Institute of Technology Management

University of St.Gallen

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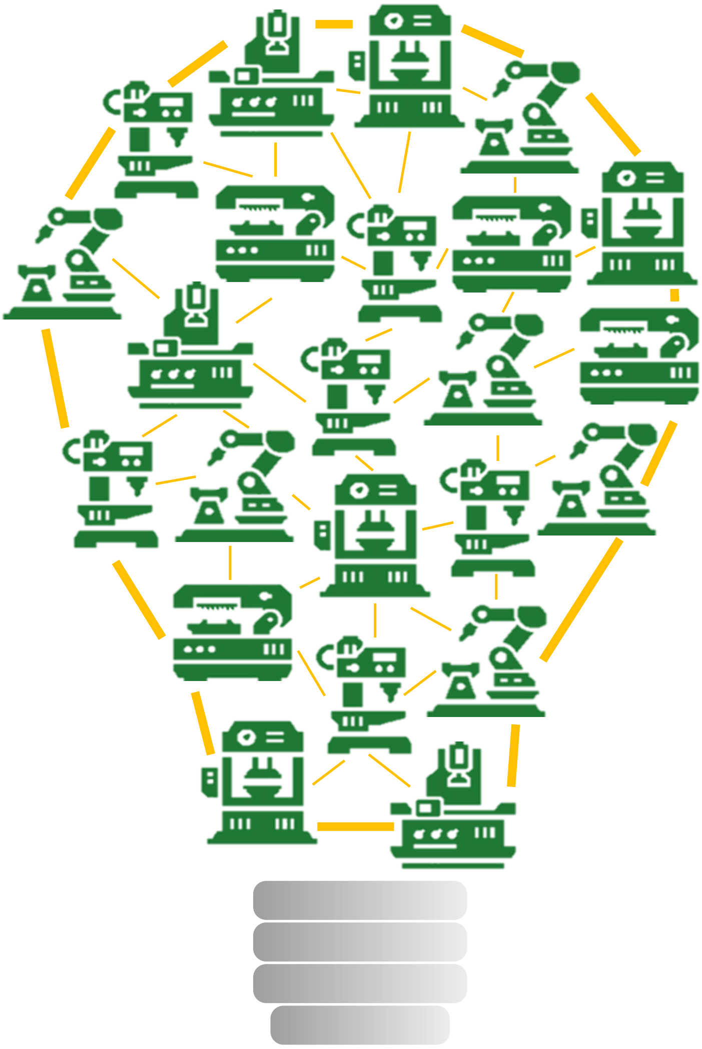

Industry Study 2016

Manufacturing Data Analytics

Personalized Report for

General Report

"From insight to impact"

Preface

Over the last few years, the data volume in manufacturing has exploded. Industry 4.0, Big Data, and the Internet of Things are predominant keywords. Through embedded sensors and other technologies, many global manufacturers are already able to gather and store large amount of data generated on their shop floor. The analysis and synthesis of this raw data can support making better business decisions - often referred to as Data Analytics. However, despite the abundance of real-time data, manufacturers struggle to unleash the full potential of their data and to turn this asset into a competitive advantage.

In the present study, we take a close look at the current situation of Manufacturing Data Analytics – focusing on three different aspects:

- Data Analytics Strategy and Organization within manufacturing companies
- Manufacturing Data Characteristics, existing Systems and Capabilities
- Business Performance Impact of Manufacturing Data Analytics

The results of this study show existing barriers and action fields for future research. We see this as a first step on the way to Data-based Manufacturing, that will help manufacturing companies to strengthen their competitive position through increased quality and productivity.

Best Regards,

Prof. Dr. Thomas Friedli
Director Institute of
Technology Management

Prof. Dr.-Ing. Robert Schmitt
Director Laboratory for Machine
Tools and Production Engineering

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What differentiates Advanced Analytics Companies*?

Executive Summary

DEFINED FOCUS AREAS

Advanced analytics companies have conducted a make-or-buy analysis and clearly defined a strategy that defines capabilities will be developed in-house and which part will be sourced externally from third party service providers. Defined focus areas help to focalize limited resources on the development of needed core competencies.

AWARENESS OF USE CASES

Formulating hypothesis and as such defining potential use cases for your data is an important prerequisite for all following steps. “Use cases” define early on which data needs to be captured and processed. Creativity as well as a good market intelligence for existing solutions are key.

QUALIFIED EMPLOYEES WITH STRONG PROCESS UNDERSTANDING

In times of increasing automation and digitalization, comprehensive process understanding of employees is dwindling. Advanced analytics companies make process understanding a key priority, invest in employee capability building and even hire additional specialists.

TOP-MANAGEMENT SUPPORT

Top-management support is a huge enabler. Projects and investments are easier to pass with top-management support. Advanced analytics companies show a significantly higher involvement of top-management functions than companies that still prevail in the phase of descriptive or diagnostic analytics.

COLLABORATE WITH KEY PARTNERS

Interaction and exchange with partners along the value chain, including customers and suppliers, but also with other companies, are crucial for the successful implementation of Data Analytics. To form a strong knowledge base most companies also engage in projects with consultants and research institutes.

*Advanced Analytics companies: predictive, prescriptive applications

DATA QUALITY REQUIREMENTS

Advanced analytics companies have strong requirements on quality of their manufacturing data. None of the Advanced analytics companies indicates that all needed data is available in the desired form. Thus, advanced analytics methods require more specific data since data quality is a major barrier.

INTEGRATED SYSTEMS

For a successful application of Data Analytics, integrated storage systems are fundamental. A common data base serves as the “Single Source of Truth” for all further processing and exploitation steps and enable a broad range of different application scenarios.

DIGITIZATION AND AUTOMATION

Digitization and automation facilitate especially the first three steps of Data Analytics – collection, storage and processing of data. Advanced Analytics Companies have already implemented digitized and automated processes for Data Analytics on the shop floor.

REAL-TIME ANALYTICS

Data Analytics can support business decisions in manufacturing. Advanced analytics companies already use real-time data and seek to integrate the decision making into the processes. Thus, reaction times can be minimized and inefficiencies directly avoided.

BUSINESS PERFORMANCE IMPACT

Advanced analytics companies better succeed in supporting business goals with Data Analytics. Costs could already be significantly reduced and quality could be improved. Nevertheless, successful companies see much more potentials in applying Data Analytics in manufacturing for the future .

Key Facts

Executive Summary

100 participants

42 Companies make use of descriptive analytics

39 Companies make use of diagnostic analytics

15 Companies make use of predictive analytics

4 Companies make use of prescriptive analytics

11 countries

are represented in the sample, nevertheless the majority of participating companies is located in the DACH-Area

52.0% of all participants have been working for more than 3 years on Data Analytics in manufacturing

89.4% of advanced analytics companies think that Data Analytics will change the manufacturing landscape extensively

5.5% of the available manufacturing data base is exploited for decision support

“Data Analytics will be pivotal to fully understand the physical processes in manufacturing (e.g. metal forming) and to reach new quality levels as a result.”

Robert Cisek
General Manager Production Press Lines
BMW AG

Asking companies how they perceive the overall impact potential of Data Analytics in manufacturing, a large proportion sees a significant chance that Data Analytics will change manufacturing extensively. More than 90% of the respondents estimate this potential as more than five on a seven-point Likert scale.

FIGURE 0.1
IMPACT POTENTIAL OF DATA ANALYTICS IN MANUFACTURING
n= 42

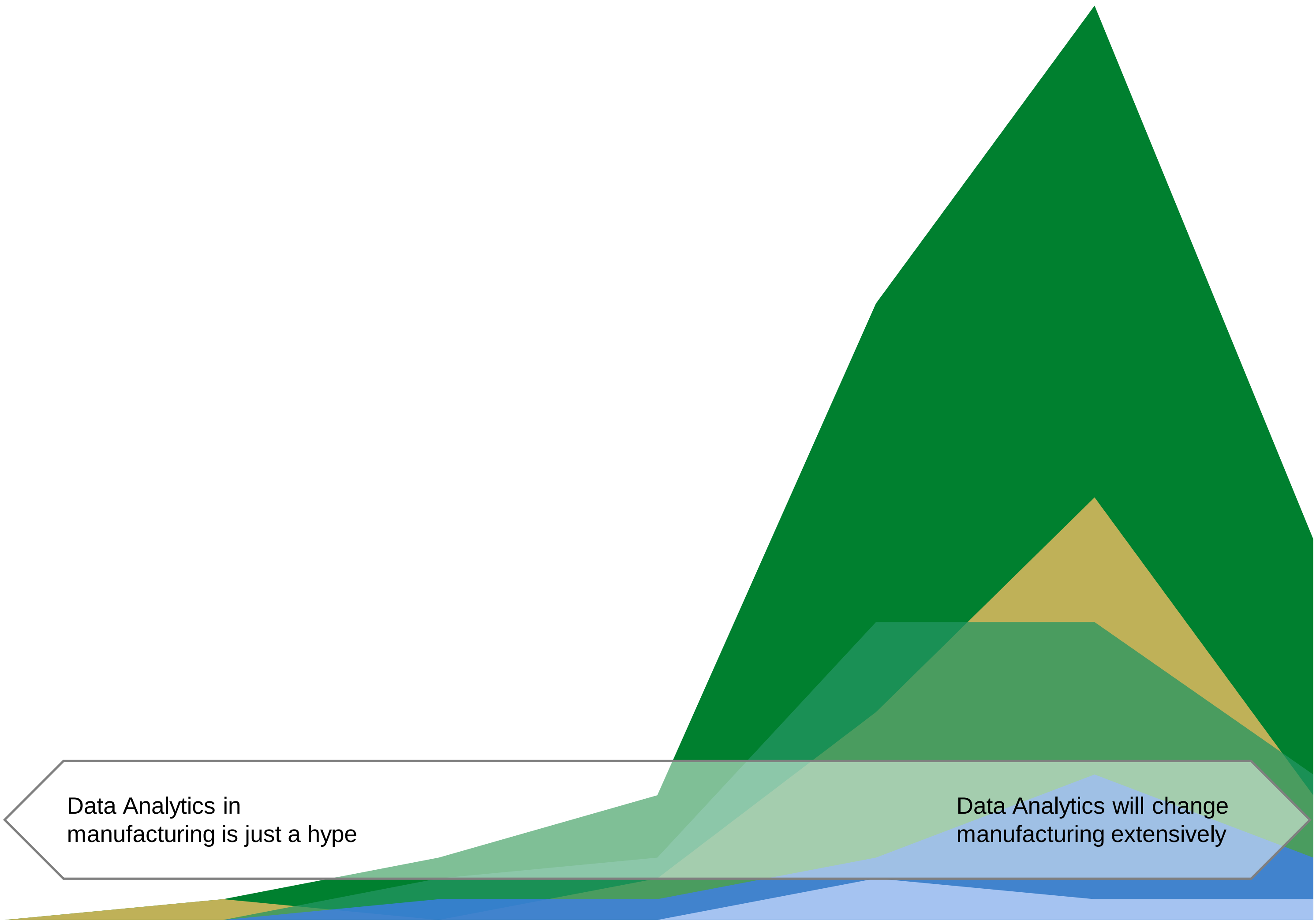
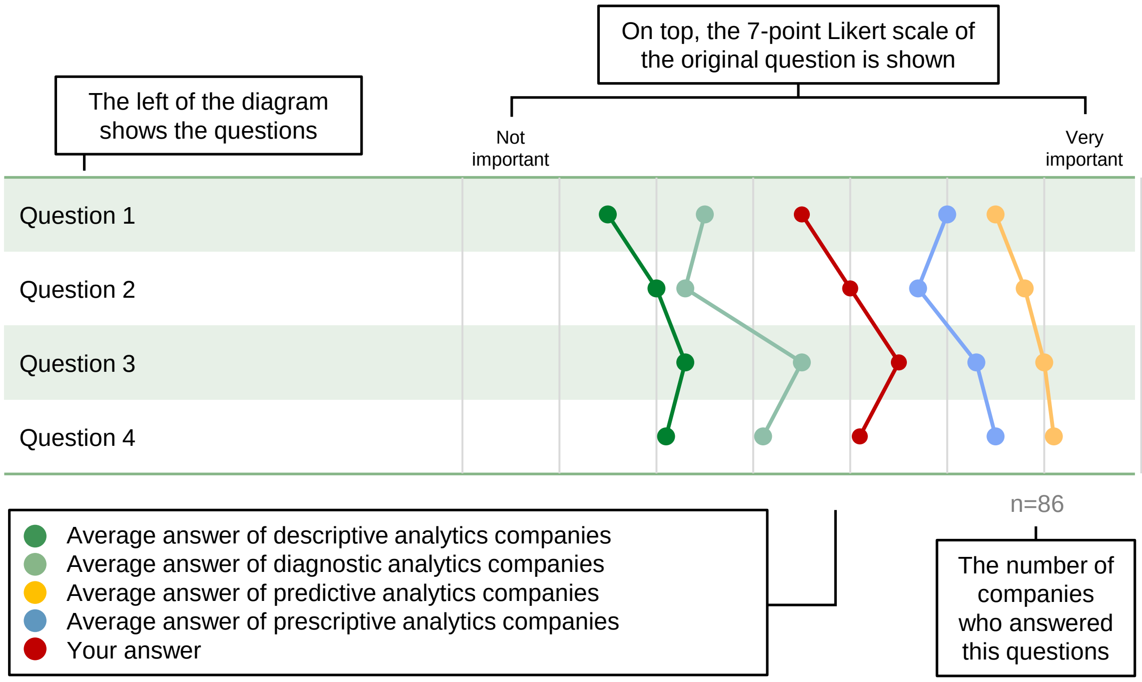


Diagram Types and Colours

Questions using a 7-point Likert Scale

Answers to questions with a 7-point Likert scale are usually displayed using a line chart. Overlapping answer points can be deduced from the used lines.

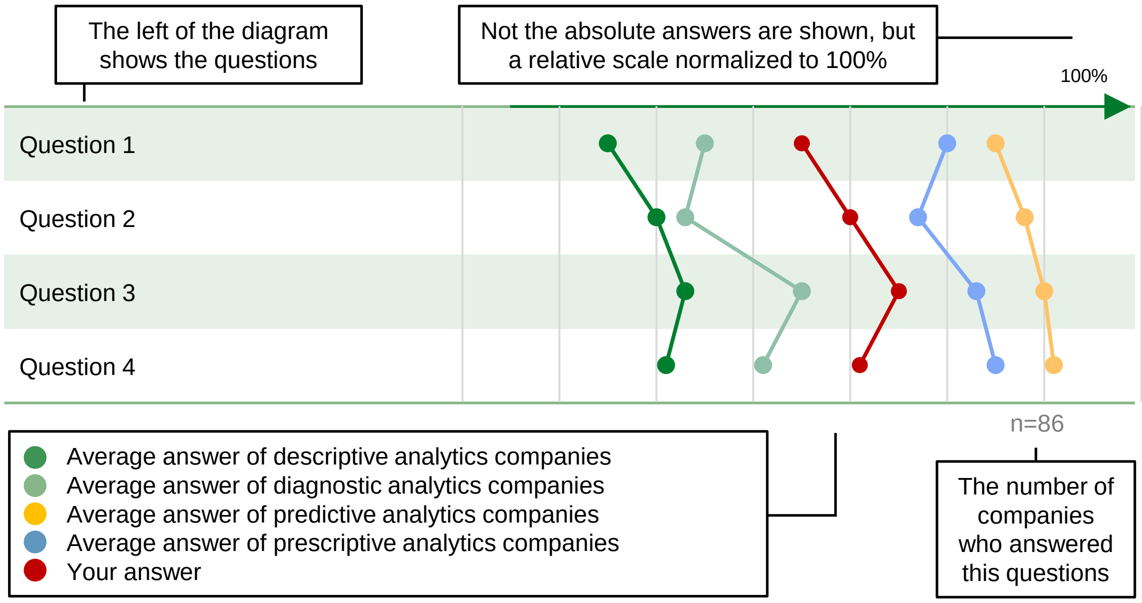
FIGURE 0.2
EXPLANATION OF LIKERT SCALE TYPE DIAGRAMS



Checkbox Questions

Answers to checkbox questions are also usually shown using a line chart. As multiple answers are possible in many cases, the scale is adjusted to 100% showing the percentage of all answers within a category.

FIGURE 0.3
EXPLANATION OF CHECKBOX DIAGRAMS



Trade-off Questions

Trade-off question visualizations show the distribution of all answers. This means that the vertical axis displays the percentage of answers of each group, not the total number of answers.

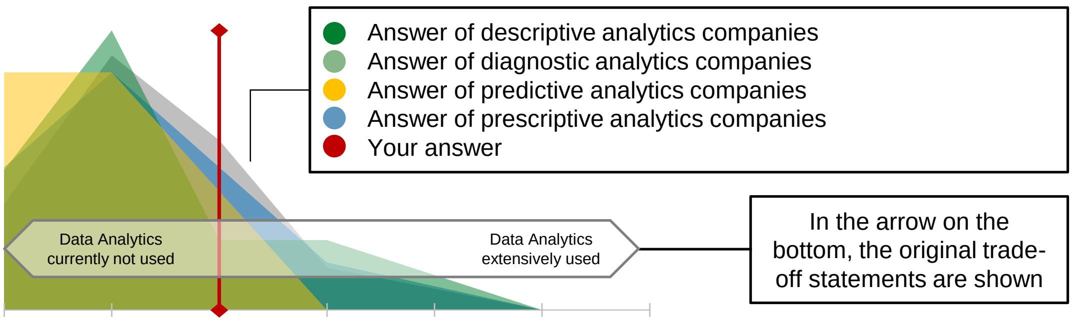


FIGURE 0.4
EXPLANATION OF DIAGRAMS FOR TRADE-OFF QUESTIONS

Competitive Priorities

To display ranking of competitive priorities, a radar chart (*also called spider chart*) is used to plot the values of each category along a separate axis that starts in the centre of the chart and ends on the outer ring. A point close to the centre on any axis indicates a low value. A point near the outer ring is a high value. When you interpret a radar chart, check each axis as well as the overall shape.

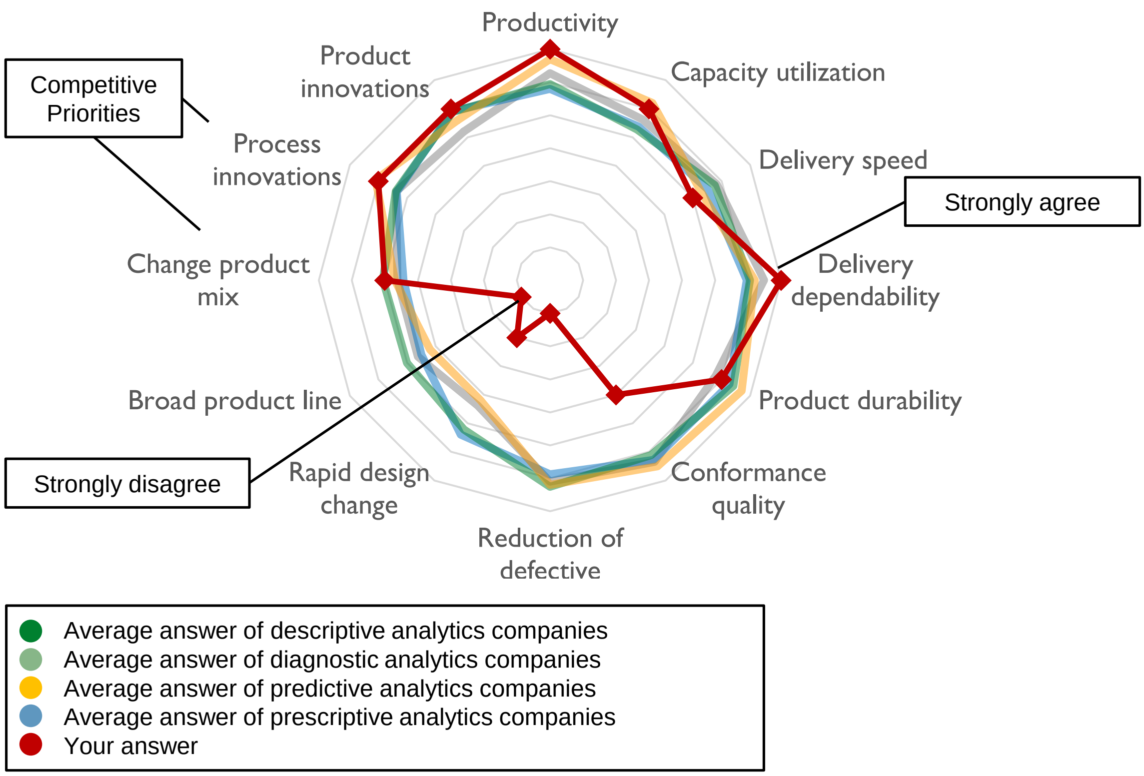


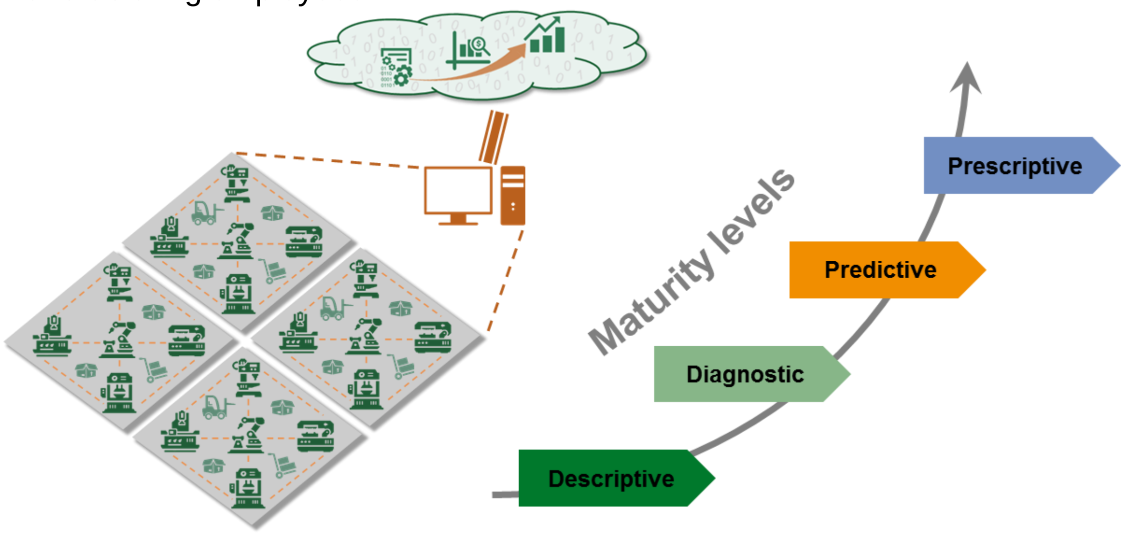
FIGURE 0.5
EXPLANATION OF DIAGRAMS SHOWING COMPETIVE PRIORITIES

Introduction

Data Analytics describes the process of turning data into information and finally into new insights and knowledge to support better business decisions. In this study, strategical and organizational aspects are examined as well as operational aspects. Therefore, the Data Analytics process is subdivided into four steps – data acquisition, data storage, data processing and finally data exploitation. In some industries, advanced data analytics methods are already the “state-of-the art”, e.g. targeted advertising and online marketing. Despite optimized analytics methods and a successively increasing data base, manufacturing companies still struggle to unleash the full potential of their data and to impact their business performance.

This study examines the current status in Manufacturing Data Analytics and focuses on shop floor data – meaning data which arises within manufacturing processes. These data comprise process data in e.g. manufacturing, transportation and storage as well as inspection data or tracking and tracing data. It could be collected through embedded sensors or even manually by manufacturing employees.

FIGURE 0.6
STUDY FOCUS AND MATURITY LEVELS



According to the existing literature, Data Analytics approaches and application scenarios can be categorized into four different maturity levels – descriptive, diagnostic, predictive and prescriptive analytics. Descriptive analytics uses data to answer the question “What happened?”, while diagnostic analytics aims to find causes and effects answering the question “Why did it happen?”. Predictive and prescriptive analytics go one step further, while trying to forecast future scenarios. Predictive analytics gives an answer on “What is likely to happen?”. Prescriptive analytics aims to give decision support for predicted scenarios (“What should be done?”). Due to its huge reputation, these maturity levels are tools to categorize the participating manufacturing companies. In this study advanced analytics companies already implement predictive and prescriptive analytics in different application scenarios.

This Report

The report at hand presents a personalized analysis of your current state in this field compared to the other 99 participants. We hope that you find this a helpful tool to better understand what to do in order to capture the value of your manufacturing data. It contains all our descriptive findings and also some additional information on Manufacturing Data Analytics.

The analysis is structured as follows:

I Peer Group Characteristics

Statistics and information on the participants

II Strategy & Organization

Strategic and organizational perspectives

III Data, Systems, & Capabilities

Positioning in a technical process of Data Analytics

IV Business Performance Impact

Value of Manufacturing Data Analytics in a business context

V Conclusion & Outlook

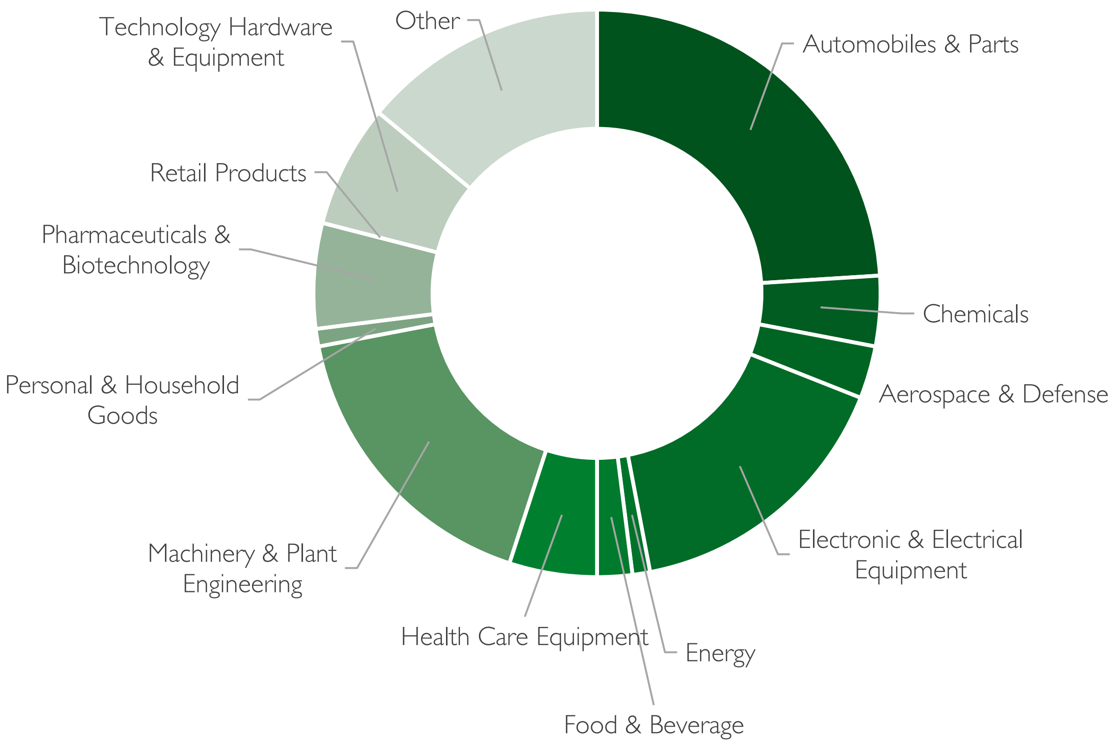
Bottom line and future perspectives

I Peer Group Characteristics

In the first section of the benchmarking questionnaire, characterizing elements of the participating companies were enquired. The following pages in this chapter give insights into the composition of the benchmarking sample regarding size, industry and competitive positioning.

Participating companies originate from a wide range of industries. Predominantly presented are the Automobile & Parts industry, Electronic and Electrical Equipment industry as well as the Machinery & Plant Engineering industry.

FIGURE I.1
INDUSTRIES OF BENCHMARKING PARTICIPANTS



According to the Industry Classification Benchmark, most of the manufacturing industries are represented within the study sample. The only prerequisite for participation was an own manufacturing process, whereby manufacturing in this study means the transformation process from physical inputs to physical outputs. Service companies and providers were not focus of this study. Finally, the wide range of participating manufacturing industries and the sample size and structure guarantee a broad validity of the results and should give a good overview about the current state in the manufacturing industry.

The following chart shows the product type of the participants. It is obvious that companies producing for the B2B (business-to-business) segment dominate the sample compared to B2C (business-to-customer) or B2G (business-to-government). Multiple answers were possible.

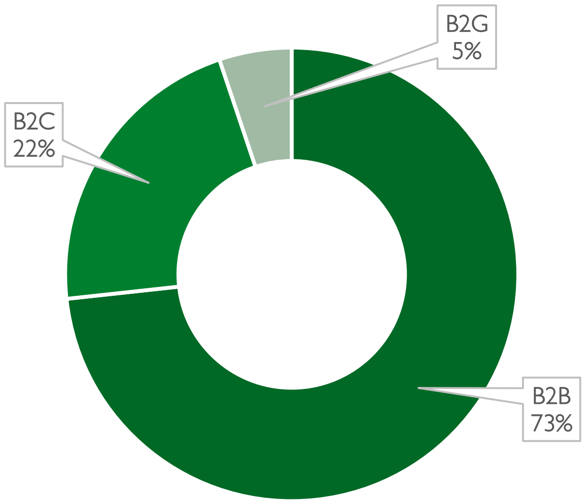


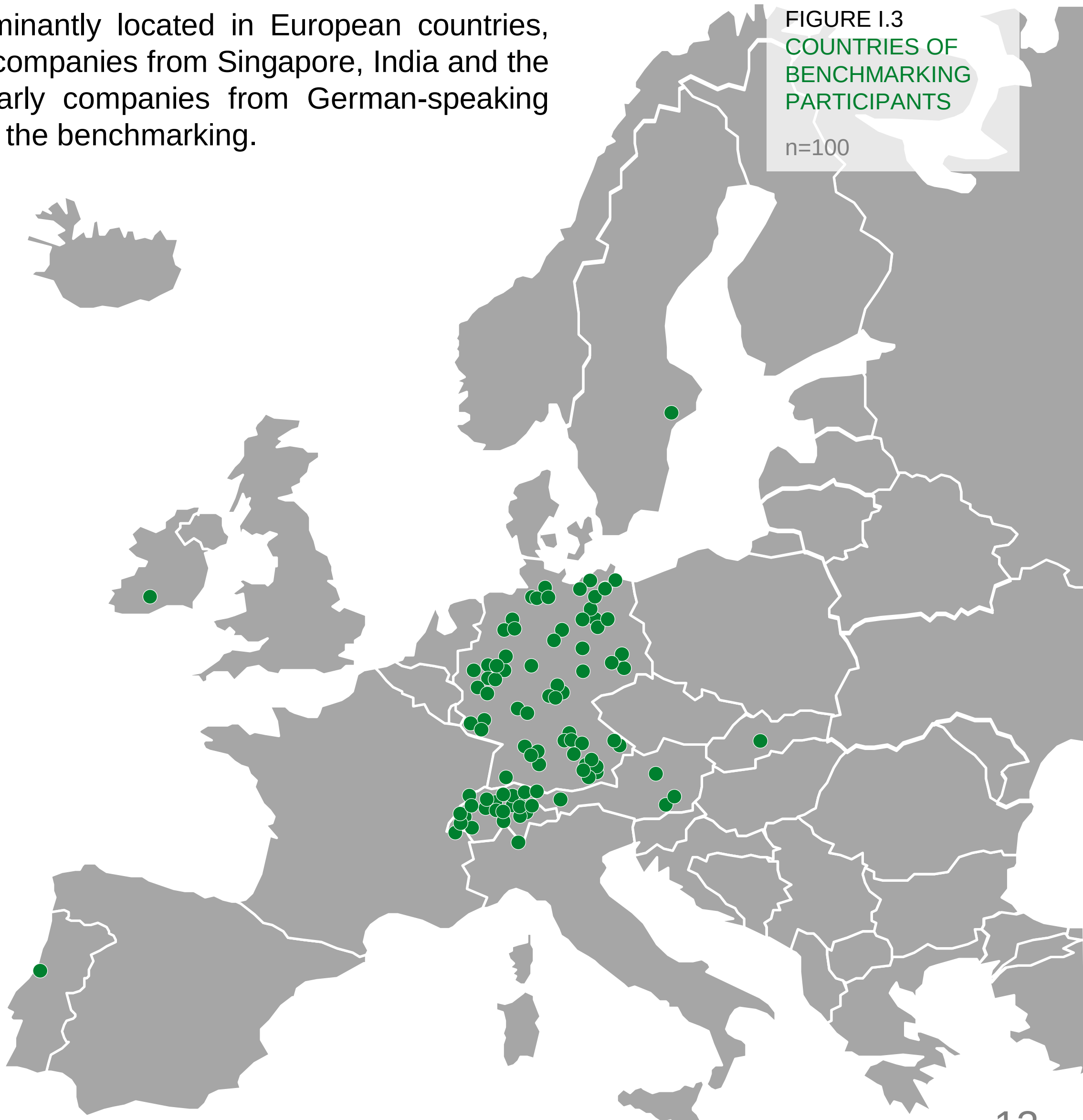
FIGURE I.2
PRODUCT TYPE
multiple answers

Participants are predominantly located in European countries, besides non-European companies from Singapore, India and the United States. Particularly companies from German-speaking countries participated in the benchmarking.

FIGURE I.3
COUNTRIES OF BENCHMARKING PARTICIPANTS

n=100

Germany	73
Switzerland	15
Austria	3
Liechtenstein	2
Sweden	1
Ireland	1
Portugal	1
Slovakia	1
Singapore	1
India	1
USA	1



Participating companies are evenly distributed in terms of customer order decoupling point. 23% of companies produce products to stock, 35% make-to-order, 19% assemble-to-order and 23% engineer-to-order. Companies with a late stage customer decoupling point are assumed to be ahead in data analytics, because they have a higher process repetition and can rely on a continuous production process. This facilitates the capture of large data samples for analysis. Especially, industries producing high value products which cannot be recycled or reworked in the case of occurring failures during production, benefit from data analytics applications. Additionally industries, in which product characteristics are hard to measure, can gain advantages by predicting product quality on the basis of process parameters. Electronics manufacturing and production of biological products in the pharmaceutical industry serve as good examples.

FIGURE I.4
CUSTOMER ORDER DECOUPLING POINT
n=100

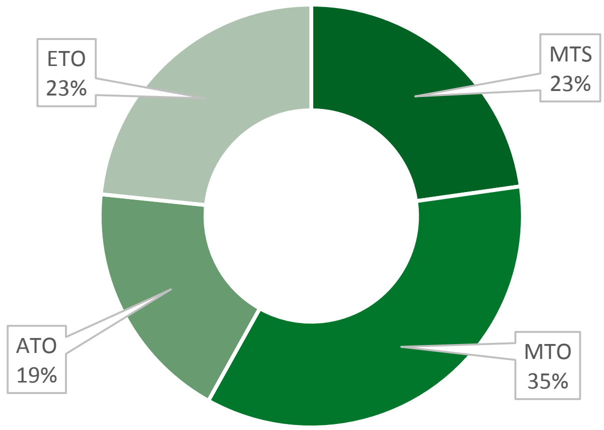
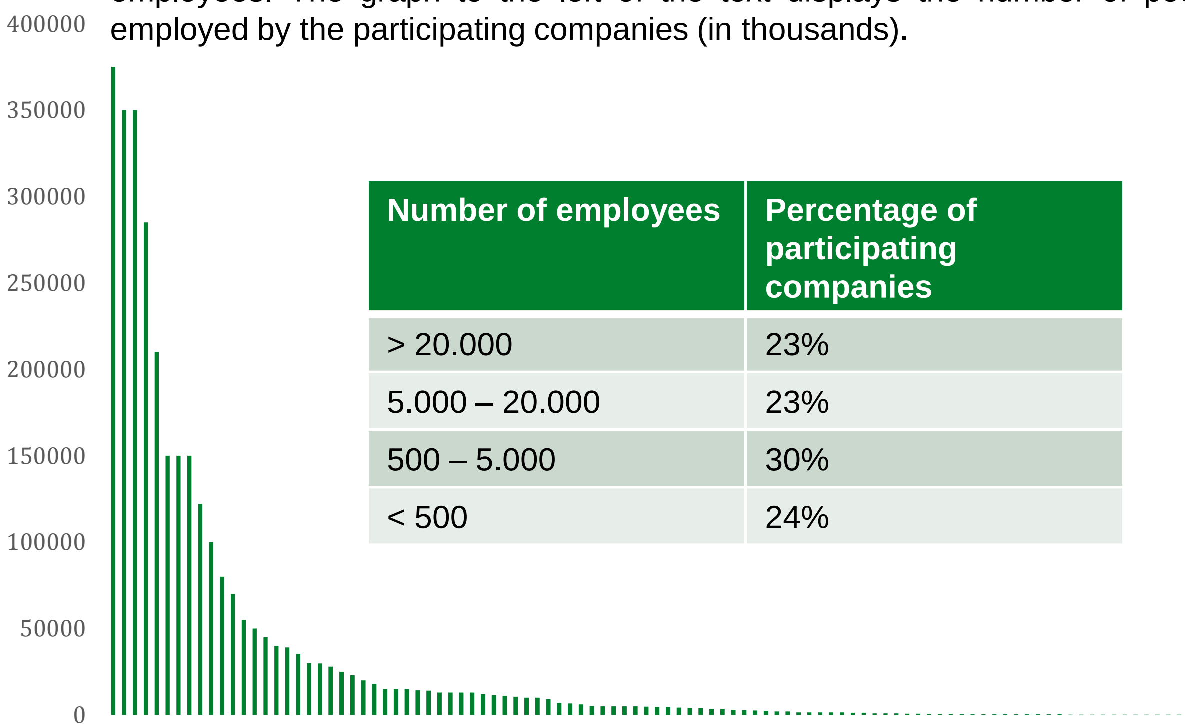


FIGURE I.5
NUMBER OF EMPLOYEES (FULL-TIME-EQUIVALENTS)
n=100

Participating companies range in size from multinational corporations with a maximum of 375,000 employees to relatively small companies who employ only a few hundred people. Approximately 23% of participants represent companies with more than 20.000 employees, 23% of participants employ 5.000 – 20.000 employees, further 30% of participating companies employ 500 – 5.000 employees and 24% of the sample represent companies with less than 500 employees. The graph to the left of the text displays the number of people employed by the participating companies (in thousands).



Number of employees	Percentage of participating companies
> 20.000	23%
5.000 – 20.000	23%
500 – 5.000	30%
< 500	24%

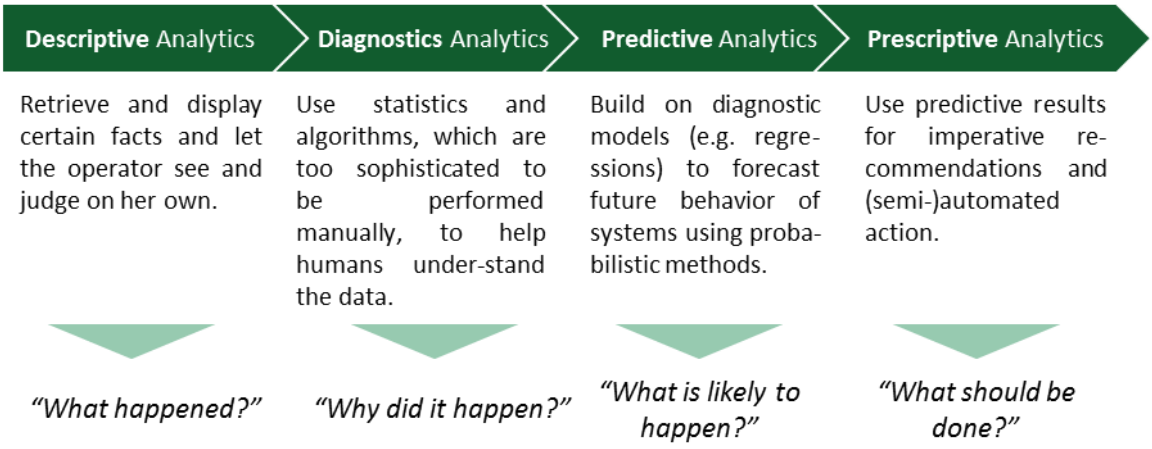


FIGURE I.6
MATURITY OF DATA ANALYTICS – EXPLANATION
n=100

Figure I.6 again explains the four different maturity levels of data analytics, namely descriptive, diagnostic, predictive and prescriptive analytics. These explanations were used as the basis for a self-assessment of all participants. The first two stages cover the aggregation and analysis of historic data, but bear no relations to future events and incidents. The two later stages are characterized by future predictions based on historic data. In the Following, companies that have successfully mastered the two later stages are classified as advanced analytics companies.

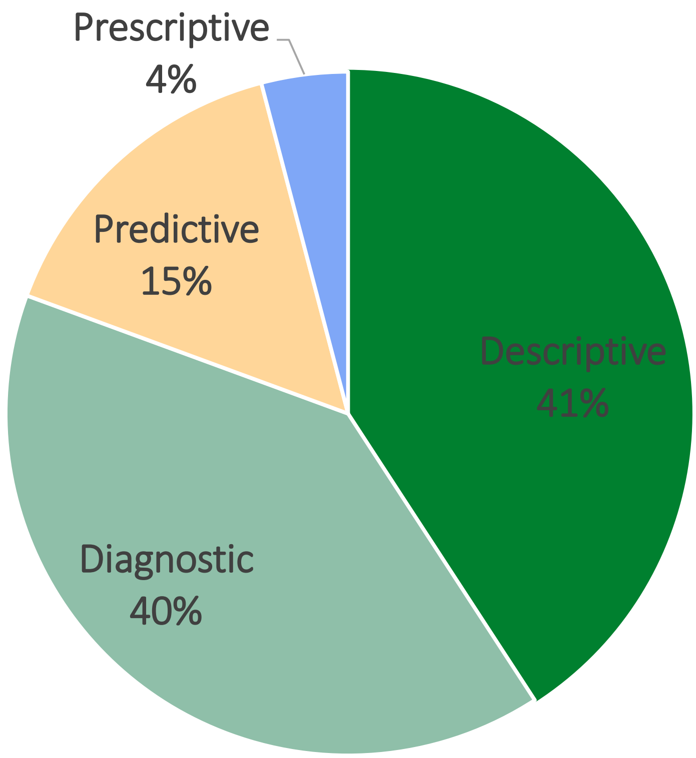


FIGURE I.7
MATURITY OF DATA ANALYTICS
n=100

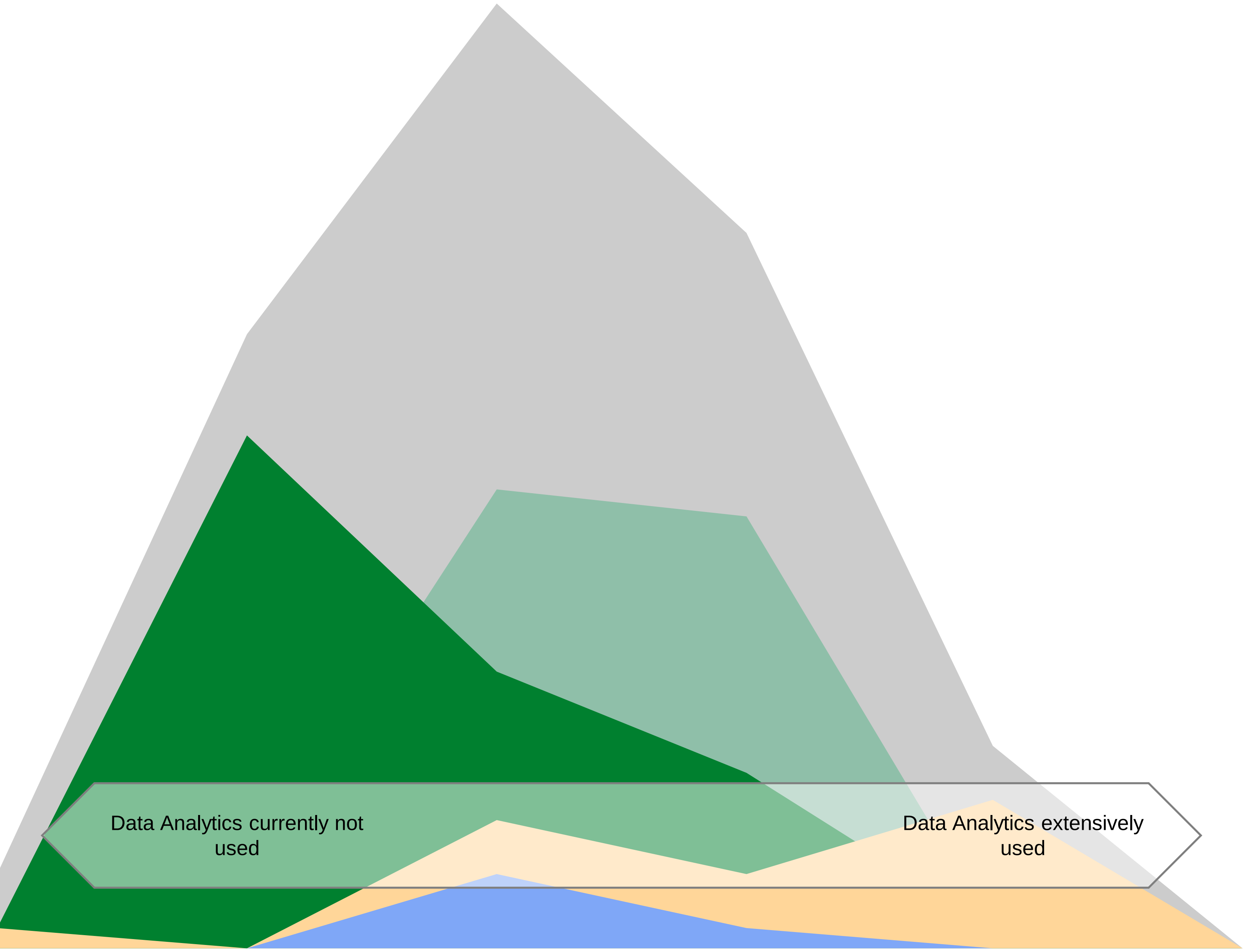
The majority of the participating companies (81%) are until today in the stages of descriptive or diagnostic analytics and so far do not make use of any kind of predictive analytics. Approximately every 5th (19%) participating company can be considered to have reached a stage of advanced analytics (predictive and prescriptive analytics). Still, a differentiation between advanced analytics companies has to be made. Most advanced analytics companies have applied predictive models on their manufacturing shop floor. But when it comes to recommendations for action and decision-making, they still rely on human capital instead of (semi-)automated actions.

"With increased automation levels (Industry 4.0), data driven decisions (i.e. Data Analytics) will become more important, as there are less human operators in the shop floor who can make decisions."

Karsten Schmidt
Senior Staff Engineer
Infineon

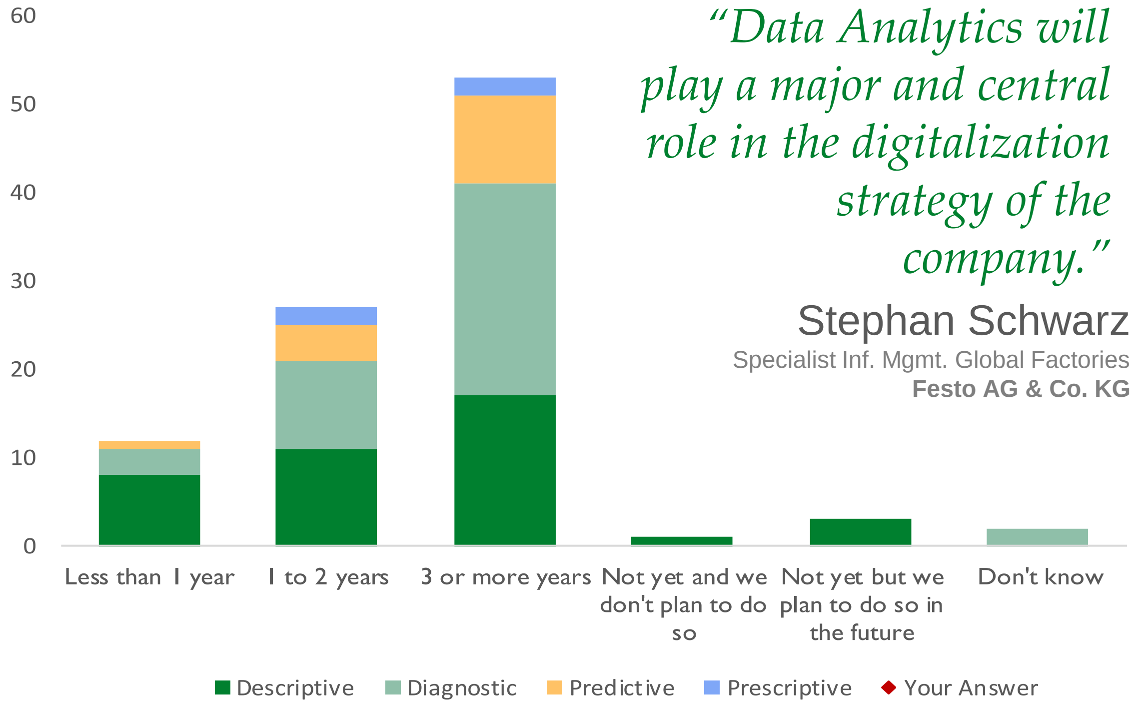
FIGURE I.8
USAGE OF DATA ANALYTICS

n=100



II Strategy & Organization

This section of the questionnaire is of largely qualitative nature. It inquires time, organizational, and strategic characteristics of Manufacturing Data Analytics in the company’s framework. Special aspects include the kind of strategy (directional approach: top-down, bottom-up, etc., and business level: corporate, functional, etc.) and institutionalization (shared services, center of excellence, etc.) of the company´s approach to Manufacturing Data Analytics. Furthermore, hierarchies, cross-functionality, and collaboration are addressed as parts of the organizational and strategic picture. This information may provide insights into how far Manufacturing Data Analytics is already anticipated in an organizational manner.



“Data Analytics will play a major and central role in the digitalization strategy of the company.”

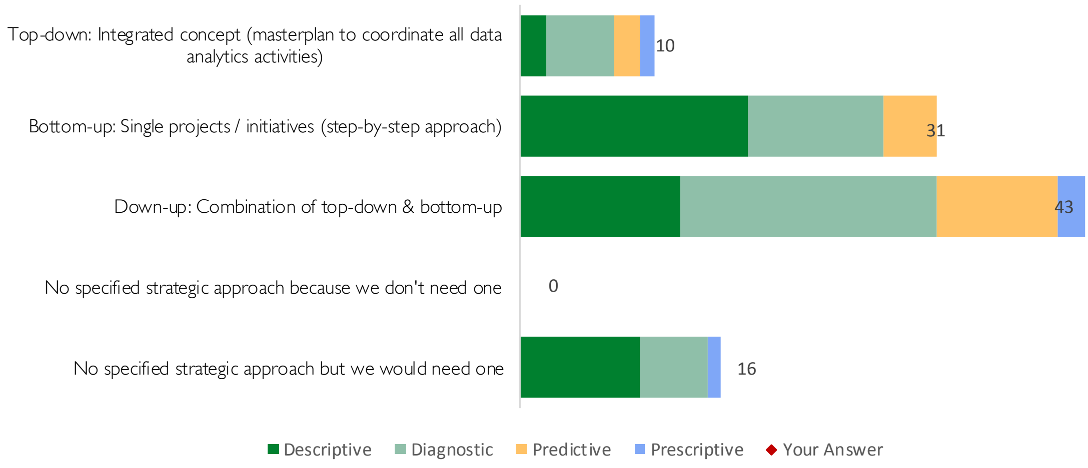
Stephan Schwarz
Specialist Inf. Mgmt. Global Factories
Festo AG & Co. KG

FIGURE II.1
YEARS OF ACTIVITY IN THE FIELD OF SHOP-FLOOR DATA ANALYTICS

n=100

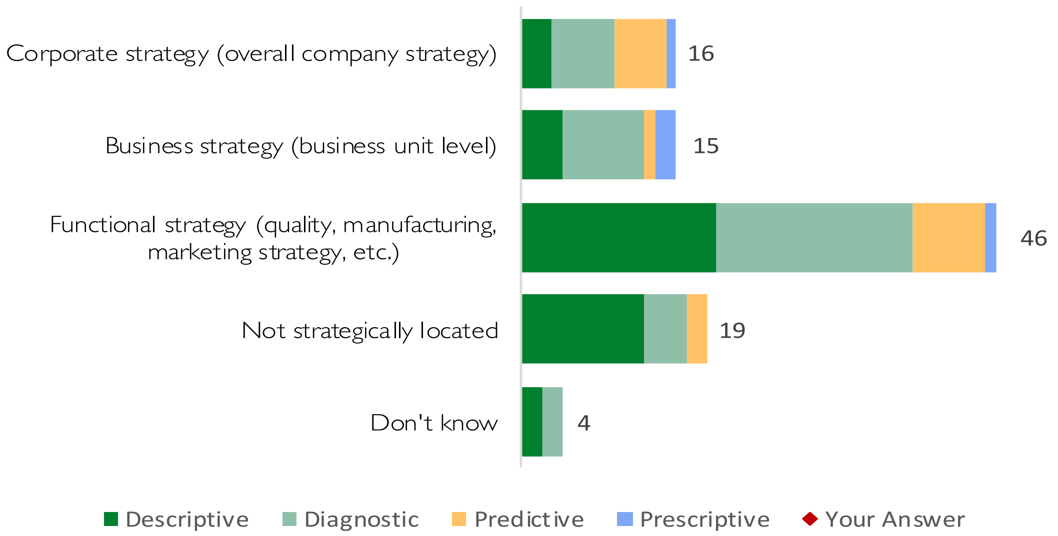
Despite the fact that more than 50% of respondents state that they have been active in the field of Manufacturing Data Analytics for more than 3 years, the majority of the participating companies has been unable to exceed the level of diagnostic analytics. This evokes the hypothesis that the transition from diagnostic to predictive analytics is a quantum leap for most organizations. The change from a historical perspective to a future orientation of manufacturing data application remains a significant challenge. Companies that have been engaged in the field of Manufacturing Data Analytics for a long time do not necessarily exhibit higher degrees of maturity. The sample contains companies in the early stage of data analytics, even after years of application and companies that have reached the predictive level within a reasonable short amount of time. Hence, a relationship between the degree of maturity and the time of engagement in this field has not been found yet.

FIGURE II.2
DATA ANALYTICS STRATEGY
n=100



When it comes to the applied strategic approaches, a strong differentiation between companies can be observed. However, it has to been acknowledged that 84% of all participants claim to have a strategy for data analytics in place and even the 16% that do not, are aware that this is essential for the future. The majority of companies decided on a down-up strategy as a combination of top-down and bottom-up strategy. Usually, first pilot projects are initiated on a shop floor level. Successful pilot projects are then scaled-up in the organization. Different on-going activities are aligned top-down to avoid the duplication of activities.

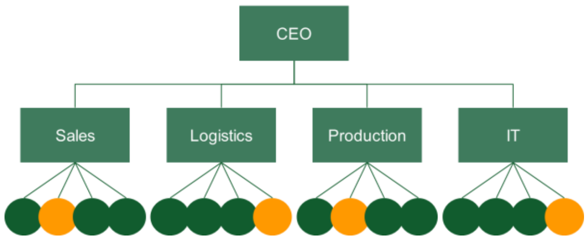
FIGURE II.3
ORGANIZATIONAL INTEGRATION
n=100



The majority has integrated manufacturing data analytics into one of their functional strategies. Nevertheless, many companies have also integrated manufacturing data analytics in higher level strategies such as business unit or corporate strategy. Again advanced analytics companies are evenly distributed and cannot be associated with only one distinct level of strategy, even though they represent a major fraction in the companies who anchored their data analytics activities in corporate strategy.

FIGURE II.4
INSTITUTIONALIZATION OF SHOP-FLOOR DATA ANALYTICS
n=100

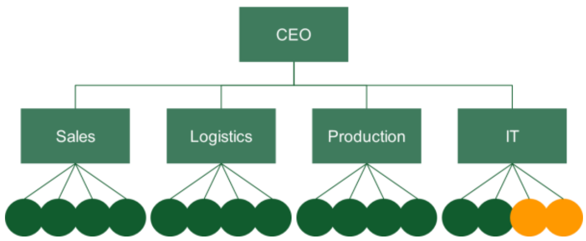
Decentralized



Integrated in functional units (analysts are scattered over different departments and do the analyses necessary for their department)

56%

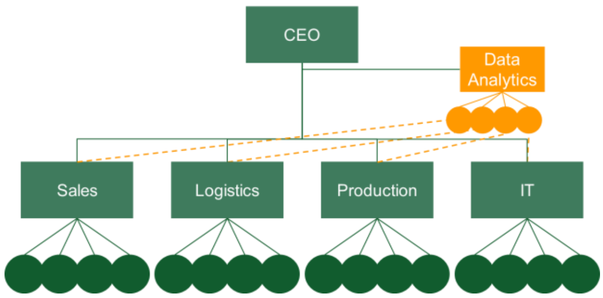
Functional



Integrated in a single functional unit (analysts are part of one functional area which is performing all analyses)

11%

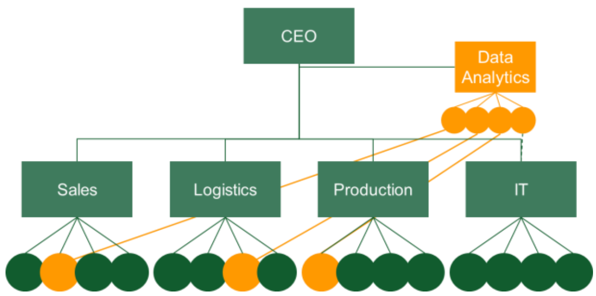
Shared Services



Organized as a shared service center (a team of specialists that can be approached as required and performs the analyses)

6%

Centre of Excellence



Organized as a center of excellence (analysts are allocated to functional units and their activities are centrally coordinated)

12%

Not Institutionalized

Data Analytics is not institutionalized within the organization

15%

Data Analytics Specialist

"In general, the usage of manufacturing data at our company differs from subsidiary to subsidiary. In some subsidiaries, they are strongly used in terms of SPC analyses to avoid out of tolerance tests."

Christian Casar

Quality Manager

Trumpf GmbH + Co.KG

Surprisingly, only 15% of respondents do not have Manufacturing Data Analytics organizationally implemented. A share of 56% has integrated experts in a decentralized manner within the organization. 11% have chosen a functional integration within their IT department. 6% have organized their data analytics activities in form of a shared service center. 12% bundle their data analytics expertise in a center of excellence. Summarizing, a variety of organizational forms are implemented in practice. However, decentralized experts seem to be the predominant form of organization.

Despite all its advantages a decentralized organization can lead to different maturity levels within the organization. Not only in relation to employee capabilities but also in terms of the degree of technical implementation. The statement above can be seen as representative for the majority of industrial manufacturers. The adoption of Manufacturing Data Analytics application levels usually differs strongly from one plant to another within organizations. Organizational forms such as shared service centers and centers of excellence result in a more homogeneous implementation level across large organizations and as thus simplify the implantation of a down-up strategy. Employees in a decentralized organization are usually only partially responsible for Manufacturing Data Analytics. In contrast, companies with a shared service center or center of excellence have a higher dedication of full time employees for this topic and generally allocate more resources.

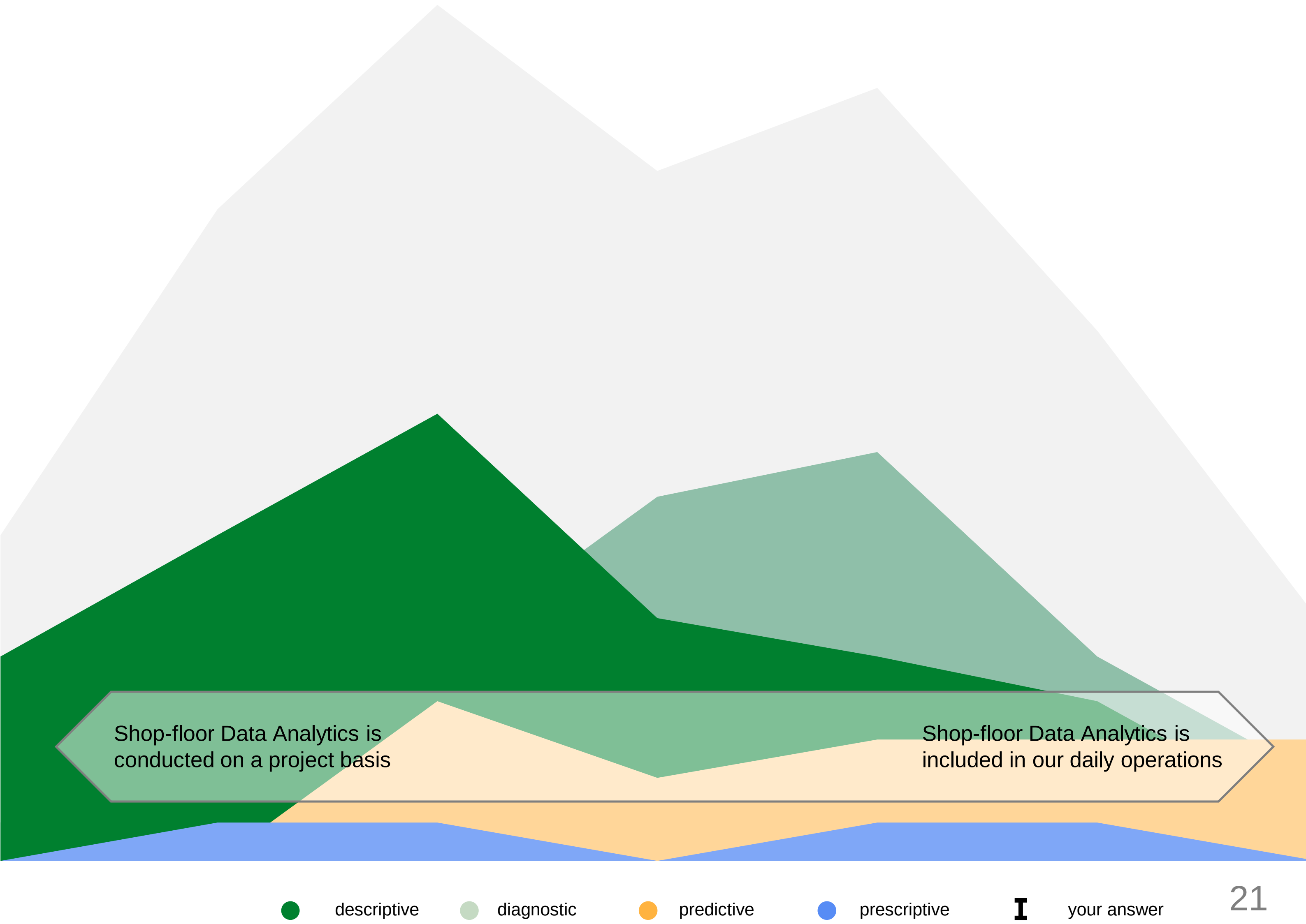
Many companies already apply advanced analytics in other functional areas such as marketing or customer relationship management. Most of them have yet been unable to activate this know-how for the manufacturing function. A frequently debated issue is whether data scientists need specific manufacturing know-how or whether it is sufficient to work closely intertwined with specialists of the technical departments. Depending on how a company answers this question, different organizational forms can be advantageous.

"For a number of years (20+), our facility has been evolving with data analytics. […] it is closely woven into the day to day fabric of the operations. Data is utilized for lot tracking, lot release, Poka Yoke, inventory control, resource alignment, prediction of failure, PM strategy, quality control etc."

Barbara Watkins
Manager Production System
Robert Bosch LLC, North America

FIGURE II.5
EXTENT OF DATA ANALYTICS INTO DAILY OPERATIONS

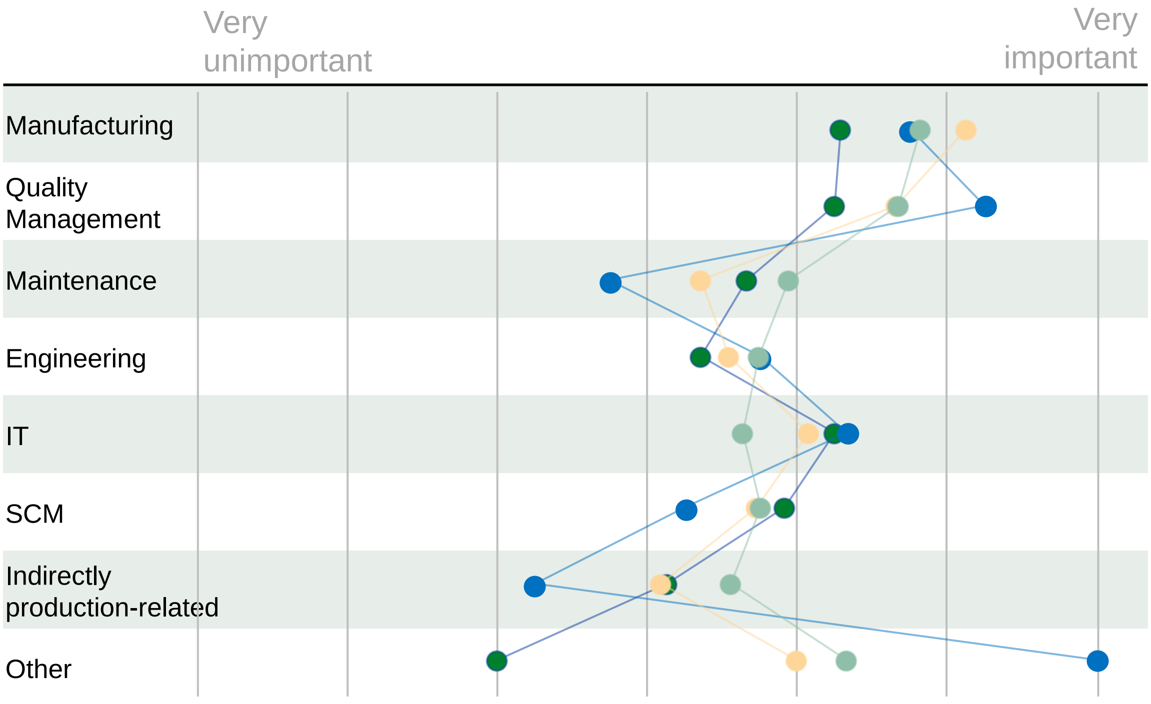
n=100



Involvement & Collaboration

FIGURE II.6
INVOLVED PARTIES IN SHOP-FLOOR DATA ANALYTICS

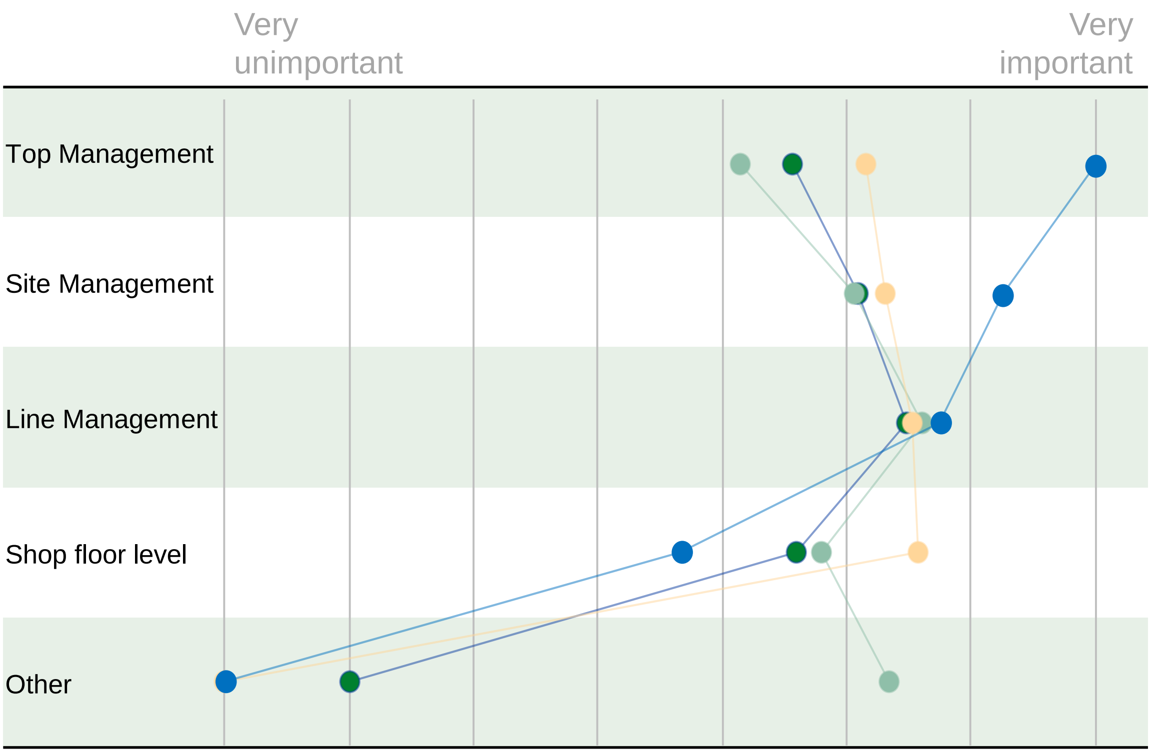
n=100



Primarily functions such as IT, manufacturing and quality management are involved. Indirectly production-related functions are of minor importance.

FIGURE II.7
INVOLVED HIERARCHIES IN SHOP-FLOOR DATA ANALYTICS

n=100



Manufacturing Data Analytics is perceived as a rather operational task. Despite that, advanced analytics companies show a significantly higher top-management commitment. Furthermore, strong involvement of site and line management are also of high importance for all companies.

descriptive diagnostic predictive prescriptive your answer

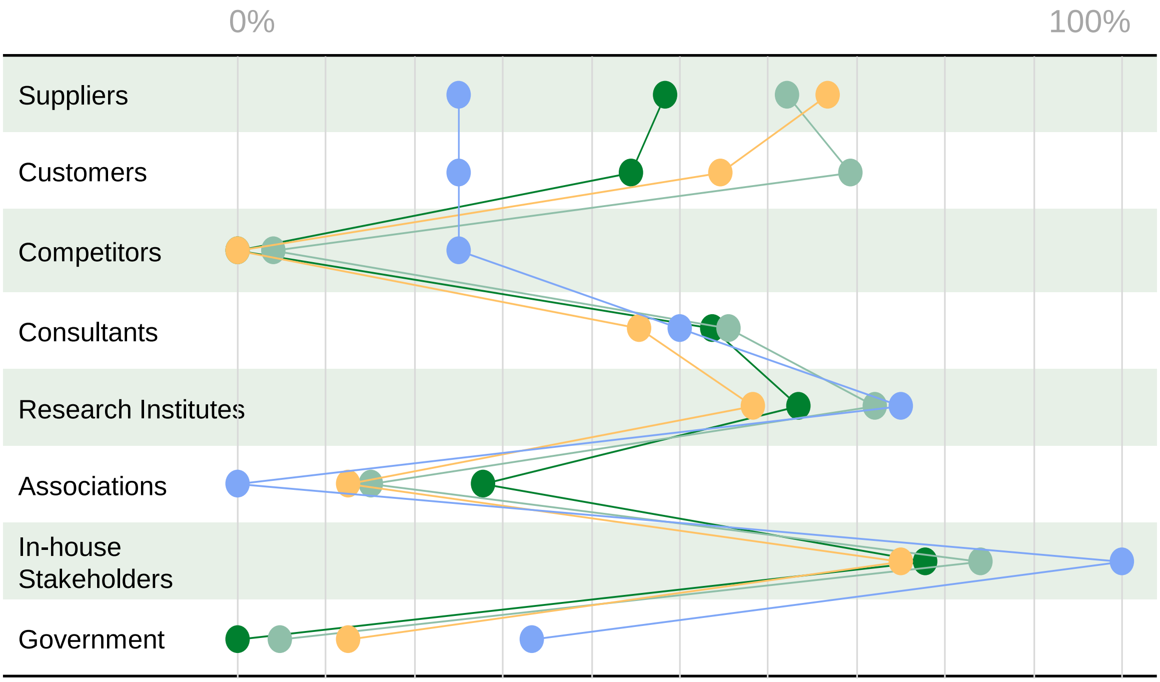
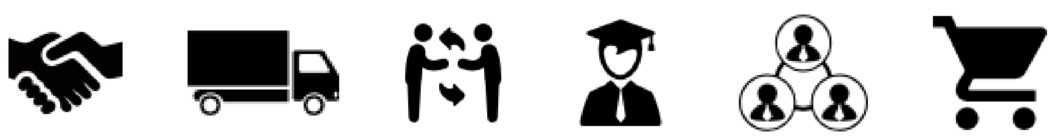


FIGURE II.8
STAKEHOLDER COLLABORATION

n=98

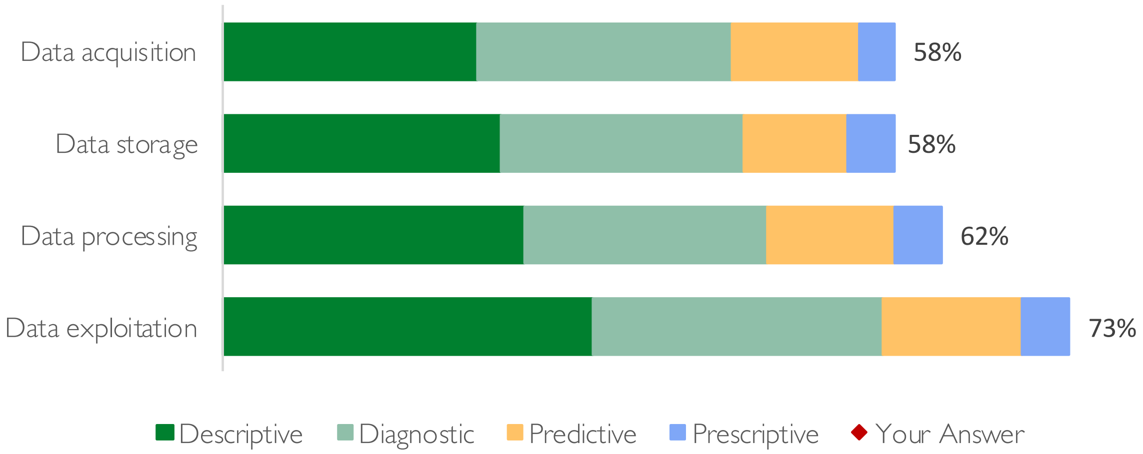
Interaction and exchange with partners is crucial for most companies. Building up internal knowledge for all categories of data analytics is time consuming and resource intensive. Therefore, companies collaborate with external institutions to speed up processes and focus their limited resources on key areas of activity. Hence, capacities and know-how are purchased externally on demand. Proceeding a make-or-buy analysis should be carried out similar to physical products to identify internal fields of activity and topics for external collaborations.

Companies generally collaborate with suppliers and customers across the whole value chain. The vertical integration of information allows to match the supplier information and customer data with data from own manufacturing shop floor. For instance, the correlation of product field performance with manufacturing data yields sustainable improvement potentials. Competitors are generally excluded from collaborations, since manufacturing data analytics is perceived as a possibility to gain competitive advantage. Notably, vast amounts of sensitive corporate data are handled, which are highly confidential and retained from disclosure. In contrast, consultancies and research institutes are valuable partners due to their neutrality and cross-industry knowledge. Research institutes are usually a good partner to build up initial knowledge, but are also eligible for companies at very advanced stages to access specialists for highly complex applications. Research institutions are often a possibility to form a community of interest or to arrange best-practice exchange between companies from various industry backgrounds. In house-stakeholders from different business units and functional areas are of very high importance, whereas collaborations with governments and associations are of low importance.



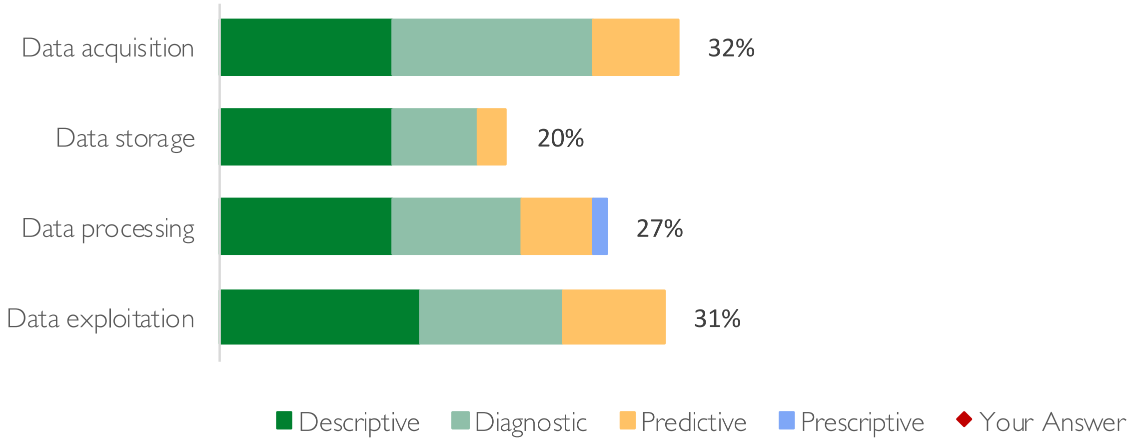
descriptive · diagnostic · predictive · prescriptive · your answer

FIGURE II.9
REASON FOR COLLABORATION – CAPABILITY BUILDING



The whole process of manufacturing data analytics can be subdivided into data acquisition, data storage, data processing and data exploitation. Among these four process steps, manufacturing companies collaborate with external partners. The reasons for collaboration with different stakeholders can be distinguished in capability building (upper graph) and benchmarking against others (lower graph). Generally, over 50% of participating companies collaborate among all four process steps of manufacturing data analytics with external partners in order to build new capabilities. The fact that 73% of all respondents seek for support in the field of data exploitation accentuates that many companies still do not know how to create value from their captured data and turn it into a real asset. A distinction between beginning and more advanced companies is not evident.

FIGURE II.10
REASON FOR COLLABORATION - BENCHMARKING



In comparison to collaborations for capability building, collaborations for the reason of performance benchmarking is of minor importance. Merely 20-30% of respondents collaborate for benchmarking reasons. The majority of the sample is still engaged in capability building and is aware that they are still in an early phase of manufacturing data analytics. Hence, they are more interested in collaborations for building new capabilities than in benchmarking reasons. As soon as manufacturing data analytics will become more mature and internal structures will have been build up, the ratio might turn around. A distinction between the beginning and more advanced companies is also not evident.

III Data, Systems & Capabilities

"[…] in parts of our production we already generate significant amounts of process and product data, which should enable us to get in part a digital shadow of our products."

Dr. Schwartze
Vice President Production Consumer, Operations Strategy & Projects
WMF Group GmbH

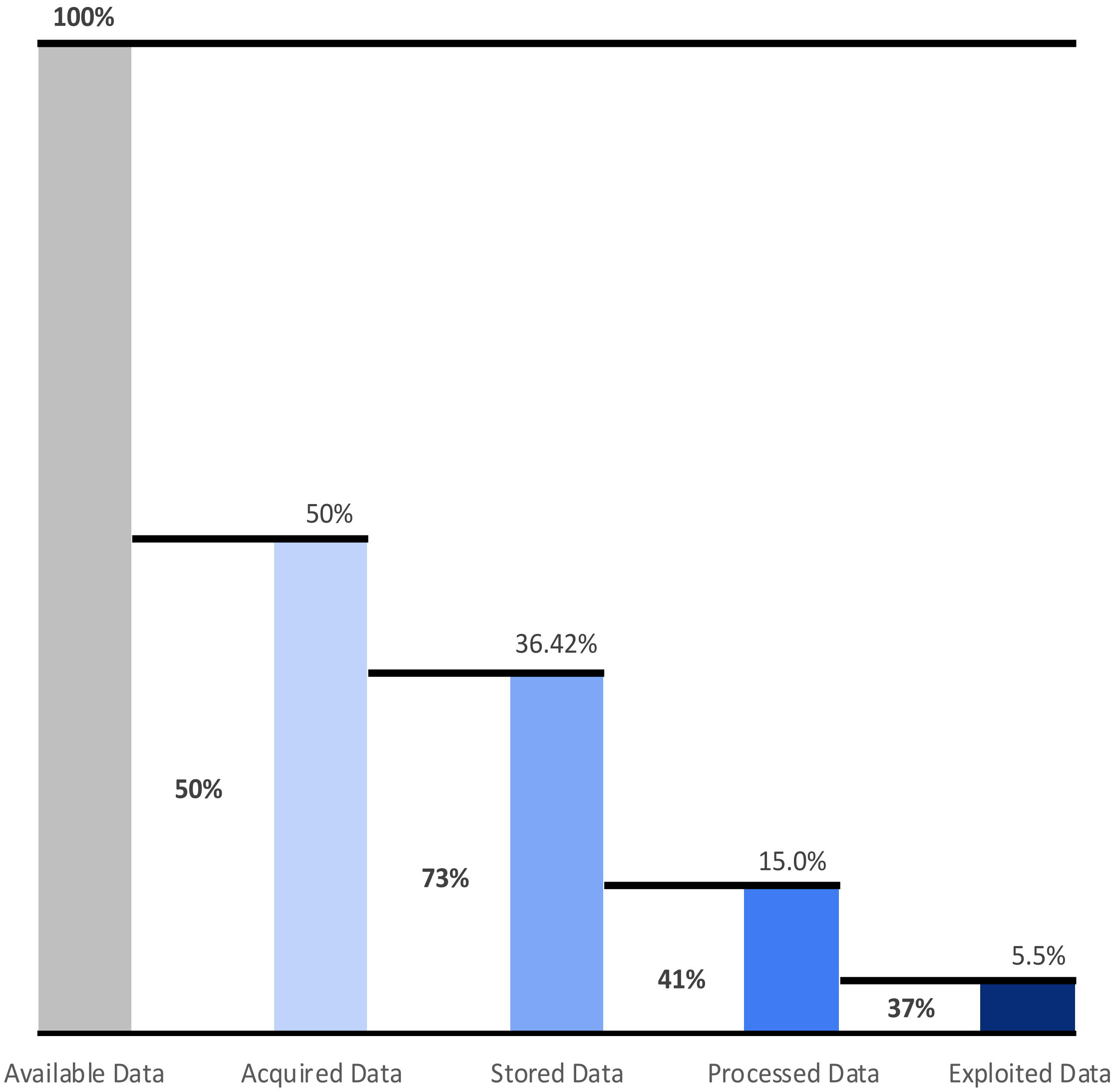
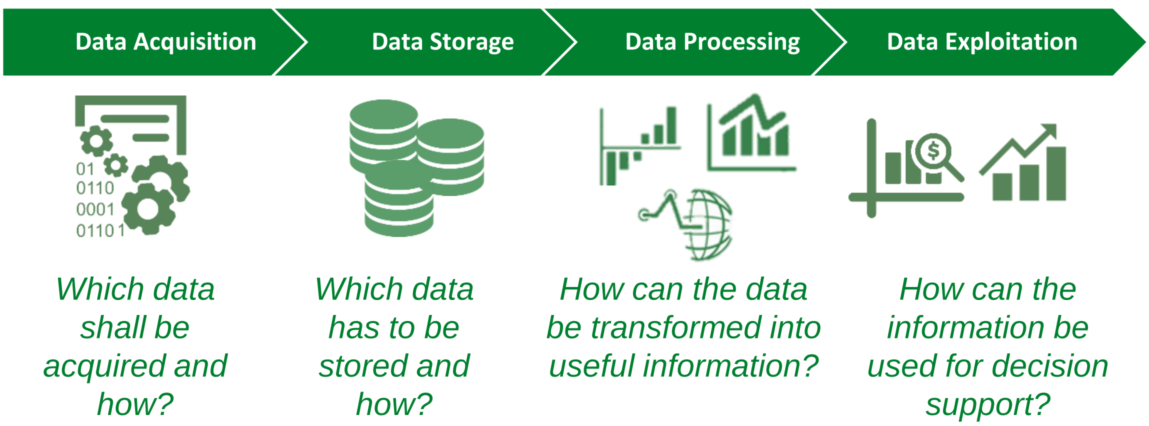


FIGURE III.0.1
AMOUNT OF DATA ACQUIRED, STORED, PROCESSED, EXPLOITED
n=100

The application of Manufacturing Data Analytics is a step-by-step process. The available data base is continuously increasing. Novel, cost-effective technologies and embedded sensors are able to gather large amounts of data. Intelligent, connected production systems (cyber-physical production systems) produce these data autonomously. The resulting overall available data base in manufacturing companies is the basis for Manufacturing Data Analytics .

In a first step, the available data has to be actively acquired by the companies. That means that companies render these data accessible by reading them from the memories of the production systems and aggregate them in a common data base. These data sets have to be stored afterwards, wherefore different approaches exist, for instance cloud or local storage. The third step, data processing, is the core step. That means existing data analytics methods are applied, depending on the maturity level of a company (descriptive, diagnostic, predictive, prescriptive). By processing, data is transformed into useful information. This can either be done by visualising data but also by finding correlations between data sets. The processed information can be exploited in the last step. Exploiting means turning processed data into advantages for the company: This can either be a support concerning decision making in business activities and manufacturing or general support in order to reach business goals.

FIGURE III.0.2
PROCESS STEPS OF DATA ANALYTICS APPLICATION



The study shows, that only 5,5% of the available data base in manufacturing companies is exploited for decision support or optimization (Figure III.0.1). This can be reduced to the challenges that occur along the different steps of data analytics in production.

Each step has its own set of challenges. Thus, the majority of data cannot be acquired, stored, processed and exploited. The following chapters analyse each step by investigating the status-quo in manufacturing companies as well as existing barriers.

To maintain or rather to improve the competitiveness of manufacturing companies the proportion of exploited data has to increase the challenges for companies in the future. The findings of this study will help to understand in order to address this problem and to initialize novel approaches for manufacturing companies.

III.1 Data Characteristics

“Data is the new oil!”

Clive Humby
Founder and Chairman
Dunnhumby

Data quality is of great importance, when processing data. Standard algorithms cannot differentiate between useful and useless data while processing. Thus, poor data quality leads to poor or even wrong results. This general principle also applies for Manufacturing Data Analytics. All gained results and insights are depending on the underlying data base. The data quality is characterized by the expectations of future users and analysts. In manufacturing companies the actual satisfaction with data is low (mean 3,47 on a scale from 1 to 7). Just one out of 100 participating companies indicates that all needed data is available in the desired form. By subdividing data quality in six different categories, the reasons for this dissatisfaction can be displayed in more detail (cf. Figure III.1.2).

FIGURE III.1.1
SATISFACTION WITH DATA
n=100

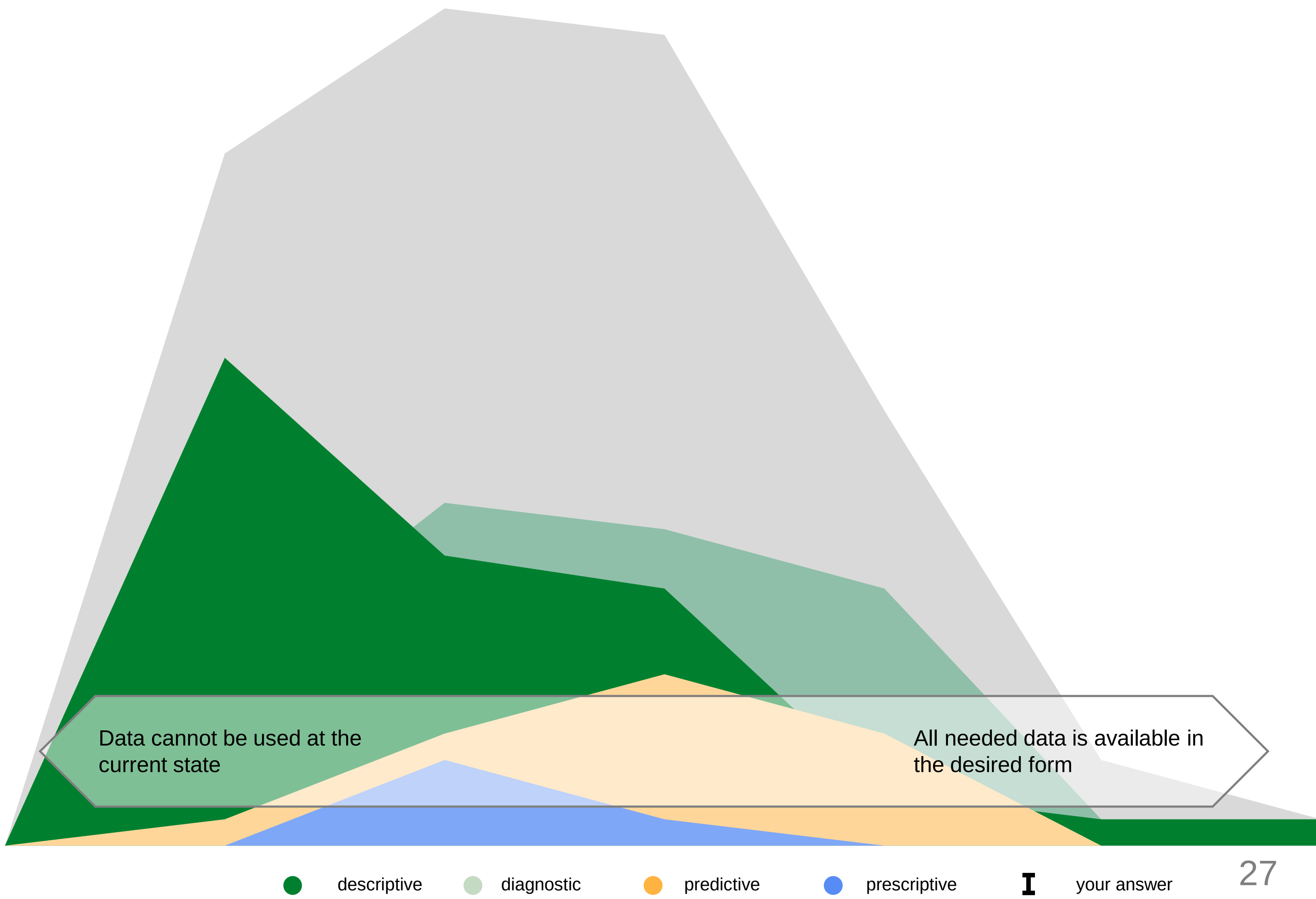
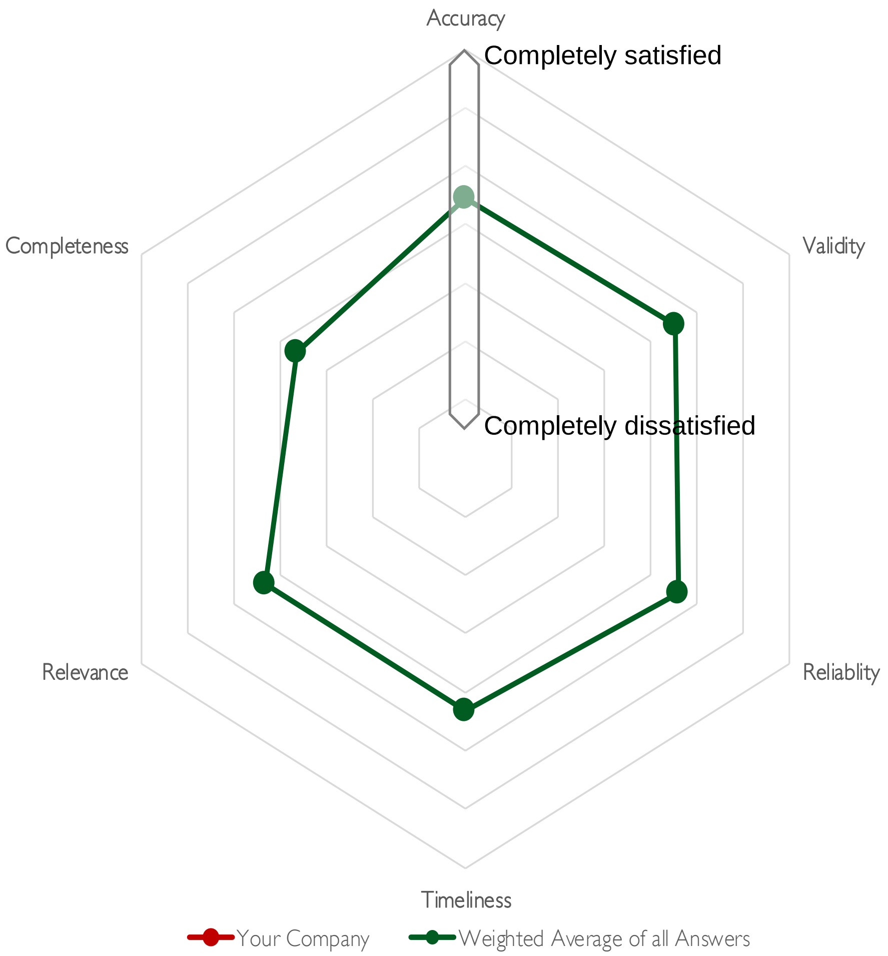


FIGURE III.1.2
KEY METRICS OF MANUFACTURING DATA

n=100



In general, quality of data can be evaluated by six different categories:

- **Accuracy** – the data shows the actual measured metric correctly, precisely and free of errors
- **Validity** – the data measures what is intended to be measured
- **Reliability** – the data collection technologies perform consistently on the intended level
- **Timeliness** – the data is collected within a time horizon which is required to exploit its value
- **Relevance** – the data contains meaningful information to address a specific problem
- **Completeness** – the collected set of data is comprehensive

Manufacturing companies see improvement potential in all six data evaluation categories. Especially completeness and relevance of data is still insufficient, which is the reason why companies reveals a lack of transparency when investigating their available data base. Furthermore, companies with a high maturity level in Manufacturing Data Analytics are least satisfied with their data quality. Advanced analytics methods may require a higher level of data quality and the employees also have a deeper understanding of their data.

It can be assumed, that the expectations of manufacturing companies concerning data quality are actually not met. That means that basic requirements for manufacturing data analytics are still missing and have to be addressed by new approaches and methodologies.

III.2 Data Acquisition

Acquiring data is the first step in order to profit from data analytics. At this point, manufacturing companies already decide which data is needed and retrieved from different, widely dispersed sensors and machines on the shop floor. As this study shows, just a small part of the potentially available data base is actively acquired by manufacturing companies (about 50%, cf. Figure IV.0.1). Most of the companies (91%) acquire process data, e.g. throughput time, followed by defect data (87%), machine parameters and product characteristics, e.g. test data (84%). Just a small fraction of companies also acquires environmental data, e.g. temperatures (53%), tracking and tracing data (38%) and expert knowledge data (36%).

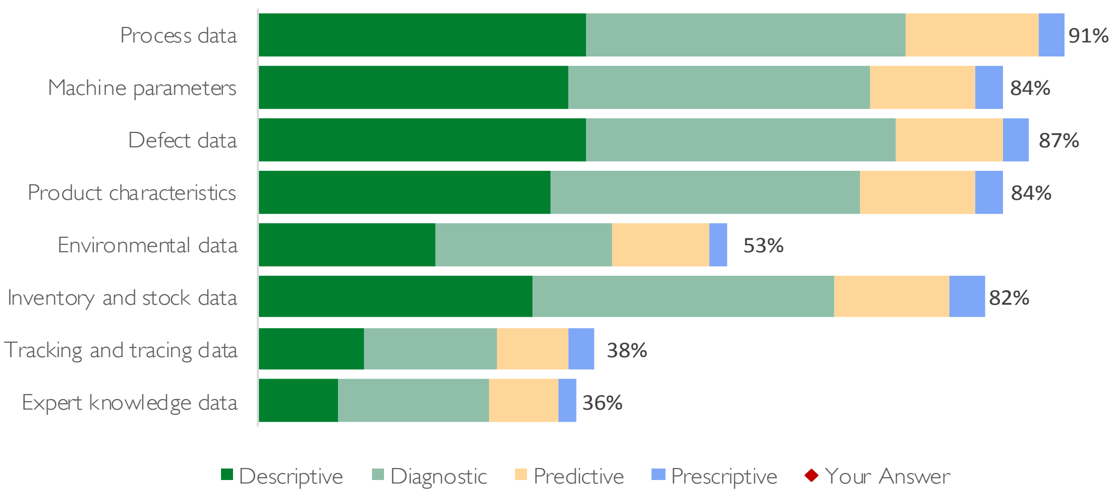


FIGURE III.2.1
COLLECTED DATA TYPES

Participating companies use different ways to acquire data on the shop floor. Today, the manufacturing industry is still far from reaching paperless factories, as postulated in the vision of the so-called “Industrie 4.0”. Even advanced analytics companies acquire over one quarter of their data analogously, meaning mainly paper-based. This fraction is higher in companies that only apply descriptive analytics methods. Advanced analytics companies have also automated their data acquisition process. Nearly 80% of data is acquired automatically. Companies that apply descriptive analytics, acquire about 50% of the data manually.

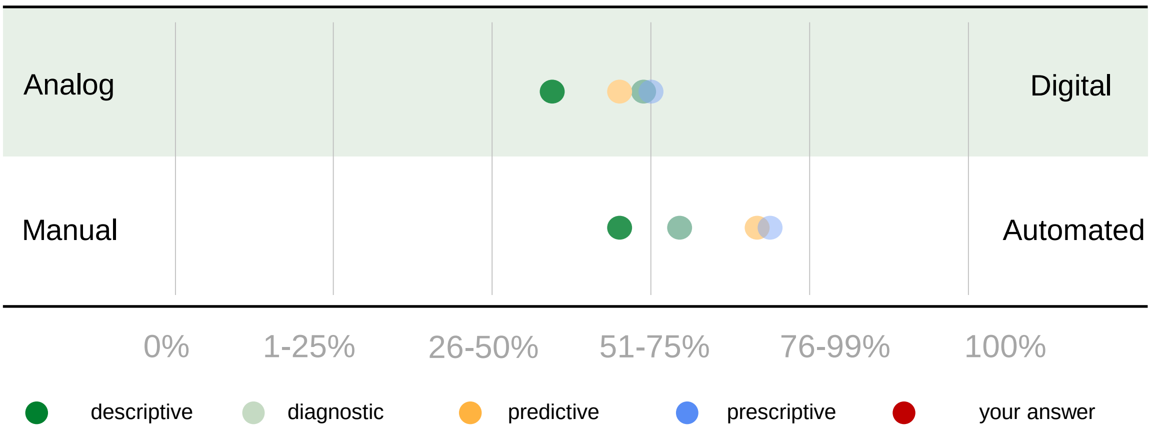
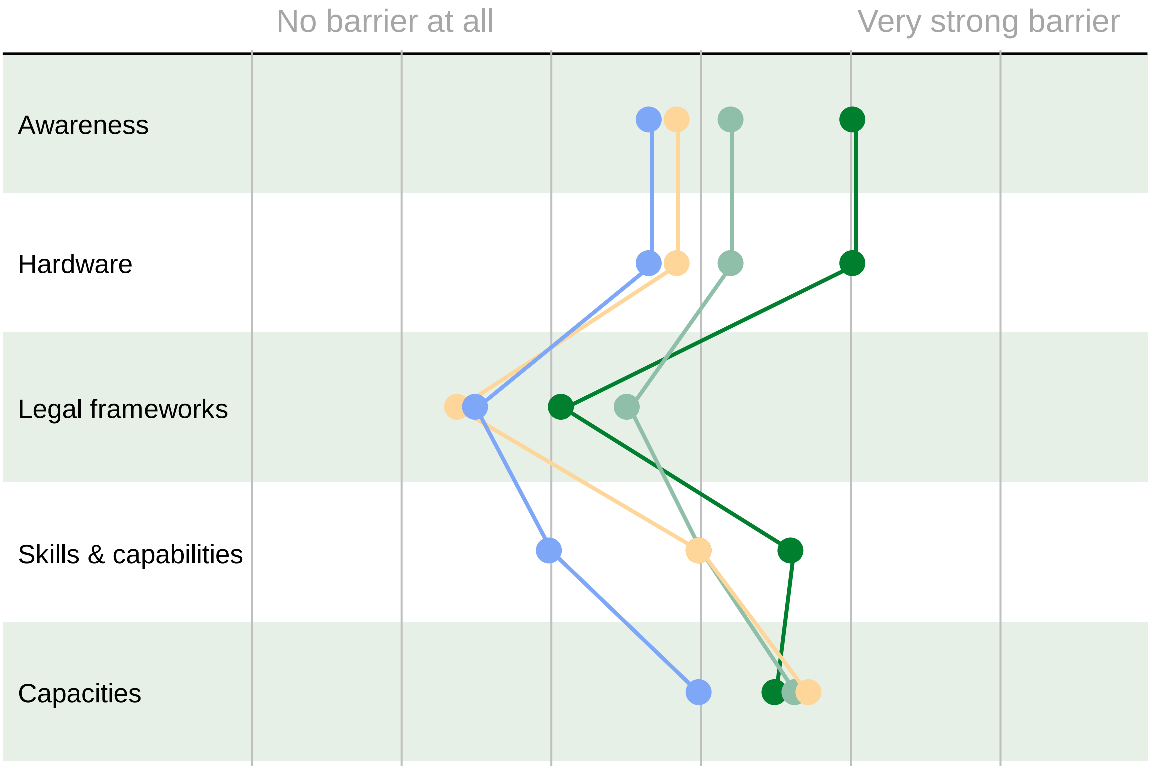


FIGURE III.2.2
COLLECTION OF MANUFACTURING DATA – ANALOG VS. DIGITAL & MANUALLLY VS. AUTOMIZED
n=100

FIGURE III.2.3
CHALLENGES CONCERNING DATA ACQUISITION

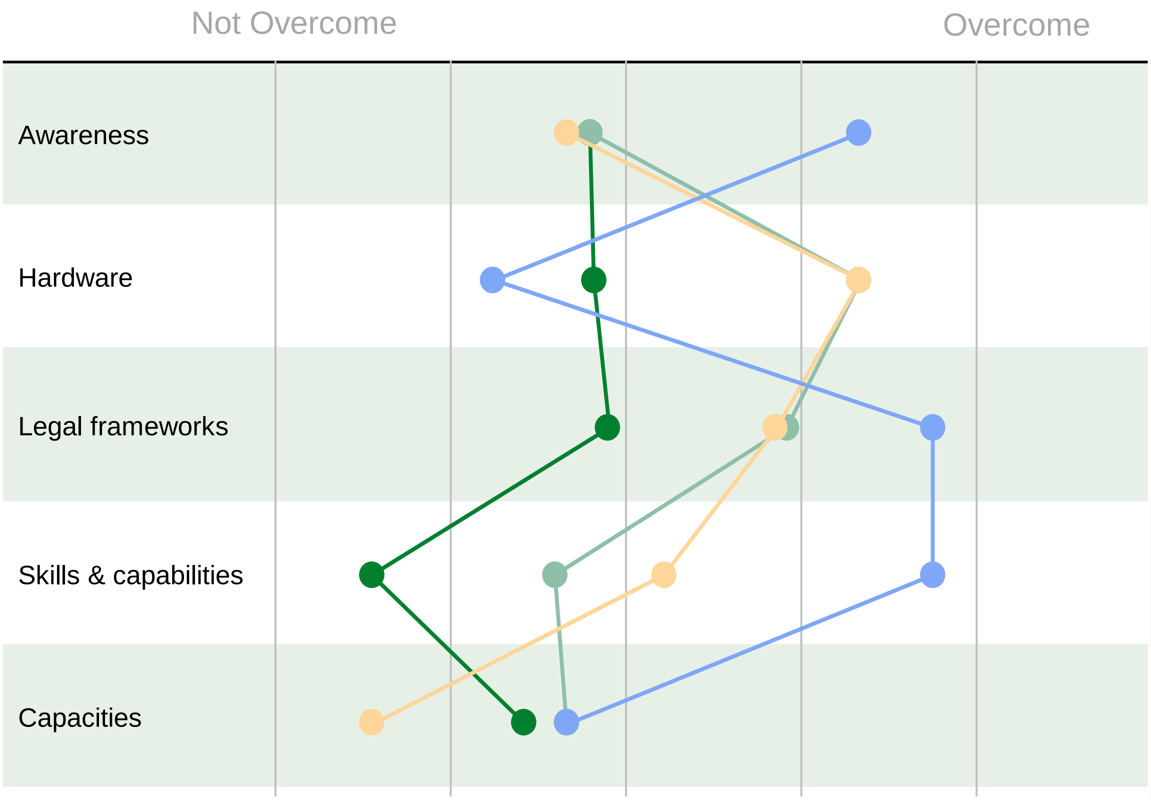
n=100



For all participating companies, a lack of capacities is most challenging in data acquisition, followed by the missing awareness of the potentials of data analytics. Legal frameworks (e.g. requirements of worker's council) as well as a lack of skills and capabilities are rated of minor importance. Overall, the existing challenges were prioritized equally across the maturity stages. The challenges have actually only been met to a certain degree. However, especially companies with a low maturity level seemed to struggle in data acquisition, in particular with skills and capabilities.

FIGURE III.2.4
CHALLENGES CONCERNING DATA ACQUISITION - ALREADY MASTERED

n=100



III.3 Data Storage

As seen in the Figure III.0.1, 73% of the acquired data is stored. Compared to other stages this is a good quota. A reason could be the broad availability and the successively decreasing costs for data storage technologies. Here manufacturing companies have multiple options on how to organize storage in the company.

Without storing data, further analytics steps won't be possible. The type of data storage also determines who will be able to generate information from these data and who can profit from the resulting knowledge. A structured approach for data storage facilitates learning from historical data even months or years later.

At the same time, data storage could be very critical to business success due to safety problems. This is why restrictions for data access are absolutely unavoidable. Thus, the choice of right systems and technologies is the most important.

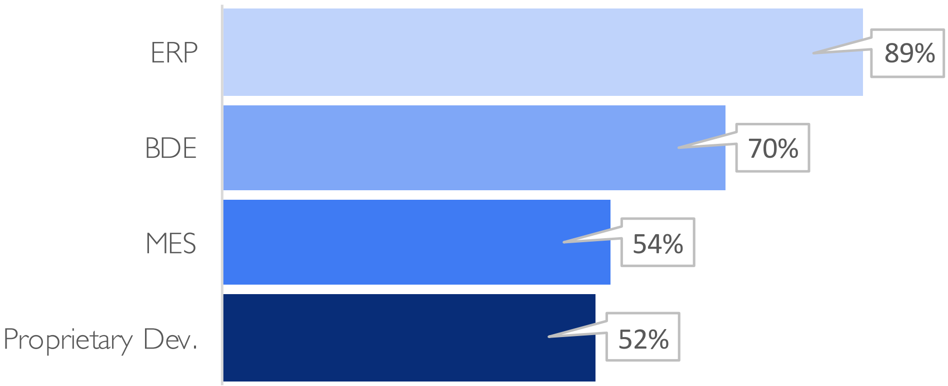


FIGURE III.3.1
SYSTEMS USED FOR DATA STORAGE

n=100

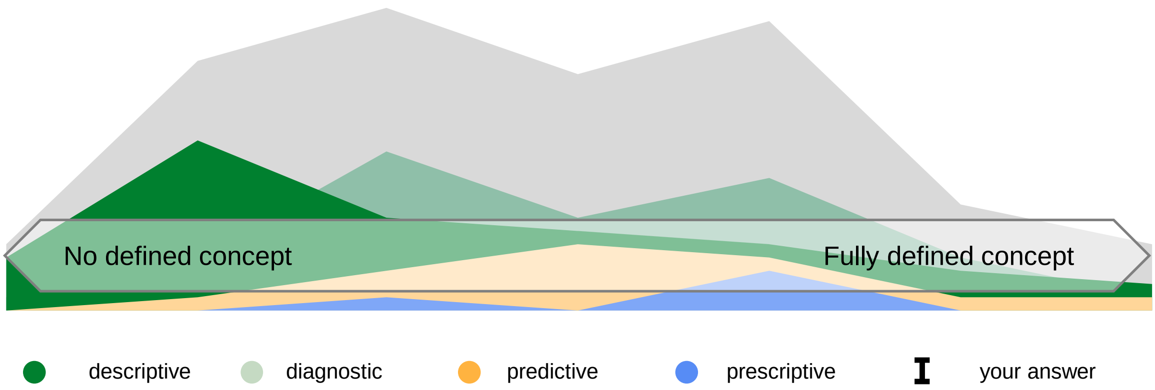
This study reveals that most of manufacturing companies have use a leading IT-system. Almost 90% have an Enterprise Resource Planning (ERP) tool for storage of relevant business data. For manufacturing data (shop-floor data) over 50% have an Manufacturing Execution System (MES) or other systems for production data acquisition (BDE).

"Cloud solutions, Big data and machine learning approaches will change the role and the possibilities for process monitoring extremely."

Tobias Fürtjes
Research Project Manager
Marposs Monitoring Solutions

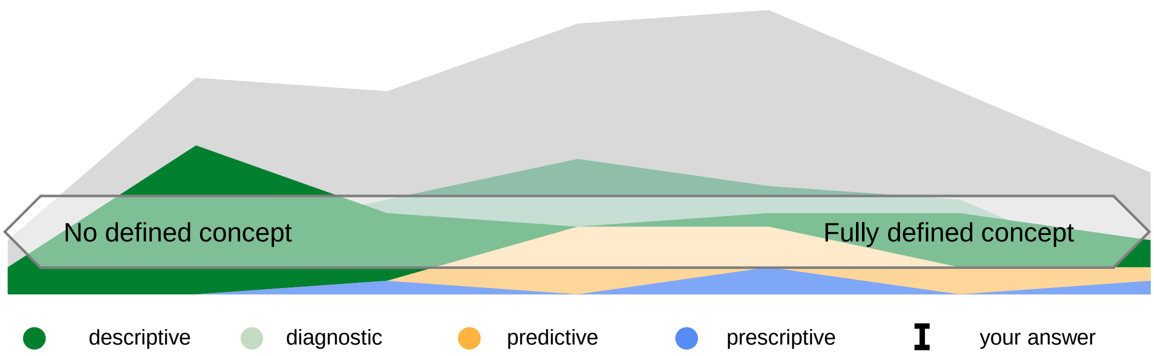
Transparency in structure and data storage systems is important for the potentials of the overall application of Data Analytics in manufacturing. Especially in companies with a low maturity level in Data Analytics. This transparency is not given due to not existing defined concepts. Nevertheless, to enable the employees to use data analytics in their operational practice, these defined concepts are inevitable for a transparent data storage.

FIGURE III.3.2
DATA STORAGE CONCEPT FOR AGGREGATION LEVEL
n=100



Data from shop floor level is mostly not stored following a specific concept regarding the aggregation level as shown in figure III.3.2. The aggregation level refers to the granularity of the data. e.g. storing real-time machine data (e.g. temperatures, vibrations) every second against storing mean values for minutes or hours. Especially in companies with a low maturity level (descriptive, diagnostic) this concept is mostly missing. This can be explained by the missing awareness for the importance of stored data for the further steps of the data analytics process.

FIGURE III.3.3
DATA STORAGE CONCEPT FOR TIME HORIZON
n=100



Also concepts for time horizon in data storage are missing in companies with low maturity levels. The time horizon refers to the time period whilst the data is stored. These time horizons could be fixed e.g. for months or years. Furthermore, the time horizons can be linked to other externally determined periods, e.g. the life cycle time of a specific product. In general, more companies do not have a concept for the time horizon of data storage compared to concepts for aggregation level. A reason is the partly existence of external requirements for time horizon in data storage, e.g. for batch or product tracing in recall actions due to quality problems.

There are two main storage options when storing data. One being the traditional way of storing data internally so that no data is transferred via the internet. This option needs own hardware infrastructures and maintenance services within the company. On the other side, there is a growing market for Cloud Services with Microsoft, Google and Amazon as the biggest players. This option allows companies to completely outsource the hardware and IT infrastructure services to specialized companies and to focus on their core competencies. Together with successively decreasing costs for these services, this seems to be a good option for manufacturing companies with low IT competencies. Nevertheless, there are still some obstacles in the manufacturing industry, as only 12% already use cloud services. The most important issue in this context is data security and the risks involved.

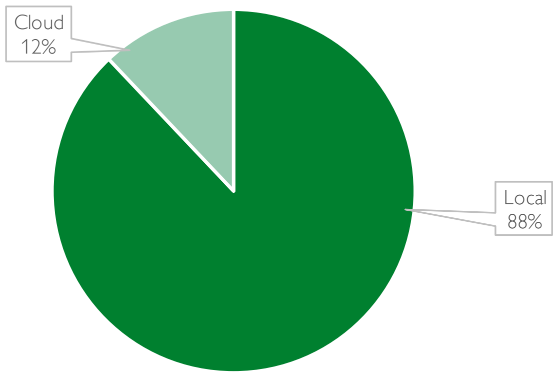


FIGURE III.3.4
CLOUD VS. LOCAL STORAGE

n=100

Data storing concepts strongly influence the accessibility of data within the company. Thus, a lack of accessibility is affecting the following steps in data analytics. In general, this study shows that in manufacturing companies the data access is very restrictive.

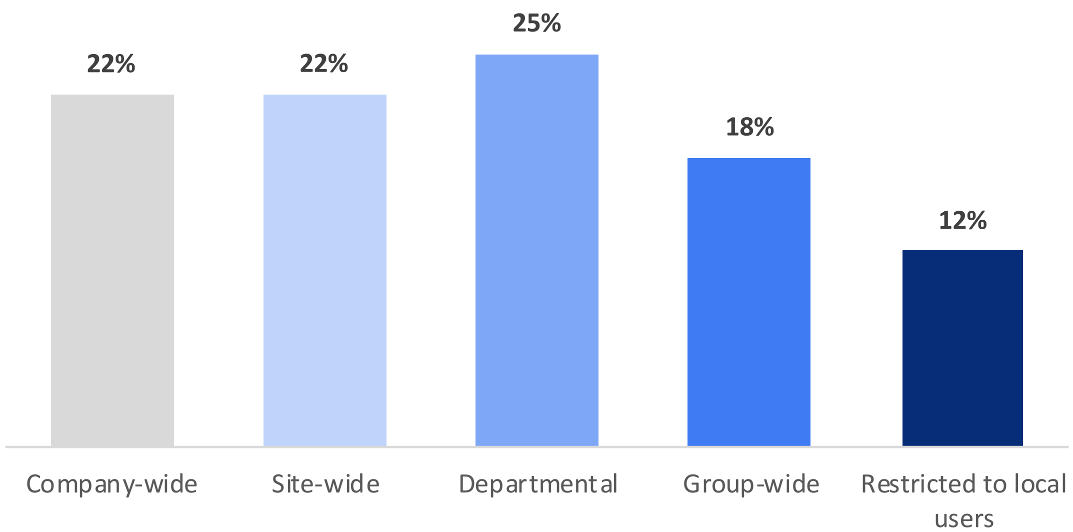


FIGURE III.3.5
DATA ACCESSIBILITY WITHIN MANUFACTURING COMPANIES

n=100

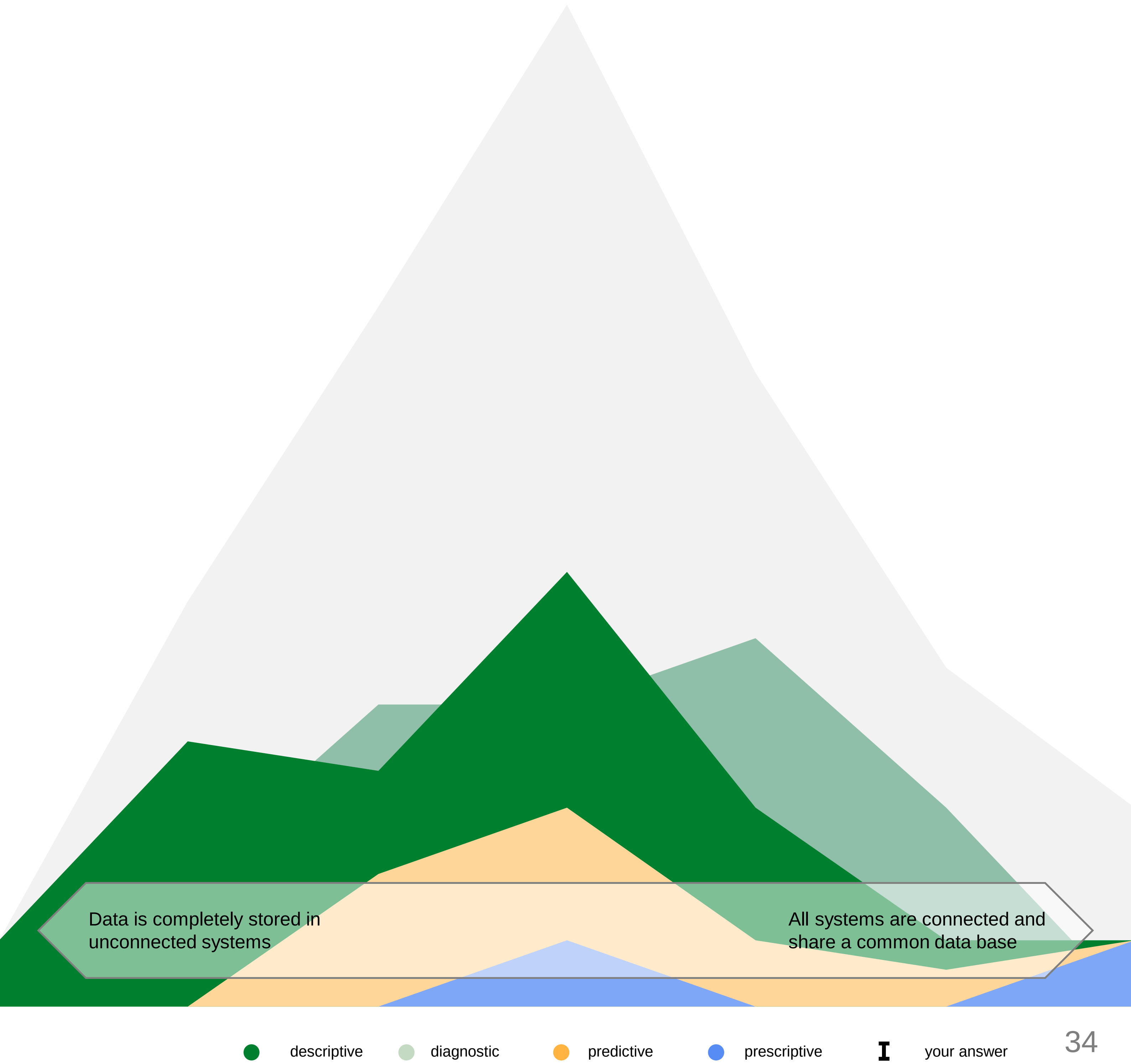
Besides the low percentage in cloud services usage, a low rate of integration of the different data processing systems and their databases is also still an obstacle in data analytics. While it is important that sensitive data is only accessible for authorized users, restrictions in manufacturing data access, e.g. due to a lack in IT-infrastructure, is a barrier that hinders new potentials in manufacturing companies.

“In future, the importance [of data analytics] will grow and more systems and processes will be linked together.”

Tobias Forkert
Head of Manufacturing
KSB AG

FIGURE III.3.6
INTEGRATION OF DATA STORAGE SYSTEMS

n=100



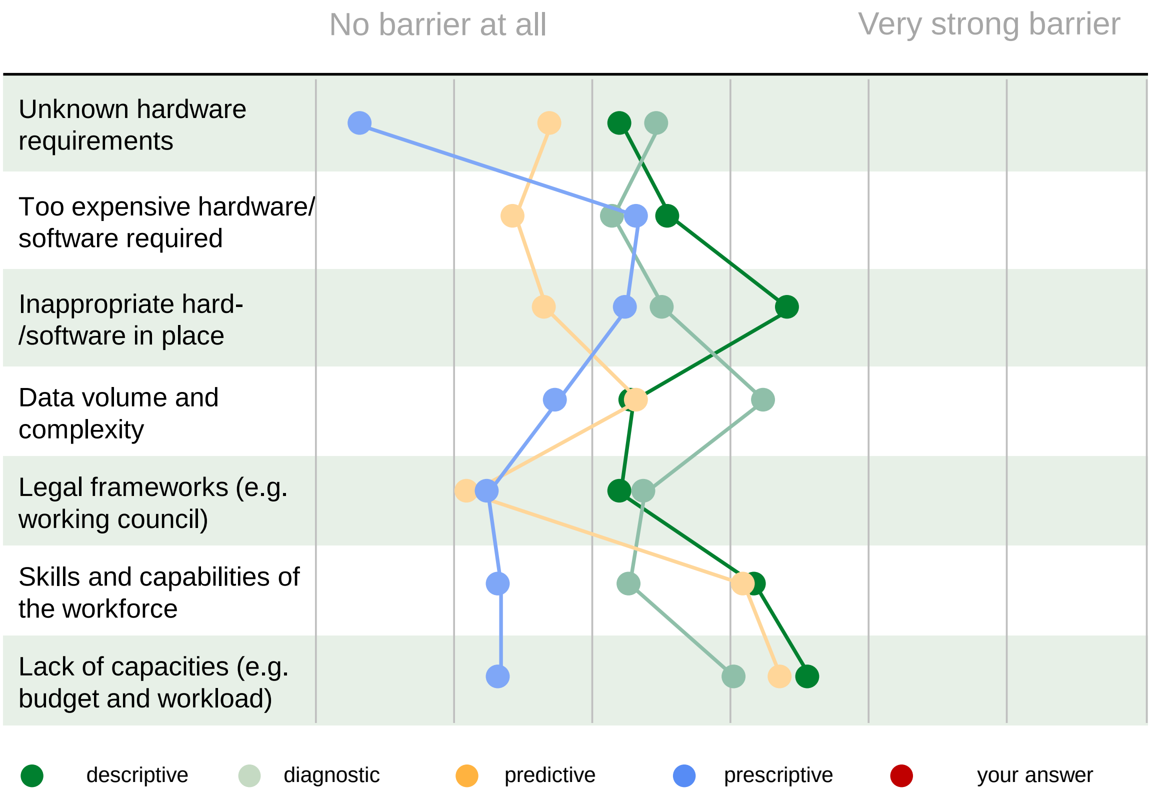


FIGURE III.3.7
CHALLENGES CONCERNING DATA STORAGE
n=98

The existing challenges concerning data storage vary between the different maturity levels. While companies with low maturity levels have the most trouble with unknown hardware requirements, companies with a high maturity level have already mastered most of these existing challenges. The data volume and complexity is also only challenging companies with a lack of experience.

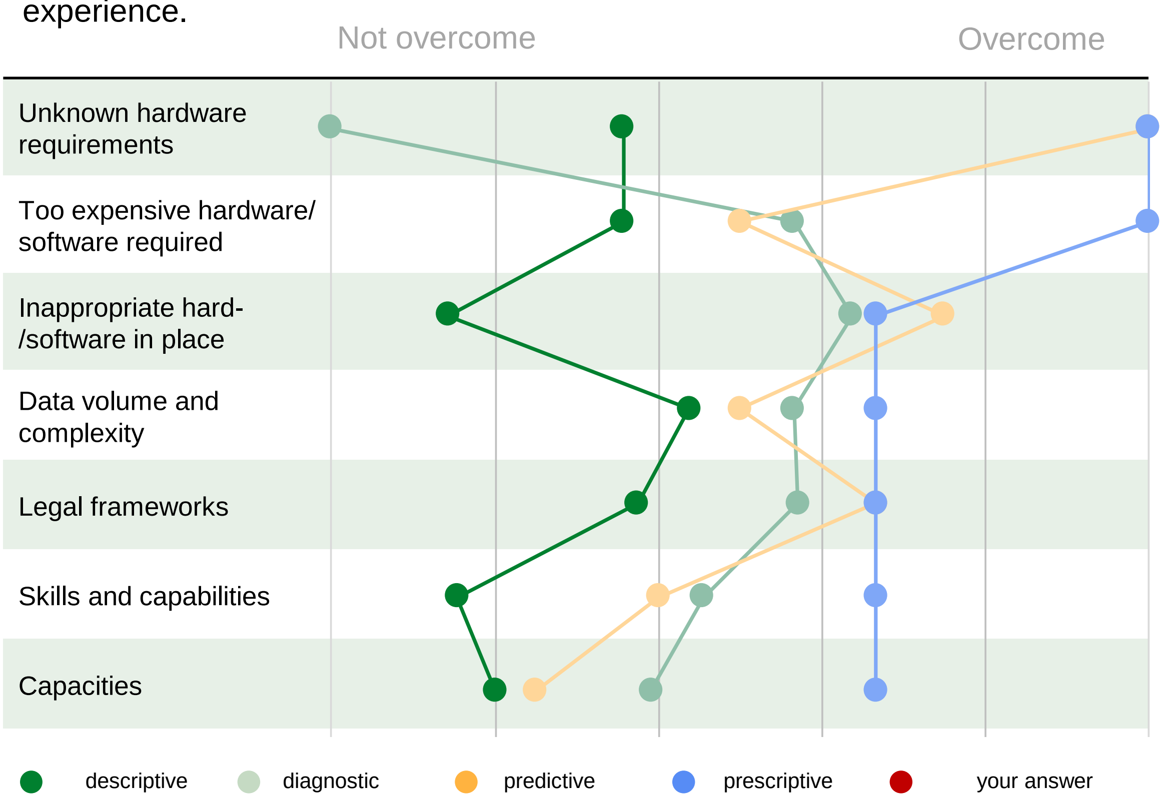
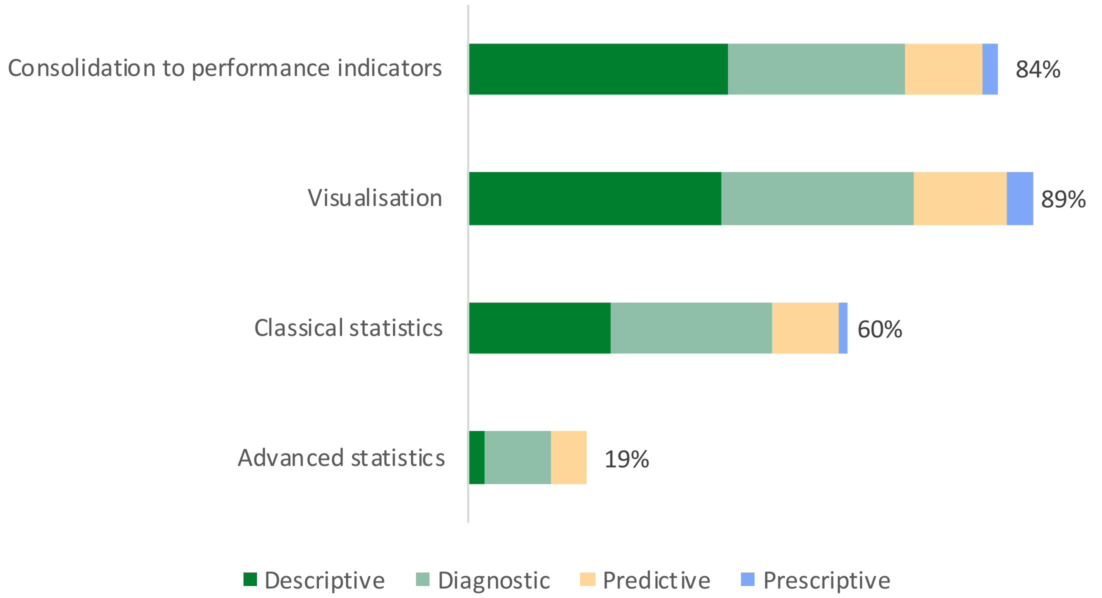


FIGURE III.3.8
CHALLENGES CONCERNING DATA STORAGE – ALREADY MASTERED
n=98

III.4 Data Processing

To enable the extraction of information from acquired data sets, data need to be processed. Besides using processed data to support decision-making, this is the step that yields the most problems. On one hand, it takes trained employees and deep statistical skills to process data. As the complexity of data sets grows ("Big Data"), the skills and capabilities of the staff have to match it. On the other hand, there are many questions needed to be answered in order to process data, e.g. choosing the right software which is a crucial step in order to support data analysts.
Therefore, processing data is not only complex but also expensive. This explains the relatively low amount of processed data at around 40%.

FIGURE III.4.1
OBJECTIVES OF DATA PROCESSING



The objectives of processing data are dependent on the maturity stage of a company. While descriptive and diagnostic maturity stages strongly emphasize consolidation to performance indicators, predictive and prescriptive maturity stages do not. For companies using predictive and prescriptive data analytics, visualizing data is most important, because these companies seek to get deeper insights and even predictions by visualizing the data.

This study also shows that manufacturing companies still focus on classical statistic methods like process capabilities or statistical process control. About 20% already try to apply advanced statistical methods, e.g. neural networks for quality predictions. Additionally, even the companies applying prescriptive analytics said that they do not use advanced statistical methods. This shows a significant lack of knowledge and skills in advanced statistical methods in the manufacturing industry and explains why Manufacturing Data Analytics is still at an early stage.

“The gained data from our machines forms the base for achieving high OEEs. Some data is currently only gathered manually - in the near future more and more data will be gained automatically by intelligent sensors.”

Frederik Ostermeier

Project Leader for Internal Production Projects

Krones AG

FIGURE III.4.2

EXTENT OF AUTOMATED DATA PROCESSING

n=100

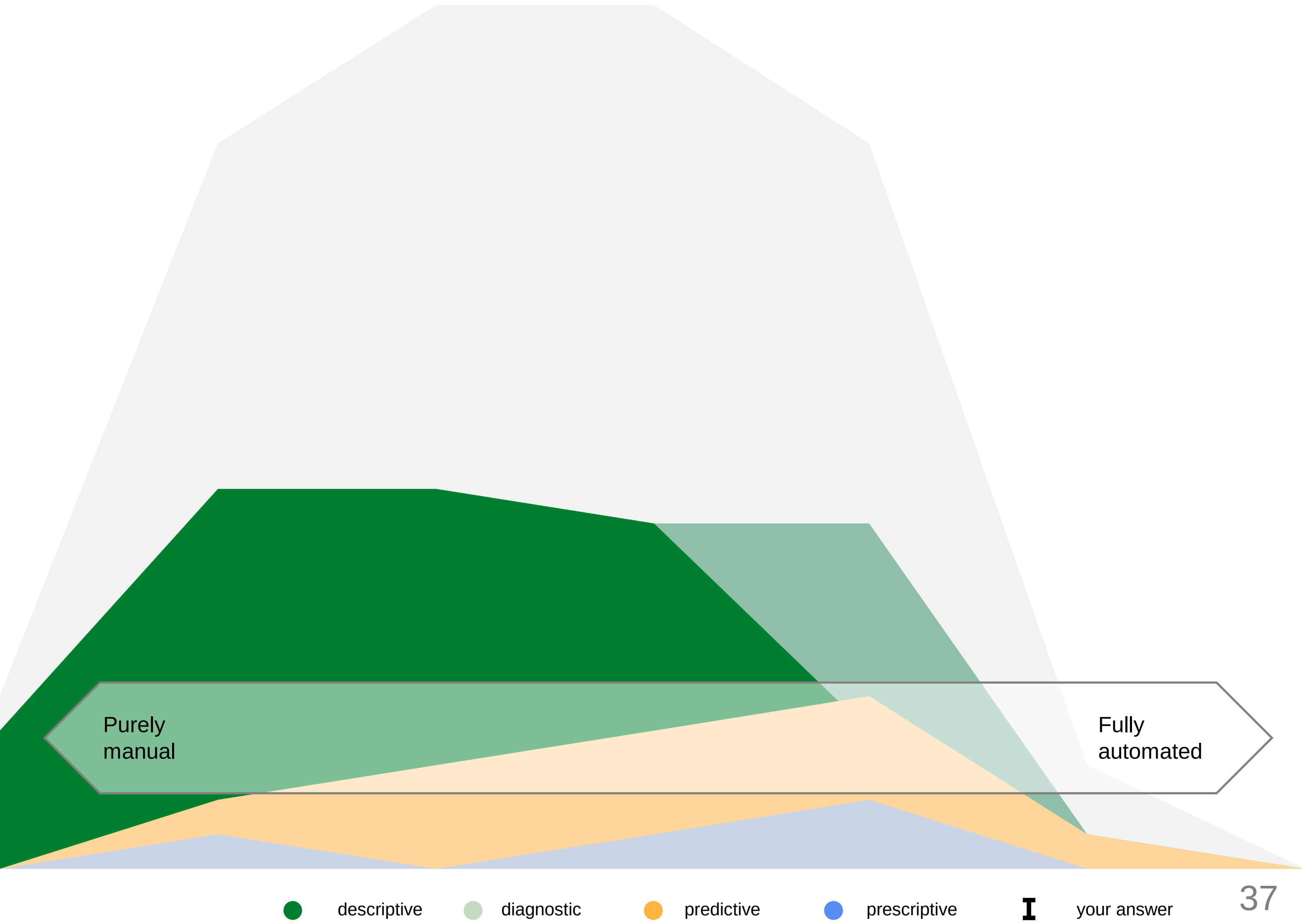
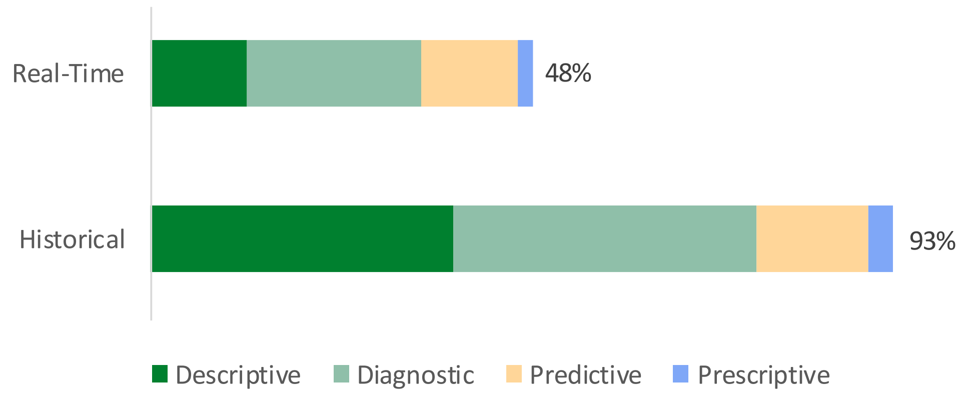
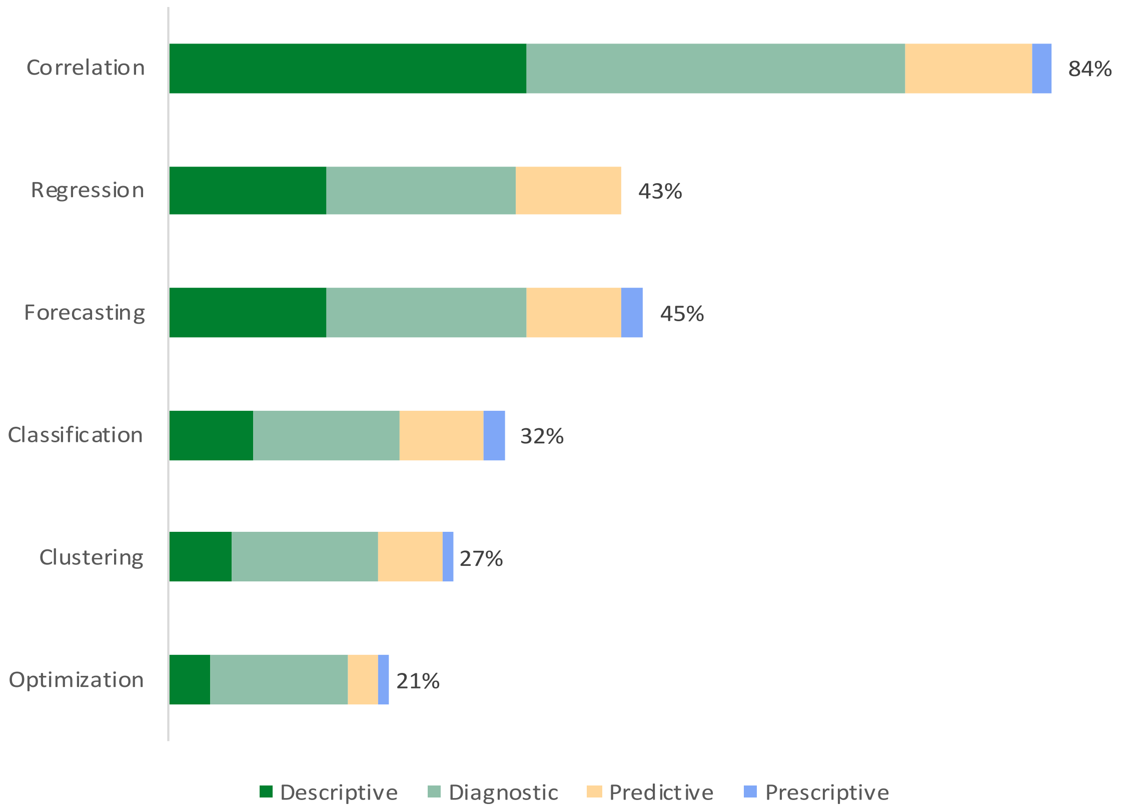


FIGURE III.4.3
TIMESCALE OF DATA PROCESSING



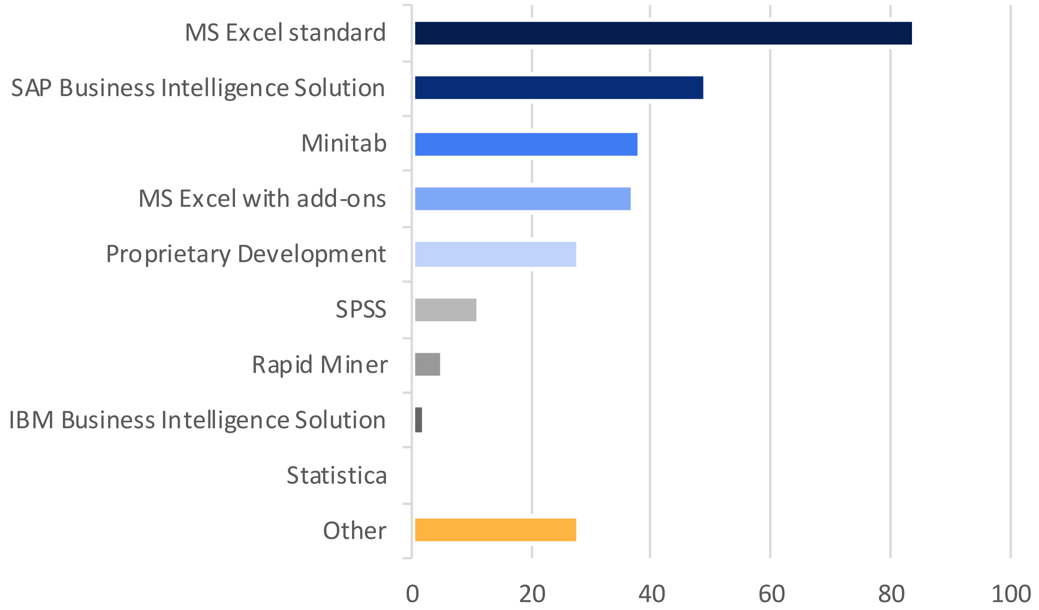
Almost all companies process data on a historical timescale, whereas around half of the participating companies process real-time data. However, differences between the maturity stages are existent as shown above. Especially advanced maturity stages are more likely to process data in real-time. If data sets were collected more uniformly the amount of real-time processed data could be increased. This might help to minimize times, e.g. between the appearance and the handling of errors and consequently reduce waste and inefficiencies in manufacturing.

FIGURE III.4.4
APPLIED DATA ANALYTICS METHODS



In the wide variety of options of analytical methods, employees need to find the one which transforms a data set into usable information the best. This is one of the most challenging activities in data processing. Again, the methods applied are dependent on the maturity stage of each company ergo the goals a company is trying to reach making use of data analytics. While correlation is by far the most popular method, regression and forecasting are also widely used. Nevertheless, the applied data analytics methods also show, that manufacturing companies still focus on the classical statistical tools and methods, nonetheless struggle to use the most advanced.

FIGURE III.4.5
USED DATA ANALYTICS SOFTWARE



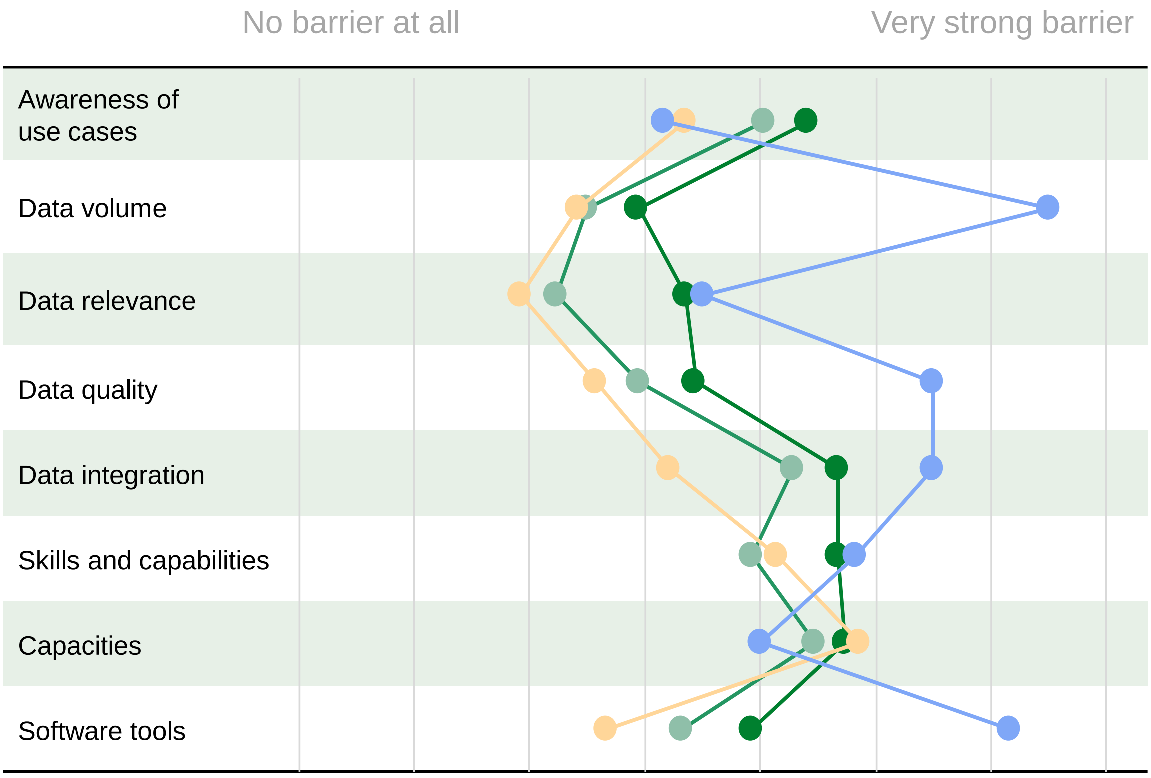
By using software for data analytics, companies mainly rely on three programs. Besides MS Excel, companies primarily use tools from SAP and Minitab. On average, a company uses 2,5 different programs to process their data. A little less than 30% of the responding companies are using software of proprietary development. As mentioned before, the right choice of software plays a key role when processing data. It needs to suit the specific data structure of a company and its needs. This might be the reason for the relatively high amount of proprietary software in use. And it is also the reason why a great number of different systems is used in manufacturing companies. All named programs and tools (Figure III.4.6) get used to process manufacturing data, e.g. for statistical analyses, visualizations or other purposes.

FIGURE III.4.6
USED DATA ANALYTICS SOFTWARE – FURTHER MENTIONING

n=27

FIGURE III.4.7
CHALLENGES CONCERNING DATA PROCESSING

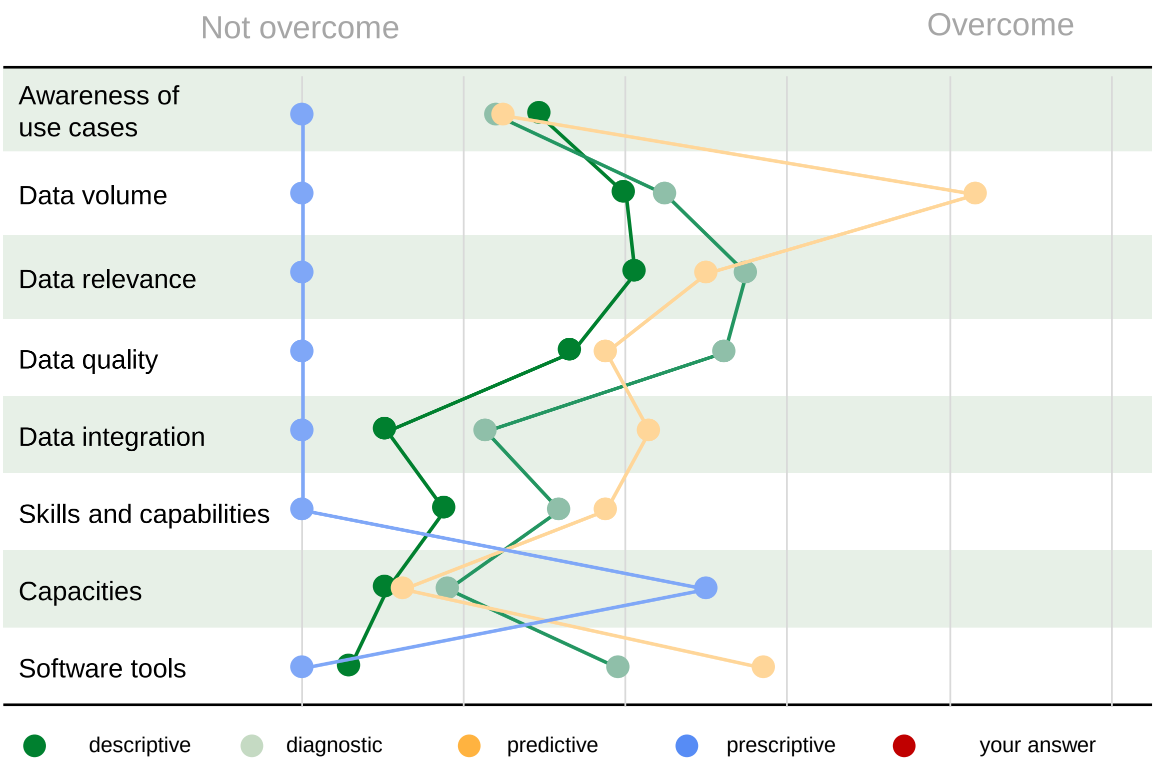
n=100



Most of the companies (~70%) are not aware of use cases for a specific set of data. About half are overwhelmed by the amount of data and do not know whether the acquired data is relevant and whether it contains potential for value generation. These trends apply equally for companies with low and high maturity levels. That shows that the data processing step is critical for reaching the next level in manufacturing data analytics. And that basics in terms of awareness and knowledge are still missing even for companies with sufficient experience.

FIGURE III.4.8
CHALLENGES CONCERNING DATA PROCESSING – ALREADY MASTERED

n=100



III.5 Data Exploitation

The last step of the data analytics process is the exploitation, which means using the new insights for decision support in manufacturing. This step is essential to transform the effort of data analytics applications into improvements, e.g. increasing cost efficiency or providing higher quality levels. Nevertheless, this study shows that only 37% of already processed data is actually exploited. Combined with the previous losses of data, this results in an overall low degree of efficiency and missing economic which is impacted by practicing data analytics in manufacturing.
The low quota of exploited data shows the difficulty of developing new application scenarios beforehand. This is necessary in order to acquire and process the right, problem-specific data. In all process steps of Manufacturing Data Analytics, the awareness of use cases and application scenarios is one major barrier. Nevertheless, the graphic below summarizes the broad range of different use case scenarios for Manufacturing Data Analytics, according to mentioning of participants.

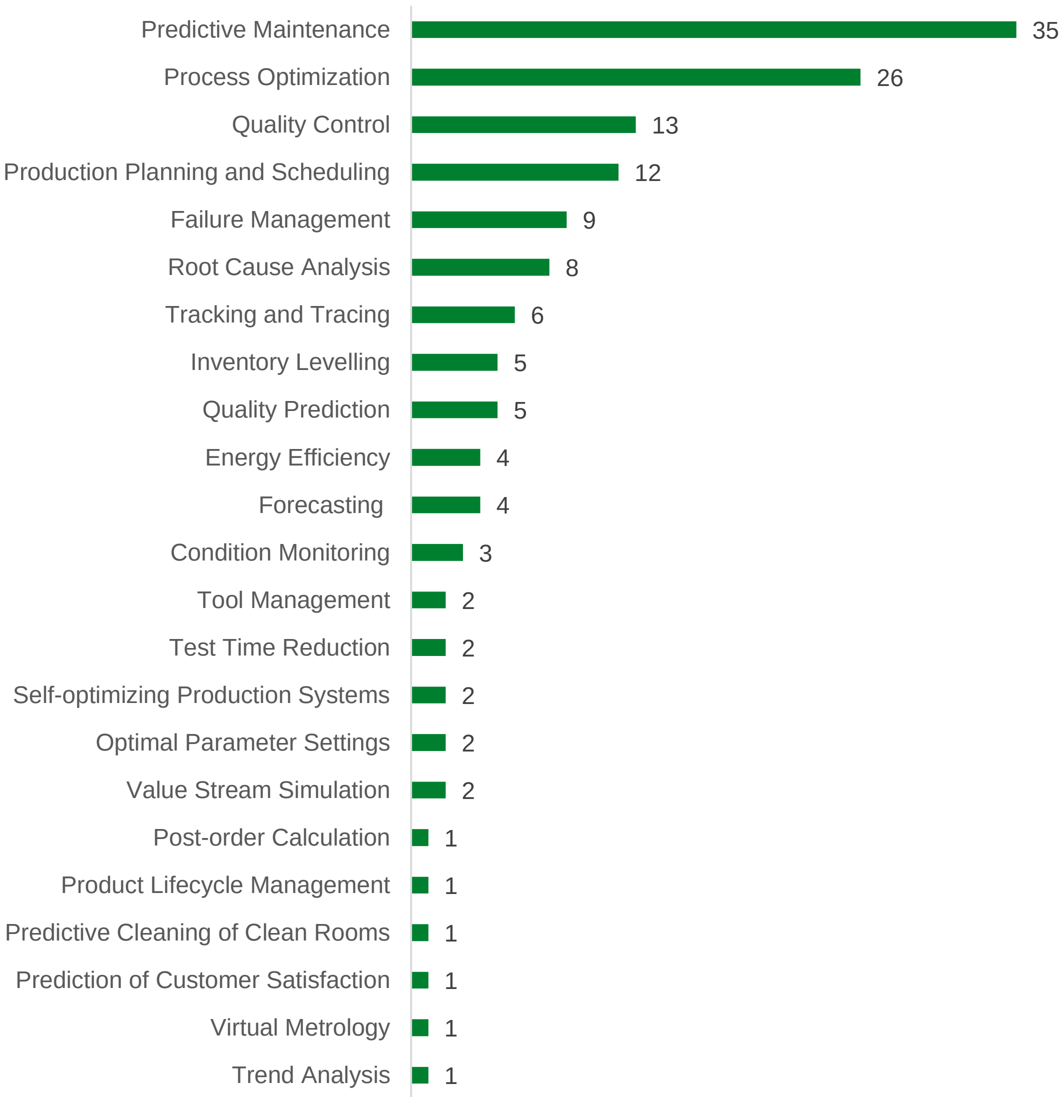
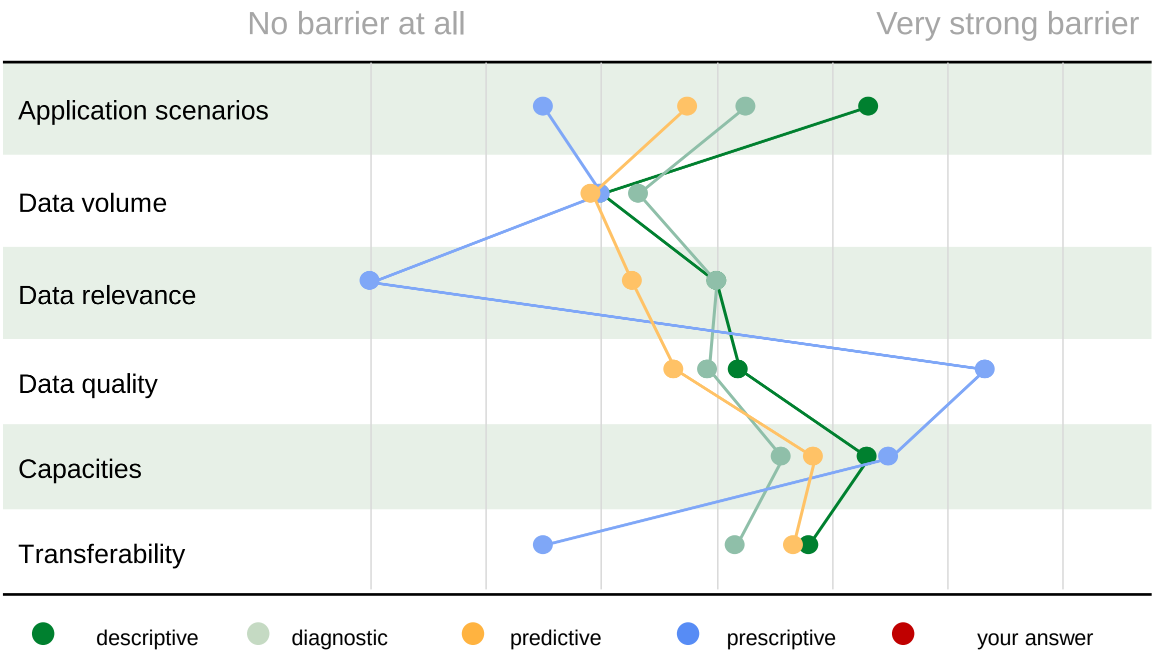


FIGURE III.5.1
USE CASE SCENARIOS FOR DATA ANALYTICS

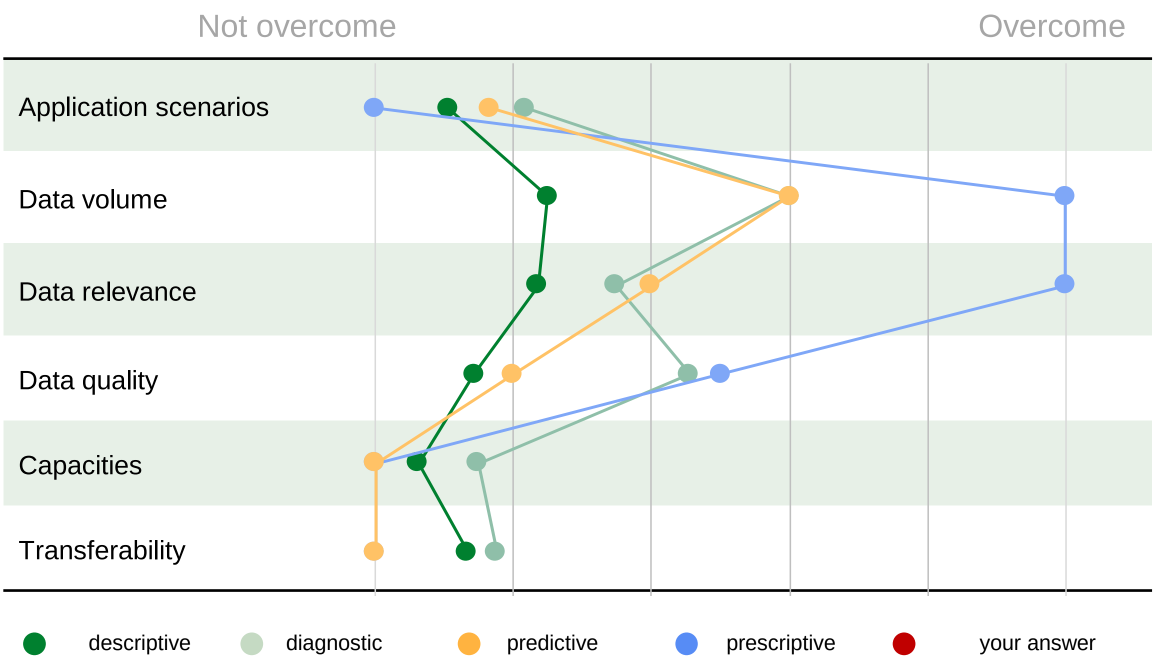
To enable manufacturing companies exploiting the potentials of data analytics, the actual challenges have to be identified. All participating companies indicate that a lack of capacities, e.g. qualified personnel or even budget, is the main reason that the potentials of data analytics cannot be completely exploited. Missing knowledge concerning potential application scenarios, is another great barrier for companies with a low maturity level. Companies with a high maturity level already have a broader knowledge, thus other barriers like low data quality are more important.

FIGURE III.5.2
CHALLENGES CONCERNING DATA EXPLOITATION
n=99



None of the identified challenges is already mastered to full extent. Even data volume, despite a broad variety of existing tools for big data analytics, is still challenging. Especially the realization of possible application scenarios is not mastered yet for most of the companies. And it has to be addressed through novel, modular and practice-oriented approaches.

FIGURE III.5.3
CHALLENGES CONCERNING DATA EXPLOITATION – ALREADY MASTERED
n=99



IV Business Performance Impact

The overall goal of Manufacturing Data Analytics is to improve business decisions and finally business performance in manufacturing. But application of Data Analytics is also an investment: Manufacturing companies are forced to build capabilities and even to invest in new hardware and software infrastructure to profit from new insights through Data Analytics. However, manufacturing companies are still reserved. This study shows that investments in the last three years have not had a significant impact on the companies' business performances yet (revenue, EBIT, market share). This also confirms that until today manufacturing companies have not yet mastered the actual challenges in data analytics and that future research is still needed.

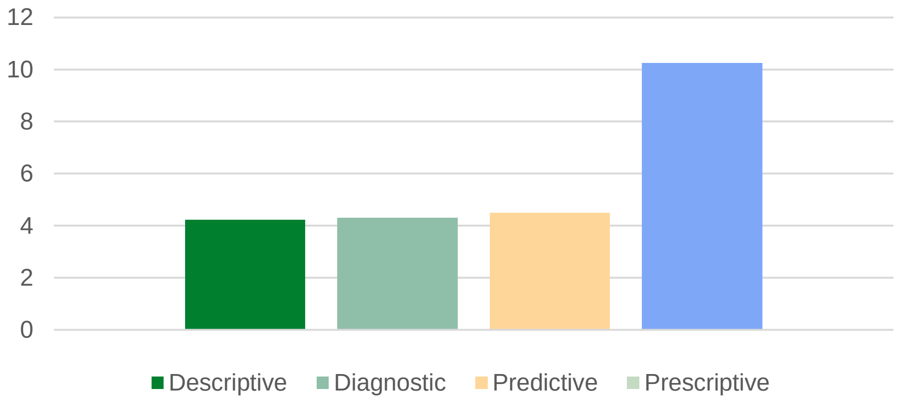


FIGURE IV.1
AVERAGE PERCENTAGE OF ANNUAL INVESTMENT BUDGET SPENT ON DATA ANALYTICS ACTIVITIES
n=100

Nevertheless, most manufacturing companies are already satisfied with their success in supporting business goals with the help of data analytics. This can be explained by the limited effort most companies have spent on data analytics activities in the past (Figure IV.1). Companies roughly invest a little less than 5% of their annual manufacturing investment budget on data analytics activities. The prescriptive maturity stage is an exception – these companies already spent up to 10% – this demonstrates that Manufacturing Data Analytics is an actual investment. The graphic below illustrates the companies' assessment of their success with data analytics – higher maturity stages also tend to rate their success on a higher level. Despite lacks in business performance impact, manufacturing companies seem to be satisfied with their success in Manufacturing Data Analytics.

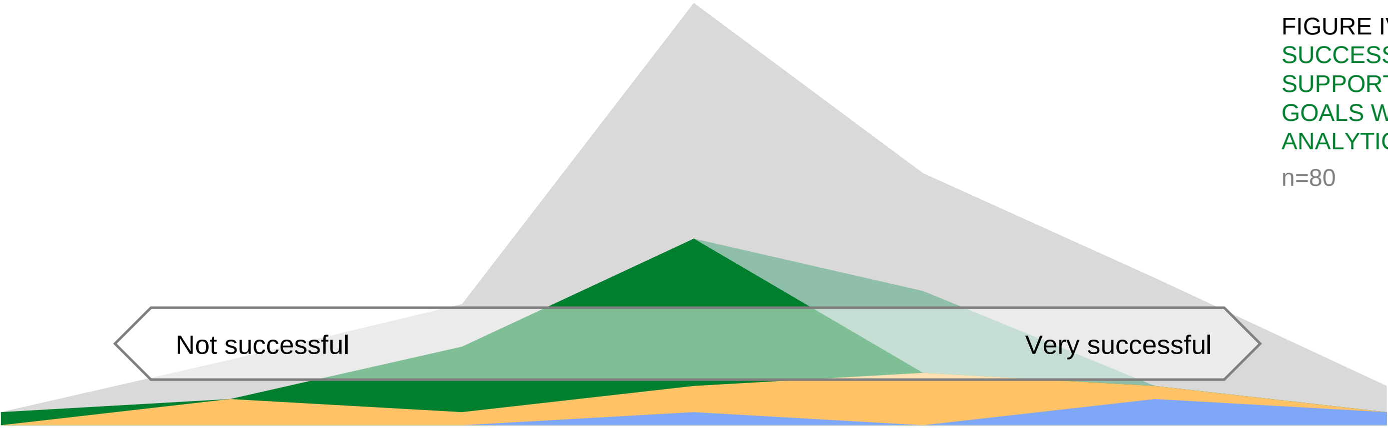
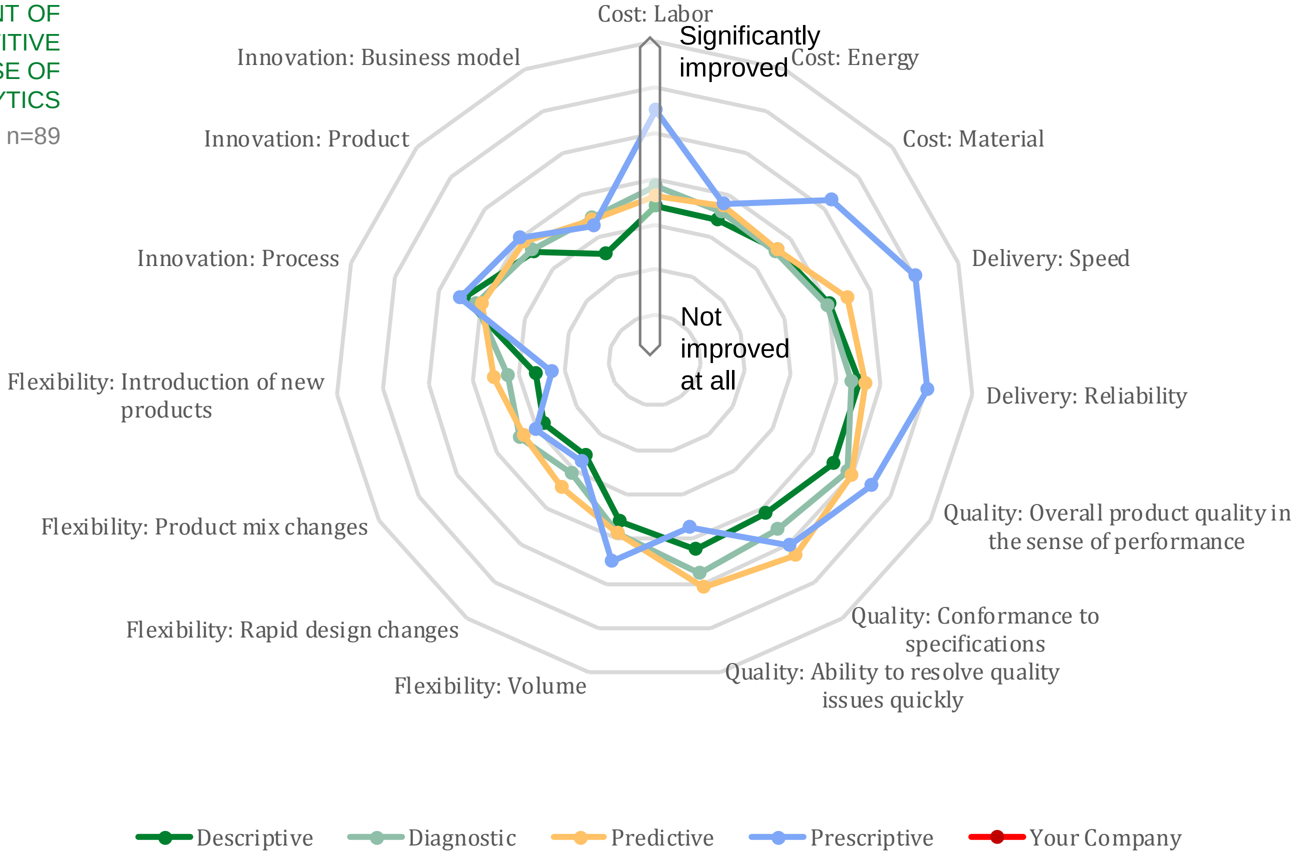


FIGURE IV.2
SUCCESS IN SUPPORTING BUSINESS GOALS WITH DATA ANALYTICS
n=80

FIGURE IV.3
IMPROVEMENT OF COMPETITIVE PRIORITIES BY USE OF DATA ANALYTICS
n=89



For successful data analytics there needs to be a measurable impact on business goals e.g. cost reduction, quality improvement, flexibility, delivery or innovation. Figure IV.3 illustrates to what degree Manufacturing Data Analytics has already affected the categories mentioned above.

Data Analytics seems to have the biggest positive impact on the category “quality”, regardless of its sub-categories. All companies agree on the positive effect of Data Analytics in this field, although the full potential has not been tapped yet. Also Data Analytics had a relatively large effect on the reliability of deliveries, delivery speed and on process innovation. Highly positive effects on the labour costs, reduced costs for material and very high impacts on the delivery speed and its reliability were reserved to the prescriptive maturity stage.

In other categories, all maturity stages seem to face equal troubles making use of Data Analytics in manufacturing, e.g. flexibility was basically not affected by using data analytics.

While there are some exceptions, it is generally true that the more advanced maturity stages seem to have greater improvements in the past compared to the less advanced maturity stages.

In general, the business impact of Manufacturing Data Analytics is actually not satisfactory. An increase in effectiveness in these categories will be necessary in the future to improve competitiveness and to enhance profit. This will also sensitize and motivate companies to invest in Data Analytics activities.

V CONCLUSION & OUTLOOK

As the preceding chapters have shown, a successful application of Data Analytics in production and the exploitation of its full potential is still a challenging task. While acquiring and storing data is manageable for most companies, processing the acquired data (41 mentions) and using it to support decision-making (41 mentions) remains difficult.

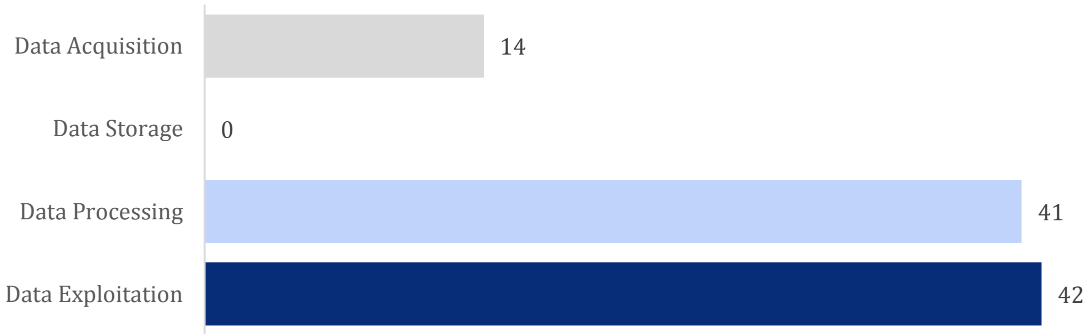


FIGURE V.1
CRITICAL STEPS IN THE DATA ANALYTICS PROCESS
n=81

There are multiple possibilities for companies in order to successfully expand in data analytics. Investing in either internal development, external acquisition or IT infrastructure were the most common choices made in order to enhance profit from data analytics in production. While most companies decided to train and educate their current staff, integrating the existing IT infrastructure is a priority for 64%. Only 33% will hire additional specialists to strengthen Data Analytics in manufacturing, whereas contracting external consultants and collaborating with customers and suppliers are popular options as well. Among the other choices that were made, introducing MES was the most popular although only 6% stated that they planned activities in fields that were not listed above.

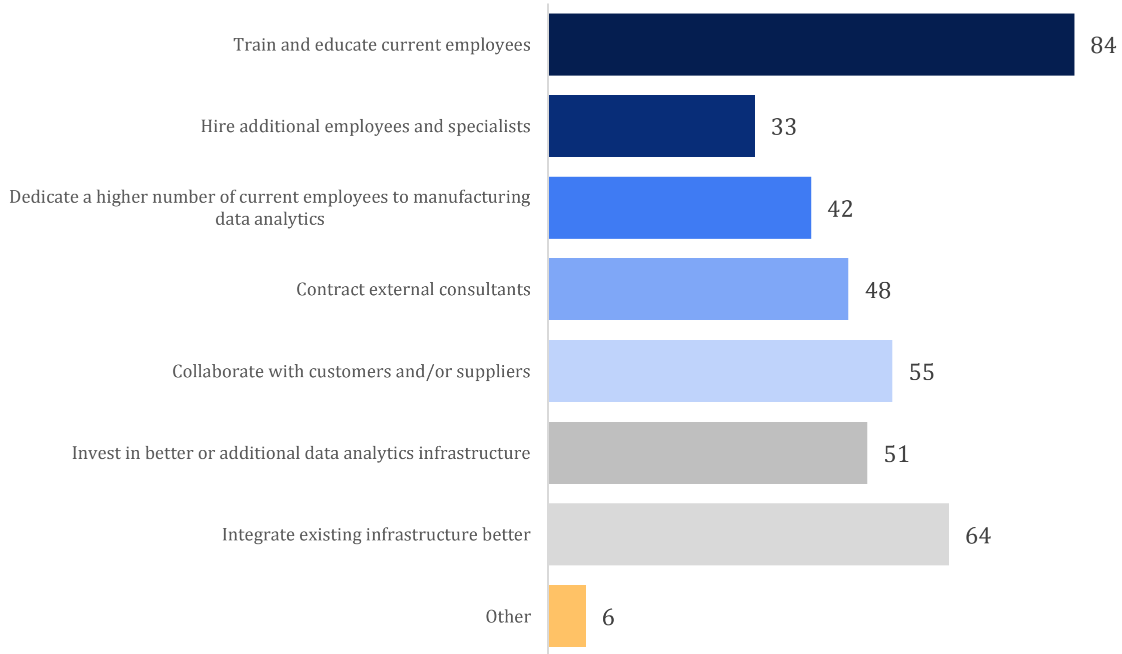
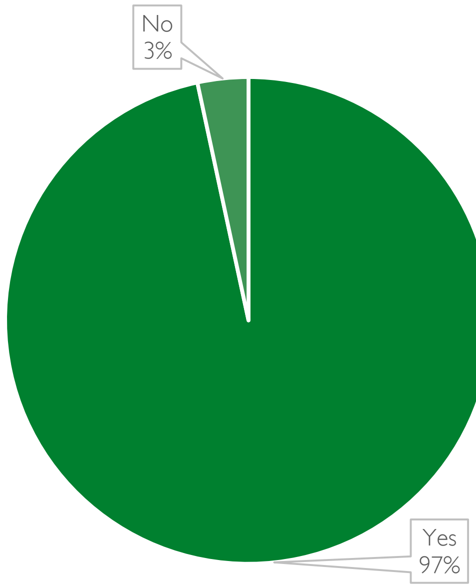


FIGURE V.2
IMPROVEMENT OF COMPETITIVE PRIORITIES BY USE OF DATA ANALYTICS
n=100

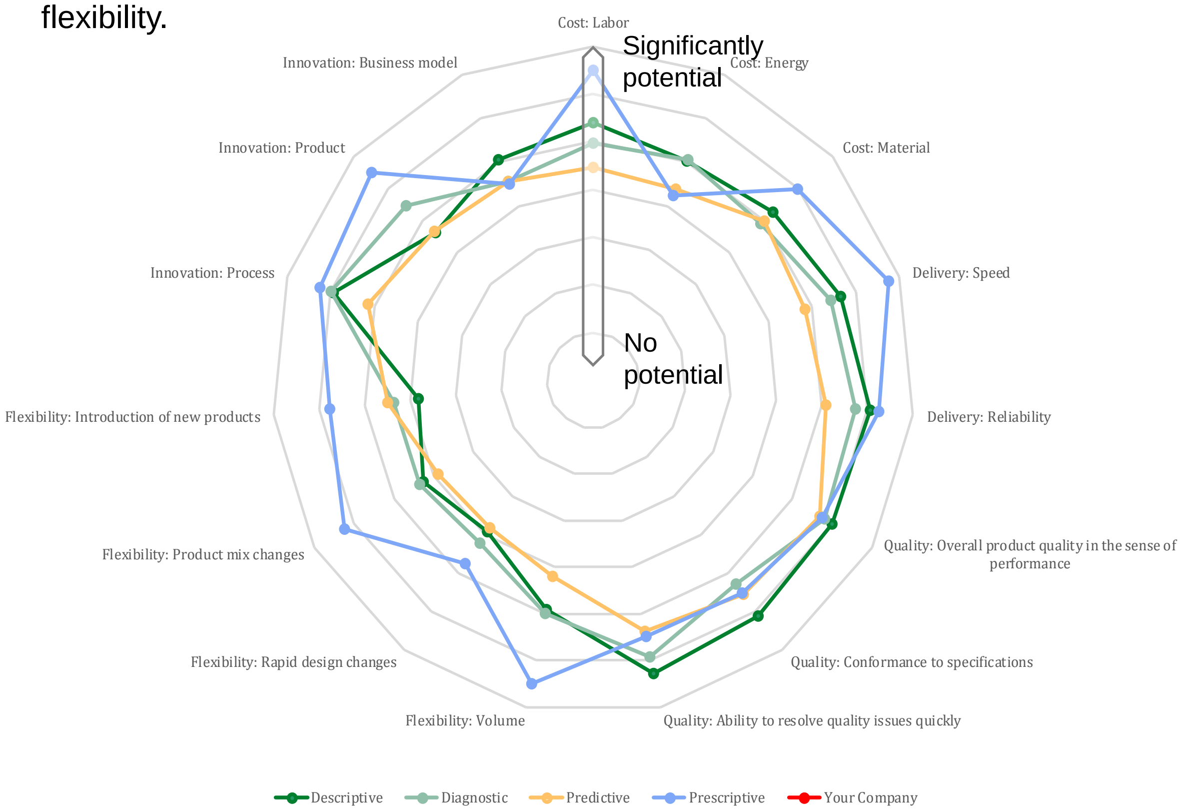
Although current efforts in the field of data analytics are not reflected in business performance improvements, manufacturing companies see big potentials for the future concerning Manufacturing Data Analytics. 97% stated that they will increase related activities in the future.

FIGURE V.3
EXPANDING ACTIVITIES IN MANUFACTURING DATA ANALYTICS IN THE FUTURE
n=89



In contrast to the rather small impacts of Data Analytics, companies are confident that if they made better use of their data, the potential improvement in all categories would be much higher than it currently is.
Especially in terms of quality and innovation process there is a lot of confidence that once data analytics in manufacturing is highly developed these categories will profit the most. The category that is believed to profit the least is flexibility. The prescriptive maturity stage has the most confidence in the potential of Data Analytics, especially in labour cost, delivery speed and flexibility.

FIGURE V.4
POTENTIAL IMPROVEMENT OF COMPETITIVE PRIORITIES BY USE OF DATA ANALYTICS
n=89



We would like to cordially thank everyone who participated in this study! We are looking forward to welcoming you to our future research and consulting activities.

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NOTES

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Institute of Technology Management

University of St.Gallen

WZL | RWTH AACHEN UNIVERSITY

Institute of Technology Management
University of St.Gallen (HSG)
Dufourstrasse 40a
9000 St.Gallen
Switzerland
☏ +41 (0)71 224 72 60

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Laboratory for Machine Tools and Production Engineering (WZL)
RWTH Aachen University)
Steinbachstr. 19
52074 Aachen
Germany

www.wzl.rwth-aachen.de

We welcome any of your comments, questions, or suggestions!

Prof. Dr. Thomas Friedli
☏ +41 (0)71 224 72 61
✉ thomas.friedli@unisg.ch

Marian Wenking
☏ +41 (0)71 224 72 74
✉ marian.wenking@unisg.ch

Prof. Dr.-Ing. Robert Schmitt
☏ +49 (0)241 80-20283
✉ R.Schmitt@wzl.rwth-Aachen.de

Sebastian Groggert, M.Sc.
☏ +49 (0)241 80-28221
✉ s.Groggert@wzl.rwth-aachen.de