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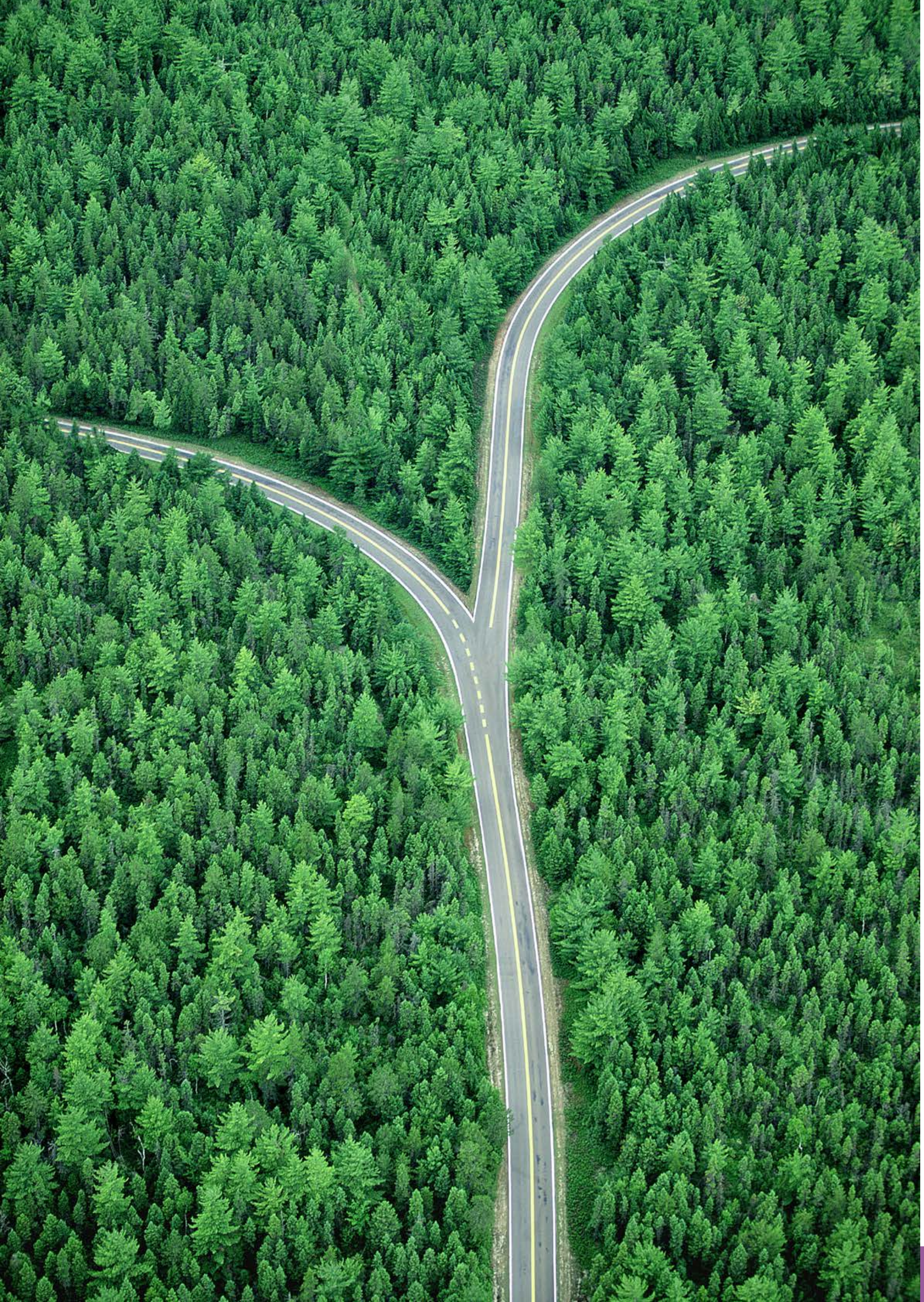
Data-driven Companies

On the path to strategic use of data

March 2021

Continuously generating value and a competitive advantage through data and artificial intelligence technology (AI) are goals to which many companies aspire. However, most companies are in a state of transformation. Using our survey on five practical challenges on the path to becoming a data-driven company, Zühlke investigated where companies stand with the strategic implementation of data. Based on this data, three typical patterns can be identified, which call for different implementation strategies.



Management Summary

What barriers do companies face on the path to becoming a data-driven company? This study explores that question. Most companies invest in data and AI projects, but many also report that the potential of these projects is only partially exploited at the company level. Based on our experience from over 100 data and AI projects, we identified five typical barriers that companies face on their path to becoming a data-driven company. For the study, we queried more than 110 international companies about these obstacles and identified the following underlying causes:

1. An inactive data innovation pipeline

Continuous, integrated planning and implementation of data and AI projects is absolutely key for a data-driven company. When this doesn't function – because the projects are focused too heavily on the technology and too little on business requirements, for instance – the innovation pipeline remains inactive. The most important tool for overcoming this barrier is active project portfolio management, by which the value-adding data and AI projects are defined, planned and conducted in accordance with the company's overarching data strategy.

2. Proof-of-concepts falling by the wayside

A large number of projects never make it past the 'proof of concept' stage. There can be two reasons for this: the PoC shows that the project is not feasible, or the transition from prototype to operational solution fails. The survey results show that both causes are relevant within companies.

3. Technically perfect solutions are not used as planned

Often, AI-based solutions are not adopted or used as planned by the user group. According to the respondents, the main reason for this was a lack of integration of the solution into existing infrastructures.

4. Competencies in the field of data

Personal skills in the field of data are a fundamental factor for the success of data and AI projects. Surprisingly, most companies already have them on hand. However, the study shows that interdisciplinary collaboration represents the greatest challenge in data projects.

5. The data itself

Naturally, the issue of data also plays a key role in data and AI projects. The most commonly cited causes for problems in this area are a lack of easy access to data and insufficient data quality.

In further analysing the study, we identified three levels of maturity in companies on the way to becoming data-driven.

1. The first company type is faced with challenges at all five barriers.
2. The second only experiences challenges in the last two fundamental themes.
3. The third type can already be described as data-driven. It is striking how many of these are small businesses.

For a successful transformation into a data-driven company, we recommend a threefold approach.

1. **Determine the vision at the C-level**
2. **Define the data strategy and establish AI portfolio management**
3. **Create the foundations on an ongoing, incremental basis and, at the same time, implement value-adding solutions. These can be used to test and readjust the corresponding foundations if necessary**

‘85 % of the decision-makers surveyed rate the potential for data and AI for their company as high. Yet just 25 % of respondents described their companies as data-driven.’

On the path to strategic use of data

The potential of data and artificial intelligence (AI) is vast and beyond dispute. By 2030, the technologies behind it are expected to generate around USD 13 trillion↗ worldwide. That means we are in the midst of a data revolution. This began about 10 years ago, when many companies took their first steps towards dealing with large data volumes under the banner of ‘big data’ (today, this is an entry-level requirement). A few years later, the focus shifted to implementing individual machine learning use cases. Although this resulted in some initial short-term wins, challenges remain in many cases. Zühlke’s experience from more than 100 data and AI projects shows that these mostly relate to operationalising use cases and thus to the generation of actual value.

If, however, such projects are approached holistically throughout the organisation with the aim of becoming a ‘data-driven company’, it will result in a multitude of precisely these sought-after value propositions. Because only by systematically deploying data and AI in every division and every function can a company exploit these competitive advantages:

1. Data-driven decisions: more effective decisions at every level of the hierarchy
2. Radical new products and services based on data and AI technology: opening up new revenue streams
3. Process optimisation: reducing costs and throughput times

One best-practice example of a data-driven company is Netflix. Founded as an online video store that mailed out DVDs, the company started applying machine learning (ML) back in 2000 – a full seven years before it transformed into a streaming service. It used recommendation engines to suggest films to customers. The company has continued to apply and improve this expertise to this day, and it is a key element in the Netflix success story. Currently, 80 % of streaming time can be traced back to recommendations↗. In 2011, Netflix finally began producing its own films and series, starting off with the television series House of Cards. The concept for this successful series arose from findings drawn from analysing data on media consumption as well as human expertise on the preferences of series fans.

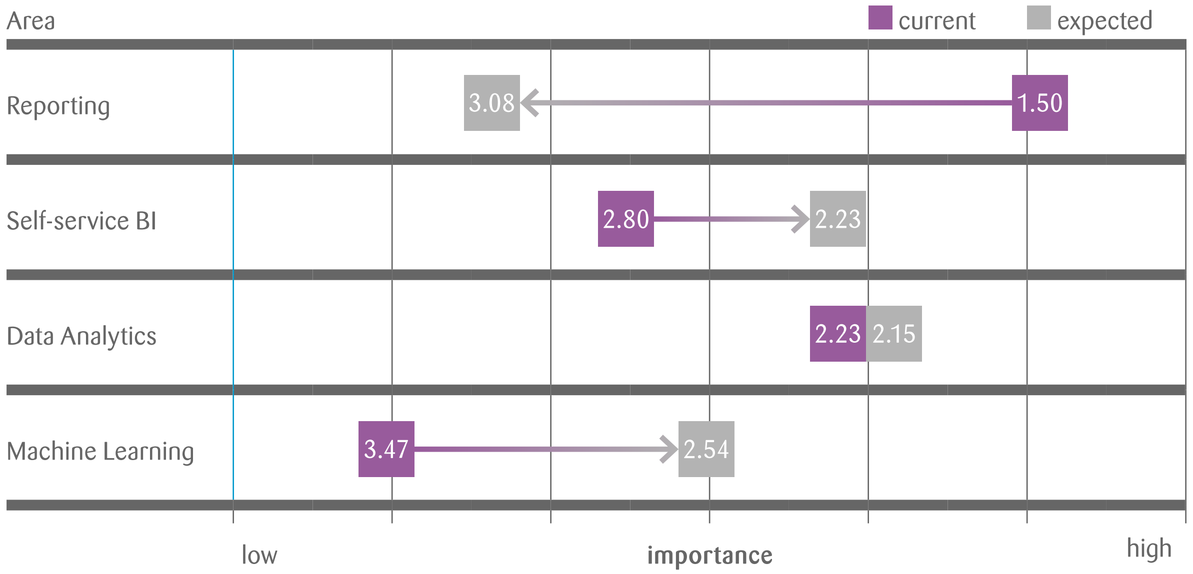
For this study, Zühlke queried over 110 international businesses on various issues concerning the subject of data-driven companies, with the goal of finding out how decision-makers view the potential of data and AI, how far companies have advanced on the path towards becoming a data-driven company, and what obstacles they’re encountering along the way.

In what form do companies use data and AI today, and how will that change in the near future? Are machine learning applications, for instance, already standard in the companies of today? To clarify these issues, we investigated which data application types (see table) will bring the greatest added value for companies today and in the near future (three years). Here, the respondent companies were asked to rate the importance of application types in ascending order from 1 to 4. As the graph on the right illustrates, pure reporting is seen as the most important application type today, but its significance is predicted to decline sharply in the coming years. By contrast, both self-service BI and operationalised ML algorithms are set to greatly increase in significance over the next three years. We interpret this result to mean that companies don't strive for complete automation but, rather, focus on using AI in specific areas where it will generate clear added value.

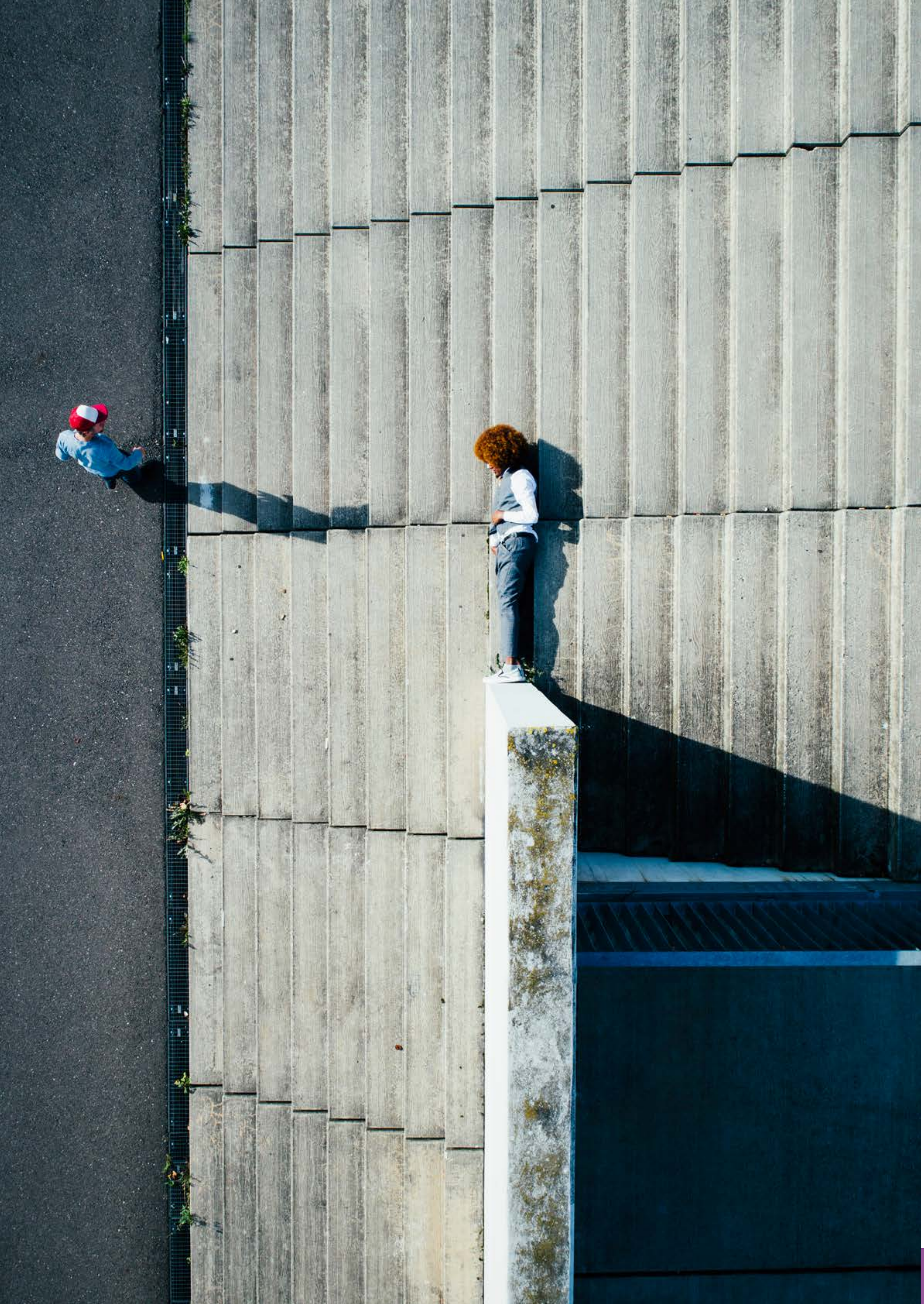
Explanations and examples of the data use cases examined

Application type	Description	Typical use case
Reporting	Regular, automatically generated reports with a defined structure and uniformly configured statistical data evaluations.	Monthly financial report
Self-service business intelligence (=BI)	Self-service BI applications enable a broad-based user group within the organisation to use data individually, in order to answer questions relevant to the business.	Research into the most sought-after products within a particular customer segment
Data analytics	Explorative ad-hoc analysis of internal and external data using script languages, carried out by specialist employees.	Explorative cluster analysis on an export of customer data
Machine learning	Operationalised algorithms that reveal new findings or forecasts based on data.	Monitoring conditions, e.g. state of material wear in the infrastructure > foundation for maintenance planning and decision-making

Importance of data use types today and in three years



In general terms, the potential for companies to gain added value from data is rated as very high. For 85 % of respondents, the potential for data and AI projects in their companies was high or very high. However, just 48 % were able to point to an AI strategy, and only 25 % described their companies as 'data-driven'. From our project experience, we have identified the roots of this discrepancy in five typical barriers to successful implementation of data and AI projects. The primary goal of this study was to determine the main causes of these barriers and to arrive at a better understanding of the current challenges in the area of analytics. In the next section, we will take a closer look at these barriers and present the study results for each one.



Typical barriers on the path to becoming a data-driven company

From our consultancy and implementation experience, we have identified five barriers facing companies on their path to becoming a data-driven organisation. The first three of these challenges are related to the realisation of data and AI projects; the last two we consider to be foundational issues for data-driven companies.

- An inactive data innovation pipeline
- Proof-of-concepts falling by the wayside
- Technically perfect solutions are not used as planned
- Competencies in the field of data
- The data itself

‘More than half of decision-makers say that AI initiatives fail due to a lack of business vision or too much focus on technology.’

An inactive data innovation pipeline

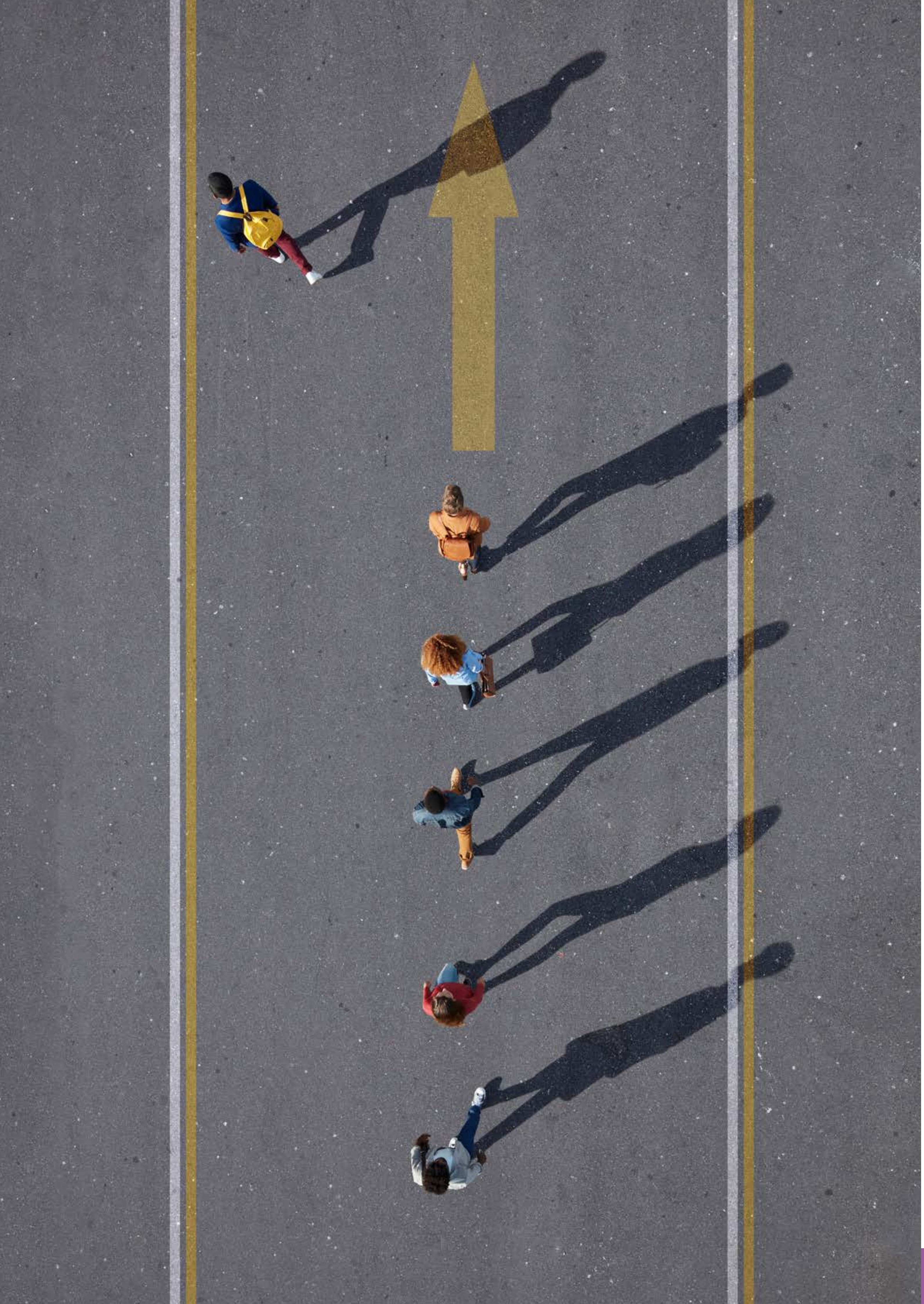
A key element for a data-driven company is an active data innovation pipeline. We take this to mean continuous, integrated planning and implementation of data and AI projects that generate ongoing value for the entire organisation. Our experience has shown that this pipeline is not yet active in many cases, which may have a variety of underlying causes. On the one hand, many AI initiatives are driven by the possibilities presented by technology (‘technology push’), with little focus on the benefit for the business. However, particularly at the start, it is important for data-driven companies to continuously demonstrate the benefits of data and AI projects. Otherwise the motivation and willingness to invest resources in this type of project will quickly dwindle. On the other hand, we see many teams aiming to develop ideas for AI use cases separately, with no coordination, and carrying out their own initial proof of concepts independently. In addition, they often lack an integrated data and AI strategy and support at the C-level. This is vital in laying the relevant foundations for successful implementation of AI use cases and securing the corresponding budgets. Examples of such foundations include a company-wide IT infrastructure or a data science centre of excellence.

Practice box

For a leading global mechanical engineering company, we ascertained that, while various departments were addressing AI use cases, no one was looking at the big picture. This meant that for a very long time, there was no support for the development of company-wide foundations, such as a central data platform.
In another example, the customer consultants at a bank responded very positively to planned use cases, such as personalised investment recommendations. However, it proved difficult to secure funding for the projects, as the specific benefits for the company and the necessary changes to the business processes could not be determined and planned in the required level of detail due to budget constraints.

The findings from our study confirm the relevance of this challenge. Of the respondent companies, 43,6 % thought that AI initiatives failed because there was too little consideration of business success or too great an emphasis on technology. The second-most common driver cited in connection with an inactive data innovation pipeline was the lack of a proper, company-wide data and AI strategy (33.6 %).

A key tool for overcoming this barrier is active project portfolio management. Companies have to be structured and coordinated as they define, develop, prioritise, and plan data and AI use cases, and they must place these in a strategic overall context within the company. A company-wide data strategy can serve as a foundation or guideline for this process.



Proof-of-concepts falling by the wayside (‘pocitis’)

Proof-of-concepts represent a barrier for many companies. In the context of development, proof-of-concept (PoC) studies serve to establish the theoretical feasibility of a plan. This milestone therefore represents a conscious checkpoint at which gatekeepers halt the progress of projects that are not feasible from a technological, economic, or organisational perspective. Many data and AI projects remain stuck in this phase even when the PoC points to a positive outlook for feasibility – a phenomenon we refer to as ‘pocitis’. In these cases, the PoC is not developed into an operationally usable solution. This is a state of affairs that we often encounter among our customers. Possible causes of ‘pocitis’ include the wrong mindset for innovation in AI use cases, an overly narrow PoC (e.g. a purely technical focus), or insufficient expertise/lack of infrastructure for operationalising use cases.

Practice box

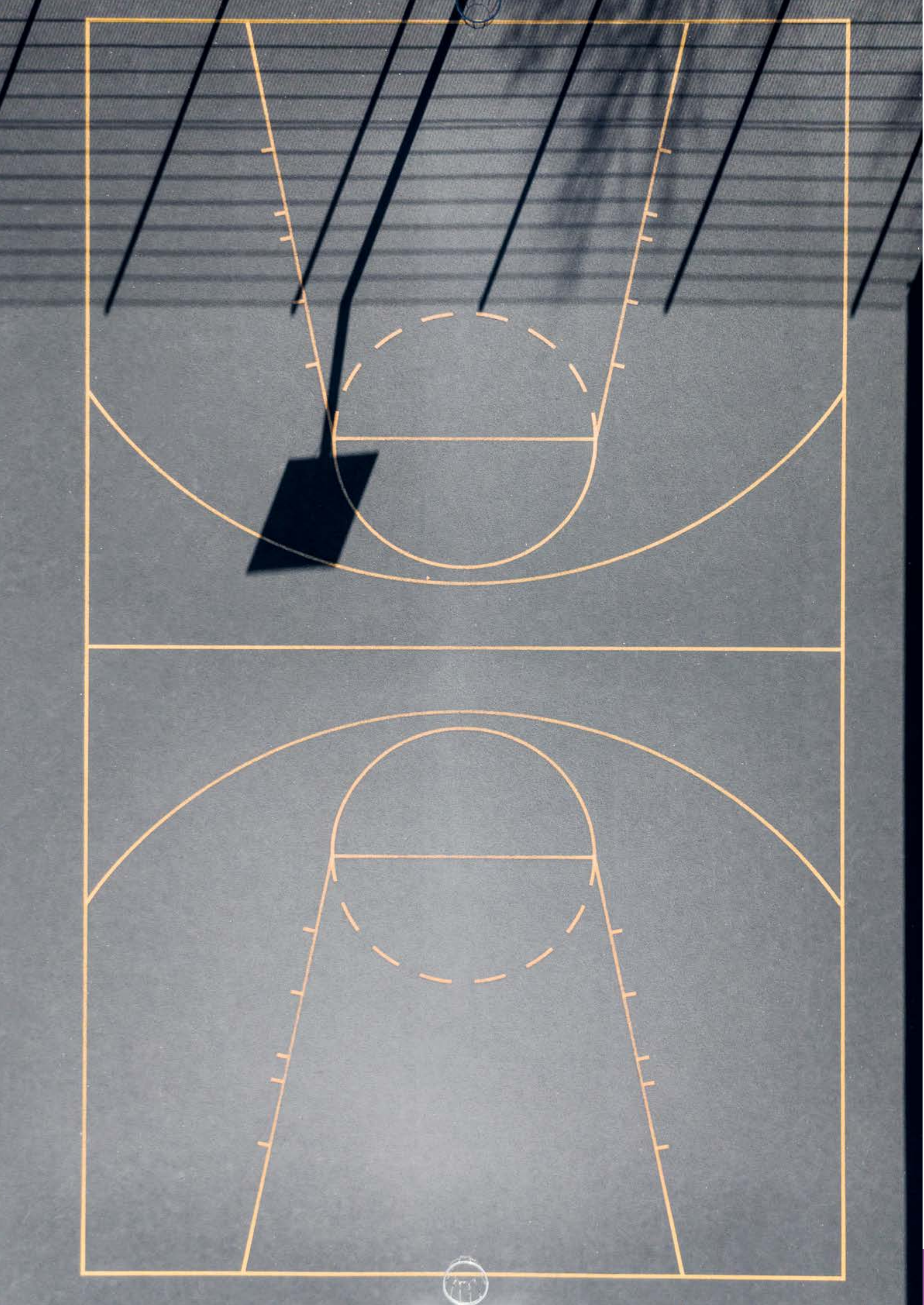
Working with the innovation team of a large transport company, we noticed that its work was not measured by the potential operationalisation or business benefits of the solutions it developed. This meant the sole focus of the team was on testing new technologies and generating new ideas; generally speaking, this is too narrow a mindset for AI innovation, because it can overlook major obstacles to getting past the PoC phase. We found one example for the second cause of ‘pocitis’ – the absence or inadequacy of infrastructure for operationalisation – in a plant construction company. Here, the project team trained the ML models with data from manual exports, which did in fact lead to very good results but couldn’t be operationalised beyond the PoC. This is because there was no option for direct data access to the customer’s systems. This kind of access would have meant integrating multiple SAP systems distributed across the globe – a project which would have cost millions.

In our study, 32.7 % of respondent companies indicated that their AI initiatives faced problems associated with PoCs.

The most frequently cited reason (40.9 %) for this problem was poor quality of data and models. This is hardly surprising; after all, these reasons can cause a negative PoC result even in the context of functioning PoC management, i.e. in these cases, the PoC serves its purpose as a ‘defined breaking point’ on projects that prove to be technically infeasible. The next two most frequent answers are more critical: ‘A negative attitude towards AI solutions’ at 32.7 % and – cited almost as often (30 %) – ‘No operational data access/lack of data platform.’

The former cause indicates a lack of IT infrastructure for operationalisation of data and AI projects. The latter, on the other hand, illustrates the extent to which operationalisation of data and AI projects is dependent on ‘soft’ factors, such as acceptance and trust in AI.

So we see that successful implementation of data and AI projects relies on essentially considering only those uses that are feasible according to strategically established criteria and from an operational viewpoint. Furthermore, projects need to allow for corresponding rollout support for ‘soft’ factors. This points to a close association between pocitis and our next topic: the lack of acceptance and usage of AI solutions in the business.



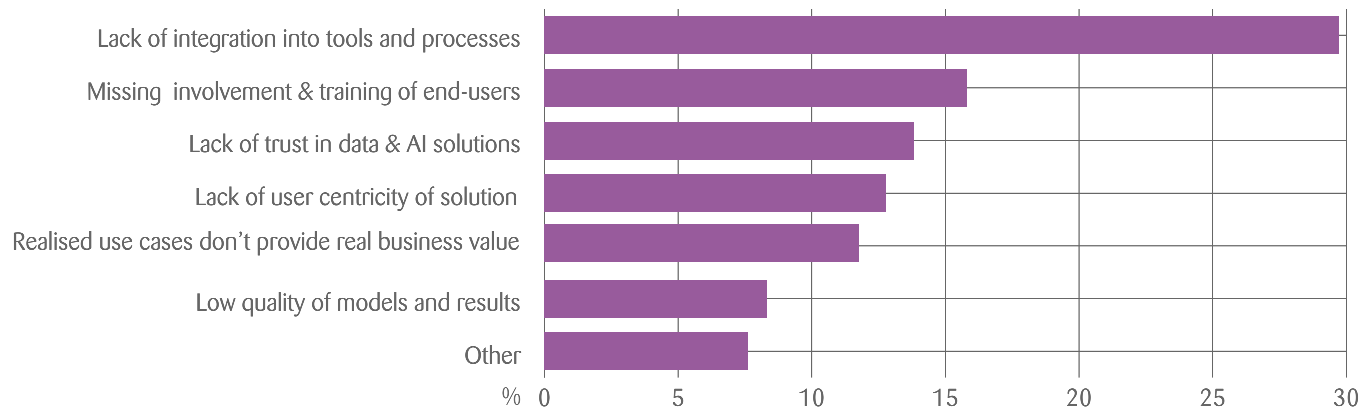
Technically perfect solutions not used as planned

A further challenge that we see as relevant in the area of implementation concerns the acceptance and usage of data and AI solutions by the business. It may happen, for instance, that a user group fails to use an application to the planned extent, even though it is close to perfect. This lack of adoption may be caused by a solution that is insufficiently tailored to real-life practice, a general prejudice against AI solutions, or reasons related to the usability of the solution (user experience).

Practice box

On one project with a manufacturer of specialist vehicles, the situation transpired as follows: to optimise planning, the company planned to develop an AI model that could forecast which replacement parts a field service technician would need at which location. Following a successful PoC, the service technicians presented a corresponding minimum viable product (MVP). From this, it emerged that most of these predicted replacement parts were either so small that the technicians always had them on hand anyway, or so large (e.g. engines) that they had to be ordered. This meant that the solution delivered no added value for the target group – a factor that should have been clarified in the solution design (known as the 'vision & scope' phase in the Zühlke process).

The study showed that failing to integrate AI solutions into existing IT tools was by far the most common reason for the target group failing to adopt the solution (52.7 %). Further key reasons cited for this barrier were insufficient training of end users and a lack of trust in AI solutions. As such, the study showed that it was, above all, a fluid integration of new AI solutions into existing systems that represented a success factor for the adoption of an AI application.



> ‘A lack of specialist resources from data & AI fields is rarely the problem – more often, it is insufficient interdisciplinary collaboration at the project level.’

Challenging foundations for data-driven companies

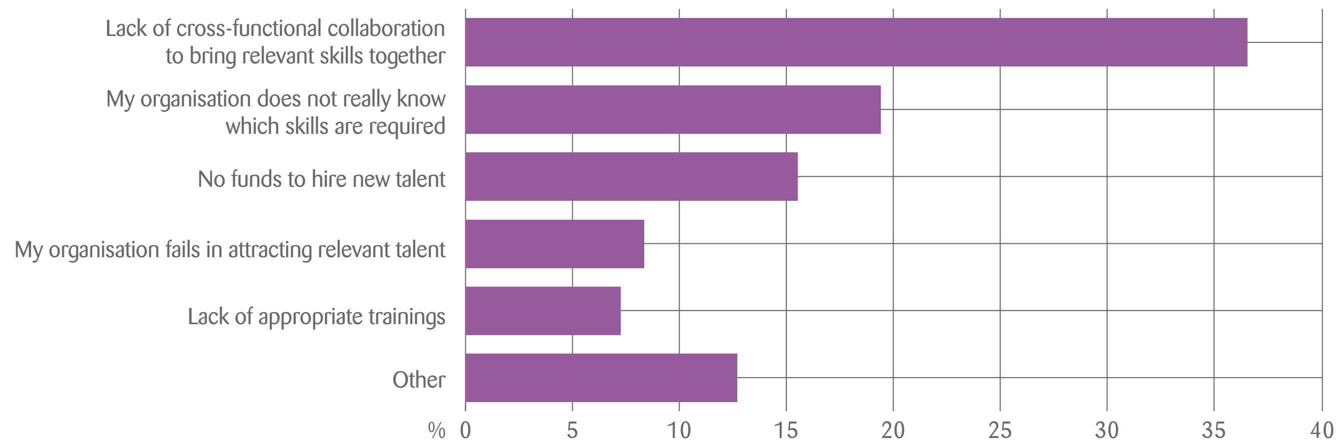
Among the foundations for data-driven companies, we include the effort and investments that are required for all data and AI projects and initiatives; in other words, the resources and capacities, organisational structures, and technical infrastructures. Here, the foundational issues of ‘competencies’ and ‘data’ regularly emerge as relevant strategic challenges for data and AI projects.

Competencies

Technical competencies that are inadequate or poorly deployed represent a major barrier for successful implementation of data and AI projects. We see this factor manifesting in different ways. Some companies are unclear what skills they need to carry out data and AI projects. Other organisations may have the right job profiles, but their specialists don’t have room to apply their skills because of sub-optimal structures. Especially in large corporations, it is often the case that particular business areas don’t even know that they have an in-house data science team. Last but not least, successful interdisciplinary collaboration at the project level shouldn’t be underestimated as a challenge on projects, as domain-specific, technical, economical, and user-related issues and requirements have to be given equal weight.

So the biggest problem in the area of competencies, according to 55.5 % of study participants, was lack of collaboration rather than lack of technical expertise. This finding underscores how important it is to deploy (in-house) data consultants who have experience of implementation projects, who are capable of building bridges between technology, business, and human users, and who can function as a kind of ‘translator’ between representatives of these groups.

The second most common answer was a lack of knowledge about the skills required for data and AI projects (29.1 %).



“Access and quality are the greatest challenges in relation to data.”

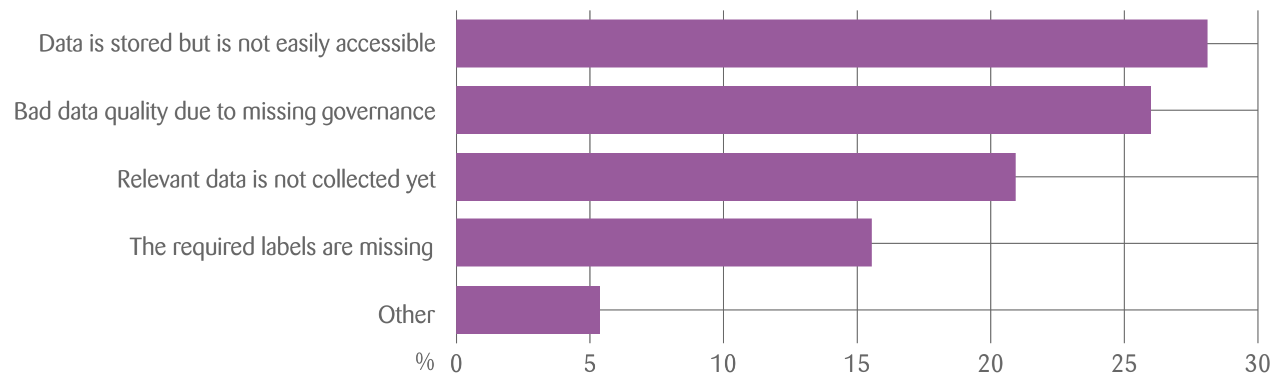
Data

The issue of data often emerges as a barrier on data and AI projects in companies as well. On the one hand, we have noticed that while many companies already have valuable datasets, they don’t make them available in a straightforward, structured way. For example, they may be stored in multiple independent systems and databases, or only exist in the form of standardised reports. But then it is not uncommon for the data not to be collected at all. This is often the case with Internet of Things (IoT) applications, for instance, where the necessary sensors and connectivity are not yet available or haven’t been available for long. Together with availability, data quality is also often cited as a barrier. We also often hear calls for the company to get its data in order before implementing any kind of data-based use case. But it is important to bear in mind that quality of data is a relative criterion, one that can only be assessed in relation to a particular application case. Company-wide data quality programmes are thus less expedient without the prospect of a concrete application.

Practice box

On a project for a renowned Swiss marketing company, we noted that the incentive scheme for the sales team was bad news for data quality. That’s because the scheme incentivised team members to capture new customers in the system. This led to many customers being included in the database multiple times, along with their subsidiaries and branches, which greatly impaired the overall data quality.
For one leading global plant construction company, we managed to retrofit operational equipment with sensors. The planned PoC for the predictive maintenance use case could only be carried out once enough sensor and error data could be collected.

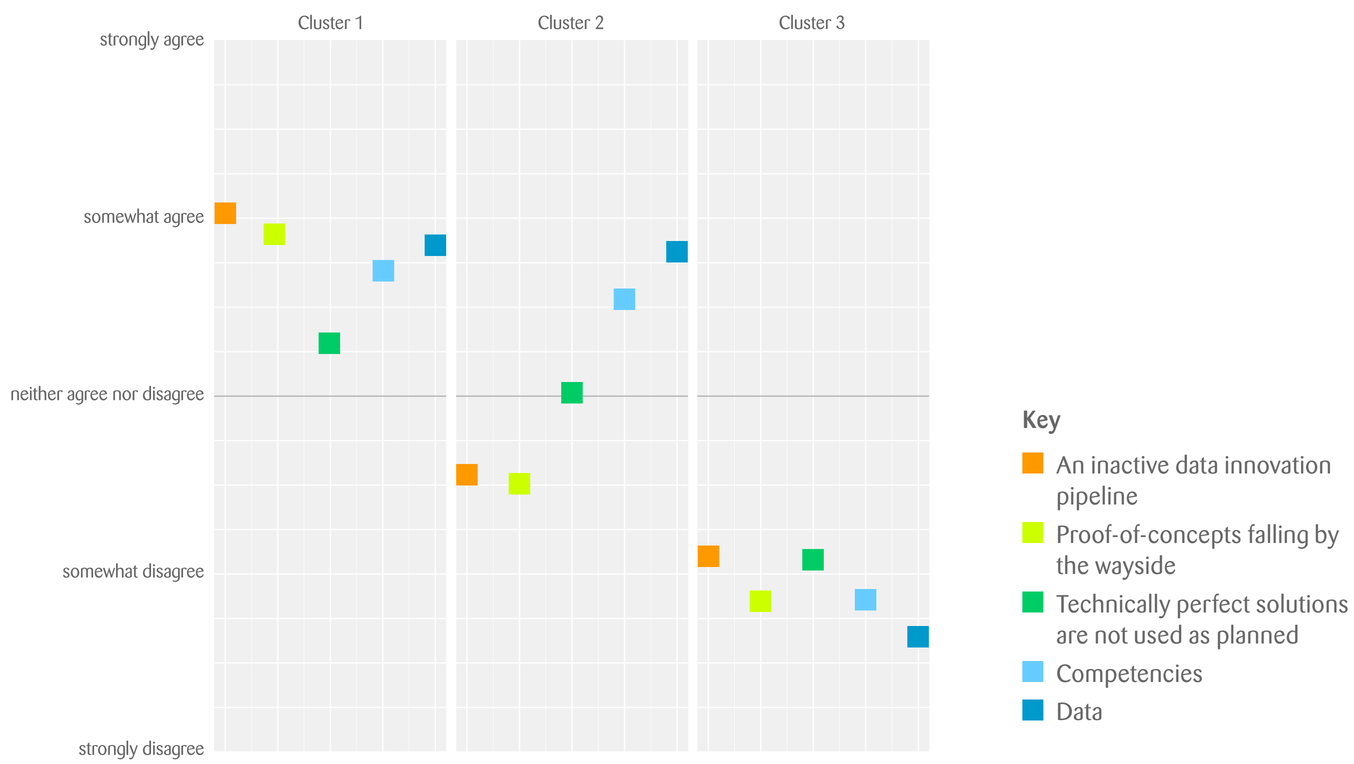
In general, the issue of data was rated as high or very high (60 % of study participants). In considering the forms and causes of this issue, 49.1 % of study participants said that while the necessary data had been gathered, it was not readily accessible. Another frequent statement was that the relevant data was of poor quality (45.5 %) or hadn’t been captured at all (36.4 %).



How far have the respondent companies progressed on their journeys?

We wanted to find out how similar or different the companies taking part in the survey were. A suitable method for showing similarities between observations with multiple variables is clustering. Based on the response to the five obstacles outlined above, we applied a k-means algorithm to determine the similarity measure for answers from the companies. This cluster analysis gave rise to three more or less distinct groups.

When we graphically arrange the average answers on obstacles (1=strongly disagree to 5=strongly agree) by cluster, interesting differentiating factors become apparent.



The companies in the first cluster agreed with all five obstacles. In the third cluster, these problems were barely apparent. In the second cluster, however, the companies agreed on issues in relation to competencies as well as data, i.e. for companies in Cluster 2, the obstacles described by us under Foundation are relevant.

The three clusters can be described as follows:

- **Cluster 1 – «Innovation»**
- **Cluster 2 – «Foundation»**
- **Cluster 3 – «Data-driven»**

Cluster 1 – 'Innovation' – recognised the potential and significance of data and AI. The journey to becoming a data-driven company was seen as an innovation project. And yet, there was a lack of holistic implementation concepts.

Cluster 2 – 'Foundation' – was further along the journey than the first cluster. Particularly apparent here were challenges with the foundations of data-driven organisations, e.g. lack of competencies.

Cluster 3 – 'Data-driven' – was most advanced along the journey to a data-driven organisation. One striking factor of this cluster is that it tends to contain smaller companies. But even these companies don't believe they have reached their goal, and anticipate an increase in relevance of data analytics and machine learning in the near future.

What does the industry comparison look like?

Are certain industries more data-driven than others? After evaluating the study, our answer to this question is a resounding 'Yes'. The answers were actually very industry-specific. The service sector already seems to have gone a step further than the manufacturing sector.

On the road to becoming a data-driven organisation, service providers report fewer obstacles on average than study participants in manufacturing and production. Of the service companies surveyed, 30% state that many of their projects don't get beyond the proof-of-concept phase; in the manufacturing sector, the figure is 37%. A similar picture emerges for business adoption: 22% of service providers are unable to use their technically perfect solutions as planned, while in the manufacturing sector it is 29%.

The following graphic provides a detailed overview of how far the sectors have progressed in their journey to becoming data-driven:

The following graphic provides detailed insights into the sometimes striking differences:

Obstacle	
Proof-of-concepts falling by the wayside	Manufacturing 37% Services 30%
Low rate of Business Adoption	Manufacturing 29% Services 22%
Lack of skills in the field of data	Manufacturing 59% Services 46%
Inactive data innovation pipeline	Manufacturing 35% Services 36%
Inadequate data & quality	Manufacturing 59% Services 58%

This is confirmed by examining the clusters: far more manufacturing companies are still at the start of their journey to becoming data-driven companies. Some 37% of manufacturing companies surveyed belong to the 'Innovation' cluster and only 22% to the 'Data-driven' cluster; in the service sector, however, 28% of companies belong to the 'Innovation' cluster and 32% to the 'Data-driven' cluster.

Zühlke's project experience shows that it's often much more difficult to implement use cases in manufacturing and production than in other industries. This means that the companies lack the relevant experience. In contrast, use cases such as product recommendations or personalised marketing seem to be much more established in the service sector. As confirmed by the results of the study, this suggests that companies that are directly connected to end customers are already much further down the road to becoming data-driven companies. Whether this is actually the case is shown by the following B2C/B2B comparison.

B2C companies seem to be a clear step ahead of B2B companies.

The B2C/B2B comparison is clear

The results of the industry comparison raise the further question of whether business relationships also have an impact on how data-driven companies operate. And the evaluations confirm it: B2C companies seem to be a clear step ahead of B2B companies.

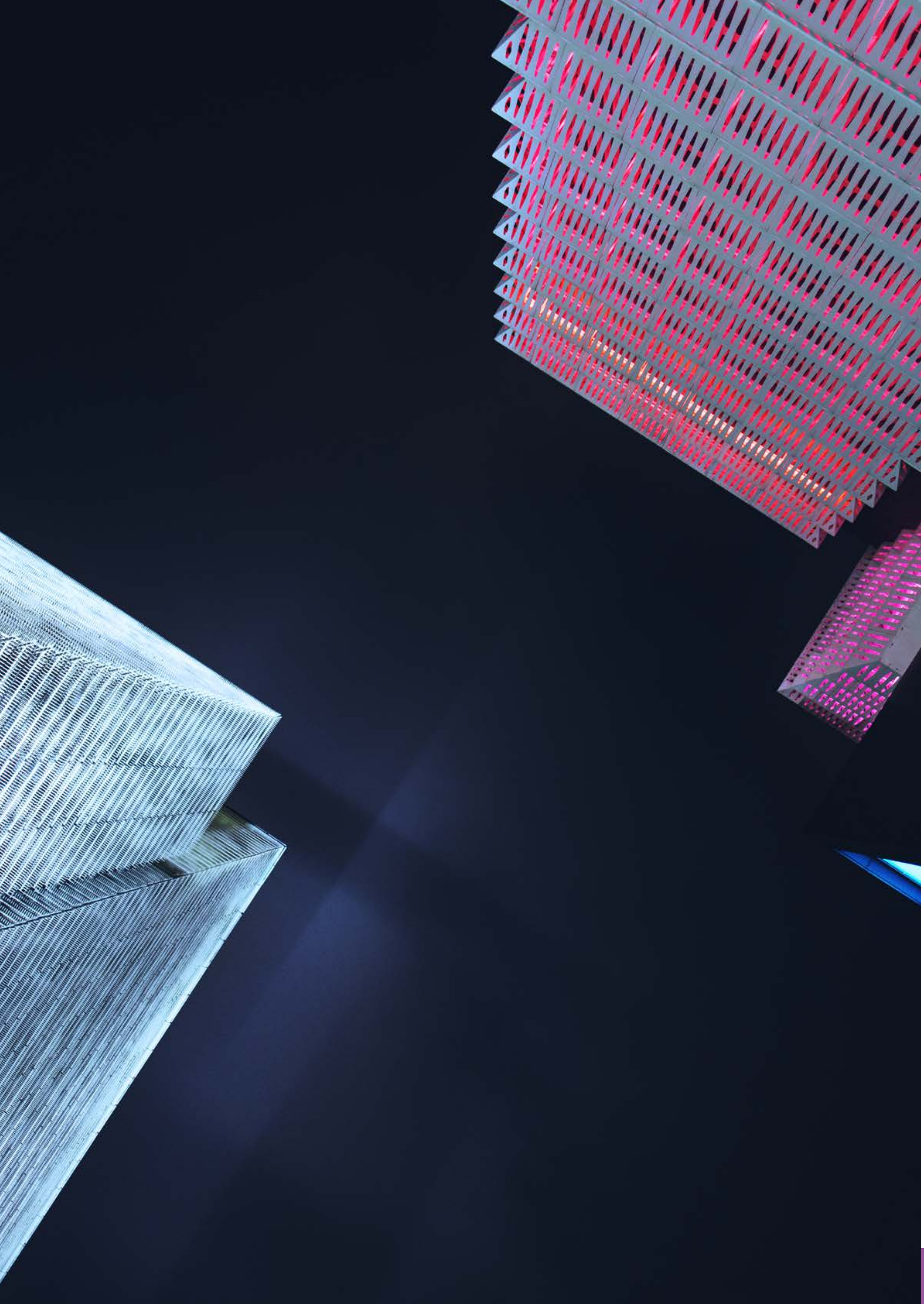
Almost 40% of B2B companies surveyed are in the 'Innovation' cluster, while only 20% are in the 'Data-driven' cluster. In the B2C sector, the situation is reversed: Almost half are in the 'Data-driven' cluster, with only 20% in the 'Innovation' cluster.

Accordingly, B2B companies report far more obstacles than B2C companies on the road to becoming data-driven companies. Almost 60% of B2B study participants report a lack of skills in the fields of data and interdisciplinary collaboration. Over 80% even rate their data and its quality as inadequate.

The following graphic provides a detailed overview of how far the sectors have progressed in their journey to becoming data-driven:

Obstacle	
Proof-of-concepts falling by the wayside	B2C 30% B2B 36%
Low rate of Business Adoption	B2C 20% B2B 33%
Lack of skills in the field of data	B2C 40% B2B 58%
Inactive data innovation pipeline	B2C 23% B2B 42%
Inadequate data & quality	B2C 40% B2B 81%

The sometimes striking differences can be explained with observations similar to those in the previous industry comparison. They confirm the assumption that end customer data makes an important contribution to the journey towards becoming a data-driven company. Over the years, B2B companies often develop very heterogeneous system landscapes, within which process or production data is generally used for the purpose of process optimisation. Acquiring, consolidating, providing and analysing this heterogeneous data is highly complex and the data quality suffers as a result. In addition, use cases such as product recommendations or personalised marketing have been key success factors in the B2C field for many years. Therefore, B2C companies have long been compelled to acquire the appropriate skills and work according to data-driven methods. This gives them an advantage in the journey to becoming data-driven companies.



Becoming a data-driven company

The survey results confirm the relevance of the barriers we identified for companies on their journey to becoming a data-driven company. From this, we can derive the following success principles for data and AI projects:

- company-wide planning and orchestration
- business orientation
- early user-involvement of AI solutions
- Fast and agile execution, plus a willingness to learn as an organisation

These four principles, as well as approaches to establishing the basic requirements have been incorporated into our Data-driven Company Framework. This consists of three main steps:

The first step in the fundamental transformation to becoming a data-driven company is decision-making at the company management level. It is worth setting up a core management team for the transformation, which must include members of upper management. The core team should develop a strong vision that sets out why the company needs to be data-driven. An important factor here is to ensure that the vision also addresses and disarms any concerns or potential resistance among staff.

The second step concerns the 'what' – developing a data strategy with the company strategy as a starting point. This is operationalised through the development of an initial portfolio of concrete projects and initiatives. Additionally, a portfolio process has to be installed that functions as an impulse generator for the project pipeline.

Finally, the third step establishes the foundations (capacities, technical data platforms, structures and processes, etc.) while the projects and initiatives are implemented in parallel. This is the key functional principle of our model: foundations are created step by step and always in relation to a concrete implementation project. This guarantees that the structures are streamlined and fit for real-world use, that they have been tested against a concrete use case, and that they can be adapted where necessary. For initial implementation projects, it is a good idea to choose use cases with sound prospects for success. These 'flagship projects' will ideally serve as shining examples throughout the company, further strengthening internal acceptance for the company transformation.

This study is designed to support you on your journey towards becoming a data-driven company, pointing out stumbling blocks while also offering potential solutions.

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Zühlke is a global innovation service provider, envisaging ideas and creating new business models for clients from a wide range of industries by developing services and products based on new technologies – from the initial vision and development through to deployment, production and operation. Our 1,200 employees are based in Austria, Bulgaria, Germany, Hong Kong, Serbia, Singapore, Switzerland, and the United Kingdom.