IESE-Penteo Study

Data-Driven Index

Diagnosis of Digital Transformation in Data-Driven Organizations

Javier Zamora
Josep Valor Sabatier
Joan Enric Ricart
Nicolás Infante Middleton

Toni Guerra Cortada
José Luis Pérez Tejada

JULY 2022

IESE Business School University of Navarra

PENTEO

IESE-Penteo Study

Data-Driven Index

Diagnosis of Digital Transformation in Data-Driven Organizations

Javier Zamora
Josep Valor Sabatier
Joan Enric Ricart
Nicolás Infante Middleton

Toni Guerra Cortada
José Luis Pérez Tejada

JULY 2022

Authors

IESE Business School

Javier Zamora
Professor of Practice Management for Information Systems
Head of the Information Systems Department

Josep Valor Sabatier
Professor of Information Systems
Indra Chair of Digital Strategy

Joan Enric Ricart
Professor of Strategic Management
Carl Schroeder Chair of Strategic Management
Center for Globalization and Strategy (GGS)

Nicolás Infante Middleton
Research Assistant

PENTEO

Toni Guerra Cortada
General Manager

José Luis Pérez Tejada
Head of Analysis

Note: All material included in this document was prepared by the authors unless otherwise noted.

Design: IESE Business School

Edited by: Caja Alta Edición & Comunicación (www.cajaalta.es)

CONTENTS

LIST OF TABLES AND FIGURES

Figures

Tables

Introduction

Penteo, a technology analysis firm with expertise in the Spanish market, and IESE Business School have analyzed the technological, business and organizational dimensions that companies need to develop to become data-driven organizations, which will in turn enable them to successfully carry out their digital transformation processes.

A joint study was conducted in order to present an index that measures the data-driven maturity of Spanish companies with the aim of answering the following questions:

How developed are Spanish companies in data-related dimensions—technology, business and organization—and how does this contribute positively to their digital transformation?

Can we define an index that measures the data-driven maturity of an organization and that is correlated with success in digital transformation processes?

Context

The analysis was carried out with the participation of 256 senior executives[1] from different companies in order to get their perspective on how prepared they are to maximize the benefits they obtain from data. The dimensions studied revolve around technological capabilities for data management, the integration of data into business control and innovation, and the organizational capabilities required to become a data-driven organization.

To carry out the study, we administered an online questionnaire between the fourth quarter of 2021 and the first quarter of 2022. This work is a continuation of the *Estudio IESE-Penteo sobre transformación digital en España* (IESE-Penteo Study on Digital Transformation in Spain), published in June 2020 (Zamora et al. 2020).

On February 23, 2022, Penteo and IESE gave a presentation on some preliminary results of this study at the Business and Technology Meeting, within the framework of the IESE-Penteo Program held at IESE's Madrid campus.

[1] Of the 256 executives who responded to the survey, 42% were CEOs, 37% were general managers, 8% were CIOs, and the rest were managers of other functional areas (see **Exhibit 1**).

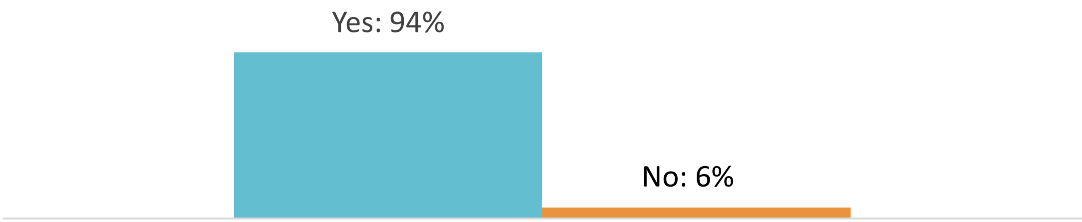
Digital Transformation and Data-Driven Strategies

Organizations have traditionally used data for control purposes via reporting systems linked to business model execution. This is referred to as a "defensive" *data strategy*. However, in a context where the pace of change is accelerating, companies need to transform themselves so that they are able use data not only for control purposes, but also as raw material for the innovation that drives digital transformation processes. This is referred to as an "offensive" data strategy. The need for such a shift of focus was already clear in the June 2020 digital transformation study, where the main points that defined digital transformation for companies reporting that they had been successful in their transformation processes were achieving greater business agility, extending innovation within the company, generating value with new business models, and achieving greater workplace productivity. The common denominator was the ability to extract valuable information from data, beyond straight reporting.

Although a clear majority of the executives who participated in the 2020 study considered data a key asset (see **Figure 1**), organizations are still far from having a consistent data strategy. One of the shortcomings identified is that the significant investments in information technology (IT) made by many companies are not sufficiently supported and complemented by initiatives that address more organizational issues, such as data governance, the creation of data-related roles, and processes aimed at ensuring data quality and accessibility.

Figure 1. Perception of Data as a Key Asset for the Value Proposition

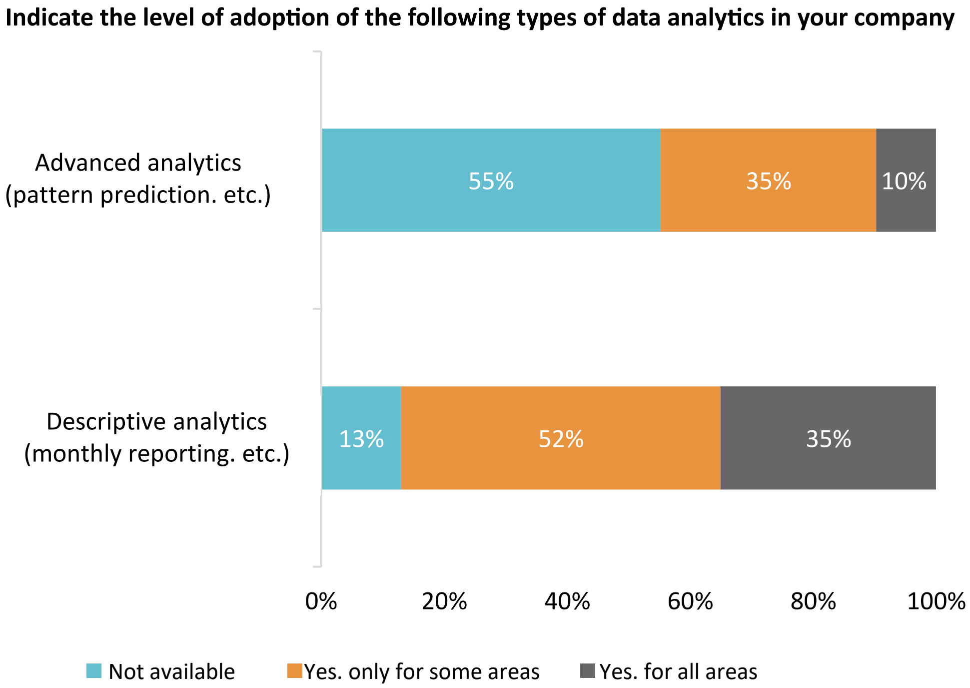
Do you consider data a key asset for generating your company's value proposition (offering)?



Source: Javier Zamora et al., *Estudio IESE-Penteo sobre transformación digital en España* (2020).

However, although 94% of executives consider data a key asset, only 35% have access to descriptive analytics solutions (see **Figure 2**). In the case of advanced analytics and artificial intelligence (AI), the figure falls to just 10%. These two numbers paint a paradoxical picture: On the one hand, they are in line with the general consensus that data is a source of value for companies, but they also indicate that data analytics platforms are not widely deployed in organizations.

Figure 2. Level of Adoption of Analytics in Business Areas



Source: Javier Zamora et al., *Estudio IESE-Penteo sobre transformación digital en España* (2020).

In fact, we find a strategy that has been inconsistent and somewhat erratic for many years: investment to improve and adopt data exploitation technologies, and a feeling that data should be strategic, but without the necessary governance, cultural and organizational structures to ensure that investment yields the expected return and that projects are carried forward on a path and in line with objectives agreed across the business rather than just in response to immediate departmental and operational needs. In this context, there is a need to define a data-driven strategy that holistically harmonizes the technological, business and organizational dimensions of data analytics.

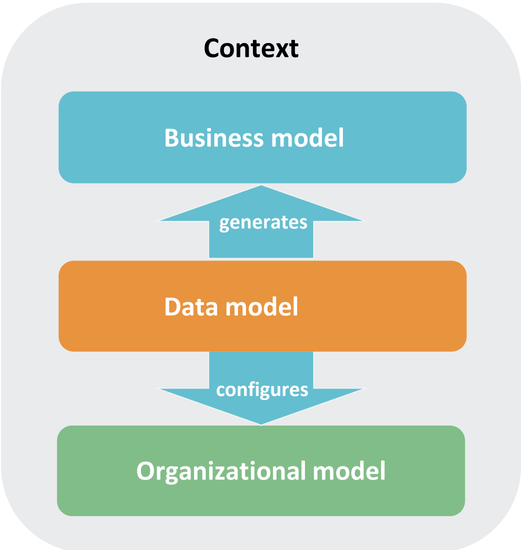
Data-Driven Organizations

As noted in the previous section, there is a mismatch between the value companies place on data and the fact that they often lack a data strategy that considers not only technology but also the way it impacts the business model and organizational model. Organizations that define and execute a multi-dimensional strategy of this kind are data-driven organizations.

Framework for a Data-Driven Organization

When we talk about data-driven organizations, we are referring to those that see data as one of their main assets and structure themselves around data in a holistic way with the aim of competing effectively in the market and the segments (context) in which they operate. This holistic structuring around data is reflected in a data-driven organizational framework developed in IESE's Information Systems Department (Zamora and Thomas 2022). **Figure 3** shows this framework. At the center is the data model, on the basis of which the business model is generated and the organizational model is configured. By putting data at the center, organizations can react more effectively in rapidly changing contexts because this approach allows them to adjust ("program") their business model in a way that ensures the best fit with the context in which they compete and to dynamically configure their organizational structure to achieve the necessary speed and agility.

Figure 3. Framework for Data-Driven Organizations



Data Model

This model encompasses all the data-related technologies, mechanisms and procedures that enable an organization to create and capture value. It includes, first, all the technological infrastructure (hardware and software) used by an organization as its operational backbone, including the single source of truth (SSOT),[2] ETL procedures, digitization of end-to-end processes through the use of corporate software (ERP, CRM, etc.), and control and reporting systems (e.g., business intelligence); second, data security, including mechanisms for protection, detection, response and business continuity in the event of a cyberattack; third, data characteristics, in terms of accessibility, usefulness and quality, as well as the reliability of the software used to process data; fourth, the programmability of the data, which refers to the modularity of the IT architecture, via internal and external APIs, and the existence of a data lake for experimentation with the data; and finally, data governance, including formal structures for corporate data governance, the existence of roles such as chief data officer (CDO), chief information security officer (CISO), chief privacy officer (CPO) and data steward, and the adoption of FATE (fairness, accountability, transparency, ethics) policies in the use of AI (Zamora 2020).

[2] A glossary of terms used within this framework is provided at the end of this document.

Business Model

The business model is concerned with how the organization uses different data interactions to create, deliver and capture value in the context in which it operates. There are four types of data-based interactions (Zamora 2017): first, interaction in the form of automation—that is, the use of data to perform more activities with fewer manual resources, through digitization and/or robotization of processes; second, interaction in the form of prediction—that is, the use of data to determine, predict or prescribe the state of a process via the use of AI algorithms such as machine learning (ML); third, interaction in the form of coordination—that is, the use of data to co-create a value proposition through the participation of different stakeholders/organizations that belong to an ecosystem and their coordination via business platforms; and finally, interaction in the form of personalization—that is, the use of data to better serve the needs of a specific customer without increasing related costs.

Organizational Model

The organizational model is concerned with the competencies and work practices that an organization must develop to drive a data culture. These competencies are classified into six meta-competencies (Káganer and Gregory 2017; Zamora and Ricart 2020) as they are independent of an organization's context and size and the sector in which it operates. The first meta-competency, outside-in thinking, refers to how an organization, through data capture, focuses on understanding customer and context-related needs. The second, learning orientation, refers to how an organization uses data to drive innovation. The third, agile execution, refers to how an organization builds value propositions iteratively by validating the value hypotheses of each iteration with data. The fourth, cross-silo collaboration, is concerned with how an organization works in a way that cuts across boundaries and silos through data sharing and use. The fifth, ecosystem participation, refers to how an organization collaborates by sharing data with partners, within an ecosystem, to co-create value propositions. Finally, the sixth meta-competency, data-proficiency, is concerned with how an organization makes decisions and executes actions based on data by incorporating new operational, technological and data governance capabilities.

Analysis Methodology

In order to obtain a more exhaustive analysis result based on the topics covered in the survey questions, their order was rearranged and a data-driven index (I_{dd}), with a minimum value of 1 and a maximum of 5, was generated. I_{dd} values are obtained as the mean of the values for the three dimensions: data model, business model and organizational model. An index value is also calculated for each of these dimensions. This value is the weighted sum of the values for each of the components, which are in turn made up of various elements that constitute that dimension,[3] as shown in **Table 1**.

Table 1. Data-Driven Index (I_{dd})

$$I_{dd} = \frac{1}{3}\ \textit{data model} + \frac{1}{3}\ \textit{business model} + \frac{1}{3}\ \textit{organizational model}$$

$$\textit{Data model} = \frac{1}{5}\ \textit{operational backbone} + \frac{1}{5}\ \textit{data security} + \frac{1}{5}\ \textit{data characteristics} + \frac{1}{5}\ \textit{programmability} + \frac{1}{5}\ \textit{data governance}$$

$$\textit{Business model} = \frac{1}{4}\ \textit{automation} + \frac{1}{4}\ \textit{prediction} + \frac{1}{4}\ \textit{coordination} + \frac{1}{4}\ \textit{personalization}$$

$$\textit{Organizational model} = \frac{1}{6}\ \textit{outside-in thinking} + \frac{1}{6}\ \textit{learning orientation} + \frac{1}{6}\ \textit{agile execution} + \frac{1}{6}\ \textit{cross-silo collaboration} + \frac{1}{6}\ \textit{ecosystem participation} + \frac{1}{6}\ \textit{data proficiency}$$

[3] In the programmability component, more weight is given to API structure than to data lake to reflect the importance of having a modular IT system.

	Weighting
I. Data model	**1/3**
Operational backbone	1/5
SSOT	1/4
ETL	1/4
Digitization of end-to-end processes	1/4
Dashboard/reports	1/4
Data security	1/5
Protection against cyberattacks	1/4
Detection of cyberattacks	1/4
Response to cyberattacks	1/4
Business continuity	1/4
Data characteristics	1/5
Accessibility	1/4
Usefulness	1/4
Quality	1/4
Software reliability	1/4
Programmability	1/5
Data lake	1/4
APIs (controllability)	3/4
Data governance	1/5
Governance	1/7
CDO	1/7
Data compliance	1/7
Data steward	1/7
CPO (privacy)	1/7
CISO	1/7
FATE	1/7
Fairness	1/4
Accountability	1/4
Transparency	1/4
Ethics	1/4
II. Business model	**1/3**
Automation	1/4
Prediction	1/4
Coordination	1/4
Personalization	1/4
III. Organizational model	**1/3**
Outside-in thinking	1/6
Design thinking, JTBD, customer journey mapping, etc.	1/2
Systematic analysis of customers using data	1/2
Learning orientation	**1/6**
A/B testing, hackathons, rapid prototyping, etc.	**1/4**
Fail Fast!	**1/4**
Bimodal operation (earn & learn)	**1/4**
Innovation-specific OKRs and KPIs	1/4
Agile execution	1/6
Agile methodology	1/2
Specific roles (product owner, scrum master, etc.)	1/2
Cross-silo collaboration	1/6
Cross-functional multidisciplinary teams	1
Ecosystem participation	1/6
Ecosystem with different stakeholders for co-creation of the value proposition	1/2
Partnership agreements with data clauses	1/2
Data proficiency	1/6
Data scientist	1/3
Data engineer	1/3
Business translator	1/3
Data-Driven Index (I_{dd})	

Of the total number of senior managers surveyed (*n* = 256), only those who responded to the entire questionnaire (*n* = 161) were considered for the analysis. Missing responses for optional questions related to the use of AI (questions 21 to 24) were replaced with the minimum possible value (1) in order not to distort the sample.a.

Market Situation

Overall Results

The average overall Data-Driven Index (I_{dd}) value for the companies included in the study is 2.91, below the midpoint of the 1 to 5 scale. This index value is the mean of the values for the data, business and organizational model indexes. Of the 161 companies included in the analysis, only 11 have an I_{dd} value above 4.00, and the highest score is 4.26. At the other extreme, we find 22 companies with an I_{dd} value below 2.00, and the lowest score is 1.19 (see **Figure 4**). **Figure 5** shows the sample values for each of the indexes.

Figure 4. Histogram of the Data-Driven Index

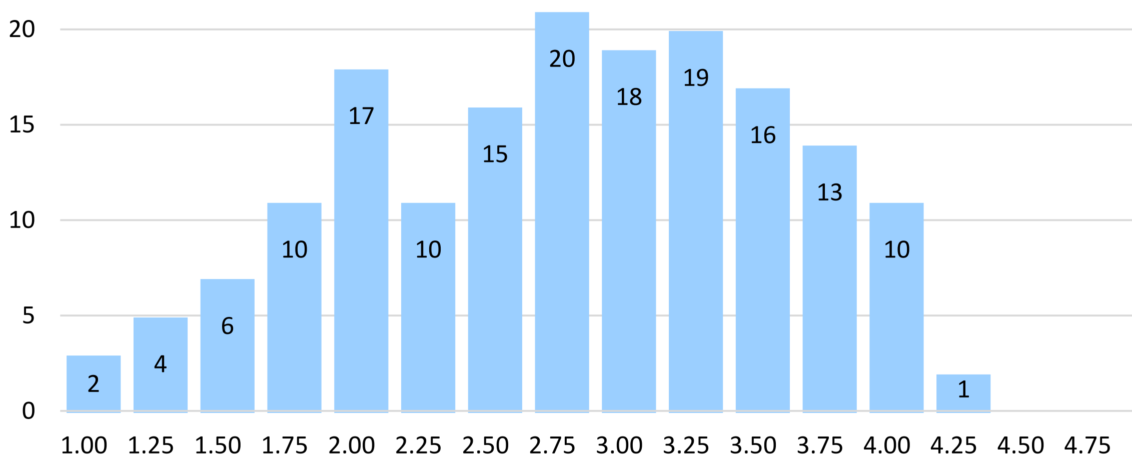
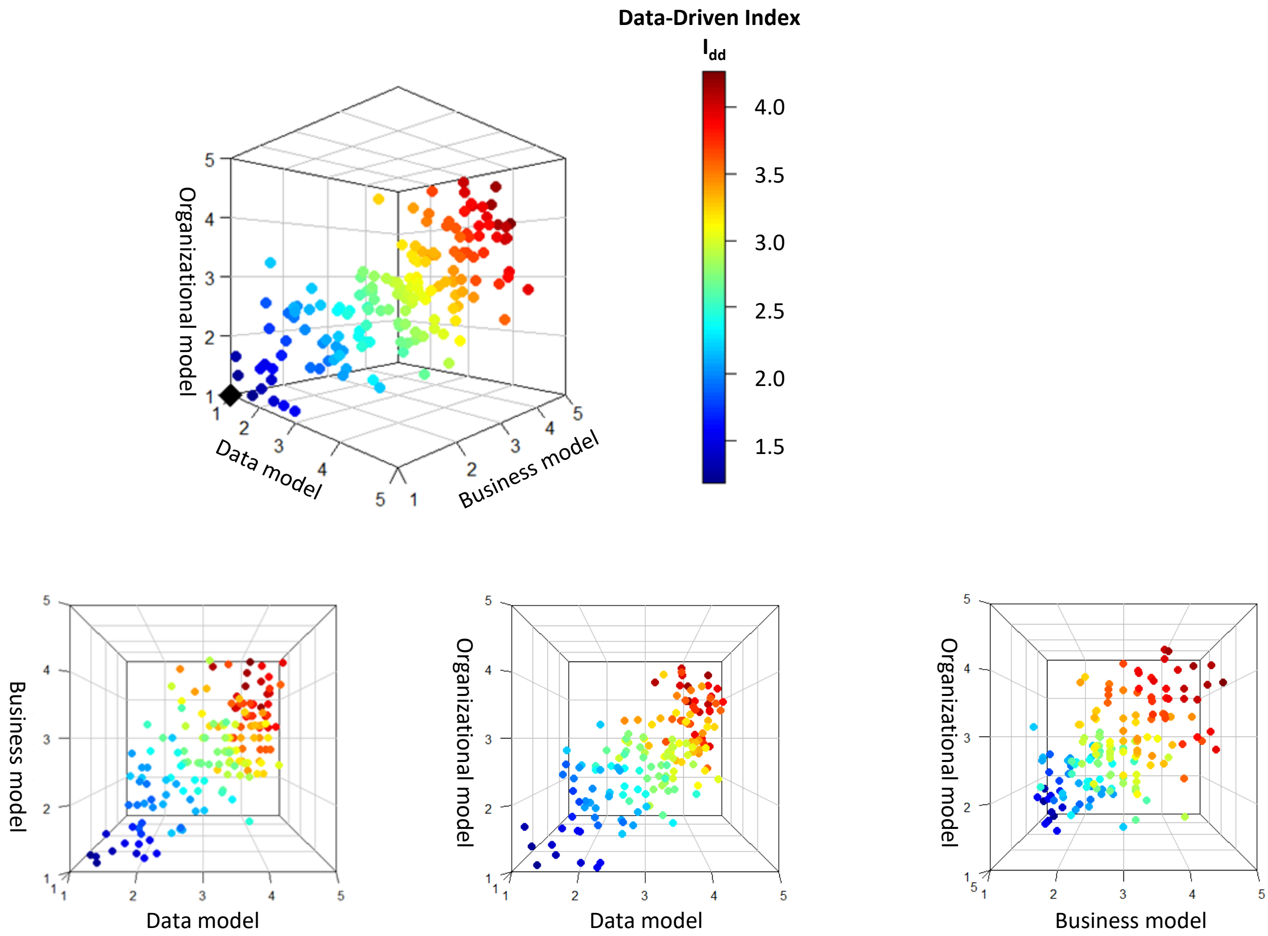
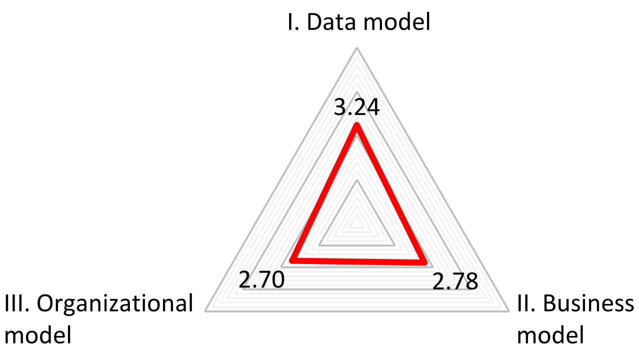


Figure 5. Dispersion of the Sample by Indexes



Fligure 6 shows that the most developed dimension in the set of companies analyzed is the data model, where the average index value is 3.24. However, this is not matched by a similar level of development in the other two dimensions. The business model is below the “pass” level, with an average value of 2.78. The companies also score low in the organizational model dimension, where the average value (2.70) is again below the pass level, which indicates that organizations lack adequate capabilities and methodologies to leverage data. The three dimensions of the index are analyzed in the following sections.

Figura 6. Radar Chart of the Data-Driven Index



Data Model

Figure 7 shows the components and corresponding values for the data model index (3.24). As the chart shows, the operational backbone value is 3.36, slightly above the pass level. This component is in turn made up of four elements, as shown in **Table 2**.

Figure 7. Radar Chart of the Data Model

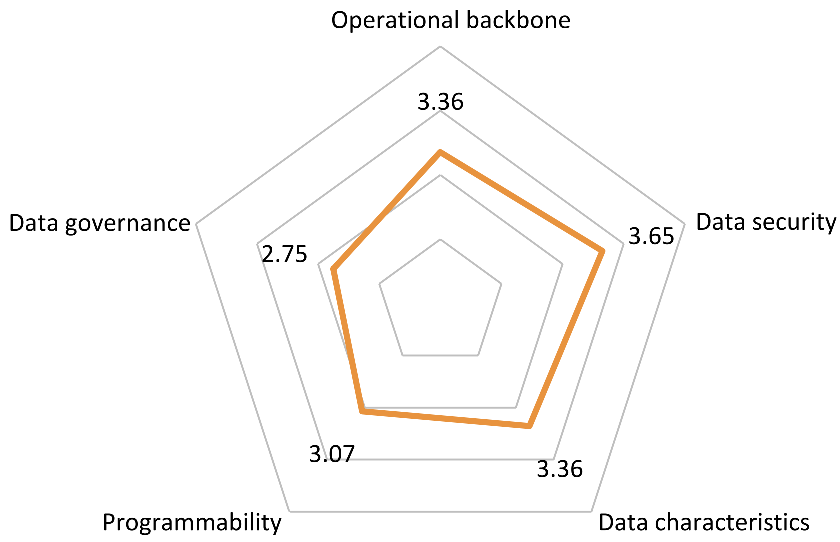


Table 2. Operational Backbone Component of the I_{dd}

Operational backbone	3.36
SSOT	3.35
ETL	3.11
Digitization of end-to-end processes	3.76
Dashboard/reports	3.22

Although digitization of end-to-end processes in organizations is high in many processes supported by transactional systems (3.76), this process is not yet complete. This data points in the same direction as the digital transformation study of June 2020, in which we found higher implementation of corporate support systems (administration, finance, human resources) than of value chain systems (marketing and customers, production and supply chain). The value that reflects the existence of a single source of truth (SSOT) through a single (logical) data warehouse is slightly above the pass level (3.35). The implementation of extraction, transformation and loading processes is far from complete (3.11 out of 5), and the presence of dashboards and reports (3.22) is mainly limited to financial areas, where there has traditionally been a greater need for reporting.

The data security component (see **Table 3**), which includes mechanisms for protection, detection and response to cyberattacks, as well as the existence of business continuity plans, stands at 3.65. This relatively higher value no doubt reflects efforts being made by organizations in response to a growing perception of vulnerability due to a substantial increase in cyberattacks in the last two years (Penteo 2021; Deloitte 2022).

In particular, concern about the impact on business continuity reached an inflection point when the first pandemic lockdowns were imposed in 2020. This preoccupation is reflected in an index value of 3.63. However, this high data security index value is not reflected in the existence of dedicated roles such as chief information security officer (CISO), where the corresponding index value is below the midpoint of the scale (2.94).

Table 3. Data Security Component of the I_{dd}

Data security	3.65
Protection against cyberattacks	3.91
Detection of cyberattacks	3.71
Response to cyberattacks	3.35
Business continuity	3.63

Data characteristics—in terms of accessibility, usefulness, quality and the reliability of the software used—are all at a medium level of development, with an average value of 3.36 (see **Table 4**). This indicates that organizations still need to make a considerable effort in this dimension to improve the entire data cycle, from data capture to data use. In some organizations, data still has to be extracted and analyzed manually, outside IT systems (e.g., in Excel files), in order to extract information from across the organization. It should also be noted that there is ample room for improvement both in the quality of data (3.32), which is linked to the low ETL score, and in the reliability of software developed for data use (3.18).

Table 4. Data Characteristics Component of the I_{dd}

Data characteristics	3.36
Accessibility	3.48
Usefulness	3.45
Quality	3.32
Software reliability	3.18

Although, as noted above, companies are beginning to adopt the paradigm of an SSOT in a single data warehouse, the development of data lakes is still at an early stage, with an index value of 2.68 (see **Table 5**). This is related to the still low level of AI (e.g., ML) use, as we will see in the business model dimension. In contrast, there is a greater presence of mechanisms for controlling the exchange of information between a company's internal and external systems, and this data flow is increasingly taking place in a more standardized way, through APIs (3.20), which is indicative of how modular or programmable an organization's IT architecture is.

Table 5. Programmability Component of the I_{dd}

Programmability*	3.07
Data lake	2.68
APIs (controllability)	3.20

*In the programmability component, more weight is given to API structure than to data lake to reflect the importance of having a modular IT system.

Finally, there is a clear deficiency with regard to implementation of data governance in organizations (see **Table 6**), where the index value is 2.75 (below the pass level on the scale used). In particular, most companies do not have formal data management roles and lack formal data governance structures (2.76), a CDO (2.45), a data steward (2.27) and a CISO (2.94). As a result of new regulations such as the General Data Protection Regulation (GDPR), companies are better prepared in terms of data compliance (3.38) and privacy management, with roles such as CPO (3.75). Clearly, very few organizations are effectively managing governance related to advanced analytics. Adoption of the FATE[4] model is low, as the average score of just 1.70 on this point indicates.

Table 6. Data Governance Component of the I_{dd}

Data governance	2.75
Governance	2.76
CDO	2.45
Data compliance	3.38
Data steward	2.27
CPO (privacy)	3.75
CISO	2.94
FATE	1.70
Fairness	1.65
Accountability	1.71
Transparency	1.73
Ethics	1.72

Business Model

Figure 8 shows the business model index and the sub-indexes for the four data interactions: automation, prediction, coordination and personalization. As the chart shows, the dominant tendency is clearly to use data in automation processes to gain efficiency, with a value of 3.40 for this component.

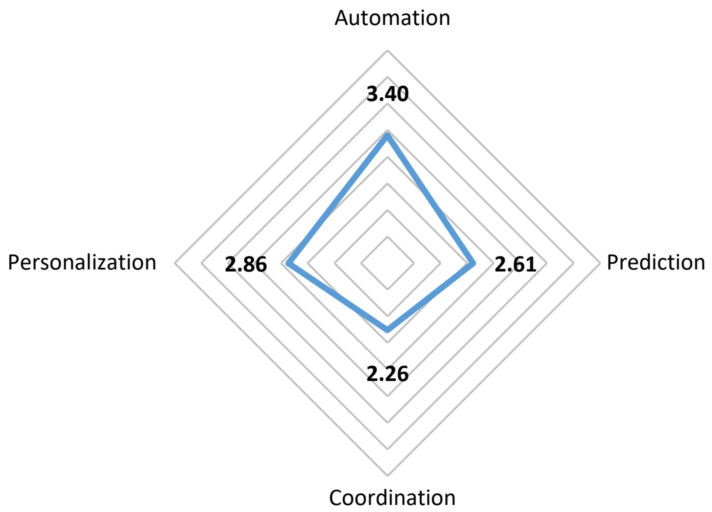
It is also worth noting that organizations are increasingly using data to personalize goods and services for their customers, where the index value is 2.86. This interaction is expected to continue on a path of gradual improvement. Forecasts made by Penteo for 2022 (Penteo 2022) indicate that B2C-oriented companies focus more investment on the analytics component than the others, and part of that emphasis is concentrated on information related to analysis and personalization of their value propositions.

For the interaction of prediction—that is, the use of data through advanced analytics and/or AI for predictive/prescriptive purposes—the index value is 2.61, which probably indicates that the use of AI in organizations is still in an exploratory phase. The adoption of prediction in business models clearly entails having an appropriate data model for training AI algorithms (large volumes of data, accessibility, quality, etc.) and appropriate roles within the organization (data scientists, data engineers, business translators, etc.).

[4] Note that questions on the adoption of the FATE model were only answered by organizations with AI projects. Those that do not yet use AI were assigned a value of 1 in the four dimensions of the model.

Finally, most organizations get a failing grade when it comes to coordination in the use of data, where the average value is 2.26. This indicates that most business models do not involve participation in ecosystems through external APIs for the co-creation of value propositions with other organizations via their coordination through business platforms. This result is correlated with the low level of programmability reflected in the data model of most organizations.

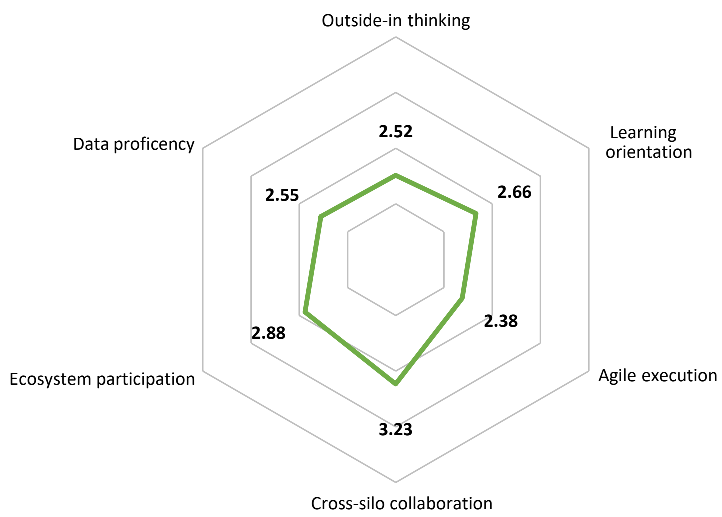
Figure 8. Radar Chart of the Business Model



Organizational Model

Figure 9 shows the components of the organizational model index and the corresponding values. The results show that the organizations analyzed clearly fall short in this dimension as they have not sufficiently developed the six meta-competencies that are key to digital transformation processes.

Figure 9. Radar Chart of the Organizational Model



As for the meta-competency of outside-in thinking (see **Table 7**), where the average value is 2.52, organizations continue to take an inside-out approach. In other words, they continue to promote existing goods and services based on their current competencies rather than taking an outside-in approach, which entails developing new competencies in order to better serve the needs of their customers.

There is still a low level of adoption of methodologies geared towards capturing customer knowledge (2.47), which include design thinking, Jobs to Be Done (JTBD) and customer journey mapping, and a low level of systematic analysis of customer needs using various data that can be captured across the life cycle of goods and services (2.57). This point was considered in our 2020 digital transformation study, where we found that these methodologies were used in less than 50% of the companies analyzed, though customer journey mapping was adopted to a greater extent in companies that had been successful in their digital transformation programs.

Table 7. Outside-in Thinking Component of the I_{dd}

Outside-in thinking	2.52
Design thinking, JTBD, customer journey mapping, etc.	2.47
Systematic analysis of customers using data	2.57

The meta-competency of outside-in thinking is closely associated with the learning orientation meta-competency, where the average value is low (2.66; see **Table 8**). We found a low level of implementation of methodologies involving experimentation (2.14), such as A/B testing, hackathons and rapid prototyping. Moreover, organizations do not exhibit a culture that promotes learning by making mistakes, based on approaches such as Fail Fast, where the average index value is 2.76. This point is confirmed by an approach that is very skewed towards business model execution, with little room for experimentation, as reflected in an index value for bimodal operation of just 2.69. Finally, the KPIs and OKRs used by organizations still do little to measure innovation processes, as the corresponding index value of 3.05 shows. This indicates that most metrics focus on performance.

Table 8. Learning Orientation Component of the I_{dd}

Learning orientation	2.66
A/B testing, hackathons, rapid prototyping, etc.	2.14
Fail Fast!	2.76
Bimodal operation (earn & learn)	2.69
Innovation-specific OKRs and KPIs	3.05

Table 9 clearly shows the low level of adoption of agile execution (the average value is just 2.38) via the adoption of iterative development methodologies based on agile principles (2.45). The low value for this component also reflects the fact that only a minority of organizations have specific roles related to agile methodology (2.30), such as product owners and scrum masters. This contrasts with the widespread use of agile practices in the IT area. It appears that such practices are not yet being transferred at scale to other functional areas of organizations.

Table 9. Agile Execution Component of the I_{dd}

Agile execution	2.38
Agile methodology	2.45
Specific roles (product owner, scrum master, etc.)	2.30

In contrast, the most developed meta-competency is cross-silo collaboration (see **Figure 10**), where the index value is 3.23, pointing to more frequent adoption of cross-functional multidisciplinary teams, which can be explained by the fact that organizations increasingly have matrix structures (in addition to functional ones) to manage corporate initiatives (innovation, cross-functional project management, etc.).

However, the level of development in terms of the collaboration of organizations beyond their corporate boundaries is significantly lower, with an index value is 2.88 (see **Table 10**), and most organizations do not participate in ecosystems for the co-creation of value propositions with others (2.93). It should also be noted that most companies still do not include a data clause in partnership agreements (2.84)—a critical factor when it comes to capturing value in ecosystems. The meta-competency of ecosystem participation is closely related to programmability in the data model and the use of coordination as an interaction in the business model.

Table 10. Ecosystem Participation Component of the I_{dd}

Ecosystem participation	2.88
Ecosystem with different stakeholders for co-creation of the value proposition	2.93
Partnership agreements with data clauses	2.84

Finally, the still low adoption of AI is correlated with the limited presence of specialized roles, such as data scientists, data engineers and business translators. The index value for data proficiency is just 2.55 (see **Table 11**), and the lack of data engineers—a critical role when it comes to preparing and cleaning data for use in AI models—is particularly notable. The index value for this point is just 2.32.

Table 11. Data Proficiency Component of the I_{dd}

Data proficiency	2.55
Data scientist	2.68
Data engineer	2.32
Business translator	2.66

Segmentation by Company Size

If the organizations are segmented according to their turnover in order to identify any significant differences in the index of data-driven maturity, we find that of the 161 companies in the sample, 116 are SMEs with an annual turnover below €150 million, and 15 are large companies with a turnover of over €1 billion. Significant differences can be observed in the corresponding I_{dd} values, which range from 2.84 for SMEs to an average of 3.35 for large companies.

In particular, the large companies have made more progress than the SMEs in terms of data strategy, especially with respect to the data model, where they score better in all components, with an index value of 3.81 compared to 3.09 for SMEs (see **Figure 10**). The biggest differences are in data security, where the index value is 4.35 for large companies versus 3.45 for SMEs. Large companies show higher adoption of cybersecurity frameworks for protection, detection, response and business continuity in the event of a cyberattack. These organizations are aware that size is a good predictor of the likelihood of suffering security breaches, and that the reputational consequences should such a breach are also likely to be greater for them. They also have more developed governance structures. This is possible because of their scale, and it is likely that regulatory requirements are also a factor. As a result, significant differences are observed in terms of data governance, where the index value is 3.50 for large companies versus 2.58 for SMEs. Big companies also score higher on specific roles for compliance (4.40 vs. 3.10), CPO (4.27 vs. 3.53), CISO (3.87 vs. 2.76) and CDO (3.27 vs. 2.20).

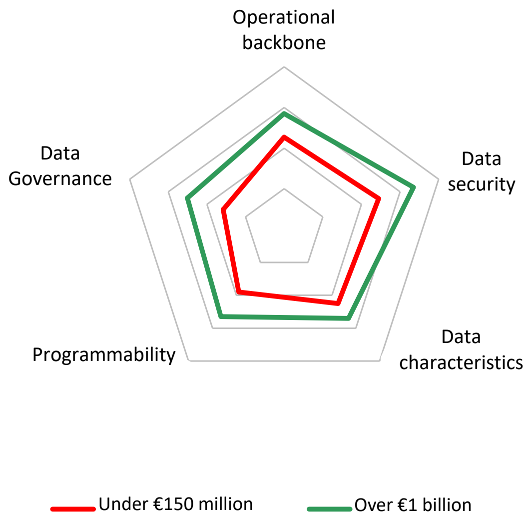
With regard to the business model, the differences between large companies and SMEs are not as marked as in the case of the data model, but there are some significant differences in the use of data for prediction (3.33 vs. 2.59) and personalization (3.47 vs. 2.84). However, in automation and coordination, the differences are not as significant.

Finally, with respect to the organizational model, large companies make more use of outside-in thinking than SMEs (3.13 vs. 2.39) and have more specific data roles—that is, they have greater data proficiency (3.53 vs. 2.44).

Based on these results, we can infer that larger companies tend to have better I_{dd} values because they have more resources to develop technological and organizational capabilities and as a result of the compliance requirements that they are subject to.

Figure 10. Data Model Index Segmented by Company Size

	Under €150 million	Over €1 billion
I. Data model	**3.09**	**3.81**
Operational backbone	3.27	3.85
Data security	3.45	4.35
Data characteristics	3.25	3.70
Programmability	2.91	3.65
Data governance	2.58	3.50



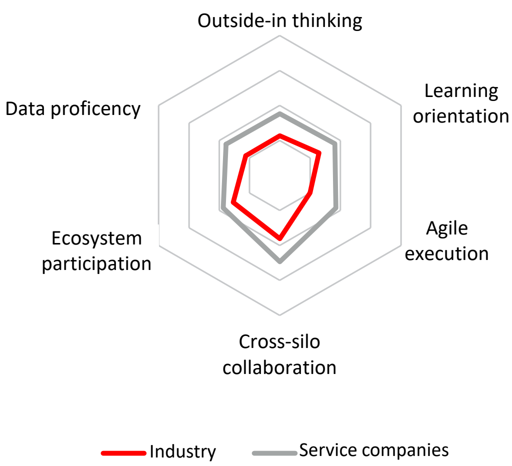
Segmentation by Sector

Of the 161 companies included in the sample, 28 operate in the industrial sector and 39 in the service sector. On average, the latter have an I_{dd} value of 3.02 compared to 2.61 for industrial companies. This difference is consistently reflected across the three dimensions of the model: in the data model index (3.27 vs. 3.04), the business model index (2.88 vs. 2.48), and the organizational model index, where the gap is most significant (2.93 vs. 2.32), as shown in **Figure 11**.

The greatest difference between the index values for specific dimensions is in the organizational model. In particular, adoption of the agile methodology is higher (2.86 vs. 2.00) and the meta-competency of outside-in thinking is more developed (2.77 vs. 2.14). This reflects the fact that service companies need to constantly adapt to their customers, and to do so they require mechanisms for continuous identification of customer needs and iterative development of goods and services, which is supported by their greater data proficiency (2.78 vs. 2.13). In contrast, the industrial sector has an index value below the overall average (2.91), possibly because the strong B2B component of this sector makes it less sensitive to rapid changes in context taking place in the consumer market. This is particularly clear in service companies that are undergoing substantial changes in the way they interact with customers, as in the case of the banking and insurance sectors, which have higher levels of I_{dd} maturity, with a value of 3.22.

Figure 11. Organizational Model Segmented by Sector

	Industry	Service companies
III. Organizational model	**2.32**	**2.93**
Outside-in thinking	2.14	2.77
Learning orientation	2.29	2.82
Agile execution	2.00	2.86
Cross-silo collaboration	2.81	3.47
Ecosystem participation	2.54	2.87
Data proficiency	2.13	2.78



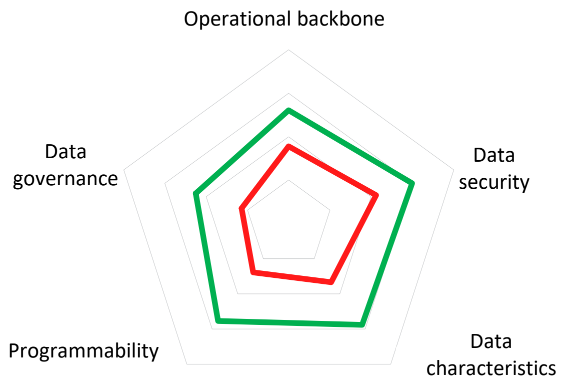
Segmentation by Degree of Success in Digital Transformation

If we compare the companies that report having been successful in their digital transformation (values of 5 or 4 for question 34) with those that say they have not been successful (values of 1 or 2), we find 46 "successful" companies with an I_{dd} value of 3.43 (0.52 points above the average) and 45 "unsuccessful" companies, with an I_{dd} value of 2.32 (0.59 points below the average). As **Figure 12** shows, this difference is significant and consistent across all three dimensions of the model, as well as in the components of each dimension: data model (3.70 vs. 2.62), business model (3.37 vs. 2.24) and organizational model (3.21 vs. 2.0). We can therefore conclude that having a **strong I_{dd} value in all three dimensions is a good predictor of success in digital transformation processes**.

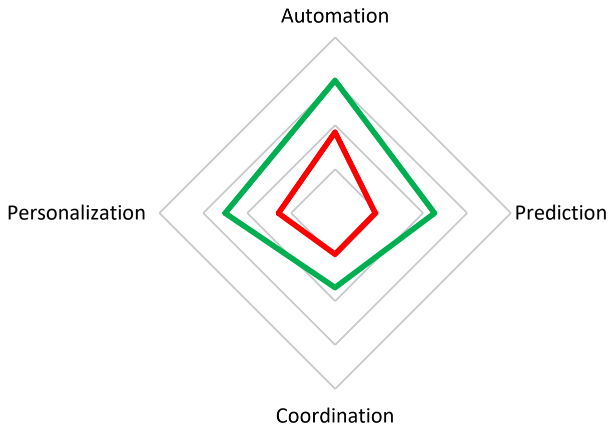
With respect to the data model, it is worth noting that “successful” companies have much more programmable and modular system architectures (e.g., APIs and data lakes), with a programmability index value of 3.77 vs. 2.39 for “unsuccessful” companies. This enables them to respond more flexibly in changing contexts. Likewise, in terms of the business model, “successful” companies make greater use of prediction (e.g., ML), with an index value of 3.26 vs. 1.91 for “unsuccessful” companies. In other words, they use data in a more offensive way, as raw material for innovation. “Successful” companies are also characterized by a high level of maturity in the use of automation (4.02 vs. 2.84). Finally, we can see that in the organizational model “successful” companies are more clearly oriented towards outside-in thinking and have adopted work practices based on design thinking, JTBD, customer journey mapping, and similar approaches, with a corresponding index value of 3.12 vs. 1.81 for “unsuccessful” companies.

Figure 12. Index Segmented by Perception of Success

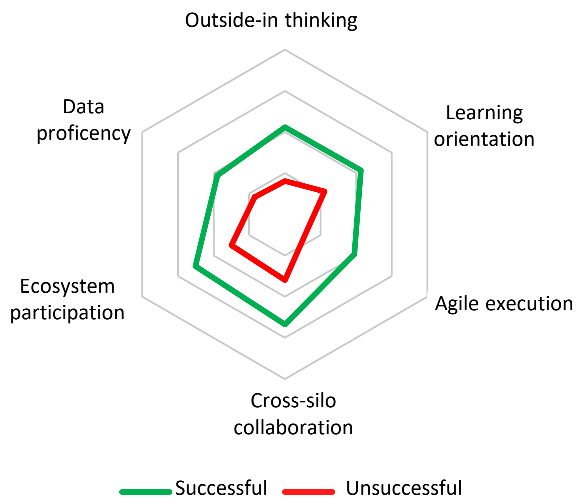
	Successful	Unsuccessful
I. Data model	**3.70**	**2.62**
Operational backbone	3.61	2.78
Data security	3.99	3.12
Data characteristics	3.89	2.67
Programmability	3.77	2.39
Data governance	3.25	2.14



	Successful	Unsuccessful
II. Business model	**3.37**	**2.24**
Automation	4.02	2.84
Prediction	3.26	1.91
Coordination	2.70	1.93
Personalization	3.50	2.29



	Successful	Unsuccessful
III. Organizational model	**3.21**	**2.09**
Outside-in thinking	3.12	1.81
Learning orientation	3.14	2.11
Agile execution	2.95	1.66
Cross-silo collaboration	3.67	2.60
Ecosystem participation	3.51	2.50
Data proficiency	2.89	1.84
Data-Driven Index (I_{dd})	**3.43**	**2.32**



It should be noted that there is no component in which "successful" companies have a lower level of development than "unsuccessful" ones. (Though less significant in some cases, the difference between the two groups is greater than 0.75 points in all of the components analyzed.) **This means there are no shortcuts when it comes to capturing the benefits of a data strategy; all components must be developed in a holistic, coordinated way.**

Technology and Business Planning

Table 12 presents information on the status of data technology plans, as reported by the organizations included in the study, in relation to the degree of success they have achieved in their digital transformation and their I_{dd} values.

We can observe that the companies which report they have an up-to-date data technology plan make up 54% of those that have been "successful" in their digital transformation. These companies also have a high average I_{dd} value (3.65). In contrast, 13% of the companies in the "unsuccessful" category report that they have a technology plan. The I_{dd} value of these companies is 2.32, well below the average. This suggests that the data technology plans of these organizations are poorly defined and/or executed. Likewise, 42% of "unsuccessful" companies report that they do not have a data technology plan and do not expect to have one in the medium term, which is correlated with a very low I_{dd} value (2.02).

We can conclude that having a data technology plan that is well-defined and effectively implemented (as reflected in an organization's I_{dd} value) is correlated with success in digital transformation processes.

Table 12. Companies That Have Developed a Data Technology Plan

Have you produced a data technology plan to support your company's development?	Successful		Unsuccessful	
	%	I_{dd}	%	I_{dd}
Yes, we have, and we keep it up-to-date.	54%	3.65	13%	2.32
Yes, we have, but we've given up on it.	-	-	9%	2.77
Not yet, but we'll have one in 2022.	22%	3.47	36%	2.56
No, and we have no plans to do so.	24%	2.88	42%	2.02

Table 13 shows the benefits that the companies expect to gain by implementing their data strategies. Most (55%) expect to improve the quality of corporate decision-making. The "successful" ones have a high I_{dd} value of 3.52, whereas the "unsuccessful" ones have an I_{dd} value of 2.37 (below average). Other expected benefits include process efficiency and democratization of access to information throughout the company, both reported by 53% of respondents. Here too there is a correlation between the degree of success in digital transformation ("successful" vs. "unsuccessful") and the I_{dd} values of the respective companies. **Based on the data shown in this table, we can infer that the I_{dd} value is a good proxy for achievement of the benefits expected from implementation of a data strategy.** In fact, most of the benefits listed in **Table 13** are related to having a solid data model, which is reflected in index values close to 4 in most cases (see **Table 14**). **Figure 13** shows how many benefits are reported by companies according to their perception of success.

Table 13. Benefits Observed According to Perception of Success

Benefits	Successful	Overall	Unsuccessful
Improve the quality of current information.	3.50	3.03	2.31
Improve the quality of corporate decision-making.	3.52	3.05	2.37
Speed up corporate decision-making.	3.49	3.16	2.66
Achieve greater efficiency in processes.	3.56	3.14	2.57
Democratize access to information throughout the company.	3.49	3.26	2.67
Improve knowledge of customers.	3.51	3.12	2.48
Empower users to access and analyze information.	3.42	3.21	2.61
Identify sources of revenue enhancement for the company.	3.47	3.19	2.71

Table 14. Breakdown of Perceived Benefits in "Successful" Companies

Benefits	Number of companies		I_{dd}	Data model	Business model	Org. model
Improve the quality of current information.	20	43%	3.50	3.8	3.4	3.4
Improve the quality of corporate decision-making.	30	65%	3.52	3.8	3.4	3.3
Speed up corporate decision-making.	24	52%	3.49	3.8	3.3	3.3
Achieve greater efficiency in processes.	29	63%	3.56	3.9	3.4	3.3
Democratize access to information throughout the company.	12	26%	3.49	3.8	3.3	3.3
Improve knowledge of customers.	25	54%	3.51	3.8	3.5	3.3
Empower users to access and analyze information.	22	48%	3.42	3.8	3.3	3.2
Identify sources of revenue enhancement for the company.	24	52%	3.47	3.7	3.5	3.2

Figure 13. Percentage of Companies With at Least *n* Benefits

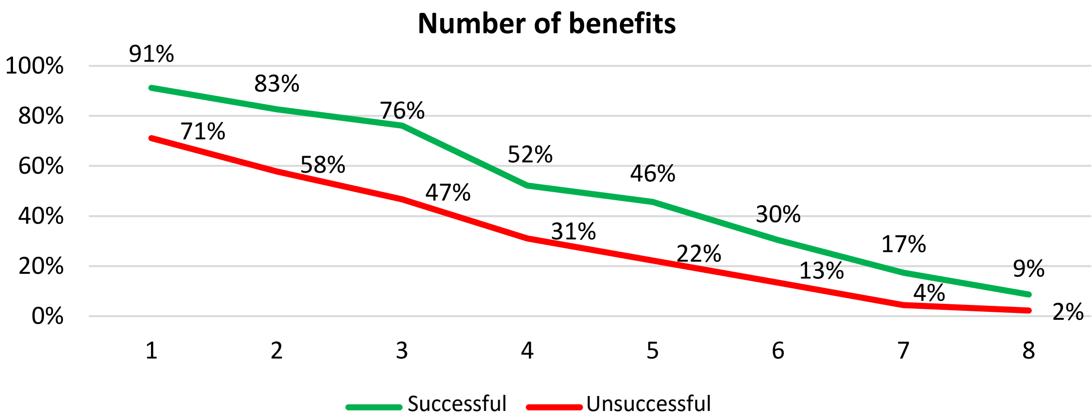


Table 15 shows the relationship between strategic positioning as regards the use of data and success in digital transformation processes and the I_{dd} value of the respective organizations. On the 1 to 5 scale used, a value of 1 corresponds to companies that use data primarily as a mechanism for controlling execution of their business model, and 5 corresponds to companies that, in addition to control, actively use data to support innovation. As the figures show, organizations that are committed to innovation and have been "successful" obtain a high I_{dd} value (3.84). At the other extreme, those that use data mainly for control purposes (value of 1 or 2) have lower I_{dd} values, and most of these organizations are "unsuccessful," which indicates that they are not immersed in transformation processes and instead focus mainly on digitizing their current business model. High I_{dd} values across the three dimensions of the index are a necessary condition for carrying out the innovation processes that digital transformation involves.

Table 15. Perception of Data as a Mechanism for Control vs. Innovation

	Successful		Unsuccessful	
Level of agreement or disagreement	**%**	**I_{dd}**	**%**	**I_{dd}**
1.0	7%	2.63	38%	2.09
2.0	11%	2.69	22%	2.36
3.0	13%	3.28	31%	2.48
4.0	50%	3.54	7%	2.49
5.0	19%	3.84	2%	3.00

1.0: Data is used primarily as a mechanism for controlling execution of the business model.

5.0: The organization also actively uses data to support innovation..

Impact of Context

Table 16 shows the changes that digital transformation entails for an organization's business model and corresponding I_{dd} values. As the figures show, companies that have not undergone a transformation (values of 1 or 2) also have a low I_{dd} value. Conversely, those that have undergone a transformation (values of 4 or 5) have a higher than average I_{dd} value.

We can conclude that digital transformation of the business model depends critically on having an I_{dd} value that can support this process.

Table 16. Perception of Data Impact According to Business Model

Level of agreement or disagreement	1.0 – 2.0	3.0	4.0 – 5.0
1. Digital transformation will entail a change in our business model.	2.44	2.81	3.00
2. Data is considered a key asset for generating the company's value proposition (offering).	2.25	2.77	2.98
3. There have been changes in the way the value proposition is constructed.	2.37	2.80	3.10
4. There have been changes in the way the value proposition is marketed.	2.36	2.78	3.10
5. There have been changes in the cost structure.	2.46	2.96	3.12
6. The cost of serving a customer has been reduced.	2.55	3.11	3.15
7. Sources of revenue have changed.	2.70	3.04	3.29

In particular, on the question of whether data is considered a key asset for generating the value proposition, a clear difference in the use of data interactions in the business model is observed between companies with values 1 or 2 and those with values of 4 or 5 (see **Figure 14**).

Figure 14. Business Model as per Question 33-2

Do you consider data a key asset for generating your company's value proposition (offering)?

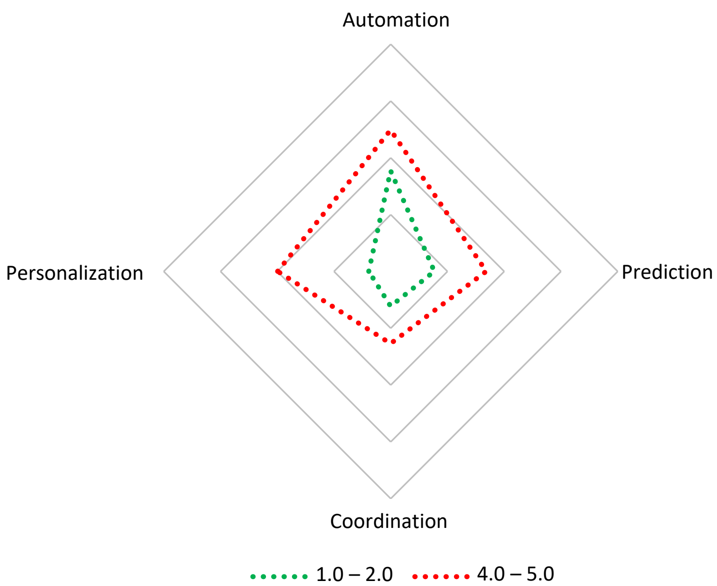


Table 17 shows statements related to changes that can occur in the context in which organizations operate and corresponding I_{dd} values according to the level of agreement. In general, we can see that organizations operating in changing contexts (values of 4 or 5) have an I_{dd} value above the average. The level of disruption in the sector in which they operate and regulatory requirements seem to be the most significant context-related factors for companies that have an I_{dd} value that is significantly higher than those that do not operate in a context of disruption and/or regulation (values of 1 or 2). **We can conclude that changing contexts spur companies to become data-driven organizations and that this is reflected in their I_{dd} values.**

Table 17. Perception of Data Impact According to Context

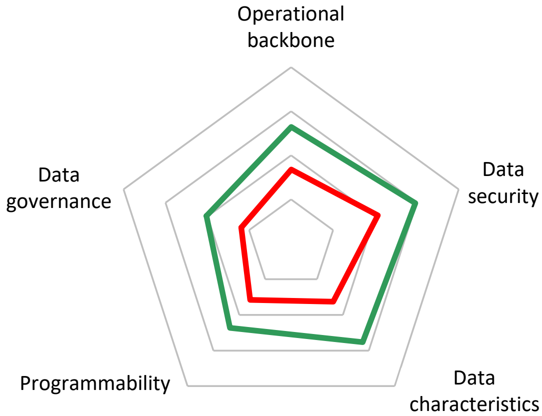
Level of agreement or disagreement	1.0 – 2.0	3.0	4.0 – 5.0
1. In recent years. new competitors and non-traditional competitors (e.g.. start-ups and/or companies from other sectors) have emerged in my sector.	2.63	3.06	3.09
2. There has been a disruptive digital transformation in the sector.	2.63	2.91	3.20
3. The way we interact with customers has changed substantially.	2.50	3.15	3.08
4. My sector is subject to strict regulation compared to other sectors.	2.80	3.14	2.98
5. Significant regulatory changes are expected in the sector due to digital transformation.	2.73	2.98	3.20
6. The governance structure of my organization facilitates digital transformation processes.	2.61	2.71	3.18
7. My organization has the capacity to allocate the resources required to carry out a digital transformation.	2.30	2.76	3.21

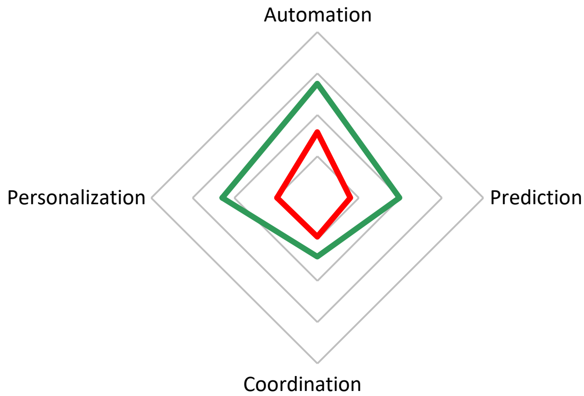
Finally, **an organization's capacity to allocate the resources required to carry out a digital transformation is a determining factor in the success of this process (78% of "successful" companies, with value 4 or 5) and is correlated with a high I_{dd} value in all of the dimensions (data, business and organizational model),** as shown in **Figure 15**.

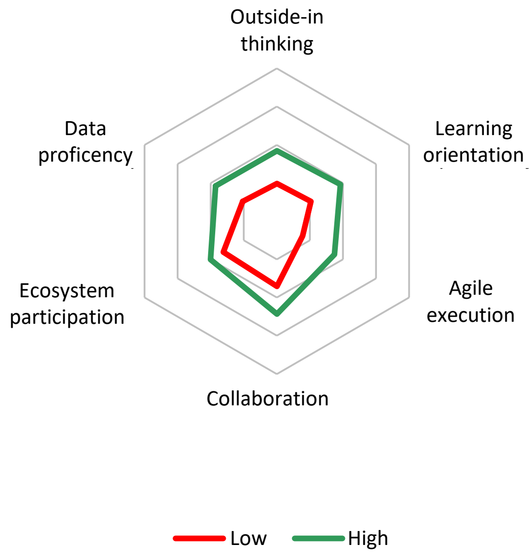
Figure 15. Index Segmented by Perception of Capacity to Allocate Resources – Question 43-7

The organization has the capacity to allocate the resources required to carry out a digital transformation.

	Low (1–2)	High (4–5)
I. Data model	**2.63**	**3.55**
Operational backbone	2.68	3.65
Data security	3.07	3.97
Data characteristics	2.63	3.76
Programmability	2.58	3.36
Data governance	2.19	3.02
II. Business model	**2.07**	**3.11**
Automation	2.59	3.76
Prediction	1.79	2.98
Coordination	1.94	2.42
Personalization	1.97	3.29
III. Organizational model	**2.19**	**2.97**
Outside-in thinking	1.99	2.84
Learning orientation	2.03	2.92
Agile execution	1.78	2.74
Cross-silo collaboration	2.71	3.43
Ecosystem participation	2.62	3.01
Data proficiency	2.03	2.85
Data-Driven Index (I_{dd})	**2.30**	**3.21**







Summary and General Conclusions

In the last two years, the importance of data as a key asset has been widely recognized, but organizations are still far from having a consistent data strategy. There is a clear correlation between successfully carrying out a digital transformation process and having a holistic data strategy that encompasses not only technology but also its impact on the business model and the organizational model. Organizations that define and execute a strategy of this kind are data-driven organizations.

In this study, we have presented a data-driven index (I_{dd}) based on a data-driven organizational framework developed in IESE Business School's Information Systems Department. The data model is at the center of this framework and is the basis for generating the business model and configuring the organizational model. Based on a 360-degree vision of the technological, business and organizational dimensions, I_{dd} values reflect in aggregate form the degree to which an organization is data-driven.

The average I_{dd} value of the companies included in the study is 2.91 on a scale of 1 to 5. This value, below the midpoint of the scale, indicates that **companies still have clear shortcomings in terms of their ability to leverage data as a key asset**. Of the 161 companies analyzed, only 11 have an I_{dd} value above 4.00, and the highest score is 4.26. At the other extreme, we find 21 companies with an I_{dd} value below 2.00, and the lowest score is 1.19.

Of the three dimensions that make up the I_{dd}, the most developed is the data model, where the average value is 3.24.The relative strength of this dimension reflects the investment that organizations have made in data-related IT systems. However, this is not matched by a similar level of development in the other two dimensions. The business model is below the midpoint of the scale, with an average value of 2.78. The average score for the organizational model is also low—just 2.70—which indicates that organizations lack adequate capabilities and methodologies to effectively leverage data. To be considered a data-driven organization, in addition to having a high overall I_{dd} value, a company must also have good values in the three dimensions of the index.

With regard to the data model, the most developed component is data security, where the average value is 3.65. This relatively high value no doubt reflects the efforts being made by organizations in response to a growing perception of vulnerability as a result of a substantial increase in cyberattacks over the last two years. This effect is most notable when large companies are targeted, given the impact of attacks in such cases. **In contrast, there is a clear deficiency with regard to implementation of data governance in organizations, where the index value is 2.76.** In particular, most companies do not have formal data management roles. In addition, there are still very few organizations that are addressing AI governance: Adoption of the FATE (fairness, accountability, transparency and ethics) model is low, as the average score of just 1.70 on this point indicates.

As for the use of data in business models, the dominant tendency is clearly to use data in automation processes to gain efficiency, with a value of 3.40 for this component. However, when it comes to using data through advanced analytics and/or AI, for predictive/prescriptive purposes, the index value is 2.61, which likely indicates that the use of AI in organizations is still in an exploratory phase.

As for their organizational model, the organizations analyzed clearly fall short in this dimension as they have not sufficiently developed the six meta-competencies that play a critical role in digital transformation processes. Most of the companies included in the study use data to control the execution of their current business model; data is used to support innovation only to a very limited extent. This skewed approach is reflected in an index value for bimodal operation of just 2.69.[5] Also worth noting is the low adoption of agile execution (where the average value is just 2.38) via the adoption of iterative development methodologies based on agile principles (2.45).

[5] Bimodal operation refers to the extent to which an organization is capable of executing a business model oriented towards generating financial returns (earn) while at the same time pursuing innovation processes (learn). The most bimodal companies are closer to a value of 5, while those with an execution orientation are closer to a value of 1 (monomodal).

This contrasts with the widespread use of agile practices in the IT area. It appears that these practices are not yet being transferred at scale to other functional areas of organizations.

There is a lack of specialized AI roles, such as data scientists, data engineers and business translators, reflected in a value of just 2.55 for data proficiency.

Larger companies tend to have a better I_{dd} value because they have more resources to develop technological and organizational capabilities and as a consequence of the compliance requirements that they are subject to. In contrast, SMEs tend to perform better when it comes to coordination and agility.

Service companies, in turn, have an average I_{dd} value of 3.02 compared to 2.61 in the case of industrial companies. The difference is even more pronounced in service companies undergoing major changes in the way they interact with customers (as in the case of the banking and insurance sectors), whose maturity in this area is reflected in high I_{dd} values.

When we segment the companies that report success in their digital transformation processes, we can infer the following:

1. A strong I_{dd} value in all three dimensions is a good predictor of the likelihood of success in digital transformation processes.
2. There are no shortcuts when it comes to capturing the benefits of a data strategy; the technological, business and organizational dimensions must be developed in a holistic, coordinated way.
3. A data technology plan that is well-defined and effectively implemented (as reflected in an organization's I_{dd} value) is correlated with greater success in digital transformation processes.
4. Organizations that focus on innovation and are "successful" obtain a high I_{dd} value (3.84). At the other extreme, those that use data mainly for control purposes (value of 1 or 2) have lower I_{dd} values, and most of these organizations are "unsuccessful," which indicates that they are not immersed in transformation processes and instead focus mainly on digitization of their current business model.

We can conclude that **digital transformation depends critically on having have a high I_{dd} value that can support this process.**

Changing contexts spur companies to become data-driven organizations, which is reflected in I_{dd} values that are higher than those of companies that operate in more stable contexts.

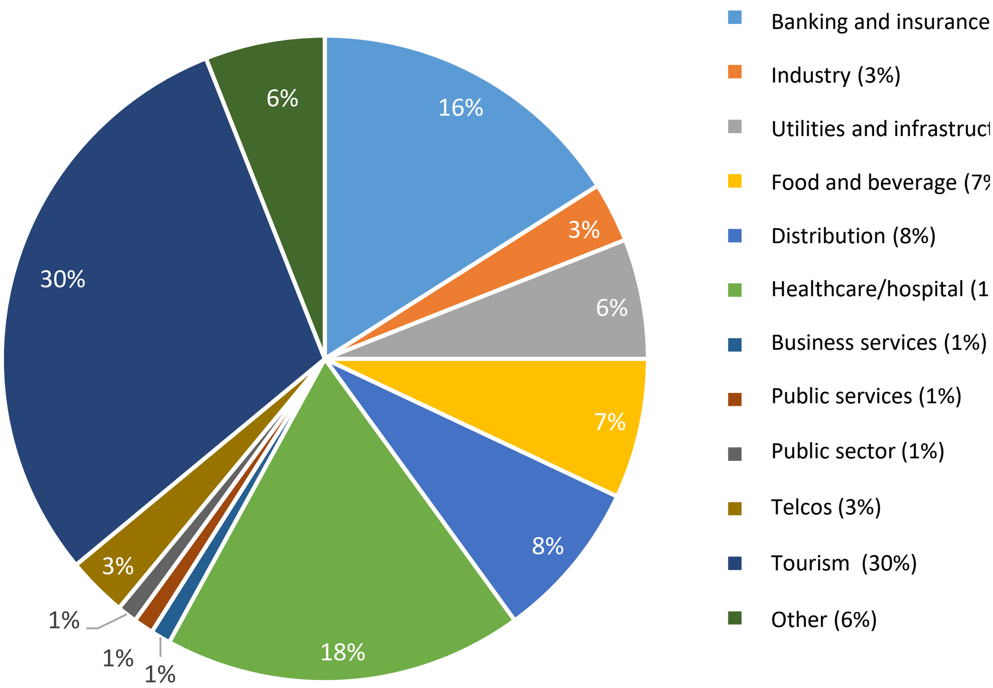
Finally, an organization's capacity to allocate the resources required to carry out a digital transformation is a determining factor in the success of this process (78% of "successful" companies, with value 4 or 5) and is correlated with a high I_{dd} in all of the dimensions (technological, business and organizational).

Exhibit 1
Study Details

Number of participating executives = 256

Research period: September 2021 to February 2022

Sectors analyzed



Size of the companies analyzed (annual turnover)

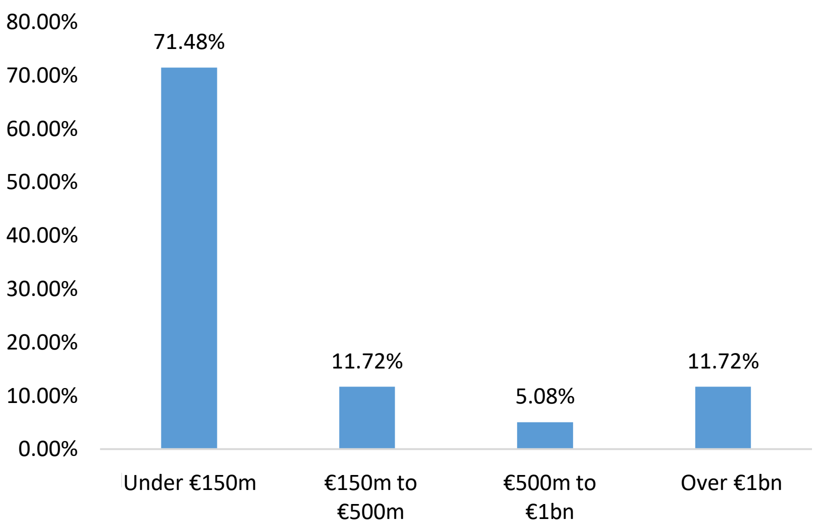


Exhibit 2
Research Questionnaire

P1. Contact details
Full name
Email address
Company
Position/area of responsibility

P2. Sector of the company/organization
Banking and insurance
Industry
Utilities and infrastructure
Food and beverage
Distribution
Healthcare/hospital
Business services
Public services
Public sector
Telco
Tourism
Other (specify)

P3. Gross income in Spain
Under €150m
€150m to €500m
€500m to €1bn
Over €1bn

P4. Number of employees in Spain
Under 50
50 to 249
250 to 1,000
Over 1,000

P5. SSOT (single source of truth)				
The organization's information resides in multiple independent databases.				There is a single data warehouse where the organization's information resides.
1	2	3	4	5

P6. ETL (extract, transform and load). A defined process that extracts data from multiple sources, transforms it (e.g., by standardizing values), and finally loads it into the organization's single data warehouse.				
The organization does not have a well-defined process for data extraction, transformation and loading.				The organization has a well-defined process for data extraction, transformation and loading.
1	2	3	4	5

Exhibit 2 (continued)

P7. Digitization of end-to-end processes				
No corporate software packages such as ERP, CRM, etc. are available.				All organizational processes are digitized and supported by software packages.
1	2	3	4	5

P8. Data lake				
The organization only has transaction information in traditional databases and/or a data warehouse.				The organization has a data lake (a repository for heterogeneous data) that is used to experiment with data.
1	2	3	4	5

P9. Dashboard/reports				
Analysis of information is performed manually or through the exchange of Excel files.				The organization has a business intelligence application for analyzing information.
1	2	3	4	5

P10. Protection against cyberattacks				
The organization does not make any specific effort to prepare for possible cyberattacks.				The organization devotes resources to active protection against cyberattacks (e.g., training, firewalls).
1	2	3	4	5

P11. Detection of cyberattacks				
The organization does not have specific cyberattack detection systems.				The organization actively monitors cybersecurity threats.
1	2	3	4	5

P12. Response to cyberattacks				
The organization does not have a defined plan for responding to cyberattacks.				There is a defined protocol for responding to cyberattacks.
1	2	3	4	5

P13. Business continuity				
The data architecture has not been designed to ensure business continuity.				The data architecture is resilient to cyberattacks (e.g., isolated redundant systems).
1	2	3	4	5

P14. *Chief security officer*				
There is no management position for information security.				There is a chief information security officer with visibility on the management board.
1	2	3	4	5

Exhibit 2 (continued)

P15. Accessibility				
Access to data is not automatic and involves manual processes.				The organization’s data is automatically accessible in real time.
1	2	3	4	5

P16. Usefulness				
Data that is not useful for the organization’s activity is stored, and other necessary data is missing.				Stored data is useful and sufficient for the organization’s activity.
1	2	3	4	5

P17. Quality				
There are no mechanisms in place to ensure data quality.				There are mechanisms to ensure that data is correct, complete, properly formatted and not obsolete.
1	2	3	4	5

P18. Software reliability				
There are no formal controls on the quality of the software (algorithms) used by the organization.				The software (algorithms) used/ developed by the organization is subject to quality controls.
1	2	3	4	5

P19. Privacy				
No active control over ownership of the data used by the organization.				Active control to ensure that all data being used is in line with current policy.
1	2	3	4	5

P20. Controllability				
Data sharing within and outside the organization is not standardized through APIs.				APIs (internal and external) are used to enable data sharing.
1	2	3	4	5

P21. Responsibility: Fairness				
Data for AI models is not cleaned to eliminate biases in training data.				An effort is made to mitigate biases in AI model training data to the extent possible.
	2	3	4	5

P22. Responsibility: Accountability				
The organization does not take responsibility for unintended consequences of using AI models.				Managers are accountable for the unintended consequences of any AI-based decisions they make.
1	2	3	4	5

Exhibit 2 (continued)

P23. Responsibility: Transparency				
AI systems are treated as black boxes; no effort is made to understand the underlying logic.				AI systems are only deployed if the logic they use is understood.
1	2	3	4	5

P24. Responsibility: Ethics				
There is no analysis of whether AI systems are aligned with the organization's values.				Analyses are performed to ensure that AI systems are aligned with the organization's values.
1	2	3	4	5

P25. Governance				
The organization does not have a formal data governance system to treat data as an asset.				The organization has a formal data governance system to treat data as an asset.
1	2	3	4	5

P26. Chief data officer				
There is no specific management position associated with data.				The organization has a chief data officer on the executive committee.
1	2	3	4	5

P27. Data compliance				
There is no oversight to ensure that data is used in accordance with regulations.				There is a person responsible for ensuring that data is used in accordance with regulations.
1	2	3	4	5

P28. Data steward				
There are no specific positions responsible for alignment with data policy in functional areas.				Each area has a data steward who ensures alignment with data policy.
1	2	3	4	5

P29. Control vs. innovation				
Data is used primarily as a mechanism for controlling execution of the business model.				The organization also actively uses data to support innovation.
1	2	3	4	5

Exhibit 2 (continued)

P30. Have you produced a data technology plan to support your organization's development?
No, and we have no plans to do so.
Not yet, but we'll have one in 2022.
Yes, we have, and we keep it up-to-date.
Yes, we have, but we've given up on it.

P31. What is the purpose or expected benefit of the plan? Indicate what benefit is being pursued, especially if the organization has a data strategy.
Improve the quality of current information.
Improve the quality of corporate decision-making.
Speed up corporate decision-making.
Achieve greater efficiency in processes.
Democratize access to information throughout the company.
Improve knowledge of our customers.
Empower users to access and analyze information.
Identify sources of revenue enhancement for the company.

P32. Indicate the extent to which you agree or disagree with the following statements regarding data interactions (internal and external) in your organization.

	1 (Strongly disagree)	2	3	4	5 (Strongly agree)
Most of the tasks that used to be manual have now been automated using technology.					
The organization uses data, through advanced analytics and/or AI, for predictive/prescriptive purposes.					
The organization shares data with third parties to co-create goods and services.					
Data is used to personalize goods and services for all the organization's customers.					

Exhibit 2 (continued)

P33. Indicate the extent to which you agree or disagree with the following statements regarding digital transformation in your organization.					
	1 (Strongly disagree)	2	3	4	5 (Strongly agree)
Digital transformation will entail a change in our business model.					
Data is seen as a key asset for generating the company's value proposition (offering).					
There have been changes in the way our value proposition is constructed.					
There have been changes in the way our value proposition is marketed.					
There have been changes in our cost structure.					
The cost of serving a customer has been reduced.					
Sources of revenue have changed.					

P34. If you have launched a digital transformation strategy in recent years, please evaluate how successful it has been.				
The strategy has failed.	Below expectations.	Expectations have been met.	Initial expectations have been surpassed.	It's been a success.

P35. How long has it taken your company to achieve tangible results as a consequence of the implementation and execution of a data-centric digital transformation program.				
After more than 3 years, we haven't been able to achieve results.	Over 3 years.	2 to 3 years.	1 to 2 years.	Less than a year.

P36. Indicate the level of use/adoption of the following methodologies in your organization.					
	1 (Not used)	2	3	4	5 (Very high)
Design thinking, JTBD, customer journey mapping, etc. (to detect unmet customer needs).					
A/B testing, hackathons, rapid prototyping, etc. (to validate value proposition hypotheses).					

Exhibit 2 (continued)

P37. Indicate the level of use/adoption of the following forms of analysis in your organization.					
	1 (Not used)	2	3	4	5 (Very high)
Systematic analysis of customer behavior based on data collected in customer journeys (digital touchpoints).					
The organization fosters a culture of trial and error in which failing fast is part of the learning process.					
The organization simultaneously executes the traditional business model (earn) and a set of proof of concepts and pilots aimed at exploring future business models (learn).					

P38. Indicate the level of adoption of the following agile methodologies in your organization.					
	1 (Not used)	2	3	4	5 (Very high)
Agile methodology has been adopted in all areas of the organization's activity.					
The organization follows practices associated with the agile methodology by assigning specific roles (product owner, scrum master, etc.).					

P39. On a scale of 1 to 5, indicate whether your organization operates and is structured mainly in functional areas or in cross-functional multidisciplinary teams.				
1 (Mainly in functional areas)	2	3	4	5 (Mainly cross-functional and multidisciplinary)

P40. On a scale of 1 to 5, indicate whether your organization has OKRs (objectives and key results) and KPIs that measure only performance (business model execution) or also all exploration processes (innovation).				
Value 1: Nothing is measured. Value 2: OKRs or KPIs for SOME business processes but NOT for innovation. Value 3: OKRs or KPIs for innovation. Value 4: OKRs or KPIs for innovation and SOME business processes. Value 5: OKRs or KPIs for innovation and MANY business processes.				
1	2	3	4	5

Exhibit 2 (continued)

P41. Indicate the extent to which you agree or disagree with the following statements.					
	1 (Strongly disagree)	2	3	4	5 (Strongly agree)
My organization participates in an ecosystem with different stakeholders for the co-creation of its value proposition.					
My organization enters into partnership agreements that include an explicit clause on data ownership and sharing.					

P42. On a scale of 1 to 5, indicate the extent to which the following roles are present in your organization (or externally) and carry out projects in line with their functions.					
Value 1: No (neither internal nor external) Value 2: EXTERNAL on a PART-TIME basis Value 3: EXTERNAL on a FULL-TIME basis Value 4: INTERNAL on a PART-TIME basis Value 5: INTERNAL on a FULL-TIME basis					
Data scientist (in advanced analytics projects)					
Data engineer (for preparation/use of data in AI models)					
Business translator (i.e., experts with a business profile and knowledge of advanced analytics)					

P43. Indicate the extent to which you agree or disagree with the following statements.					
	1 (Strongly disagree)	2	3	4	5 (Strongly agree)
In recent years, new competitors in my sector and new non-traditional competitors (e.g., start-ups and/or companies from other sectors) have emerged.					
There has been a disruptive digital transformation in the sector.					
Interaction with customers has changed substantially.					
My sector is subject to tight regulation compared to other sectors.					
Significant regulatory changes are expected in the sector due to digital transformation.					
My organization's governance structure supports digital transformation processes.					
My organization has the capacity to allocate the resources needed to carry out a digital transformation.					

Glossary

Term	Explanation
A/B testing	Development and launch of two versions of the same element (good/service) and subsequent measurement of which one works best.
Accessibility	The organization's data is automatically accessible in real time.
Accountability	Managers are responsible for unintended consequences when decisions are made based on AI models.
Agile models	These models focus on timely and continuous delivery of value. The main feature is therefore quick, continuous deliveries. The product is divided into different parts with value in such a way that each one is completed and delivered in just a few weeks. This methodology encompasses several approaches used in software development in which requirements and solutions evolve through the collaborative effort of self-organized cross-functional teams with feedback from customers or end users. The values and principles of agile methodology underpin a wide range of approaches to software development, including the scrum framework and the kanban system.
API (controllability)	There are APIs (internal and external) that enable data sharing in line with access rights defined by the organization.
Automation	Most tasks that were previously manual have now been automated using digital technologies (digitization of processes, robotization, Industry 4.0, etc.).
Bimodal operation (earn & learn)	The organization systematically executes the traditional business model (earn) while at the same time experimenting with a set of proof-of-concepts and pilots to explore future business models (learn).
Business continuity	Data architecture is resilient to cyberattacks (isolated redundant systems, backups, etc.)
Business translator	The organization has experts on business profiling and advanced analytics whose role is to frame business problems and act as a link between the business and data scientists, defining complex data-related requirements that reflect the strategic priorities of customers.
Chief data officer (CDO)	The organization has a chief data officer on the executive committee whose role is to manage and ensure data quality and develop a data strategy, among other functions.
Chief information security officer (CISO)	The organization has a chief information security officer with visibility on the management board. The security function is independent of the operation of technological infrastructure.
Chief privacy officer (CPO)	The organization conducts active monitoring to ensure that all data used is in line with privacy policies in place.
Co-creation of value	The organization seeks to create value by reaching out to and engaging in a dialogue with customers, employees and suppliers to involve them in defining their interactions with the company.
Coordination	The organization shares data with third parties (e.g., via external APIs) to co-create goods and services (e.g., participation in commercial platforms).
Cross-functional multidisciplinary teams	The organization operates and is structured primarily in cross-functional multidisciplinary teams that include technical and business disciplines, among others.

Term	Explanation
Customer journey mapping	A methodology that involves mapping each stage that a person goes through from the moment a need arises until they make a purchase, which makes it possible to determine which stage generates the most value in terms of the customer's experience as they form a connection with the company.
Dashboard/reports	The organization has a business intelligence application to analyze its information.
Data compliance	The organization has a person responsible for ensuring that data is used in accordance with existing legislation/regulations.
Data lake	The organization has a data lake—that is, a repository for heterogeneous data (sensor data, social media data, transactional data, etc.) that is used for data experimentation (visualization, advanced analytics, machine learning models, etc.).
Data engineer	The organization has staff who focus on preparing data for use in AI models.
Data scientist	The organization carries out advanced analytics projects (e.g. AI-based predictive systems) with the participation of its own data scientists.
Data steward	Each functional area and/or business unit has a data steward who ensures that data in their area/function is aligned with the organization's data policy.
Deep dive	Quickly immersing a group or team in a problem-solving or brainstorming situation.
Design thinking	A methodology that involves first defining a problem and then implementing solutions, always with the needs of users/customers as the central focus of the development concept. Design thinking consists of five steps.
Detection of cyberattacks	The organization actively monitors cybersecurity threats; for example, by contracting the services of a SOC (security operations center) from which information systems are actively monitored.
Digitization of end-to-end processes	All organizational processes are digitized and supported by software packages (ERP, CRM, etc.).
Ecosystem with different stakeholders for co-creation of the VP	The organization participates in an ecosystem with different stakeholders for the co-creation of its value proposition and coordinates them through a business platform.
Ethics	The organization performs analyses to ensure that the AI systems used are aligned with its values.
ETL	The organization has a well-defined process that extracts data from multiple sources, transforms it (e.g., by standardizing values), and finally loads it into a single data warehouse. This process is known as ETL (extract, transform and load).
Fail Fast!	The organization values and fosters a culture of trial and error in which failing fast is a key part of the learning process.
Fairness	The organization takes steps to mitigate biases in training data for AI models to the extent possible.
Governance	The organization has a formal data governance system to treat data as an asset.

Term	Explanation
Hackathons	Organization of events and collective experiences to achieve a common goal through the use of technology (with the aim of solving specific business problems). Hackathons are usually linked to development and programming environments but are also used in other contexts.
Jobs to Be Done (JTBD)	A methodology that seeks to understand the factors that cause customers' interests to evolve rapidly. JTBD focuses on the functional, social and emotional dimensions that drive customer decision-making.
OKRs and KPIs focused on exploration (innovation)	OKRs: objectives and key results. KPIs: key performance indicators. These are indicators that measure not only performance in the execution of the business model but also exploration processes (innovation). Most OKRs are cross-cutting in function of the various goods and services that an organization produces/offers.
Open innovation	Participation and/or coordination of third parties (external to the company) in the process of investing in innovation (customers, suppliers, start-ups, etc.).
Partnership agreements	Agreements with partners contain specific clauses regarding the exchange, use and data exchanged via APIs.
Personalization	The organization uses data to better serve the needs of its customers, offering highly personalized goods and services for all of them.
Prediction	The organization uses data, through advanced analytics and/or AI (e.g., machine learning), for predictive (e.g., equipment maintenance) and/or prescriptive (e.g., decision support) purposes.
Product owner	Ensures that the scrum team is working smoothly from a business perspective. The product owner helps the user write user stories, prioritizes them, and places them in the product backlog.
Protection against cyberattacks	The organization allocates resources to actively protect against cyberattacks (e.g., training, firewalls, anti-virus systems, updates, etc.).
Quality	The organization has mechanisms in place to ensure that its data is correct, complete, not obsolete, and properly formatted.
Rapid prototyping	Development and presentation to users of prototypes in relatively rapid iterations to converge on a viable version of the product.
Response to cyberattacks	There is a defined protocol for responding to cyberattacks.
Scrum master	The person responsible for compliance with the scrum framework rules. Ensures that the rules are understood by the organization and that work is carried out in accordance with them. Removes obstacles to achievement of the sprint goal. Advises and provides the necessary training to the product owner and the team of developers.
Software reliability	The software (algorithms) used/developed by the organization is subject to quality controls.
SSOT (single source of truth)	There is a single data warehouse where the organization's information resides.
Systematic analysis of customers based on data	Data on customer interaction with the organization's goods and services is systematically collected and analyzed.
Traditional and waterfall project management	A single value delivery with a sufficiently complete initial definition that includes purpose, functionality, design and construction.
Usefulness	Stored data is useful and sufficient for the organization's activity.

About Penteo

Penteo is an independent IT analyst with local specialist knowledge whose mission is to support organizations in their technology and digitization strategy. Penteo offers a service specially designed for managers with influence or responsibility in IT-related business decisions, providing them with expert knowledge and support.

Over the course of more than 25 years, we have collaborated with over 200 top-level companies and institutions. Our knowledge and impartiality allow us to help organizations make the right decisions to maximize the value of technology for the business while minimizing risks, time and costs.

Penteo is part of a group with Aczeda and Tendit, which specialize in the implementation of leasing solutions in financial institutions and manufacturers/distributors. This enables us to offer our customers a comprehensive service that includes equipment leasing.

Toni Guerra Cortada, general manager at Penteo, and José Luis Pérez, the company's head of analysis, collaborated in this study.

Toni Guerra Cortada is the general manager of Penteo and has led the company since 2020. He has extensive experience in the technology sector, where he provides support to organizations, digital leaders and teams facing digital challenges. He also draws on his expert, independent knowledge to advise CIOs in IT decision-making. Toni also leads business development and strategic partnerships at Aczeda and Tendit, helping organizations leverage leasing with services as a way to acquire technology.

Jose Luis Perez is the director of analysis at Penteo. He has over 20 years' experience in business transformation through information technology and outsourcing and extensive experience throughout the full IT life cycle and in IT strategic planning. He also has experience in IT cost efficiency programs and IT organizational strategy.

About IESE Business School

IESE Business School is the graduate business school of the University of Navarra. The school was founded in 1958 as the Instituto de Estudios Superiores de la Empresa (IESE) in Barcelona, where it has its main campus. In 1963, IESE formed an alliance with Harvard Business School (HBS) and launched the first two-year MBA program in Europe. Today, it is one of the world's leading business schools, with campuses in Barcelona, Madrid, Munich, New York and São Paulo. The school is ranked among the top ten in the world in Executive Education, Master of Business Administration (MBA) and Executive MBA rankings.

This study was conducted by IESE's Information Systems Department with the participation of professors Javier Zamora, Josep Valor Sabatier and Joan Enric Ricart, and research assistant Nicolás Infante Middleton.

Javier Zamora is a professor of Management Practice and head of the Information Systems Department at IESE Business School. He holds a PhD in Electrical Engineering from Columbia University, an MSc in Telecommunications Engineering from the Universitat Politècnica de Catalunya, and an IESE General Management Program certificate. He is the academic director of IESE's executive programs in Digital Transformation. His current areas of interest focus on data-driven organizations and artificial intelligence and its impact on digital transformation.

Josep Valor Sabatier is a professor of Information Systems and holder of the Indra Chair of Digital Strategy. He holds a PhD in Operations Research from the Massachusetts Institute of Technology and a DSc in Medical Engineering from Harvard/MIT Division of Health Sciences and Technology. Josep teaches classes on information systems management, media management, and technology management and strategy—primarily to senior executives. In the field of in-company training, he has participated in projects for major organizations such as Abbott, the World Bank, BASF, BBVA, Ericsson, Henkel, 3i, ING, KPMG, Oracle, Santander, Sony, Technicolor, Telefónica and Vodafone.

Joan Enric Ricart, fellow of the SMS and EURAM, is a professor of Strategic Management and directs the Carl Schroeder Chair at IESE Business School. In 1993, he was appointed director of the Department of Strategic Management, a position that he held until July 2016. He was also director of the doctoral program (1995–2006) and associate dean for research (2001–06). He has served as founding president of the European Academy of Management (EURAM), president of the Strategic Management Society, vice president of the Ibero-American Management Academy, director of the Center for Globalization and Strategy, academic co-director of IESE Cities in Motion, and academic director of the UN Center of Excellence for PPP for Cities. He is also a member of the advisory board of the Future of Urban Development and Service Initiative of the World Economic Forum.

Nicolás Infante Middleton is a research assistant in the Information Systems Department of IESE Business School. He holds a master's degree in Leadership in Digital Transformation from the University of Barcelona and a degree in organizational psychology from Pontificia Universidad Católica de Chile. Currently, he is also a researcher at this Chilean university. He has worked in different sectors, mainly as a business partner or consultant in companies such as Accenture and CCU (Compañía Cervecerías Unidas), which belongs to Heineken. He has also collaborated with multinational companies such as BHP Billiton.

References

Deloitte. *El estado de la ciberseguridad en España. Post pandemia: un camino inexplorado.* Madrid: Deloitte, 2022.

Káganer, Evgeny, and Robert W. Gregory. “Dialectic of Digital Mindset in Digital Business Strategy Execution” (working paper). IESE Business School, 2017.

Penteo. *Market Trends – Integradores Ciberseguridad 2021*. Penteo, 2021

Penteo. *Strategic Report – IT Priorities 2022.* Penteo, 2022.

Zamora, J. “¿Es posible programar modelos de negocio?” *IESE Insight* 33 (2017): 23–30.

Zamora, J. “Managing AI Within a Digital Density Framework.” In *The Future of Management in an AI World: Redefining Purpose and Strategy in the Fourth Industrial Revolution*, edited by J. Canals and F. Heukamp, 205–35. London: Palgrave Macmillan (IESE Business Collection), 2020.

Zamora, J., and J. E. Ricart. “Radiografía de la transformación en España. Seis metacompetencias críticas.” *Harvard-Deusto Business Review* (2020): 20–37.

Zamora, J., J. E. Ricart, T. Guerra Cortada, and J. L. Pérez Tejada. *Estudio IESE-Penteo sobre transformación digital en España*. IESE Business School, 2020.

Zamora, J., and L. Thomas. “Organizing for Connected Data” (working paper). IESE Business School, 2022.