytics and reporting activity. In equipment maintenance for example, failure rates were analyzed to support maintenance-related decisions such as which equipment to test and when. [1], [2]

The early analytics tools used for query and reporting were sold as "*do-it-yourself*" solutions for computer science experts. In the mid-1970s, several vendors began offering tools that allowed a non-programmer to delve in the world of data access and analysis. It thereby created the domain of Business Intelligence and allowed for the next level of structured **analytics-enabled decision-making**. In maintenance for example the use of (ex-post) pattern recognition led to preventive maintenance programs. Critical equipment was intelligently monitored according to its calculated failure probability. [3], [4]

The role of analytics further increased through innovations in data mining methods, data warehouses, client-server systems and eventually Big Data repositories. This development lead to **decisions that**

EXHIBIT 2: How analytics evolved in the industrial context



were analytics-driven. In the maintenance industry, for example, condition-monitoring became the norm. Condition monitoring led to a visualization of critical sensor readings, thereby giving humans a real-time view on equipment status and driving mission-critical decisions such as which bearing to replace.

MANY DECISIONS ARE NOW STARTING TO BE AUTOMATED BASED ON DATA AND ANALYTICS, OFTEN IN REAL-TIME

Today, the relevance of analytics for decision-making is gaining interest thanks to the availability of machine-learning tools and the Internet of Things. Many decisions are now starting to be **automated based on data and analytics**, often in real-time.

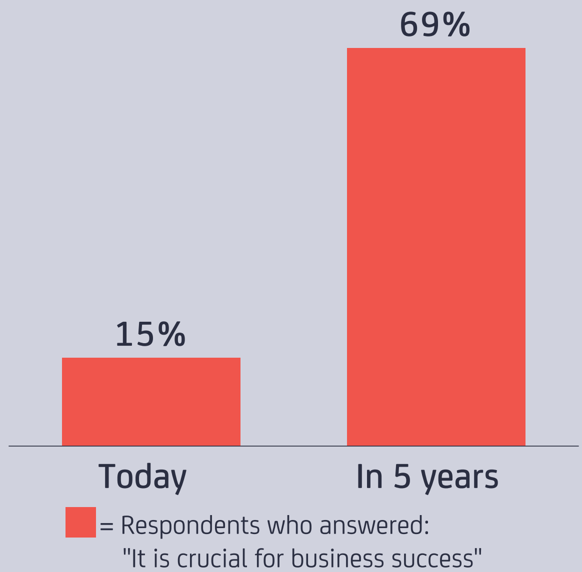
The maintenance industry is further advancing: What started as failure rate analysis is now becoming predictive maintenance 60 years later. Sensor readings are analyzed in real-time and algorithms make predictions on the remaining lifetime of individual equipment. In many instances these processes are becoming so automated that the decision-making process does not require human interaction anymore.

2.2 Status quo – Firms see the importance but are just getting started

Most decision-makers acknowledge the huge importance Industrial Data Analytics plays in the automation of important decisions and processes

EXHIBIT 3: Industrial Analytics to play a crucial role in organizations in 5 years

Question: *What role does Industrial Data Analytics play in your organization?*



69% of survey respondents believe data analytics are crucial for business success in 5 years. However, only **15%** of respondents think it is already crucial today.

While **68%** of survey participants say they have a company-wide data analytics strategy, **46%** have a dedicated organizational unit and only **30%** have completed actual projects (Out of the remaining 70%, most firms have ongoing projects or are in a prototyping phase, however)

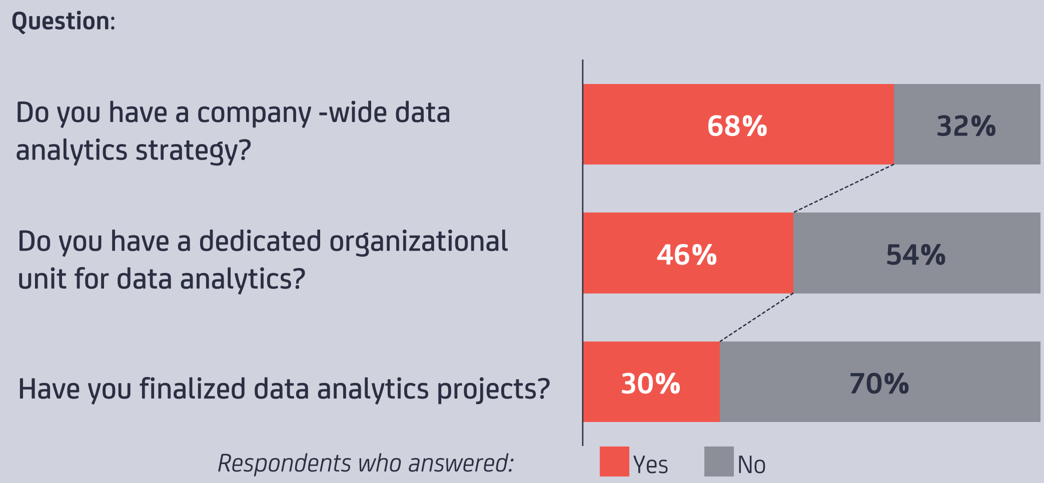
“

We see lots of quick wins in the coming years through IoT.

.

Head of connected products at a crane manufacturer ”

EXHIBIT 4: Many companies have a data analytics strategy but few have completed projects



2.3 Value Drivers – Industrial Analytics enables new revenue streams

When looking deeper at the value of today's Industrial Analytics projects, it is important to separate analytics-enabled revenue streams from analytics-enabled cost reduction efforts.

INCREASED REVENUE IS THE BIGGEST VALUE DRIVER FOR INDUSTRIAL DATA ANALYTICS PROJECTS

The biggest value driver for Industrial Data Analytics projects is clearly on the customer-facing/revenue-generating aspect of the business. **Increased revenue** is the main driver (33% - weighted score), followed by **increased customer satisfaction** e.g., through better service or more individualized offerings (22% - weighted score).

Efficiency gains and **cost cutting** score very low with only 3% of respondents (weighted score) seeing these aspect as a major benefit of Industrial Data Analytics.

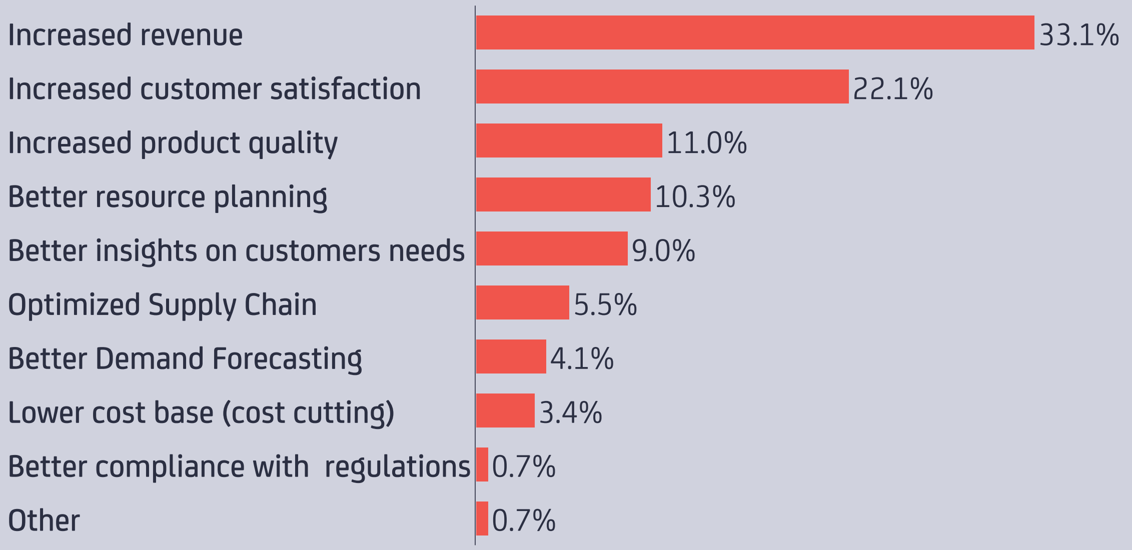
So how should firms think about generating revenue or decreasing their costs?

2.3.1 Three typical new revenue streams

- **Upgrading existing products**: Enhancing the existing products with new features (e.g., a manufacturer of construction equipment is now offering an additional feature to track vehicles in real-time in a neat dashboard)
- **Changing the business model of existing products**: A predominant theme is the shift towards offering Products-as-a-Service (e.g., due to the ability to analyze data in real time, a manufacturer of compressors is now selling cubic meters of compressed air over time, instead of selling the compressor equipment as a one-off)

EXHIBIT 5: Increased revenue and customer satisfaction as biggest benefits of Industrial Analytics

Question: *What are the biggest benefits of Industrial Data Analytics for your company?**



*The survey specifically asked for the top three benefits. The ranking was generated by giving points – three points for first biggest, two points for second biggest and one point for third biggest benefit – The percentage is based on the overall number of points.

- **Creating new business models:** Some companies are starting to enable new services in a connected ecosystem (e.g., Insurance companies are increasingly partnering with industrial companies to create so-called usage-based insurance packages that are for example based on the driving behavior data of individual people).

2.3.2 Three typical ways to reduce costs

- **Data-driven process optimization**: Analytics outcomes are often visualized in dashboards that are assisting the workforce operating the plant. These real-time knowledge-based insights can drive workers' actions (e.g., Intelligent Plant Floor Dashboards on tablets help production supervisors optimize daily manufacturing operations regardless of where they are on the shop floor)

- **Data-driven process automation:** As more and more industrial processes and workflows become automated, intelligent data models help orchestrate actions requiring less human intervention (e.g., Real-time fault detection on products during the manufacturing process helps in automatically reducing scrap-related costs)

- **Data-driven product optimization**: Analytics can help reduce product costs. A manufacturer of specific lighting systems, for example, needs to guarantee a certain product lifetime to his customers. Traditionally the manufacturer "*over engineered*" certain components of the solution in order to ensure that the required lifetime could be guaranteed. Thanks to Industrial Analytics, this manufacturer is now able to analyze the product usage in detail. The manufacturer has started to reduce the specifications for those components that do not have a large impact on product lifetime

– thereby significantly reducing costs without impacting guaranteed product performance.

2.3.3 Industrial Analytics Applications across the value chain

Employing Industrial Analytics related projects often results in bringing together the **entire industrial ecosystem** collaborating with **partners, suppliers** and often integrating further with **customers** and their needs.

79% of respondents see predictive and prescriptive maintenance of machines as the most important application of Industrial Analytics in the coming 3 years. This is closely followed by customer/marketing-related analytics (77%) as well as the analysis of product usage in the field (76%). It is interesting to note that visual analytics (e.g., dashboards) is widely regarded as an important application. Cybersecurity analytics (e.g., improving product or equipment security for example through anomaly detection) and analytics of moving goods (e.g., fleet management) play a minor role.

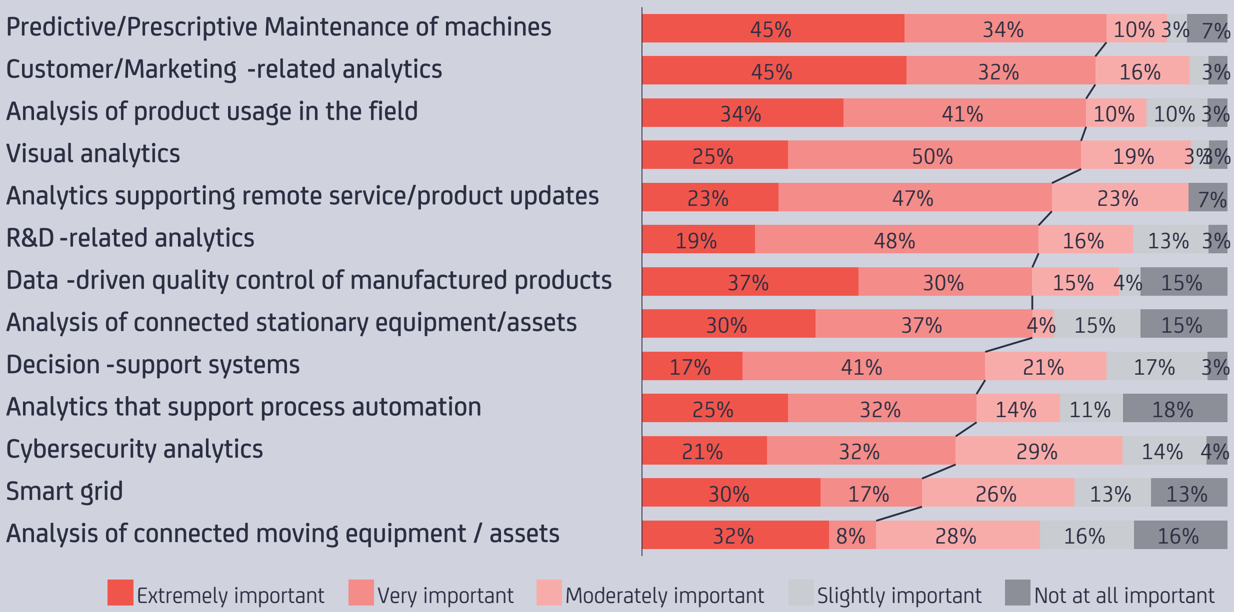
Typical applications of Industrial Data Analytics across the industrial value chain include:

2.3.3.1 R&D

- Analyzing **product usage characteristics** in the market and feeding back the generated data into the next-generation development cycle (e.g., Identifying parts failure during product usage through sensor readings and improving its characteristics gradually).

EXHIBIT 6: Predictive maintenance and Customer-related analytics as most important applications

Question: *How important are the following Industrial Data Analytics applications for your company in the next 1-3 years?*



2.3.3.2 MANUFACTURING / OPERATIONS

- **Predictive Maintenance** on equipment, machinery and assets (e.g., rescheduling the maintenance plan to act prior to equipment failure - according to historical and real-time machine performance analysis).
- **Decision-support systems for industrial processes** (e.g., using data from operations to automate purchase order or production scheduling decisions).
- **Manufacturing network optimization** (e.g., correlating and optimizing performance across multiple plants).
- **Optimizing individual machine parameters** for smooth operations and optimal quality (e.g., correlating cause and effect of parameters such as machine speed).

2.3.3.3 LOGISTICS / SUPPLY CHAIN

- **Condition monitoring** of moving assets (e.g. goods in-transit)
- Cross-supplier **supply chain optimization** (e.g., analyzing warehouse stock levels and real-time supply data to forecast shortages, reduce overall inventory levels and bring efficiency to the supply chain)
- **Fleet management** (e.g., analysis of transportation data and fuel consumption to optimize the distribution network)
- **Strategic supplier management** (e.g., Continuously analyze quality metrics of individual suppliers)

2.3.3.4 MARKETING / SALES

(Although not necessarily classed as Industrial Analytics, these need to be mentioned as well)

- **Product usage-related analytics** for strategy and marketing (e.g., tracking usage patterns for better customer targeting and positioning)
- Tracking, optimizing and individualizing **consumer interaction and conversion** (e.g., by analyzing social media and website traffic)
- **Analytics-driven after sales** (e.g., analyzing product usage in real-time, offer suitable services and propose suitable upgrades according to the usage behavior)
- **As-a-service business models** (e.g., selling specific products as a subscription instead of making a one-time sale)
- **Real-Time identification and response of individual customer needs** (e.g., gaining customer insights to deepen customer relationship and/or business opportunities, including business partners)

2.4 Understanding Analytics

2.4.1 Analytics 101

There are several ways to classify analytics. On a high-level, the type of analytics required is determined by:

- the **question it seeks to answer**
- the **amount of resources** its algorithms required
- the **kind of solution** that needs to be designed

EXHIBIT 7: Analytics evolution towards real-time, predictive, and prescriptive

Descriptive/ Diagnostic analytics	Real-time analytics	Predictive analytics	Prescriptive analytics
What happened?	**What is happening now?**	**What could happen?**	**What should happen?**
e.g., the correlation between machine failure and product quality	e.g., the visualization of the current equipment status	e.g., the prediction of equipment failure	e.g., the optimization of equipment inputs to receive the right raw materials in the right amount just in time

The following terminology has prevailed in order to group the different types of analytics according to the question they seek to answer:

1. Descriptive / Diagnostic analytics are used to describe what happened in the past and why it happened (e.g., how many defect parts were detected, the reason for their failure, whether a threshold level has been exceeded). Usually, Descriptive Analytics gain insight from historical data using reporting, scorecards, or clustering.

2. Real-time analytics describe what is currently happening (e.g., the current location of the product, details on the progress of the manufacturing processes, or detection of faulty parts).

3. Predictive analytics entail algorithms that engage in forecasting of future incidents (e.g., the possibility of a defect showing up, expected inventory levels, and anticipated demand levels). Predictive analytics signals the need for an action (e.g., to notify the technicians to repair the machine, reschedule the inventory or the production plan). The main goal of predictive analytics is to identify potential issues before they occur. Most often Predictive Analytics use statistical and Machine Learning techniques.

4. Prescriptive analytics provide advice on the best possible actions that the end-user should take. In other words, it answers the "*what should happen*" type of question. Prescriptive analytics requires a predictive model with two additional components: actionable data and a feedback system that tracks the outcome produced by the action taken. For example, an algorithm suggests the optimal proportion of materials that are needed for the production of a product, or a Machine Learning algorithm leads a robot to take the shortest path on its way to pick up the product from the warehouse shelves.

THE ANALYTICS COMMUNITY IS SLOWLY SHIFTING ITS ATTENTION TOWARDS REAL-TIME, PREDICTIVE, AND PRESCRIPTIVE ANALYTICS

The analytics community is slowly shifting its attention from Descriptive Analytics to the latter three types of analytics, as these promise a whole new level of value and have only been enabled by technology in the last 5-10 years (e.g., IoT, Big Data technology).

Some sources also cite "Automated analytics" as a fifth analytics type and the ultimate end goal of analytics. Instead of presenting a recommendation to a human, as in prescriptive analytics, automated analytics take action on the results of their analysis.

Besides aforementioned types of analytics there are several other important aspects when working with analytics such as:

- **Size/volume and "**nature**" of the data** to collect and analyse - namely small/big, structured/unstructured data.
- **Type of data sources** connected - Internal/External, time-series /log-file, etc.
- **Analytics architecture** – cloud architecture vs. on-premise deployment.

2.4.2 Deep-dive: Machine Learning

Machine Learning is a crucial element, especially for advanced and predictive analytics. It describes a set of techniques that extract knowledge from data so that systems can take smart and even autonomous decisions. Through Machine Learning algorithms computers can recognize patterns, learn from experience and continuously improve the efficiency and accuracy of the output. The benefits are manifold for businesses across all industries, and also to end-users that consume products and services with incorporated Machine Learning components in them.

The concept has its roots in the early **1950s** when scientists tried to program computers to win logic-based games and enable networks of computers to perform certain tasks. By the 1960s these computers were able to perform pattern recognition and, as the computational power and the available storage capacity increased, these techniques were available for a wider area of applications, outside the laboratory.

Today, Machine Learning, has advanced as a set of sophisticated algorithms that can handle complex data and teach computer systems to learn. It is considered a cornerstone of Artificial Intelligence (i.e., scientific methodologies that try to teach computer systems intelligent behaviour). Machine Learning algorithms will be the driving force of Artificial Intelligence applications.

Popular applications of Machine Learning algorithms today include spam filtering in e-mail accounts or recommendation engines for e-commerce platforms and music streaming services. In terms of industrial applications, Machine Learning algorithms are the basis to improve machine performance and optimize entire manufacturing processes.

Mathematically speaking, Machine Learning draws together methodologies from the areas of computational statistics, mathematical optimization, and Data Mining. The main groups of Machine Learning algorithms are the following: Linear regression, association rule learning, clustering, classification, Bayesian networks, Markov chains, decision-tree models, random forest, artificial neural networks, and genetic algorithms.

Data Scientists usually classify Machine Learning into four different types: **Supervised, unsupervised, semi-supervised, and reinforcement learning.**

- In **supervised learning**, the training data for the algorithm <u>**includes**</u> desired outputs. A typical application of supervised learning is face recognition of individual people in a set of pictures.
- In **unsupervised learning**, the training data for the algorithm <u>**does not include**</u> the desired outputs. As unsupervised learning algorithms usually do not know what to look for, unsupervised learning mainly involves pattern recognition for a given

input variable. The output is usually data sorted in clusters. If an algorithm, for example, is not told what a human face looks like, it would likely start with clustering human-looking faces in contrast to horse faces or dog faces.

- In **semi-supervised learning**, the training data for the algorithm already **includes some** of the desired outputs. It can be seen as a mix of supervised and unsupervised learning.
- In **reinforcement learning,** the training data for the algorithm **does not include** the desired outputs but the use of suitable algorithms gets rewarded. The goal is to find an action or a good behavior of the system for each particular situation so that it maximizes the long-term benefits. Reinforcement Learning is applied in autonomous driving vehicles which need to ensure a safe and steady driving in ever-changing conditions (e.g., the car must react quickly and correctly when a small child suddenly runs on the road – safe driving gets rewarded)

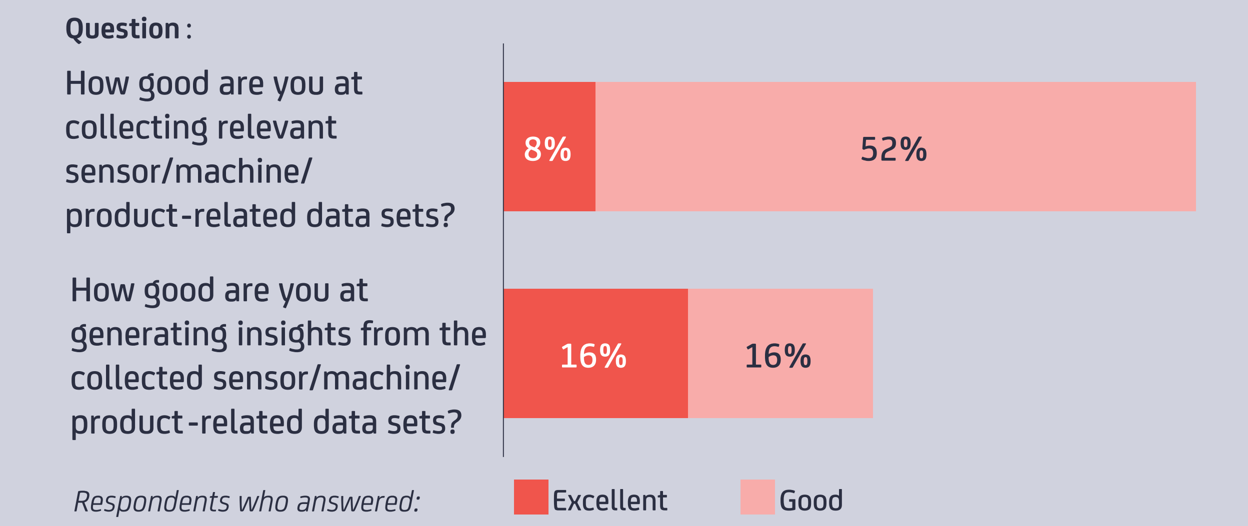
"Deep Learning" is the current buzzword for neural networks, a particular form of Machine Learning stimulated by the way human neurons work. It was invented in the 50s and 60s, but has rarely been used due to the lack of computing power and amount of available data. Deep learning is now the driving force behind today's best algorithms in image recognition, natural language processing (NLP), speech recognition and many other similar areas.

Machine Learning in general is considered as a key technology to develop true artificial intelligence (AI), and today is a **crucial element for data-driven decision-making** in all kinds of businesses. It is the "*catalyst*" that enables smart systems to extract value from the available data.

2.4.3 Deep-dive: Analytics for IoT

With the Internet of Things gaining importance for industrial companies, understanding the specific characteristics of analytics applied to sensor data is important. While **60% of survey respondents** feel that

EXHIBIT 8: Companies struggle with generating insights from the collected data



they are good or excellent at collecting sensor data, only 32% feel that they are good or excellent at getting the right insights.

IoT-based data analytics differs from other types of analytics – typical characteristics of IoT-based data analytics include:

1. Data Analysis: Instead of performing ex-post (descriptive) analysis, IoT often requires an element of **real-time** analysis. Real-time analysis requires the software tools to be connected to the stream of data and take actions in milliseconds.

2. Data size: Due to the large number of sensors and machines (in many instances also optical/ video data) IoT often stretches the demands of technology to store and handle these Big Data streams.

3. Data quality: There is a whole new set of **noise** present in the sensor data that needs to be dealt with (e.g., a vibration sensor on a machine may show an unwanted amplitude just because a truck is driving by).

4. Data types: The data produced through these sensors often comes with time-stamp protocols, which may result in a new need for databases that are organized according to those stamps.

5. Applications: Data analytics applications for IoT need to deal with a new set of use cases (e.g., predictive maintenance, autonomous production, etc.). As with all new applications, relatively few people have experience in implementing the algorithms for these new problems.

6. Architecture: A new challenge to analytics architectures is the ability to perform decentralized analytics, i.e. certain critical analytics on the device (at the edge) and other analytics in the cloud.

Because analytics for IoT requires new approaches and different skills there is a new set of IoT Analytics experts and companies emerging and analytics companies are building up specific capabilities for handling data produced by the Internet of Things.

2.5 Paradigm shifts – How analytics reshapes industrial principles

Industrial Analytics advancements have a far greater effect than just enabling selected new business cases – in many ways it changes some long-held paradigms in rather conservative industrial settings.

CHANGING SOME LONG-HELD PARADIGMS IN RATHER CONSERVATIVE INDUSTRIAL SETTINGS

2.5.1 Agile product development

Gone are the days of waterfall-based project planning. "*Agile*" is becoming the new norm. The agile methodology has its roots in the toolbox of the Toyota Production System that revolutionized the way manufacturers handle continuous improvement processes in the 70s, 80s, and 90s. The software industry adapted this approach in a framework called "*Scrum*", however the general contemporary term is "*Agile*".

In short, agile describes a set of principles under which solutions evolve through the collaborative effort of self-organizing cross-functional teams. It promotes aspects such as iterative and incremental testing and face-to-face communication.

With the Internet of Things, there is a new approach performing agile project work on physical objects (e.g., enabling the ability to remotely analyze products and remotely deploy software updates). The car manufacturer Tesla is at the forefront of this development. Tesla has an "*over-the-air-fix*" which allows the company's engineers to change software and applications remotely. New features and feature improvements (e.g., the autopilot) can be deployed while the car is sitting in the customer's garage.

It is not only about the software. Product and maintenance-related data which loops back to product design will also help engineers to refine sketches and come up with better designs. As a first step, many companies have already started to integrate design bill of materials (BOM) with manufacturing and maintenance BOM. By gathering and analyzing information from different processes and feeding this information back into product design, it is possible to get a better understanding of product behavior and problems associated with using an existing module in a new product design.

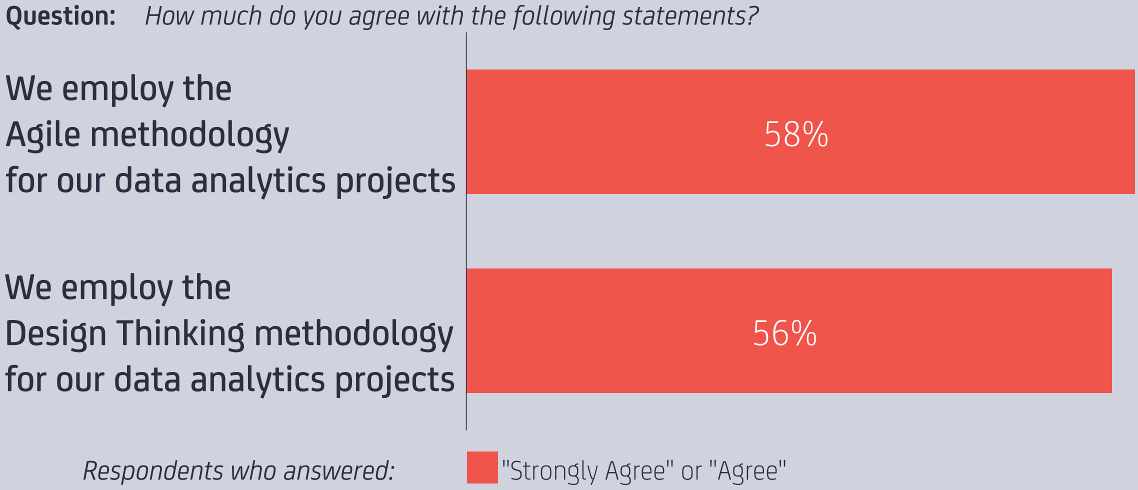
Agility is achieved through collaboration between different elements in the value chain as well as short iterations that last from one to four weeks and include so-called "*sprints*". Agile, as well as Design Thinking, are already widely accepted concepts with **58% of survey respondents** indicating that they employ the agile methodology for their data analytics projects already today.

2.5.2 Platforms and open ecosystems

Traditionally, manufacturing was a closed world that consisted of interactions between specialists and a few chosen third-parties. This ecosystem is now changing. The success of Apple in creating a platform that lets developers create and sell new applications is encouraging industrial companies to pursue a similar path. Industrial companies such as the agricultural equipment manufacturer John Deere or the crane manufacturer Liebherr are building platforms that connect their equipment with other equipment and

EXHIBIT 9: Agile and Design Thinking are already used widely today

Question: *How much do you agree with the following statements?*



allows customers and third-parties to work on added-value applications.

Another example is GE Digital, who is creating an industrial app marketplace. Software developers, Data Scientists and design thinking specialists are collaborating to develop a platform that lets third-party companies develop new industry applications.

For now, the applications and services provided through these platforms are limited. However, just like Apple's app store was initially limited to certain apps, many of the opportunities may still be beyond our imagination.

2.5.3 Changed software architectures

In the last decade a well-accepted 5-layer automation pyramid has been defining the software architecture for industrial processes. ERP systems are at the top of the pyramid, MES systems below, SCADA systems in the middle, PLC and DCS systems on the fourth level and the actual input/output signals at the bottom.

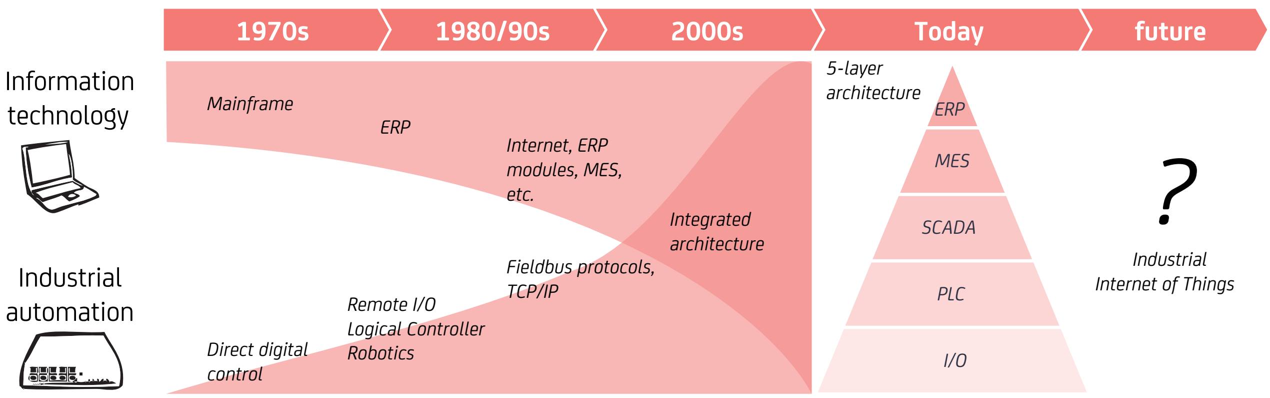
IoT architectures and corresponding analytics capabilities are possibly changing this picture.

Today, for example, Manufacturing Execution Systems (MES) are the essential component that link shop floor operations to ERP (Enterprise Resource Planning) systems and other connected systems such as PLM (product life cycle management). Traditionally, management decisions have been taken in this environment based on performance, quality and agility.

Cheaper sensors and integrated information are however now making shop-floor entities smart agents which can process the information to take autonomous decisions. In this context, we may see smart processes and smart products that communicate within this environment and learn from their decisions, thereby improving performance over time.

Following this trend, MES agents may be vertically integrated into higher level enterprise planning and product change management processes, so that these entities are able to synchronously orchestrate the flow of data, rather than go through each layer individually.

EXHIBIT 10: Beyond a layered system – Why IoT is a game changer for industrial analytics



ERP = Enterprise Resource Planning MES = Manufacturing Execution System SCADA = Supervisory Control and Data Acquisition PLC = Programmable Logic Controller I/O = Input/Output signals Source: IoT Analytics

2.5.4 Manufacturing-as-a-Service

Forward thinking manufacturers are considering new ways to use capacity that does not necessarily belong to them. Consider how Uber and Airbnb create value by using assets that they do not possess. The same movement may take over the manufacturing industry as it seeks to advance agility in product development and market testing.

As an example, FirstBuild, a partnership between GE and Localmotors, is a micro factory that crowd sources and manufactures automobiles. GE and Localmotors use this concept to design, build prototypes and test the market for new products. If the products prove to be attractive to the market, they will find their way to GE manufacturing sites for mass production.

Dassault MySolidWorks is another example. It is a virtual online community of companies that specialize in CNC Milling, injection molding, 3D Printing and sheet metal manufacturing. This platform gives clients the opportunity to use Dassault‘s software not only to create designs but also to put users in contact with manufacturers who then reply to a bid in hours. Protolabs, Dassault’s partner for this project, is now able to generate thousands of quotes per day for its clients – thanks to the online community.

The manufacturing-as-a-service trend requires perfect visibility into the flow of product and data in order to take momentum and is therefore highly reliant on IoT Data and the corresponding analytics.

Hewlett Packard Enterprise

3 Industrial Analytics Case Studies

3.1 HPE – Enabling predictive maintenance for wind turbines

COMPANY	HEWLETT PACKARD ENTERPRISE
Project name	Windpark Management 4.0
Industry	Wind energy
Use Case	Predictive maintenance of wind turbine components
Date	2016
Analytics type	Predictive / Machine Learning
Data volume	High
Connection type	IoT

3.1.1 Business case

Hewlett Packard Enterprise has developed a **novel wind energy farm management solution**, called Windpark Manager 4.0 that is based on latest Internet of Things, Security and Big Data technologies.

The solution enables wind farm operators to efficiently monitor all operations of the wind park, the IT equipment as well as individual turbines. Key features of the system are **real-time root cause analyses**, a robust **security framework** and the ability to perform **predictive maintenance**.

The effects are manifold: In early trials the new wind park management system allowed a control center to double its capacity of monitored wind turbines without adding any personnel. The new root-cause-analysis tool also led to the avoidance of expensive helicopter trips to verify the functioning of offshore turbines, as the tool can accurately pinpoint network connectivity problems that may cause the operations team to believe there is a turbine failure e.g., rotor standstill.

3.1.2 Background

Wind turbines are traditionally managed by so-called SCADA systems that allow for remote monitoring and control of a limited number of parameters. These systems (around since the 1970s) are evolving from their early-days but have distinct limitations when it comes to functionality, network security and ability to perform large data analyses.

HPE are now merging the existing SCADA architectures of different wind turbine vendors with its IoT and IT Datacenter management offering as well as integrating their Big Data analytics capabilities.

Hewlett Packard Enterprise

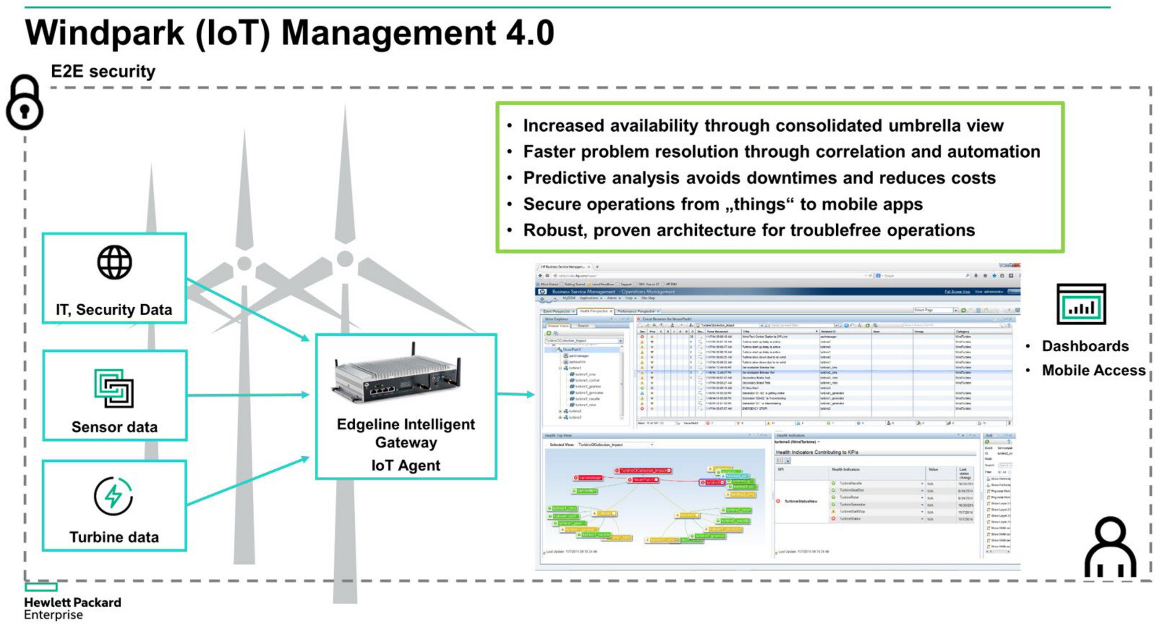
3.1.3 Approach

The HPE engineers set out to develop specific agents which run on top of the individual SCADA systems and help collect and normalize the data of any turbine model as well as all the increasing IT and wireless components in the park. Each turbine is equipped with an intelligent gateway which sends up to 300MB of data that gets generated each day via a secure socket layer protocol (https) to the central server.

Data stored locally in a relational operational database is merged, optionally in the cloud, with other useful data sets such as weather forecasts in an unstructured common data lake. With this setup the system collects data from over 500 different sources and compiles it into one single 360-degree view across all elements of the windpark.

In addition to the ability to monitor this data on a dashboard, the system enables predictive maintenance for individual turbine parts. Over time the system correlates historic operational data and builds a statistical model that predicts the likelihood of upcoming system failures and pins it down to individual locations and parts. In case of an upcoming failure, the alert is pushed out onto a mobile device of the corresponding service personnel in charge.

EXHIBIT 11: HPE Windpark (IoT) Management 4.0



Hewlett Packard Enterprise

3.1.4 Challenges & Learnings

BUILDING THE PREDICTIVE MAINTENANCE MODEL

In order for the predictive maintenance system to run accurately, HPE engineers had to build and train the model. A team of Data Scientist and mechanical engineers initially engaged in a data discovery phase during which they validated the data sets, correlated different parts of the data and used their Data Science knowledge to reduce the number of parameters that should be taken into account for the model. In a second step they built the model by applying useful algorithms to these data sets. In a third step, the engineers assessed the model in terms of quality and performance and together with the wind park engineers validated the value the model brings to everyday operations. The outcome of the model lets you know how close you are to failure and if needed, an alert is generated indicating for example, that a bearing is likely going to fail in 3 hours.

KEEPING THE MODEL ACCURATE OVER TIME

The engineers realized that over time the performance of the predictive maintenance model degrades. In order to mitigate, they introduced a cycle of data re-creation and re-discovery which ensures the model stays valid at all times.

INTEGRATING THE DATA INTO EXISTING BUSINESS PROCESSES

Most companies demand the wind park management solution to integrate into the existing enterprise software architecture. Only then can the full benefits of the solution be reaped (e.g., the existing SCADA system should automatically shut down a turbine if an upcoming failure may lead to major part damages). HPE therefore takes an open approach and integrates with major software vendors. The company even works with competing analytics vendors such as Tibco or Tyco to integrate their toolsets into the overall solution.

3.1.5 Looking forward

This showcase focuses on predictive maintenance but the solution is also able to support the investment decision-making process and supply-related topics such as verifying the correct BOM items have been received on-site. The Windpark Manager 4.0 solution is just one of many IoT & Big Data applications that HPE supports. In particular, this solution builds on HPE's 25 year experience in managing complex, heterogeneous and distributed datacenters, as well as its own data warehouse and database technologies HPE Vertica and HPE Idol.

HPE is further building out the capabilities and believes it is impeccable for wind park managers to adopt such a solution in the future. One should note that the wind park management 4.0 is a blueprint that can easily be adopted by other industries in which critical remote assets need to be managed.

Hewlett Packard Enterprise

3.1.6 About Hewlett Packard Enterprise

3.1.6.1 COMPANY OVERVIEW AND CONTACT DETAILS

COMPANY	HEWLETT PACKARD ENTERPRISE
Headquarters	Palo Alto, California, USA
Founded	January 1st, 1939
Employees	240,000
Website	hpe.com

Name	Erika Hoffmann
Position	Manager Big Data Analytics Partners
Email	erika.hoffmann@hpe.com
Telephone	+49 162 290 19 12

3.1.6.2 COMPANY DESCRIPTION

Hewlett Packard Enterprise is an industry leading technology company that enables customers to go further, faster. With the industry's most comprehensive portfolio, spanning the cloud to the data centre to workplace applications, our technology, market leading Software and services help customers around the world make IT more efficient, more productive and more secure.

3.1.6.3 PRODUCT / SERVICE PORTFOLIO FOR INDUSTRIAL ANALYTICS

HPE Vertica is the industry's first comprehensive, scalable, open, and secure platform for Big Data. HPE Vertica, a massively scalable analytical database platform, is custom-built for realtime analytics on petabyte-sized datasets. It supports standard SQL, Python and R-based analytics, and offers support for all leading BI and ETL vendors. Reference customers include Facebook, Uber, New York Genome Centre. (Free HPE Vertica Community Edition at www.vertica.com/community).

HPE IDOL: The quest to make computers "*intelligent*" is as old as computers themselves. The phrase artificial intelligence produces notions of a robot-controlled future in which humans have been rendered largely obsolete. But HPE IDOL next-generation enterprise search and data analytics platform uses pioneering techniques in artificial intelligence to automate and enhance the processing of human information—not to take the decision away from humans, but to help us make the best one. We call this approach augmented intelligence. HPE IDOL is an advanced enterprise search and data analytics tool for unstructured data with machine learning that lets you search and analyze text, image, audio, and video from virtually any source. Reference customers include large public sector (Surveillance, Safe/Smart City, etc.) and health care customers.

HPE Haven OnDemand: With over 70 APIs for speech, video, text and predictive analytics, HPE Haven OnDemand brings the power of machine learning to any developer. HPE Haven OnDemand Combinations enables developers to improve time to market and ROI for app development and IT modernization projects with rapid integration of cognitive services designed to accelerate self-service development with fewer lines of code, reduced testing with reusable APIs, and improved app performance with fewer API calls and less latency. Combinations is the fastest possible way to add intelligence to apps and increase ROI. It's like plug and play Machine Learning for Enterprise apps. Largest reference customer: Philips (Free HPE Haven OnDemand Developer Edition at www.havenondemand.com).

3.2 Comma Soft AG: Reducing complexity-driven costs in the automotive industry

COMPANY	COMMA SOFT AG
Project name	Product Complexity Reduction
Industry	Automotive Tier-1
Use Case	Optimizing available product variants
Date	2015
Analytics type	Descriptive
Data volume	High
Connection type	On-premise

3.2.1 Business Case

Comma Soft AG supported a large multinational **car manufacturer** in reducing **production-related complexity costs** by analyzing all of its product variants. The elimination of rarely chosen product variants and very costly product options led to millions in cost savings.

3.2.2 Background

Car buyers demand individualized offerings. Whether it is exterior looks, engine power or interior – the range of configurations go into the millions, sometimes even billions. Car manufacturers are thus constantly caught between the need to cater to these needs and the urge to keep complexity-driven production costs down. Take the steering wheel as an example. In this case, just the combination of different cruise controls, lane warning systems, and control stalks leads to 80 possible configurations that need to be ready for assembly. Related cost is driven up by an increased need for product design, increased storage capacity and lower product quality.

EXHIBIT 12: Manufacturing Environment

3.2.3 Approach

Firstly, Comma Soft consultants gathered data from 3 sources:

1. The configuration choices available to the customer
2. The actual customer orders from the past years
3. The bill of materials (BOMs) and its related rules (e.g., which parts fit together with other parts, etc.)

After cleaning and validating the data, the team built a data model that was able to cut through the enormous amount of data quickly enough to perform all necessary analyses. After a few weeks of work the team was able to perform the actual data analysis. The team built a mix of supervised and unsupervised Machine Learning algorithms to understand the effect certain configurations have on the overall cost structure (e.g., analyzing customer configuration trends over time). In addition, a browser based visualization interface was developed in order to discuss various results with senior management. The tool gave management the ability to interactively "*click through the car configuration tree*" to immediately see the cost effect of certain actions.

3.2.4 Challenges & Learnings

PREPARING THE DATA SETS

One of the key early challenges was to ensure data consistency. With data being pulled from different sources and the Data Scientists coming from outside the company operations, several workshops between manufacturing experts and Data Scientists were necessary to ensure that all of the rules applicable in the real world were properly mapped into the data models. A 15-inch wheel rim, for example, does not fit together with a 17-inch wheel – this rule may be intuitive for humans but unfortunately not for a data model that is lacking this association rule.

ACHIEVING QUICK DATA SEARCH FUNCTIONALITIES IN HIGHLY COMPLEX DATA SETS

With data relations in the area of 100 billion connections (n:m relations) a classical relational database was not suited for solving this kind of problem. Therefore, the team had to pivot existing data rooms, define new suitable index structures and build custom search trees using a map-reduce methodology to access data nodes quickly. The resulting search tree was able to deliver results in milliseconds.

USING AGILE DEVELOPMENT PRACTICES

The project turned out to be a lot more difficult than anticipated. A key success to coming up with meaningful results quickly was the use of agile development practices. Iterating quickly and often ensured that the Data Science team was able to extract the important know-how from the manufacturing experts.

3.2.5 Looking forward

Comma Soft is working on similar complexity reduction efforts in a number of other industries. Analyzing enormous data sets such as this one has only become possible in the past 5 years on the back of massive improvements in hardware processing power (e.g., increase in random access memory). The cost savings that can be achieved from such projects are instrumental for manufacturers who are seeking cost efficiencies in global markets.

3.2.6 About Comma Soft AG

3.2.6.1 COMPANY OVERVIEW AND CONTACT DETAILS

COMPANY	COMMA SOFT AG
Headquarters	Bonn, Germany
Founded	1989
Employees	135
Website	http://www.comma-soft.com

Name	Anja Hoffmann
Position	Board Assistance
Email	anja.hoffmann@comma-soft.com
Telephone	+49 228 9770-159

3.2.6.2 COMPANY DESCRIPTION

Comma Soft AG, founded in 1989, belongs to the innovation leaders at the interface of IT and Business in Germany. With more than 135 employees, Comma Soft AG and its interdisciplinary teams addressing business IT strategy, processes & organization, technology & infrastructure, data analytics, Data Science and security, serves numerous companies with various DAX corporations amongst them. Pioneering In-Memory technology and current Big Data technologies designed to quickly process large data volumes, Comma Soft provides its customers with competitive advantages – with new approaches for the digital transformation, innovative IT architecture and cutting-edge technologies such as the Data Science solution INFONEA and the implementation of new security standards.

3.2.6.3 PRODUCT / SERVICE PORTFOLIO FOR INDUSTRIAL ANALYTICS

Comma Soft supports optimizing business challenges with state-of-the-art methods from Advanced and Predictive Analytics, from Machine Learning up to Cognitive Computing. More than 25 years of experience in the business-oriented analyses, organization, and management of information and knowledge meet an interdisciplinary team of Data Scientists, analysts, business consultants paired with experts in Big Data technology as well as Data Security & Information Rights.

Practical examples:

- Complexity Management: reducing the variant diversity in production industry with high component complexity
- Predictive maintenance: predicting the downtimes of machine components
- Industrial Internet: analyzing machine data in the context of the Industrial Internet of Things / digital transformation of manufacturing

3.3 Kiana Systems – How to pick the right pill out of over 1,000

COMPANY	KIANA SYSTEMS
Project name	Automated real-time sorting of pills
Industry	Healthcare / Packaging
Use Case	Predictive quality assurance
Date	2015
Analytics type	Real-Time / Machine Learning
Data volume	Medium
Connection type	On-premise

3.3.1 Business Case

KIANA implemented a pioneering data-driven solution directly into the production line of a large pharmaceutical company to enable the automated real-time sorting of thousands of pills into individual patients' weekly blister boxes. KIANA used NIR (near-infrared) spectroscopy and Machine Learning to identify and sort different pills within 3 milliseconds and reduce the error rate by several levels of magnitudes to 10^-6 compared to the existing manual process. The system works even for a vast range of different auxiliary substances used in pills and can constantly judge its own level of competence.

3.3.2 Background

To improve patient medication management, hospitals and retirement homes across Germany are sorting pill subscriptions into weekly boxes, so-called blisters. To date, this sorting process has been largely manual, time-intensive and in some cases error-prone with serious consequences for patients. KIANA was approached by a large pharmaceutical company to develop an automated data-driven approach to revolutionize individualised medication sorting.

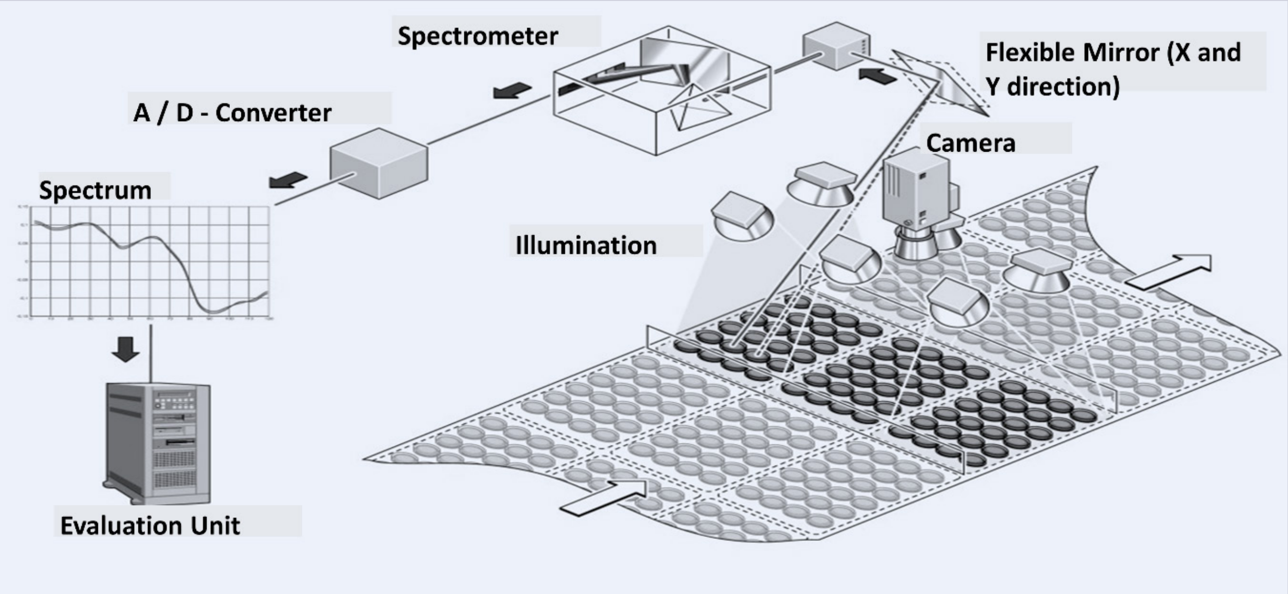
3.3.3 Approach

The first approach using an optical difference detection tool could not be accurately realised. After a detailed analysis KIANA decided to implement NIR-spectroscopy (near-infrared spectroscopy) to identify each pill accurately. After collecting 256 points of measurements on near-infrared properties, a classification algorithm to determine the type of drug using the Fisher discriminant was developed. Also a feature of the system is that it can judge its own current level of competence. When the system realizes, that its classification rate is decreasing, it will send commands to the factory with instructions to change the order in which pills are introduced into the sorting process. As a result, a self-judging and automated pill sorting process was realised.

3.3.4 Challenges & Learnings

Almost immediately, it became clear that just an analysis of optical data would not be enough to identify each pill accurately. Another method had to be selected to reach the desired speed and minimum error rate. KIANA decided to apply NIR-spectroscopy to determine the chemical composition of a pill. However, as a result of the large amount of auxiliary substances and the accompanied variance in pills, powerful Machine Learning algorithms had to be developed to spot the spectra which contain the crucial information. Due to the given time frame, the collected information from spectra had to be compacted. With a reduction of the pill dimensions, the help of an adapted version of the Fisher discriminant and Machine Learning methods developed by KIANA, the required error rate and time frame could be achieved. After implementing the classification software into the inspection module of the packaging machine, KIANA successfully solved the challenge of integrating further processes (e.g. organizing the sequence of incoming goods) seamlessly.

EXHIBIT 13: Kiana Systems Example



3.3.5 Looking forward

In order to ensure a continuing competitive advantage for the client, KIANA is continuously asked to further improve the implemented software. KIANA has already doubled the number of pills (over 2,000 different ones) the classification software can correctly identify. Also, KIANA further modified the algorithms such that they can identify pills through packing film. Although this classification system was developed for the pharma industry, the methods used can be adapted for every other industry that has to handle similar classification problems.

KIANA SYSTEMS

3.3.6 About Kiana Systems

3.3.6.1 COMPANY OVERVIEW AND CONTACT DETAILS

COMPANY	KIANA SYSTEMS
Headquarters	Saarbrucken, Germany
Founded	2001
Employees	20
Website	http://www.kiana-systems.com/

Name	Ushananthan Ganeshananthan
Position	CEO
Email	kgushan@kiana-systems.de
Telephone	+49 (0)172 / 285 7012

3.3.6.2 COMPANY DESCRIPTION

KIANA Systems is one of the leading companies for Big Data analytics, Data Mining and Machine Learning technologies based in Germany. The company was founded in 2001 as a spin-off of the renowned German Research Center for Artificial Intelligence (DFKI) initially under the name of Mineway. For the direct benefit of its clients, KIANA remains at the forefront of scientific advances in the Data Sciences through conducting R&D projects and engaging in research collaborations with leading academic institutions.

3.3.6.3 PRODUCT / SERVICE PORTFOLIO FOR INDUSTRIAL ANALYTICS

KIANA helps companies to build IoT platforms and develops bespoke data analytics and Machine Learning software solutions for industrial applications in order:

- to predict failures of machine parts and machines
- to conduct root-cause analysis of quality issues
- to optimize production line scheduling
- to minimize energy costs
- to implement smart self-learning product features (e.g. Smart home, Smart appliances, Smart UX…)
- to optimize pricing of original components and spare parts
- to forecast demand and increase efficiency of supply chains

KIANA has, for example, helped to build one of the most efficient factories to sort pills and personalize medicine. Near-infrared spectroscopy combined with a classification algorithm based on the Fisher discriminant was introduced into the production line to identify and sort over 2,000 pills within 3 msec and reducing the error to 10^{-6}.

KIANA has developed a real-time optimal pricing solution for an industrial company selling over 12,000 different products. KIANA analyzed extensive sales data and developed a sophisticated self-learning real-time pricing model. The result is a significant profit increase, better competitive pricing and higher sales probabilities.

4 Industrial Analytics: Making it happen

4.1 Project approach – Starting an Industrial Analytics project

There are 2 distinctly different ways of approaching individual data analytics projects:

A. Hypothesis-driven approach
(Starting from a hypothesis or problem to be solved – with data being analyzed according to the hypotheses).

B. Explorative approach
(letting the data talk by exploring unknown patterns, clusters, cause-effect relations and singularities from anomaly-detection – followed by a discussion on insights and a continuous development of the hypotheses). Based on these initial indications hypotheses are then built and the process merges into the hypothesis-driven approach.

The classical approach to data analytics projects is somewhat similar to the following process:

1. Start with problems to be solved or articulate expectation on analytics approach

2. Develop a process and decide on the approach, either hypothesis-driven or explorative – as discussed above

3. Define the data requirement (functional / non-functional)

4. Define data access (ETL-process), e.g., how/when/in which format will data be extracted and delivered

5. Build the data architecture and model

6. Select the technology & integrate

7. Check data quality (completeness, consistency, plausibility, calculate limitations of analytics possibilities, identify limitations)

8. Apply analytics methods (analyze, model, code, learn, etc.)

9. Discuss results, modify models, generate new hypotheses

10. Iterate until the targeted accuracy is achieved

11. Put the solution into production

12. Monitor and adopt when necessary

Although you may refer to the standardized "*CRISP Cross Industry Standard Process for Data Mining*" for a standardized definition of the process, reality shows that there is no single master methodology fits all kinds of projects – especially in advanced data science approaches.

Generally speaking approaches and methods deployed vary depending on:

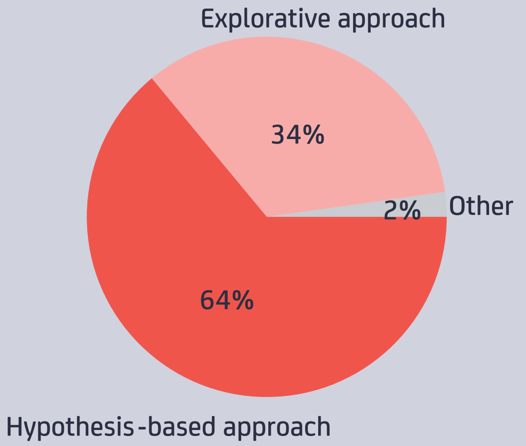
- **Project objective**
- **Methods and models applied** (i.e. supervised or un-supervised learning)
- **Data infrastructure**
- **Data sources**
- **Data types given** (structured, unstructured, volume, stream or static).

34% OF PROJECTS ARE PERFORMED IN AN EXPLORATIVE MANNER

In a world in which the technological boundaries are not clear to most decision-makers, in which agile methods are used in order to build prototypes and in which the amount of digitally-enabled business cases continue to rise, the **explorative** approach is increasingly used. Respondents of the survey indicated that on average **64% of industrial data analytics projects** are performed today using the hypothesis-based approach. 34% of projects are performed in an explorative manner for which it is initially not clear what problem will get solved and how.

EXHIBIT 14: Most firms use the hypothesis-based approach

Question: *What percentage of your Industrial Data Analytics projects are implemented using the following approach?*



When we are invited to present our technology to potential customers there is often no pre-set agenda. Instead, we hold creative workshops to explore potential digital solutions. We jointly develop ideas of what could be achieved, then develop use cases and discuss how HPE technology can help.

Ulrich Pfeiffer, Director HPE Software EMEA

Our approach has been both explorative and hypothesis-based. Rather than building a business case that caters to a specific need we are building a vision and at the same time we are ensuring the data is explored to see how that could help in achieving our vision.

Director of connected solutions at a major crane manufacturer

4.2 Tools/Technology – The backbone of Industrial Analytics

It makes sense to segment Industrial Analytics technologies & tools into 4 separate modules:

1. Data sources - that generate the data

2.Necessary infrastructure – that transmits, stores and processes the data

3. Analytics tools – that manage and make sense of the data

4. Applications – that bring data to life and generate the actual value

Exhibit 15 gives a broad overview of the four modules and possible components in the industrial context.

Diving deeper into analytics, there are a wide range of analytic software packages available.

The survey reveals that the **role of spreadsheets** (e.g., Microsoft Excel) for industrial data analytics is expected

EXHIBIT 15: Typical technology modules for Industrial Analytics - Including typical components in Industrial settings

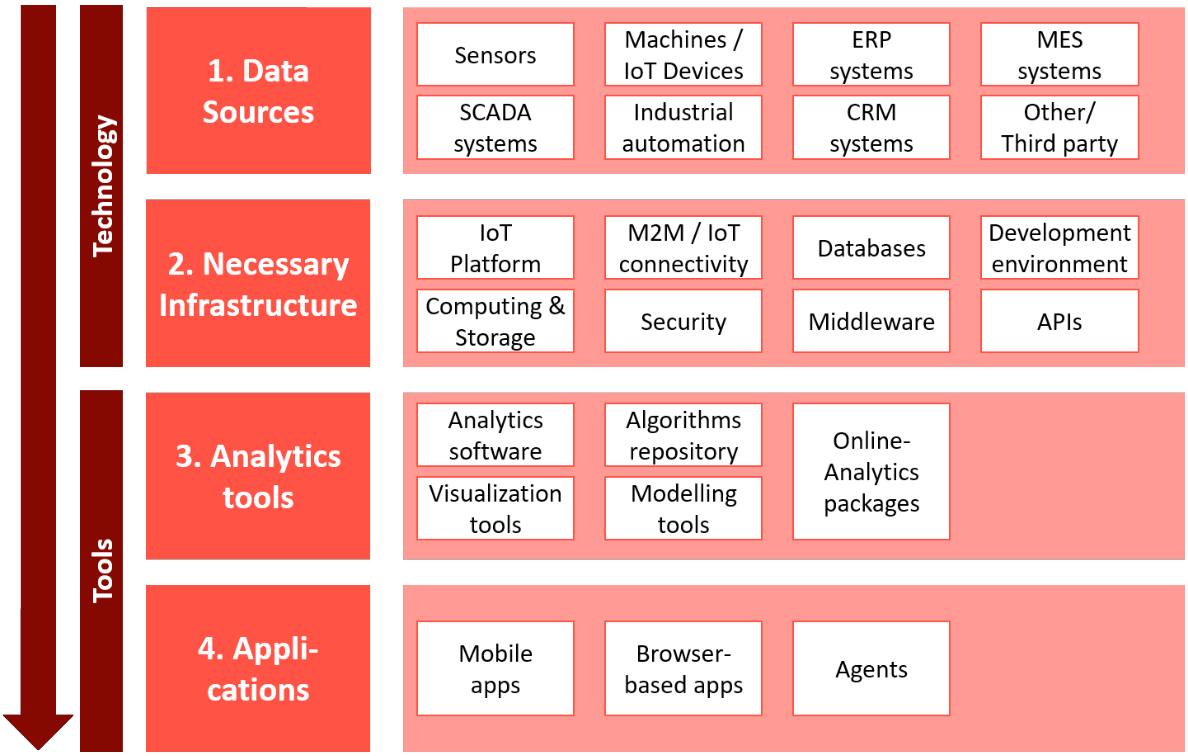
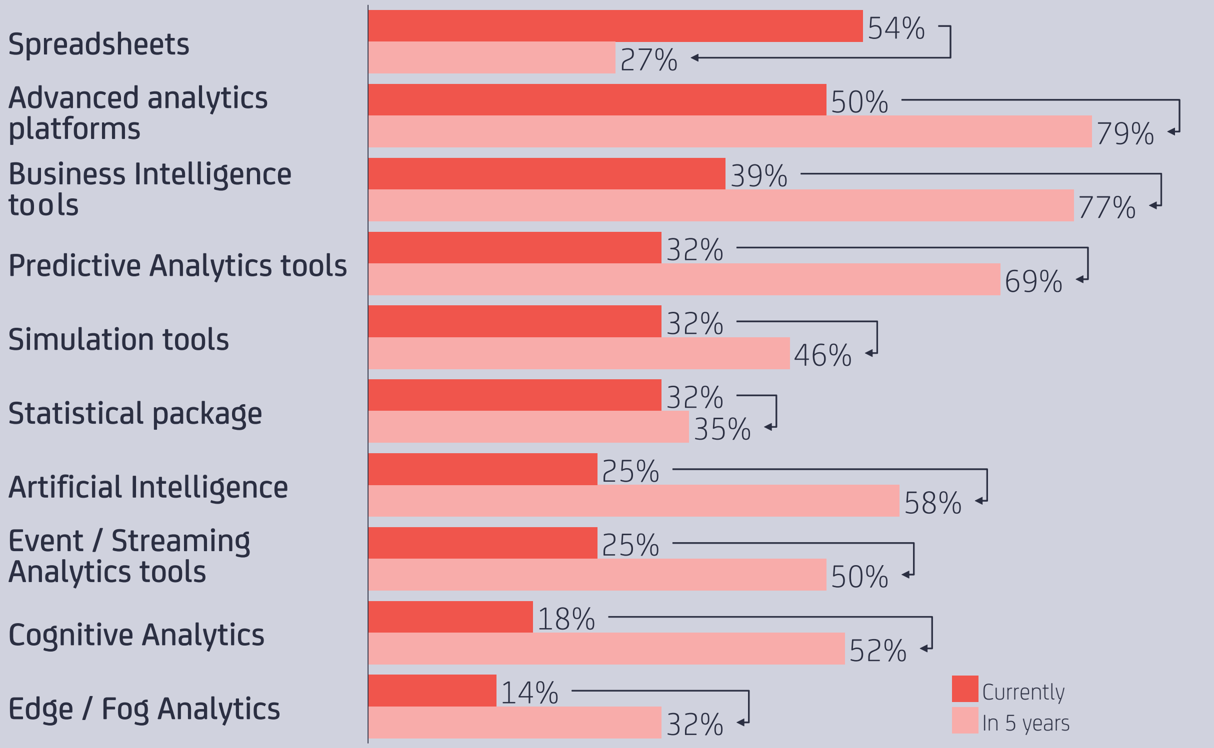


EXHIBIT 16: Increasing role of Advanced Analytics and Business Intelligence

Question: *Which role do the following technologies play in your industrial data analysis? – Now and in 5 years**



*Percentage of people who answered: *"Important"* or *"Very Important"*

to decline (i.e., 27% think it is important in 5 years vs. 54% today).

All other analytics tools surveyed are expected to gain in importance. Notably **Advanced Analytics Platforms** such as SAS Advanced Analytics Suite (from 50% to 79%), **Business Intelligence Tools** such as SAP Business Objects (from 39% to 77%), and **Predictive Analytics tools** such as HPE Haven Predictive Analytics (from 32% to 69%).

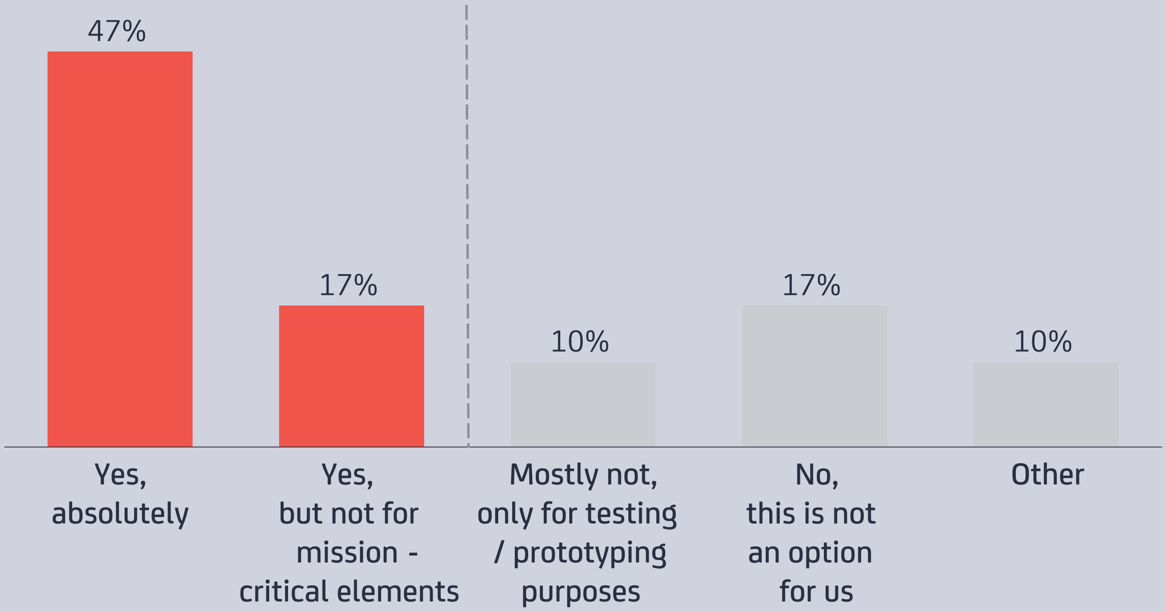
A key driver for the upward trend in the above mentioned technologies is the growing adoption of open source software tools.

Today, Linux/Unix is the major platform for cutting edge machine learning. Python and its exhaustive library ecosystem has emerged as a key programming language. However, it is still heavily competing against the traditional open source workhorse for econometrics and statistics, R. Relevant Python libraries include Numpy, Pandas, SciKit Learn, OpenCV, Keras, Theano and Tensorflow to name a few.

Many companies including Google (Tensorflow) and Amazon (Alexis) now actively make their software open-source, hoping to reap the community benefits while maintaining an edge through additional internal development that goes beyond the open-source code.

EXHIBIT 17: Wide adoption of open-source tools and technologies

Question: *Do you use open -source tools/technology for your Industrial Data Analytics project?*

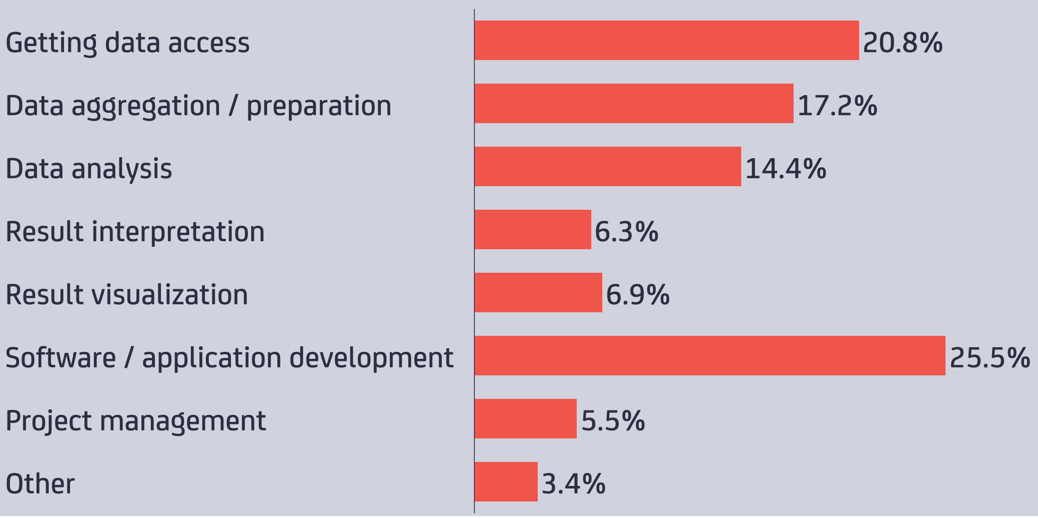


Nearly two thirds of all survey respondents (64%) **use open-source tools** such as Python and its library ecosystem, Apache Hadoop/Spark, R, or Knime for their data analytics projects. Only 17% of respondents indicated that it is not an option for them.

Most costs in Industrial Analytics projects incur in the initial phases of getting **data access** (21%), **aggregating the data** (17%), and performing the **data analysis** (14%).

EXHIBIT 18: Most Industrial Analytics related costs in software and application development

Question: *What percentage (%) of the industrial data analytics project budget goes to the following?*



Project management (6%), **result interpretation** (6%), and **result visualization** (7%) all play a minor role in terms of overall costs. The costliest individual cost item, usually incurs in relation to **software and application development** as well as the related enterprise system integration (26%). Depending on the complexity of the system architecture and the problem at hand, these cost buckets may shift – the survey results should however serve as a good indication for anyone budgeting their Industrial Analytics projects.

> *Today, we are observing a strong misbalance between the cost and the value structures of data analytics. The value gets unlocked in the analysis phase but the most time and resources are required in the data preparation phase prior to the actual analysis. Digital Leaders must therefore gain an understanding of how to automate, scale and accelerate data preparation in their organizations.*
>
> **Frank Poerschmann, Board Member at the Digital Analytics Association e.V.**

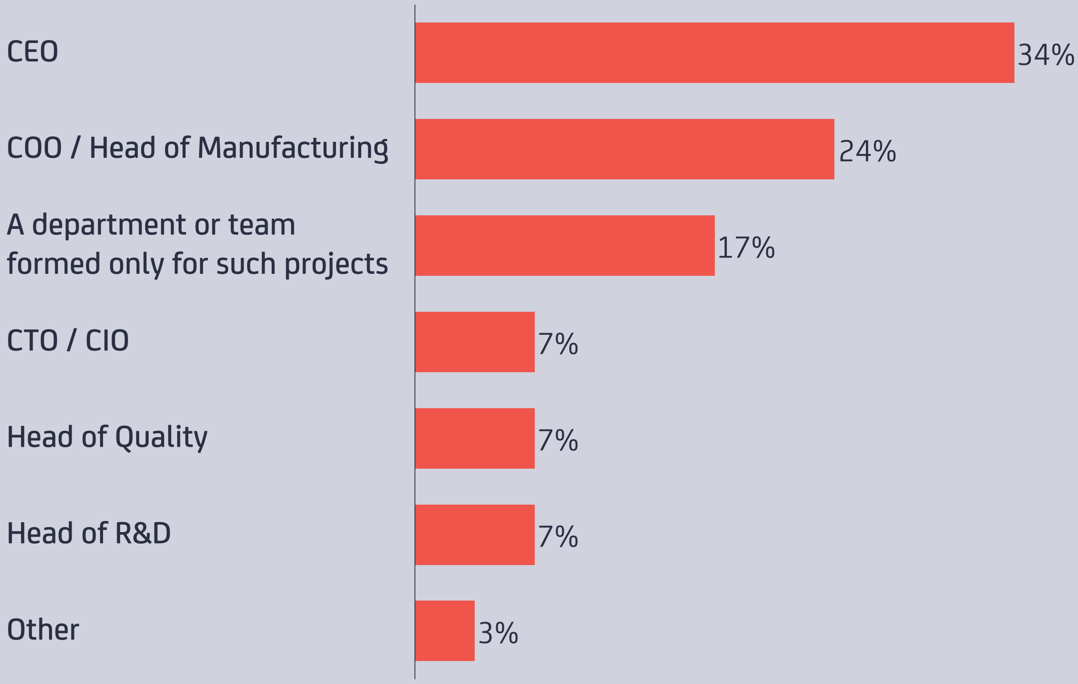
4.3 Organization – Aligning company structures for Industrial Analytics

Analytics projects often bring together a number of people from different departments and do not fall into one of the traditional functional corporate departments such as Marketing, Sales, Operations or Maintenance.

34% OF INDUSTRIAL ANALYTICS PROJECTS ARE CEO-DRIVEN

EXHIBIT 20: Most Industrial Analytics projects are CEO-driven

Question: *Who drives your Industrial Data Analytics projects?*



With analytics gaining importance and not having a natural home-ground it is perhaps not surprising that 34% of survey respondents indicate that it is the CEO who drives Industrial Analytics projects.

17% of respondents indicate that a dedicated project team is driving such projects, 24% indicate that it is the COO that is driving such projects, and 7% mention the CTO/CIO. The remaining 17% of Industrial Analytics projects are driving by individual departments heads such as R&D and Quality.

55% OF INDUSTRIAL ANALYTICS PROJECTS ARE OUTSOURCED IN AN EXTERNAL DATA LAB, DIGITAL LAB, INCUBATOR OR ACCELERATOR

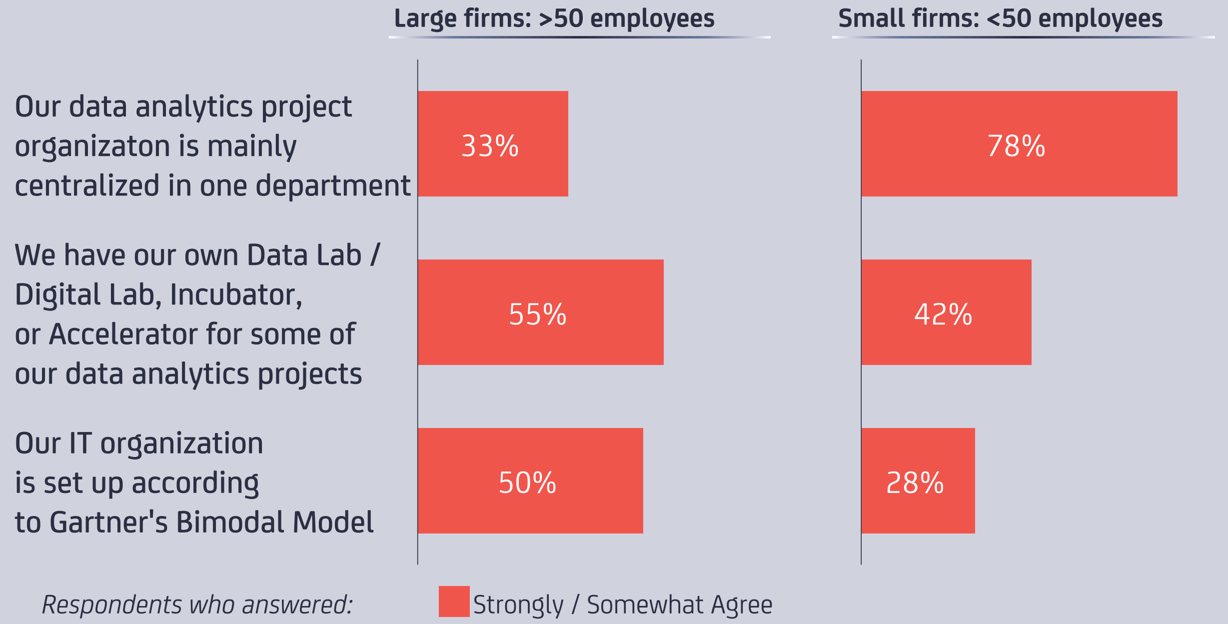
The survey further reveals that large **corporations have not centralized data analytics in one specific department** (Only 33% of respondents indicate so). Rather, many large industrial companies are **outsourcing some of their data analytics activities in an external Data lab, Digital lab, incubator or accelerator** (55% of respondents).

Due to the growing volume, complexity, and strategic importance of data we may see more companies creating new dedicated data groups that consolidate data collection, aggregation and analytics, and are responsible for making data and insights available across functions and business units.

These new data organizations are often led by a c-level executive, the **chief data officer** (CDO), who reports to the CEO or sometimes to the CFO or CIO. He or she is responsible for unified data management, educating the organization on how to apply data resources, overseeing

EXHIBIT 21: Large firms do not centralize data analytics organization

Question: *How much do you agree with the following statements?*



data rights and access, and driving the application of advanced data analytics across the value chain. (Source: Digital Analytics Association).

4.4 Required skills – Staffing for Industrial Analytics

Industrial Data Analytics projects usually happen at the intersection of industrial equipment, IT/IoT technology and Data Science. Project are therefore made up of a team with a variety of skills.

4.4.1 The project team

A typical Industrial Analytics project team is made up of

- An overall manager with experience in **project management** and skills in communication and stakeholder management
- An **industrial expert** who knows the equipment, products and processes well
- A **data engineer** who is an expert in data technologies
- A **data developer** who specializes in the algorithm and application development
- A **Machine Learning expert** who possess deep mathematical know-how of advanced optimization algorithms
- A **data analyst** who performs various analysis and knows how to prepare the data for the decision-makers

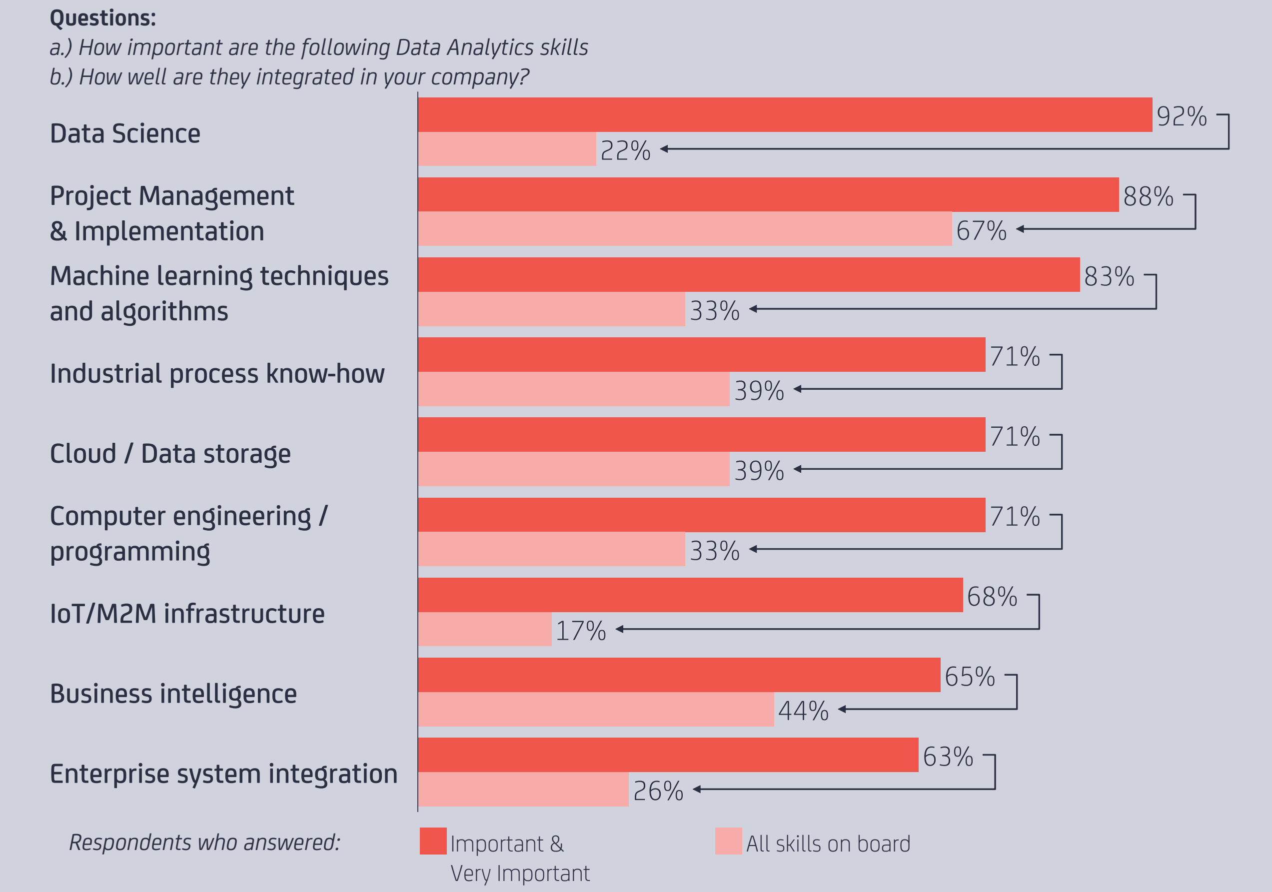
The latter four form the Data Science team. One should note that due to the rapidly developing analytics community and the nascence of the topic, a lot of these terms are not yet commonly accepted.

Exhibit 23 shows that the **biggest skill gap is currently in staffing this required Data Science expertise.** (92%

EXHIBIT 22: Typical Industrial Analytics Project Team

		←	Data Science		→
Project manager	Industrial expert	Data engineer	Data developer	Machine learning expert	Data Analyst
• Project planning and management • Communication with customers • Collaboration with partners • *Digital Strategy and Leadership*	• Deep knowledge on the industrial topic at hand • Technical equipment know-how • Knowledge of the business processes within the organization	• Information technology expert with wide knowledge of data technologies • Processes, architecture, data modeling, preparation for analysis and modeling	• Development and optimization of algorithms • Integration of the algorithms in applications	• Know-how on algorithms and best practices in ML • Data modeling (esp. predictive and prescriptive analytics)	• Performing the data analysis using statistical and mathematical methods • Preparation of results, often visually

EXHIBIT 23: Biggest skill gap in Data Science



of respondents say it is important or very important but only 22% of respondents have all necessary skills on board). **Machine Learning** as an integral part of Data Science scores slightly better but still indicates an important gap (83% vs 33%).

ONLY 22% OF COMPANIES HAVE ALL NECESSARY DATA SCIENCE SKILLS ON BOARD

Other deficiency themes emerge around **IoT/M2M infrastructure** (17%) and **enterprise system integration** (26%).

Project management seems to be less of a worry in the minds of respondents (67% indicate they have all skills on board).

4.4.2 Deep-dive: Data Science

With Data Science being such an important skill for the success of Industrial Analytics projects, firms need to make recruiting and training for Data Science a strategic priority.

First of all, firms should learn and address the specific needs of data-professionals. Enterprises that have identified analytics to be relevant to their business, typically build specialized business units separate from

IT, BI or business domains, acting as internal analytics service providers.

Research based capability maturity models (e.g., by the International Institute of Analytics) or specified skill & capability assessments (e.g., by the Digital Analytics Association) find their way into the organizational planning and development of these enterprises.

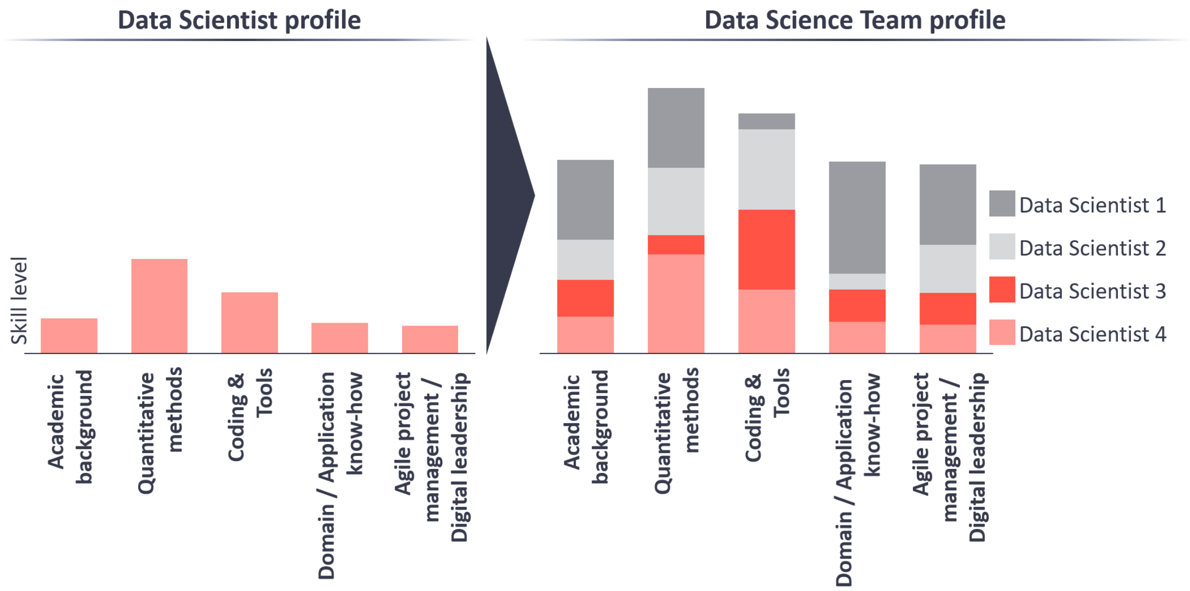
Governments and the education industry is now fostering the development and expansion of data analytics as a profession by itself on various professional levels. The city of Hamburg has for example officially established a vocational training program for digital analysts – on a non-academic level.

Despite strong initiatives on data analytics education a demand-supply mismatch is forecasted for the next decade. [8]

Firms need to realize that the reason why it is so hard to acquire these skills is also related to high expectations towards individual Data Scientists or Data Analysts.

> *It is easy for us to find plenty of skilled Data Scientists who have a solid mathematical background. We struggle, however, to find Data Scientists who can apply this know-how in industrial settings. A Data Scientist who doesn't know what parameters he or she is currently correlating is practically worthless because it usually does not lead to meaningful results.*
>
> **Senior project manager at an industrial optimization consultancy**

EXHIBIT 24: Data Scientist Profile & Data Science Team Profile



A Data Scientist should bring in skills in five distinct functional areas:

- Academic background
- Quantitative methods
- Coding & Tools
- Domain / Application know-how
- Agile project management / Digital leadership

One rarely finds Data Scientists that are rockstars in all of these 5 areas. The key is to build an interdisciplinary team that in total brings in all of these five skills.

A well-working team with a diverse skillset can make a great project team – given that the overall skills are well-balanced across the 5 categories.

4.5 Implementation Challenges

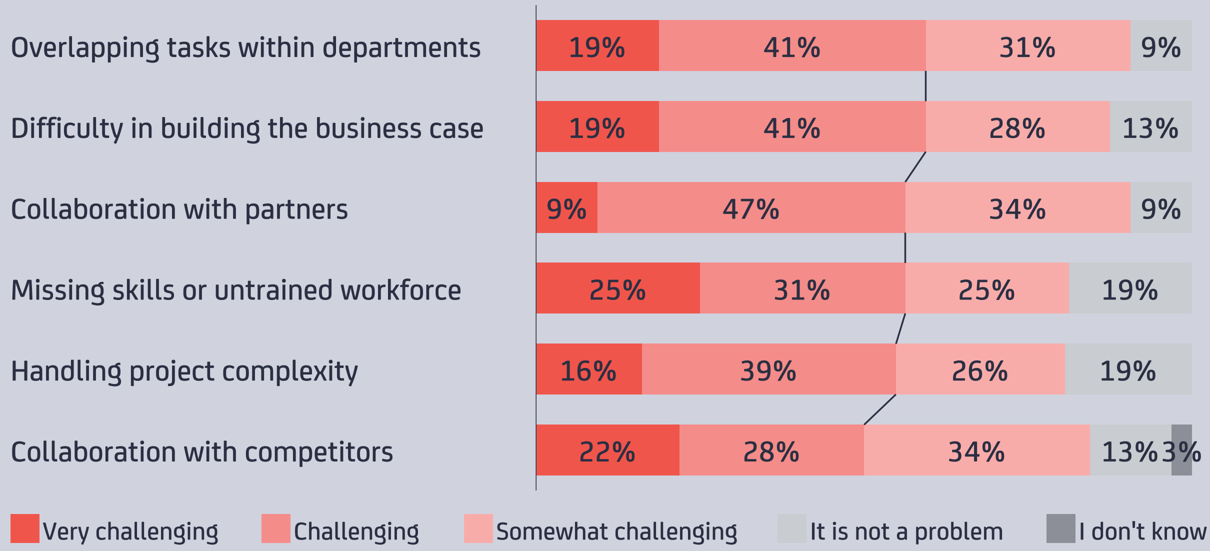
4.5.1 Business challenges

Survey respondents indicate that **overlapping tasks with departments** (60%) and the **difficulty in building the business case** (60%) are the most important business challenges for their Industrial Analytics projects.

Handling project complexity (55%) and **collaboration with competitors** (50%) are less of a challenge. While not a problem for all, "missing skills or untrained workforce" seems to be a major challenge for some companies (25% say it is very challenging – more than any other category).

EXHIBIT 25: Business/Organizational challenges for Industrial Analytics

Question: *How challenging are the following issues within your Industrial Data Analytics projects?*



4.5.2 Technical challenges

In terms of technical challenges, the picture is a lot more diverse. The biggest challenge is clearly the **interoperability between different system** components of the overall data analytics architecture (78%). Both **data accuracy** (62%) and **gaining insights from data** (62%) are further challenges. Gaining **data access** is clearly the least of all technical challenges (42%).

> *We have the data but still struggle making sense of mass data. For example, when a machine breaks down on the shop floor the detailed information of what happened is only available a few hours later when the nightshift needs to understand what happened earlier in the day to avoid further downtime.*
>
> **Production manager at a Food&Beverage firm**

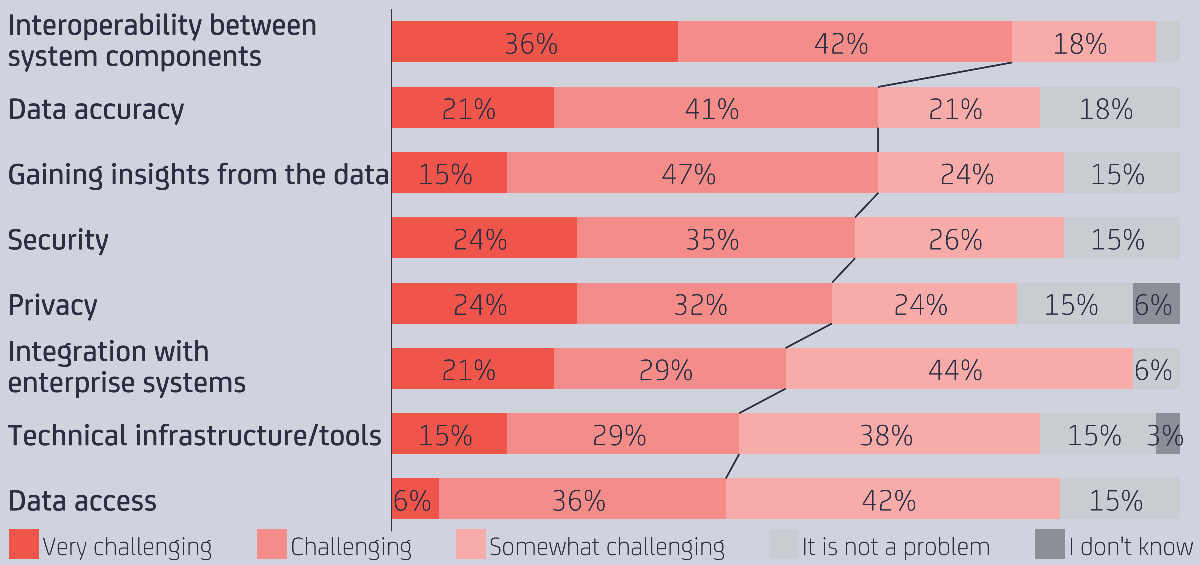
4.6 Further Leadership Recommendations

People engaging in Data Science projects should acquire good know-how in the topics covered in this study, namely: The project approach, the available tools and technology, how to align the organization, which skills to acquire and which challenges to expect and mitigate.

> *The most critical success factor for Industrial Analytics lies in the hand of management: Implementing clearly defined data governance mechanisms and providing guidance through an enterprise-specific code of conduct for all data users.*
>
> **Frank Poerschmann, Board Member Digital Analytics Association Germany e.V.**

EXHIBIT 26: Technical challenges for Industrial Analytics

Question: *How challenging are the following issues within your Industrial Data Analytics projects?*



Additional aspects that have not been covered in the previous chapter are noted below:

1. Shape the digital mindset. Top-level management commitment and incentive structures play a key role in making fundamental changes happen. Executives should:

- Make the broader Digital Agenda a priority for the company, integrate relevant projects into the corporate strategy and communicate actively
- Promote an open and agile attitude that allows for flexibility and promotes failure as a means to achieve the desired goal.
- Build project teams that bring together a diverse skillset
- Invite external partners who help cut through the complexity, bring in external experience and missing skills.
- Promote cross-training and skill enhancement of current employees towards "*digital*" and analytics skills.
- Educate middle and top-management on the new paradigms, limitations, chances and the risks of data driven business
- Initiate a management discussion on the "*role of data in organizational decision-making*" (as data-driven and data-supported decision making puts pressure on managers used to rely on intuition and experience only)

2. Define strategic roles. Build data capabilities in the organization and define ownership for developing the competencies throughout the organization.

3. Start small. Start with single pilots and PoCs (Proof of concept) to learn about the value, processes, and approaches

4. Define a capability roadmap. Derive requirements for the skills needed, technology tools, service providers & overall data ecosystem

5. Embrace a data governance strategy. Define data governance on the top-level and decide on a necessary code-of-conduct for data users (internal & external)

6. Perform a support function enablement. Build channels within procurement for high-speed activation of external data and analytics services. Involve progressive, data-business experienced legal advisors in business development teams. Integrate data analytics development in HR, run a skill assessment and develop a capability development plan on organizational and individual level.

YOUR INDUSTRIAL ANALYTICS INVOLVEMENT

If you liked the Industrial Analytics Report or if you are interested in a content-related discussion on any of the topics covered in this study, feel free to reach out to the authors at IoT Analytics, the Digital Analytics Association, or the study sponsors.

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6 Appendix

6.1 Methodology of the Study

6.1.1 General

The study was conducted between April to August 2016. Its content is made up of four parts

1. General research from books, publications, and the internet

2. Results of recent research performed by IoT Analytics on the topics of Industry 4.0, IoT and Analytics

3. Results from 8 industry expert interviews who provided deep insights into the area of Industrial Analytics

4. Results from an industry survey of 151 industrial decision makers

All content was reviewed and approved by the Industrial Analytics Steering Committee of the Digital Analytics Association Germany.

6.1.2 Survey

The survey presented in this study polled the opinion of 151 business executives in the area of Industrial Analytics. 20 individual questions were displayed with varying degrees of detail. Please find below detailed information on the survey participants:

EXHIBIT 27: Question: What type of organization do you represent? N=151

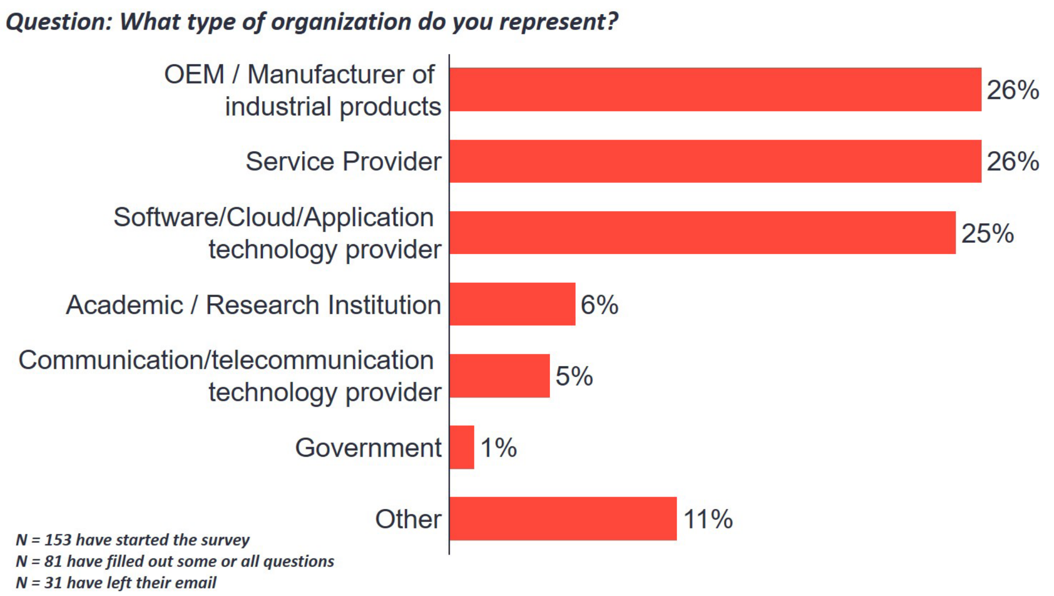


EXHIBIT 28: Question: In which sectors is your company mainly active?

EXHIBIT 29: What is the size of your company / organization? – Number of employees

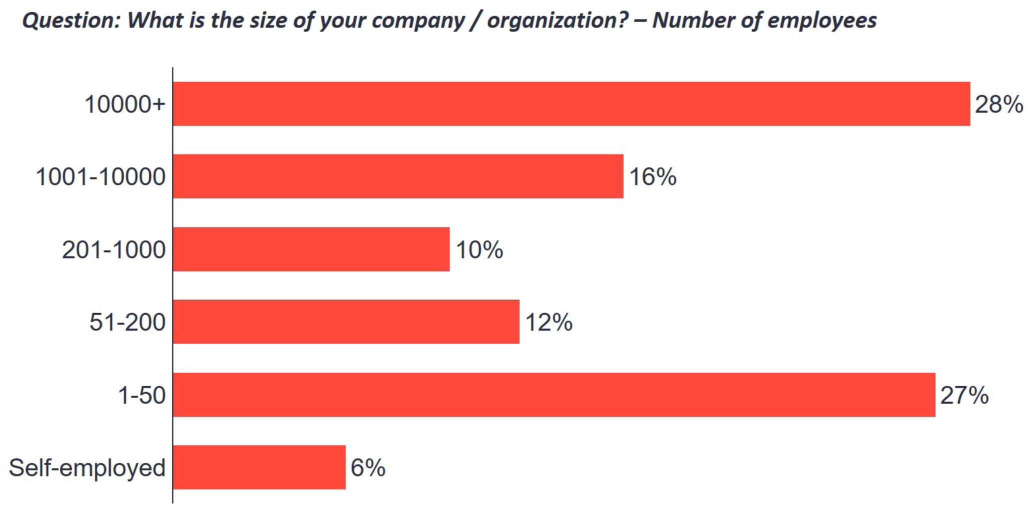


EXHIBIT 30: Question: What best describes your current position in your company?

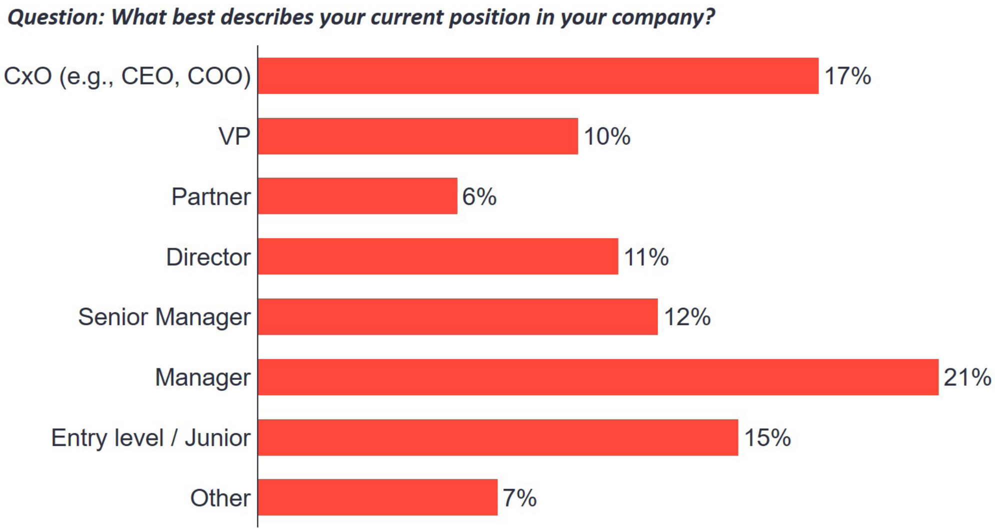


EXHIBIT 31: Question: In which department do you work?

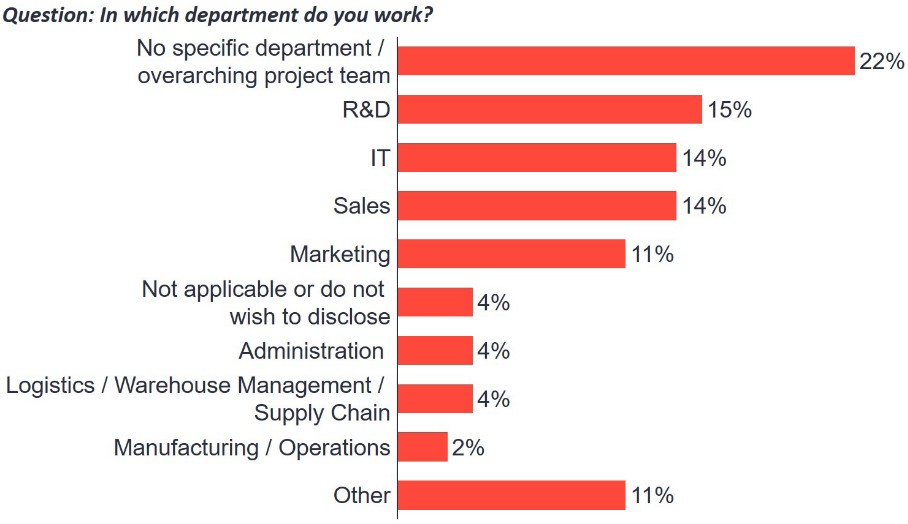
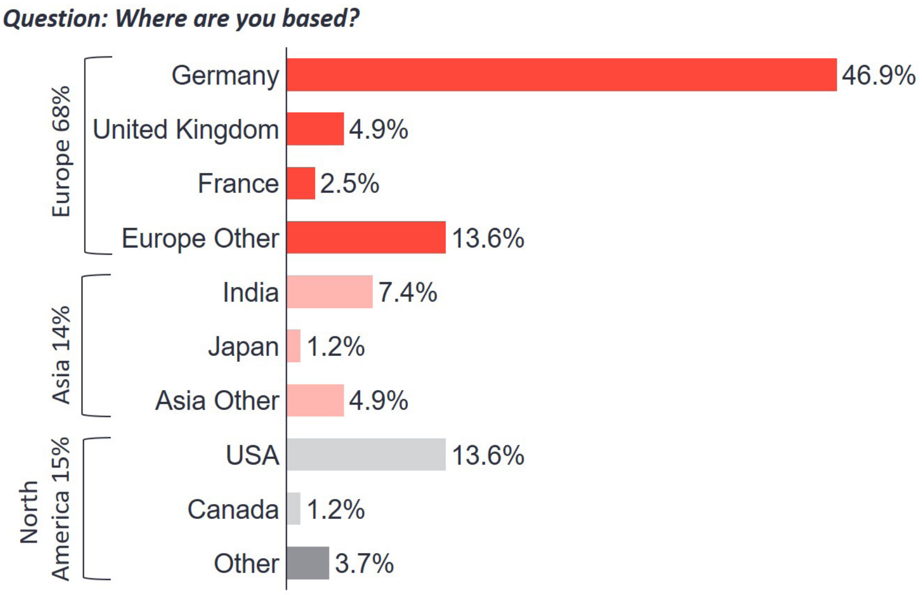


EXHIBIT 32: Question: Where are you based?



6.2 About Digital Analytics Association Germany e.V.

DIGITAL ANALYTICS ASSOCIATION GERMANY

For more than 10 years the Digital Analytics Association with its more than 5.000 members globally drives the professionalization of data-driven professions. As an independent, non-for-profit organization this engagement is carried out in Europe by the "*Digital Analytics Association e.V.*"

DAA e.V. activities are focused on the development of digital competencies, especially in digital-analytics and data-science, for institutions, experts and management. A major emphasis lies on the development and promotion of young professionals. The services of the DAA cover professional qualification, networking, digital-leadership development and knowledge transfer.

6.3 About IoT Analytics

IOT ANALYTICS

IoT Analytics is the leading provider of market insights and industry intelligence for the Internet of Things. More than 30,000 IoT decision makers rely on IoT Analytics' data-driven market research every month. IoT Analytics tracks important data around the IoT ecosystem such as M&A activity, startup funding, job developments, and company activity. The product portfolio includes: 1. Free insights on IoT markets and companies, 2. Focused market reports on specific IoT segments, 3. Go-to-market services for emerging IoT companies. IoT Analytics is headquartered in Hamburg, Germany.

You may get directly in touch with the main author:

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6.4 Special thanks

The editorial team would like to thank all of those who have been instrumental in getting this study published, namely:

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- **Michaela Tiedemann** - Alexander Thamm Data Science GmbH

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- **Alexander Thamm** - Alexander Thamm Data Science GmbH
- **Peter Sorowka** - Cybus GmbH
- **Frank Poerschmann** - Digital Analytics Association e.V.

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