DAIN STUDIOS

Data & AI Maturity

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Why do you need to care about Data & AI maturity?

Starting to use **data & AI** in an organization is hard. Based on a recent survey[1] 99% of Fortune 1000 companies are investing in data & AI capabilities, yet only 29.2% of them reported achieving transformational business outcomes and only 24% say their companies are data-driven. With all the investments in digital transformation in the past years, why are we seeing so little improvement in data & AI maturity?

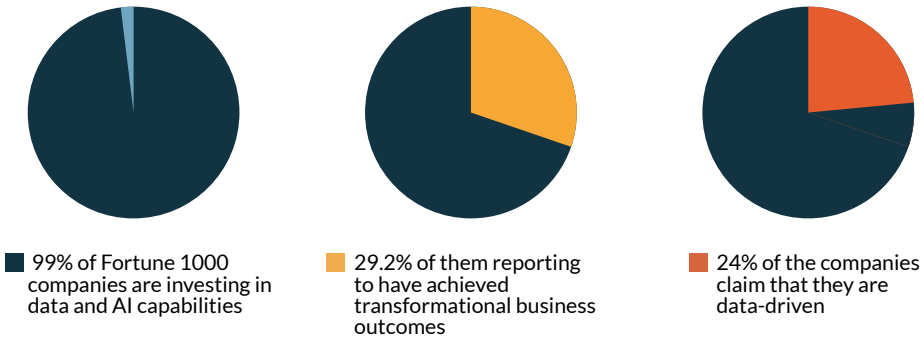


Fig. 01: *Investments in Data & AI by Fortune 1000 companies*

One reason is that successfully harnessing the potential of data requires new organizational capabilities. So far, the investments made in many companies have focused on the adoption of the latest digital technologies, such as data storage, processing power and analytics solutions. While sophisticated tools can be critical to increase the level of data & AI maturity, technology alone isn't enough to extract true business value. A shift in the management mindset is needed too, and enterprises need to focus more on the elements of data & AI transformations that have largely been neglected until now.

At **DAIN Studios** we have executed dozens of projects that have helped our customers in their data transformation strategies and implementations. We have seen where organizations struggle with their data transformations and have learned to recognize the common pitfalls. One key takeaway is that fully understanding the state of data & AI maturity requires a structured framework. Only then can you assess your current state, identify the links between organizational and technological capabilities, and determine the way forward.

The content of the data & AI maturity assessment naturally varies from organization to organization. However, based on our collective experience from various industries and regions across Europe, we have identified commonalities in how the most essential data capabilities can bring every enterprise forward. Our goal is to help organizations with valuable insights evaluate and improve their use of data and artificial intelligence in today's complex environment.

1 https://hbr.org/2021/02/why-is-it-so-hard-to-become-a-data-driven-company

Four steps to competitive advantage

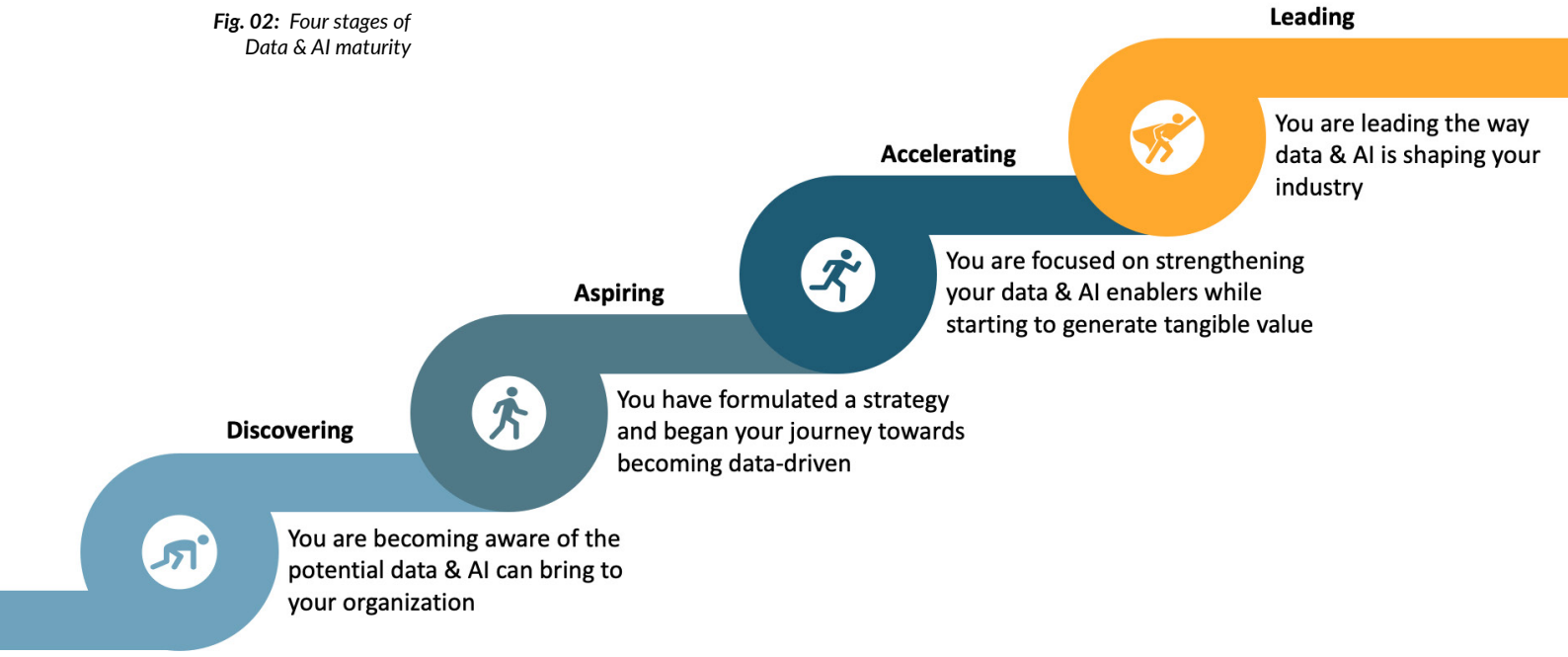
Info: Take the Maturity Quiz to find out on what level your organization is at.

Whether you are the CIO, CDO, head of data or the lead of analytics, you have one common objective: to elevate your organization's data & AI maturity. To achieve this, you will need to set goals, prioritize, track progress and convince other members of the leadership team that investments in your area will bring the company forward. Communicating your targets and achievements will require a common understanding of the journey your organization is on.

At **DAIN Studios** we distinguish four stages of maturity: Discovering, Aspiring, Accelerating and Leading. Although described here as discrete steps for convenience, in practice the maturity stages reflect a continuous spectrum of development.

The journey begins with the **Discovering** phase, where mostly ad-hoc actions drive the company towards becoming aware of the potential that data & AI can deliver, while the leadership begins to realize the need for a more systematic approach and directed investments in developing the respective capabilities. At **Aspiring**, the data strategy is more articulated, the organization has a better understanding of the landscape, and where they want to progress. At this stage, investments are targeted to prioritized initiatives, but the company is not yet generating value from data at scale. **Accelerating** organizations see their first data use cases entering production, bringing money to the table: the first proof that efforts are starting to pay o This can raise excitement to embark on more initiatives towards making the company data-driven. **Leading** organizations have already built capabilities that allow them to develop and deploy data use cases continuously and reliably. They are able to track progress and value, monitor and improve algorithms, and invest in all relevant elements of the data & AI transformation as needed. Data for these organizations has become a competitive advantage.

Fig. 02: *Four stages of Data & AI maturity*



The fundamental elements of Data & AI strategy

Sometimes the leadership understands the importance of becoming data- and AI-driven but feels inadequate in their own knowledge about the subject. That is a good sign. Many universities and consultancies offer data & AI training for business leaders, and a customized data & AI workshop can be an effective way to get clarity on strategic priorities. A word of warning though: occasionally business leaders make the mistake to focus on statistics, computer science, and coding in their desire to enhance their understanding of AI. While coding is a critical skill for data scientists and data engineers, business leaders are better off putting their efforts into creating an effective company environment for data & AI. That means setting business goals, hiring the right people, educating the workforce, committing to investments, and implementing an effective operating model and organization for data & AI. This is best done by setting clear targets and incentives for the organization and following up on them.

Fig. 03: *The Data & AI strategy building blocks*

At this point, the challenge is to structure the vast array of topics that need to be on the leadership agenda when defining and executing the data & AI transormation. Over the years we have found that it is useful to distinguish between **Impact drivers** and **Enablers**. While the impact drivers are supporting the transformation with top-down commitment, the enablers are more directly contributing to the realization of use cases with human and technological capabilities. And although it is important to plan with a long-term road-map for developing these enablers, it is equally important that these investments are tied to tangible use cases. In the end, enablers won't generate value by themselves if they are not applied to the data & AI use case portfolio. Finally, what makes these elements work together in reality is a well-functioning operating model that defines the day-to-day responsibilities, interaction and ways-of-working with the data, the tools and the people involved.

Impact drivers & leadership

Any large scale transformation starts with establishing a vision and strategy. Less than 30% of Fortune 1000 companies claim to have achieved transformational impact from investments in data & AI[2]. Coincidently, just 30% of them have developed a well-articulated data strategy. While these numbers are not one-to-one, they underline our experience that many data & AI transformations fail to break the barrier of success due to a lack of strategic vision, leadership support and a strong focus on value generation: what we call the impact drivers.

Fig. 04: 30% of Fortune 1000 companies have developed a well-articulated data strategy

2 https://hbr.org/2021/02/why-is-it-so-hard-to-become-a-data-driven-company

Strategy & Vision

A significant part of business strategy today is digital transormation, i.e. integration of digital technology into all areas of business. Since data is crucial to many digital initiatives, digital transformation will only work when it is equipped with the right data.

Creating a data strategy is a common way for organizations to align data & AI development with overall business objectives. To be clear, data strategy typically supports the overall corporate strategy, not the other way around. Its purpose is to make sure that stakeholders share a common long-term direction and goals for using data & AI. Thus the data strategy helps the organization move forward with the various enablers that need to be developed to support these goals. Enablers are organisational skills or technological capabilities that are needed to support the overall data & AI transformation of an organization.

Companies in their data & AI **Discovery** phase typically do not have a data strategy, or it is not officially documented. One of the first steps you can take is to understand what opportunities others in your industry are already taking advantage of. Based on this, you can formulate your own vision for the use of data and align this vision with the overall strategic objectives of the company. Some **Leading** organizations already have their data strategy strongly integrated with their overall strategy, to the extent that using data and analytics in all organizational functions is considered the norm.

One public utility company we advise asked us to aid with their demand process and prioritization of data use cases. During the project it became clear that relatively good processes were already being implemented. The real issue was the disconnect between the management and the data & analytics team. There was no clear vision where the organization is headed with all the investments into data. The data and analytics team didn't know where to focus, and the management didn't receive the business value that they were expecting. The proposed solution was to take a step back and start with setting and communicating a common vision for the use of data across the organization.

Use Cases & Value Generation

Commonly, the use of data in an organization starts by sponsoring ad-hoc projects or pilots, possibly executed by external vendors. The business goals are often too high-level and non-actionable, the outcomes of the pilots are not carefully monitored, and the results are commonly forgotten when the project ends. Usually these kinds of pilots don't generate substantial direct business impact and are difficult to replicate. The collected value from these experiences is more indirect – understanding what could be achieved with data if you were to invest in the technology. To aid with use case development, we have implemented an **Analytics Playbook** with several of our clients successfully. The Analytics Playbook is a set of guidelines and instructions, created together with clients, that document how to build data use cases in practice within the context of a specific organization.

For an organization to elevate its data & AI maturity, the business value in a use case needs to be identified and monitored from ideation through delivery, all the way to production and operation. Careful use case design enables more direct business value to be extracted by the project. And as a side effect, the delivery usually becomes faster, as the team has a better understanding of the expectations and objectives from business stakeholders.

> **Data use cases create business value by improving, optimizing or changing business processes.**

Lastly, data use cases create business value by improving, optimizing or changing business processes. In other words, failure to integrate the results into business processes means that value is left on the table. This may sound like an obvious step, but all too often we see project results ignored under the excitement for the technology itself. To make that change permanent and effective requires adaptation in the way people make decisions and take action based on the newly found insights and predictions, i.e. you need to ensure the data is guiding the processes going forward.

Consider the case of a Nordic retail chain that wanted to use AI to detect delays in its supply chain. A detailed analysis was prepared explaining the top five reasons why the deliveries were occasionally delayed. The supply chain managers indicated that they were already aware of these reasons, as they had manually analyzed the data over many decades. A more structured approach to developing the use case idea and value hypothesis, considering what was already known to the organization would have allowed the project to skip directly into solving the 'unknown' issues, delivering impact earlier without hindering the otherwise large investments in data & AI capabilities.

Leadership

Based on our experience, business leaders need to be highly involved in all aspects of the execution of data & AI strategies and the capabilities that the supporting initiatives encompass. We observe that fully committed leadership has been one of the common denominators for success in digital transformations and becoming a data-driven company.

This involvement may span from openly recognizing data as a strategic topic to one or all executive team members having responsibility for data & AI initiatives. Data transformations require significant changes, new roles need to be introduced and new skills need to be acquired. It will not take place automatically by just declaring data & AI a strategic objective. The teams working on the initiatives will face conflicts of interest, trade-offs, and lack of direction. It is critical that the leadership is involved and continuously supports the transformation. One possibility is to assign an executive sponsor to data & AI transformation, which ensures that the topic is permanently on the leadership agenda.

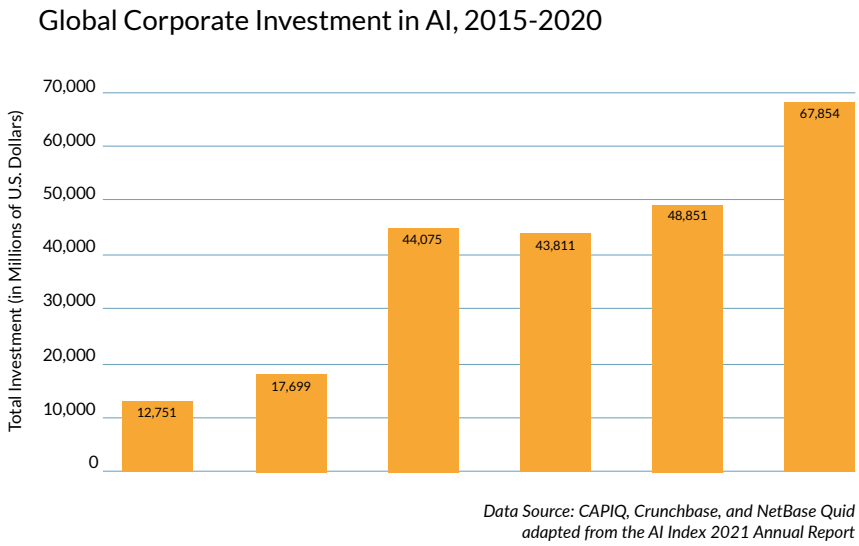


Fig. 05: *Global corporate investment in AI is on the rise*

Finally, improving data maturity requires adequate financial support from the organization to ensure the other enablers can be developed. Especially in the early stages of data transformation it is important to have a central budget available for building first enablers and capabilities. In our experience that speeds up the start significantly, as it avoids lengthy budgeting discussions.

We often advise our clients on the importance of leadership commitment and support to data & AI initiatives. What is commonly forgotten is that this is equally a journey for the leadership, just as much as for the organization. Initial excitement is welcome, but you need to ensure that the data culture sticks among the executives. This can require behavioral changes too, as being data-driven cannot be a one-off initiative. You can hold a keynote presentation on the importance of AI for your organization, but the real change will come from truly understanding, re-emphasizing and playing the role of a data-driven executive every day of the week, 365 days a year.

Human enablers

Artificial intelligence allows humans to focus on the tasks that really matter. Rather than replacing us, AI can take care of steps in the chain of inference, predictions, decisions and subsequent actions that are too time-consuming, tedious or difficult to do at scale for the human brain. To make AI work effectively and ethically in any setting, it must be paired with organizational, cultural and human capabilities, along with clear privacy and ethics principles.

Organization & Culture

Data transformations do not happen overnight; they require changes to an organization, its culture, and its ways of working. An important aspect is that data analysis is not only "data science" reserved for the data team but a change in how decisions are made by thoroughly analyzing data. To underline that, some organizations have even opted to use the term "decision science" in place of data and analytics.

To be successful with decision science, a close interaction between business and technology stakeholders is a must. The data team members need to understand the business they are dealing with. Similarly, the business stakeholders should have a reasonably good understanding of the concepts of data science, especially how to apply data use cases for their business area. Having this understanding on both sides helps with the stakeholder interaction considerably.

Since businesses, corporate culture, and skills differ from company to company, there is no one-size-fits-all solution to organizing your data teams. While a center of excellence may be the right structure in certain settings, its role and influence must change as the organization becomes more data mature. Ideally, it is important to design the organization with clear purpose and structure, to have the right competencies available in the right teams dispersed throughout the entire organization.

Apart from improving the understanding between stakeholders, formal governance processes need to be implemented to ensure decisions, responsibilities, and escalation paths are clear for everyone. The purpose of this "operating model" for data & AI development is to ensure all enablers and impact drivers are working together seamlessly in practice.

A good data culture helps to ensure that investments in data maturity are fully utilized. Coming back to the term decision science, a good data culture means that data is sought to back decisions, whenever relevant data and analysis can be made available. The organization should transform from gut-driven to data-driven.

A large European telecommunications provider faced the challenge of accelerating impact from data & AI projects across several countries. One key initiative was to revamp the data teams to support their individual local organizations. A hub and spoke model with a data & analytics center of excellence was established, with the goal of enabling the local units to deliver their own solutions to their respective markets. This struck an optimal balance, since the local units required a certain degree of independence – due to differences in both external market trends, customer needs and internal maturity – while being provided with common capabilities (e.g., data science experts) and technologies (e.g., common data platform) from the central organization.

Human Skills

For most organizations, the introduction of data and advanced analytics capabilities means the introduction of new human skills and professional disciplines. While organizations typically already have internal or external skills for managing data, data warehouses, and report development, managing greater volumes of data and advanced analytics requires new skills. Additionally, understanding and applying data to decision-making is important to ensure the efforts will have a sustainable impact on the business. Hiring or contracting skills to an organization is difficult in today's market where data talent is in high demand. Therefore, a clear human skills plan is needed to ensure the relevant capabilities are available when and where needed.

> **At optimum, the external resources ensure that the company is progressing steadily on their data & AI journey, internal resources are continuously learning and internalising newly acquired knowledge, and the leadership is keeping an eye on where the whole team is headed.**

At the start of their data journey, organizations typically require external resources to help put together a strategic plan and potentially help with the implementation of the first data use cases. Using externals is logical in the first stages when your own data team is non-existent or small. Externals that have worked and learned from similar projects in the past are invaluable in helping to give the right direction and making the first success stories. However, using external resources extensively will increase the budget and decrease the development of in-house skills. The goal is to find the right balance between externals and internals. At optimum, the external resources ensure that the company is progressing steadily on their data & AI journey, internal resources are continuously learning and internalizing newly acquired knowledge, and the leadership is keeping an eye on where the whole team is headed.

Similarly to the balance between externals and internals, the data team should have the right balance between seniors and juniors matching the overall data maturity. As demand for skills often varies between projects, a variety of seniority levels helps to assign tasks and keep the team motivated. Moreover, a well-designed career path and harmonized titles in the data team help with attracting and retaining talent, juniors and seniors alike. Leading organizations can attract the best-in-class talent, which further boosts their maturity.

Data literacy is the ability to read, understand, create, and communicate data as information. Throughout the whole organization, data literacy skills are needed to ensure the insights from the analytics team are correctly understood and appropriate actions are taken. Data use cases will have limited impact if the organisation is not ready to exploit the results for improving the business and operations.

As a whole, there are many skills to be fulfilled in the transormation. Some can be hired, some outsourced, but more importantly, the whole organisation's knowledge of data & AI must be lifted. This is necessary to meet general data literacy requirements, establish a culture of innovation with data, and allow smoother

communication between business and data teams. In addition to general training, special training should be made available for the data team members to upskill their expert knowledge.

After reorganizing the data teams in a hub and spoke model, the second challenge for the telecommunications provider was to understand and improve their internal capabilities in delivering data use cases. The solution started with stocktaking the current skills and setting an ambition level both for the central and the local country organizations. This exercise highlighted the specific upskilling requirements, allowing the center of excellence to provide a tailored training program to their employees. Most importantly, it did not only include pure technical training, but rather a mix of technical and non-technical lectures and exercises, broken into three major target groups: leadership, data professionals and business stakeholders. In addition to elevating the data skills within the organization, the program created excitement, momentum and cohesion across different units that strengthened the data culture within the company.

Privacy & Ethics

Privacy and ethics of using data & AI are important and hot topics. While these don't necessarily speed up the data transformation, they ensure that using data conforms to legal and ethical standards. Failing to comply with these standards may result in severe consequences.

Data privacy (or information privacy) is an area of data protection that concerns the proper handling of sensitive data including, notably, personal data but also other confidential data, such as certain financial data and intellectual property data. Personal data means any information that can be used to distinguish or trace the identity of an individual, or when combined with other personal or identifying

information that is linked or linkable to a specific individual. In the European Union, UK, California, and many other regions, data privacy legislation defines a frame for how privacy data is to be handled. At the minimum, data privacy should comply with these legal and possible contractual requirements. However, this is often not enough. The basic level means that the mandatory requirements are fulfilled, but not that the privacy-related responsibilities are clear and processes efficient.

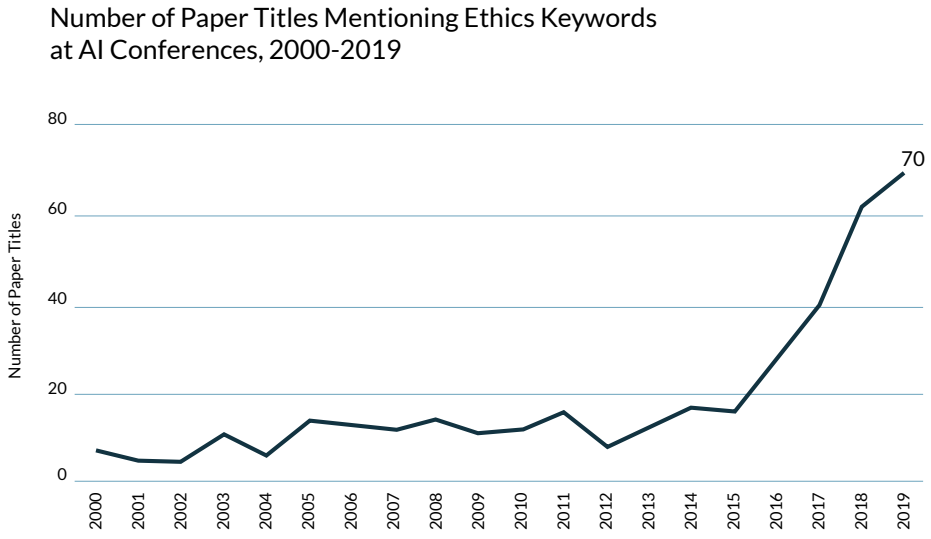


Fig. 06: *Number of academic paper titles mentioning AI ethics has more than tripled in 5 years*

Data Source: Prates et al.
The AI Index 2021 Annual Report

There are no clearly defined rules for evaluating AI ethics, as there are or evaluating data privacy. The European Commission has issued a proposal of an AI law that may become the first benchmark for regulating data & AI, but that will come into effect in 2022 at the earliest. Meanwhile, organizations should define their own guidelines for ethical use of data, and establish governance processes to enforce them. Guidelines should be defined from a starting point of what is generally acceptable as air use o data within the industry and the broader societal context. What sets leaders apart in this area is the ability to translate, communicate and embed the general guidelines into the day-to-day operations of every employee working with data. Clear guidelines illustrate to the organization what data privacy and ethics mean in practice.

DAIN Studios carried out a data strategy project for the City of Helsinki in 2019-20. A big part of the complexity in using data in a city is assuring compliance with legal requirements. Requirements for data use in a public organization go much further than what GDPR includes, which prevents using predefined data utilization rules. The solution for the city was to establish a data utilization working group that meets regularly and assesses new data use cases. The city's organization benefits now from having this single authority and process for approving legal and ethical uses of data. Making a set of rules for legal and ethical use for all data use cases may be difficult, but having a clear process for evaluating use cases is a step in the right direction.

Technology enablers

Technology stands at the core of any data & AI transformation. It enables today's organizations to turn data into insights. Technology in the context of data & AI does not only mean the algorithms and functions that generate model output but fundamentally include the associated data assets and the overall architecture that the solution is embedded in. The interplay between these three elements is essential in making data & AI work for you.

Analytics & AI Portfolio

The analytics and AI portfolio comprises a wide set of analytics solutions, starting from simple reports, visualizations through automated dashboards all the way to applied machine learning solutions providing predictions and decisions to various business problems.

Traditionally, business analysts have focused on reporting what has happened within a limited set of business functions. Modern analytics aims much further than such reporting and attempts to predict unknown attributes (be it future or simply undiscovered values), using historic and contemporary data that spans across multiple business domains. To enable the use of data across silos, organizations should broaden the scope of analytics, aiming to use a wide range of different data sources and develop a comprehensive picture of what is happening in the business.

> **Having a systematic approach to understanding, selecting and evaluating the right solution is more likely to result in value creation for the business than forcing state-of-the-art algorithms on simple problem sets.**

Maturity means that the organization is capable of using advanced techniques if the problem requires it, not that deep learning is applied to any problem they face. Having a systematic approach to understanding, selecting and evaluating the right solution is more likely to result in value creation for the business than forcing state-of-the-art algorithms on simple problem sets.

Another important indicator of maturity is how the analytics & AI portfolio moves beyond deployment. Monitoring, testing and upgrading the analytics solutions are necessary to maintain model performance (due to data and model drift). Leading organizations are capable of incorporating the latest functions smoothly, timely and reliably into their existing solutions, not only maintaining but continuously testing and tweaking the models to perform better. Similarly to the widely applied, life-cycle-oriented software development practice DevOps, MLOps is a guided methodology extending the principles of continuous integration/continuous delivery (CI/CD) to re-training and deploying machine learning solutions.

One of the core aspects that differentiates software development is reusability. Similarly, many analytics solutions can and should be reused within the organization, at least partially. This requires that the analytics teams maintain a portfolio mindset, creating well-packaged solutions internally, with the ambition that they themselves or other parts of the organization with similar capabilities can re-use them. Reusability creates benefits by speeding up development that reduces cost and time-to-market and also improves reliability as already tested methods are utilized. To improve reusability organizations should store developed algorithms and create a culture of reusing the methods from the portfolio if they see fit. Analytics teams can use common package libraries, shared development notebooks, feature repositories and many other tools and practices to boost this knowledge sharing.

Data Assets

Any analytics solution is as good as the data behind it. As a first step, acknowledging that data is a core asset to your company will raise the level of ambition you have with treating this new asset. Ensuring data quality and usability is a real challenge that many organizations struggle with today.

Data quality issues might be easy to spot, but the overall quality is a combination of multiple factors. As an example, for a successful marketing campaign, customer data needs to be unique, accurate, and timely. Data quality dimensions capture the attributes that are specific to your business context. In general, there are six data quality traits: data needs to be accurate, complete, consistent, timely, valid, and unique.

In addition to data quality, data assets have to demonstrate usability. We often evaluate the usability of the data assets according to the FAIR principles. Is the data **F**indable, meaning does the data have sufficient documentation and meta data supporting it? Can the data be easily **A**ccessed, are access and authentication processes transparent and efficient? Is the data **I**nteroperable, can it be combined with other data sources and integrated into data pipelines effortlessly? And is the data **R**eusable, is it presented in a format that allows wide usage without significant data wrangling and reformatting? Using the aforementioned dimensions can give you an objective view of the quality and usability of your existing data assets.

The breadth of new data capture is the next important aspect. Most organizations primarily capture data generated internally by their core activities, and they are not very systematic in doing so. Many embark on their data journey saying "we first need to make sure that we collect all possible data, later we will figure out what to do with it". While it is true that not collecting data is a lost opportunity, collecting large amounts of data without a purpose can introduce significant headaches and storage costs. It is easy to slip into aimless data collection at an early maturity phase, and the longer this practice continues, the more likely it is that the data will never generate value for the business. We consistently advise our clients to think through their most important data entities (e.g., customers, products, suppliers) at an early stage and build their data collection around these entities. Leading organizations are able to establish so-called 360 views around their key entities with data captured both from internal activities and external sources in a unified, consistent manner. This is what will make data assets truly rich and useful for analytics purposes.

Collecting, maintaining and orchestrating data of sufficient quality to analytics users and applications are the primary goals of data management. Setting up the data governance principles and practices, assigning clear data responsibilities (ownership, stewardship, etc.) and establishing the decision bodies are fundamental steps in creating a well-functioning data management organization. A good indicator for data management maturity is a well-defined data ontology, a transparent data catalogue, meta data consistently shared across the company, and clearly layered data stored in appropriate solutions. Leading organizations take a data-first approach and aim to productize their data assets such that they could be shared outside the company at any time (if need be) via standardized protocols, such as documented APIs.

For example, data mesh is a newly arising paradigm that benefits large organizations with disparate datasets serving many applications and end-users. As opposed to common belief, data mesh is not a technology. It is a set of principles that help you organize and govern your data assets in a federated manner. What that means is dividing your data into respective data domains and delegating responsibility to dedicated data product owners, who are responsible for bringing their own data product to their consumers within or outside the company. The main responsibility of the central data infrastructure team becomes setting up and maintaining the technology that enables data product owners and their teams to serve productized data assets to their stakeholders.

Zalando, a highly data-driven European fashion retailer, is one of the leading examples for adopting data mesh to organize their data assets. Their analytics journey goes from having fundamentally centralized data assets in data warehouse(s) to later on establishing a data lake. However, their central data infrastructure team realized that they are facing two fundamental shortcomings: (1) they were becoming the bottleneck in scaling their data assets sufficiently, and (2) there was unclear ownership of the data being served. Creating business domain ownership of the data helped Zalando resolve both problems. The central data infrastructure team's new responsibility became to maintain the platform that the data product owners use to make their data available through productized channels. Having ownership placed closer to the business puts the responsibility for data assets in the hands of people having the most understanding and influence on the quality of the data[3].

Architecture & Technology

The role of data architecture is to establish the technological backbone to adequately capture, process and serve data to reporting views, dashboards, end-user applications, models in production, as well as a sandbox for data scientists and analysts to use for exploratory work and model development. When an organization is still in early maturity, most data I/O processes are manual or semi-manual tasks. At this point, increasing the level of automation and establishing the first data pipelines should become the primary ambition. If done right, this will eliminate tedious human labor, improve reliability and enable the first analytics use cases to enter production. The first data pipelines will begin to emerge, together with the need to maintain them.

As the vendor landscape is evolving quickly and predicting the future is difficult, it will become paramount to address the constant change in requirements and the technologies serving these needs. Evolutionary architectures are built with this constant change in mind and many Leading organizations are now able to design modular, flexible systems, where data pipelines are easier to upgrade, test, rerun without negatively impacting the rest of the architecture.

Next up is the technology stack, serving the data architecture and analytics needs of the organization. Adequate storage and data processing solutions will fit current and future needs to collect, store and serve the data in various outlets. Today's cloud providers offer a plethora of services that make it easy to scale and introduce new

3 https://databricks.com/session_na20/data-mesh-in-practice-how

functionality as needed. Yet, in reality, many organizations will need to combine a mix of local storage, own private cloud or hybrid cloud solutions due to legacy systems and out of information security concerns.

> **Organizations that invest in setting up and maintaining these platforms will see positive effects ripple through their data organizations. They will enable new use cases, attract best-in-class data talent and overall reduce the time-to-production of their analytics solutions.**

With the rise of modern data and machine learning platforms, data professionals can have access to integrated development environments and deployment services on top of the storage and computation resources provided. Organizations that invest in setting up and maintaining these platforms will see positive effects ripple through their data organizations. They will enable new use cases, attract best-in-class data talent and overall reduce the time-to-production of their analytics solutions. However, to live up to the ambition of becoming data-driven, companies need to focus on bringing analytics closer to every employee, not only data professionals. Self-service business intelligence (BI) applications allow any user with basic knowledge to leverage data in their decision-making process.

Finally, analytics solutions should not live in isolation. Data (or information) architecture is part of the overall IT architecture. One common pitfall in data & AI projects is to solely focus on delivering prediction results from data, not considering how those results will be consumed by other downstream applications. Deploying an analytical solution into other applications usually requires additional work from the application side, requiring collaboration and preparations, as source applications often have their own development teams with separate backlogs and development priorities. Thus, thinking the deployment stage very late can put development on hold for a significant amount of time, which can be particularly frustrating as the organization has already spent time and effort on solution development. Regardless, tangible business impact will only be achieved with a fully integrated end-to-end solution. To prevent this, time and time again we encourage our clients to consider the end-to-end solution architecture from the early stages of any analytics solution development process. The best approach is to close the loop first, meaning that the development team should focus on creating a simple end-to-end working prototype, before delving further into the development and performance tweaking of the analytics model.

Guidance in the maze of Data & AI transformations

It is easy to lose focus in the buzzing world of data & AI, how it impacts modern-day businesses and what you can do to elevate your organization's maturity.

When asked about their data & AI maturity, companies state that almost half of them have started scaling AI[4]. Analyzing the text from corporate earnings calls, and com-paring them between 2013 and 2020, there is a clear trend from mentioning "cloud", "big data" and "machine learning" towards the dominance of "artificial intelligence"[5]. But this does not mean companies are automatically succeeding in extracting busi-ness value from AI, and rather highlights the shift between using different keywords for data & AI transformations that have been capturing the attention of corporate leadership since the early 2000s.

In this white paper, we have outlined the various elements that we find fundamental in succeeding with data & AI transformations. To help you avoid the hype and un-derstand where you are on your path to becoming a data-driven company, we have created the DAIN Studios data & AI maturity model.

Together with our expert consultants, you can use our model to gauge your current state across the fundamental building blocks of successful data & AI execution. You can identify key focus areas and build your road map with tangible next steps to guide you from Discovery to data & AI Leadership.

The model successfully links together our experience from consulting and leading data & AI organizations across numerous industries, leveraging the accumulated knowledge of DAIN Studios' diverse team of engineers, scientists and strategists. This makes our model uniquely comprehensive, practical and easily tailored to your needs.

Our recommendation: take the Data & AI Maturity Model Quiz to find out the maturity level of your organization.

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4 The State of Responsible AI: 2021

5 Prattle & Liquidnet, 2020

DAIN Data & AI Maturity Model

		Discovering	Aspiring	Accelerating	Leading
Impact drivers	Strategy & Vision	No documented data & AI strategy	Data & AI strategy created within a specific technology domain, e.g., IT or analytics	Data & AI strategy is complete and broadly aligned with overall business strategy	Data & AI is an integral element of the business strategy, vision and offering
Impact drivers	Use Cases & Value Generation	Ad-hoc generation of data & AI use cases, lacking systematic prioritization and follow-up	Use cases are structured, but often around technology rather than business value	Use cases are linked to business value generation	The business value of use cases is consistently identified, assessed, and tracked throughout the solution's lifecycle
Enablers	Leadership	Unclear leadership support for data & AI initiatives	Data & AI is a stated leadership priority but limited concrete action taken to date	Leadership supports and invests in accelerating impact from data & AI	Leadership understands and drives continuous transformation into a data-driven organization
Enablers	Organization & Culture	Data is not a dominant topic in the organization, data capabilities are ad-hoc and unorganized	Desire to improve and organize data capabilities with appropriate governance processes	Data capabilities organized and supported by fit-for-purpose governance processes	Organization views data as a competitive advantage, and can handle internal and external data & AI requirements with ease
Enablers	Human Skills	Very few data professionals covering wide range of data topics, expected to drive data & AI transformation	Established data roles/functions but the organization struggles to find or develop the right capabilities internally	Data roles are filled with required seniority, dedicated training programs for both expert and non-expert staff	Able to attract best-in-class data talent at all levels, all employees have a basic level of data literacy
Enablers	Privacy & Ethics	Focus on basic compliance with GDPR and contractual data requirements, but often with scattered responsibilities	Responsibilities are defined but guidelines, processes, and awareness of wider AI ethics topics are limited	Established process for managing data privacy, users well-informed. Data & AI ethics principles defined but limited implementation.	Privacy, data & AI ethics principles are understood across the organization and embedded in daily work processes
Enablers	Analytics & AI Portfolio	No advanced analytics deployed, focus primarily on reporting use cases	Advanced analytics algorithms are in piloting phase	Some advanced analytics are deployed in production, but continuous implementation and monitoring is still a challenge	Advanced analytics are routinely deployed with continuous monitoring and improvement
Enablers	Data Assets	Data storage is highly siloed, access by ad-hoc request, data quality uncertain	Need for improved data assets is recognized, initiatives launched to improve quality and (re)usability	Data is available in unified and interoperable quality via central access and clearly defined data ownership	High-quality data are delivered through productized channels to support internal and external use cases
Enablers	Architecture & Technology	Data processing is primarily a manual task, technology stack is unable to support scalable AI solutions	Some automated data processing, understanding of tool requirements and gaps	End-to-end data pipelines are established, introducing enterprise data & analytics platforms	Use cases supported by automated data processing and a fit-for-purpose technology stack

DAIN STUDIOS

About the authors

György Paizs
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György is an analytical problem solver with an in-depth understanding of data science and business strategy. At DAIN Studios, György is focused on delivering structured, well-articulated results throughout every step of the project, helping our clients break down their business problems and matching them with data/analytics solutions. Previously, György was a Senior Management Consultant with a focus on solving top-management problems for Danish and international clients. György is passionate about analytics and AI, demonstrated by his hands-on data science projects completed as part of an extensive coding training in Berlin. György holds a master‘s degree in Advanced Economics and Finance from Copenhagen Business School and a bachelor‘s degree in International Business.

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Arttu is a seasoned business developer, strategist, and product management professional with work experiences from startups and corporations. At DAIN Studios, Arttu is helping customers to define their vision and strategies for utilizing data in optimizing existing business or creating new business from data. Arttu is building plans and supporting implementations of data driven businesses. His previous work experiences include working in the heart of digital service development at Kesko, northern Europe’s #3 retailer, and Nets, a Nordic leader in digital payments and identification. Arttu holds a MSc in Computer Science from Helsinki University of Technology and is always curious in finding ways to build better products and services.

Niina Hagman
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Niina is a strategic thinker and energetic, solution-focused doer with strong analytical skills. At DAIN Studios, she helps customers succeed in their digital transformation by creating and implementing data and AI strategies, and generating data-driven business value. Before joining DAIN Studios in 2019, she was privileged to work in fast-paced and constantly evolving industries in media and telecom for over a decade. Niina Hagman has extensive experience working at many organizational levels as a professional, senior manager and leader; from strategic board room work to hands-on operational guidance. Niina Hagman has a Master Degree in Artificial Intelligence from the University of Turku and she has a Master of Science in Economics.

About DAIN Studios

DAIN Studios is a boutique consulting firm specialized in making data & AI work for any organization; from strategy to execution. The DAIN Studios team combines extensive business experience with deep data and AI skills, gained at multinationals, start-ups and management consulting firms. We have successfully executed digital, data, and data-science transformation programs in several international companies.

Based in Helsinki, Berlin and Munich, our team brings in an international and diverse perspective into the latest developments and best practices, and continuously strives to support customers in the best possible way.

It is the combination of business, data, technology and AI skills that makes the team at DAIN Studios effective in making data & AI work for your business.

Contact us to learn more about how we can help you on your data & AI journey!

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