DYNAMIC BIG DATA CAPABILITIES: LONGITUDINAL CASE STUDY

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Introduction

Artificial intelligence (AI) and big data are contemporary trends that are used in a growing number of economic and social processes (Obschonka, Audretsch, 2020). The research on AI focuses on economic (Brynjolfsson et al., 2011) managerial (Acemoglu, Restrepo, 2019), social (Makridakis, 2017; Mayer-Schonberger, Cukier, 2013), innovation-related (Sambamurthy et al., 2003; Saunders, Brynjolfsson, 2016) and venture creation processes (von Briel et al., 2018). Still, many companies are struggling with the implementation of AI. These projects concern many analytical techniques, many technologies, and cover many areas of business, which makes it difficult to achieve tangible benefits (Belvisi et al., 2016; Lemon, Verhoef, 2016).

The aim of this article is to develop a big data capabilities framework that contributes to the success of implementation of AI initiatives in organisations. The concept of big data capabilities is based on the dynamic capabilities framework (Eisenhardt, Martin, 2000).

Dynamic big data capabilities

Dynamic capabilities refer to the group of organisational skills, behaviour, processes, and routines (De Mendonca, De Andrade, 2018). They determine organisational processes that integrate, create, and reconfigure internal and external resources aimed at adapting to quickly changing conditions of the business environment (Teece et al., 2016). The framework is a well-established theoretical concept that has many empirical implementations (Bratnicka-Myśliwiec et al., 2019). It ranges from the strategic management area to the domains of human resources management, marketing, innovation, entrepreneurship, and information and knowledge management. There are several dimensions of dynamic capabilities: (1) the use of systems in an organisation to filter information from the environment, (2) the creation of structures and systems to support decision-making, and (3) the continuous adaptation to changes (Eisenhardt, Martin, 2000; Teece, 2007; Teece et al., 2016).

Dynamic capabilities related to data and information management have been categorised as business intelligence (BI) capabilities. BI capabilities were defined by Hostmann et al. (2007). BI capabilities can be divided into technological and organisational capabilities (Gupta et al., 2020). Among the technological abilities, there are: (1) data sources, (2) data types, (3) the level of data integration, (4) tools for users to access data and (5) data reliability. Organisational capabilities include (6) level of risk while decision making, (7) IT infrastructure flexibility and (8) the level of intuition when conducting data analysis. The concept of BI capabilities has been theoretically established and has been a subject to a number of empirical verifications (Akter et al., 2016; Mohammadi, Hajiheydari, 2012; Wixom et al., 2014).

Sun et al. (2020) proposes a model incorporating factors in technological, organisational, and environmental contexts that may influence an organisation's ability to adopt big data strategies. These capabilities are often linked with a company performance (Rialti et al., 2019), innovation, agility, and integration with business processes (Fosso Wamba et al., 2017). However, the current emergence of AI and machine learning field, requires a more specialised approach that takes into account the specificity of AI systems. AI systems include such elements as data structures (AI systems are based on heterogenic data repositories), data analysis techniques and management of business definitions and the maintenance of machine learning models (Hercheui, Ranjith, 2020). These issues are not included in dynamic capabilities (which are quite general in nature), nor in specialised BI or data management capabilities (Tiguint, Hossari, 2020). Machine learning capabilities can be identified as digital artefacts (platforms and infrastructure) (Nambisan, 2017), data processing tasks (von Krogh, 2018) or analytical processes (Ng, 2018).

The proposed big data capability framework, thus includes the following elements:

1. Infrastructure flexibility – capability covers the data life cycle. It determines how quickly the data infrastructure is able to adapt to specific business needs (e.g.: new data areas).
2. System integration – covers the level of data integration between IT systems. It also includes feature engineering and feature extraction aspects of AI modelling.
3. User access – includes tools, technologies, and processes that the company uses in order to access and analyse data.
4. Data reliability – covers specific aspects of data quality. Data quality has many dimensions, all of which are important for building AI models; however, some of them can be managed in different ways. Thus, the term data reliability (not quality) is used.

The conceptual model assumes that big data capabilities contribute to increasing data awareness in organisations and support AI driven goals. Each capability has assigned metrics that allowed the measurement during the study (Table 1).

Research method

To achieve the objective of the study, a qualitative, interpretive research strategy was adopted, with a single longitudinal case study. The approach is particularly effective when the boundaries of the phenomenon are blurry or not fully defined. Overall research process was carried out based on the methodology of Eisenhardt (1989):

1. Preparation of the study.
2. Choice of cases.
3. Development of research tools.
4. Conducting the survey.
5. Analysis of the collected material.
6. Verification of the adopted dentitions/refine hypotheses.
7. Comparison with other studies.
8. Summary and theoretical contribution.

The company selected for the case study is a retail company, that sells household appliances. In order to comply with confidentiality standards, the pseudonym Sigma is used as a name of the company. The unit of analysis are projects that use AI algorithms. Case selection was neither statistical nor purely personal; the organisation was chosen by using the following criteria:

- use of IT systems – to be able to benefit from AI, the organisation should provide a certain level of IT competency;
- scale of market activities – for the benefits of AI to be measurable, it is necessary to have mature

Table 1. Big data capabilities — summary

Capability	Impact on AI driven goals	Capability metrics
Infrastructure flexibility	• Reduce time to market in data-driven projects • Faster data delivery for business users	• Time to market in delivering data intensive projects
System integration	• The ease of data integration • The use of technology in data integration	• Type of data integration used: physical, virtual, no integration
User access	• Provide techniques for advanced data analysis • Deliver technologies used to report and analyse data. Including: business intelligence, data science platforms, reporting, etc.	• The use of reporting platforms, BI tools, and self-service data analysis
Data reliability	• Deliver data quality measures • Deliver data governance practices	• Data quality measures, including a data adequacy and data latency

Source: own study

processes that can be supported by advanced analytics;
- complexity of the product (offering) – the complexity of the offering determines the level of complexity of marketing activities and demand management, which makes the analytical systems find business case.

Sigma is a company operating in the retail trade of electronic goods and household appliances. The company has over 200 stationary stores that are mainly located in shopping centres and shopping malls. The company also sells its products on the Internet on dedicated websites. Sigma communicates with its customers by means of advertising (e-mail, text message, TV, radio); telephone customer service; websites and in stores. The company has several million registered customers.

Sigma belongs to an industry that is characterised by a large number of customers, large number of products, extensive sales network and aggressive competition. These factors make the phenomenon of big data capabilities desirable in the company. Also, it is a large organisation, in terms of the number of employees, the volume of turnover and the number of customers.

Research data has been collected from several sources to provide high reliability of the study. The projects were studied retrospectively through intensive, nondirected interviews with top executives, IT management, members of middle management and IT staff members. Formal (semi-structured) interviews were recorded, and informal interviews were documented with extensive case notes. The author decided to focus on the areas of sales (including e-commerce) and marketing. However, due to the subject of the study, interviews were also conducted with IT staff who were responsible for analytical systems and data repositories. The collected material includes five structured interviews and 4 in-depth (unstructured) interviews. The duration of a single interview ranged from 30 to 50 minutes. The interview process was based on a snowball method (Bryman, Bell, 2007): contacts for further interviews were collected on the basis of discussions with and the indications of previous respondents.

The subject of the study is to verify the state of big data capabilities in 2017 and 2021 and the approach to implementing AI-based projects. The dynamics of changes in the capabilities over the years has been described. For this purpose, two data-driven initiatives were analysed:

1. Implementation of the direct marketing support system in 2017 (project A). The system serves several functions including customer segmentation based on customer behaviour (based on machine learning algorithms); predictive models linking customers to their most likely products and deduplicated, cleansed customer databases.
2. Implementation of the demand forecasting system in 2021 (project B). The system involves the use of complex machine learning algorithms to determine the planned number of products sold by region, store, and time frame.

Both projects were analysed in the defined big data capabilities framework. The collected material was reduced to a consistent template compliant with the framework. Template analysis provides a framework for the collection of data originating from various sources in a predefined structure. With the use of templates, the researcher can organise the data into codes and dimensions according to the assumed operationalization (King et al., 2004).

Research results

The analysis was divided into sections in accordance with the adopted classification of big data capabilities. Each capability has its status determined in 2017 (project A) and 2021 (project B).

Brief summary of findings are presented in Table 2, while detailed results are described in next subchapters.

Infrastructure flexibility

Project A (2017)

The main purpose of the implemented system (marketing analysis system) was to support activities related to direct marketing. The AI algorithms were used to identify customer segments (groups of customers that differ significantly from each other while customers in a given group have similar characteristics). The second role of the system was to select products that are likely to be purchased by individual customers. From a business perspective, Sigma has defined the project goals as:
- Increasing revenues and profits related to direct marketing through better matching of products and the method of communication with customers.
- Dividing customers into groups (segments) based on customer activity (frequency of purchases, sensitivity to marketing, etc.).
- Identifying customers with a high probability of purchasing the product.

The main challenge was the large number of data sources (IT systems) with a variety of data stored in these systems. Additionally, Sigma struggled with the difficulties of manual data analysis as well as the identification of target groups for marketing campaigns.

The approach to projects was strongly rooted in economic evaluation. The management board expressed its willingness to implement the project, but only if it could produce measurable business results. It was difficult to prove measurable indicators because the current direct marketing process based on customer segmentation using the expert method (without the use of advanced data analysis). In such an environment, it turned out to be impossible to determine measurable benefits a priori. To address this limitation, a decision was made to implement a limited version of the system, but in a very short time. The scope of the pilot project covered:
- the integration of customer data from multiple source systems,
- feature (variable) extraction and engineering,

- customer segmentation,
- predictive models.

All project tasks were carried out with agile approach and with little involvement of the IT department. The aim of the pilot project was rapid implementation of predictive models and implementation of a pilot marketing campaign based on the models built. Sigma presented high flexibility of the IT infrastructure and an agile approach to innovative projects and techniques of data analysis. Much emphasis was placed on the quick customisation of reports and data repositories to accommodate new needs.

Project B (2021)

The flexibility of the information infrastructure in 2021 is comparable to that measured in 2017. The agile approach is still present and developed. The management board of Sigma is aware that this approach contributes to the improvement of competitive advantage.

However, the scale of the delivered projects increased significantly, as did their number and complexity. The agile approach to analytics meant that the emphasis on time-to-market had an impact on architecture and data management processes. Sigma has many analytical data repositories dedicated to individual business stakeholders. This makes data management difficult, especially in terms of data redundancy, knowledge of the data stored in repositories, data quality management or business definitions. In general, Sigma lacks data governance processes.

Data integration

Project A (2017)

One of the main modules of the implemented marketing system was the customer profile database. As indicated by one of the respondents: ”We are now collecting customer data. We deduplicate them and integrate them with various systems. But this model is not appropriate. We load data once a day, and this is not enough to implement trigger-response campaigns ”. The trigger-response marketing campaigns indicated by the respondent include actions based on data from a few seconds. For example, on a website, Sigma can present an offer that best suits the customer who has just visited the website. The drive to integrate customer data is also visible during the acquisition of knowledge about customer behaviour: ”... we try [...] to understand the customer, the one in the brick-and-mortar store, and [we] link this data with data from the online store. We know that customers move between sales channels, but we don’t have it as accurately measured as we would like. We do not know whether John Smith, who comes out with the TV from a stationary store, has visited our website before or not. There are some initiatives in the company in this direction, which will allow us to allocate and optimize marketing resources better”.

The overall focus of data integration in Sigma is on an economic basis: a more efficient allocation of financial resources to marketing campaigns. More knowledge about

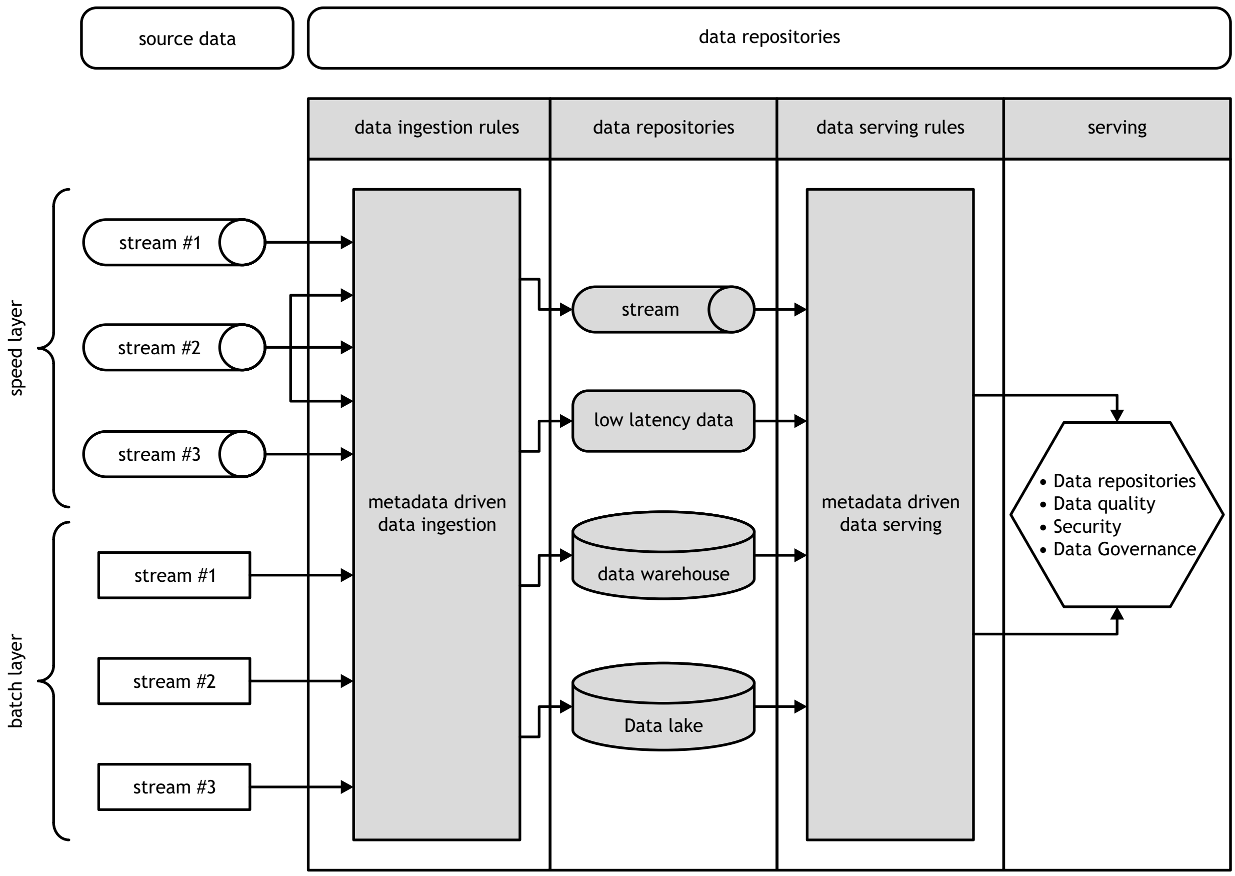

Figure 1. Metadata driven architecture
Source: own study

the customer, combined with organisational processes, which allows personalisation of the offer, leads to a better match with the content of advertisements.

Project B (2021)

The implementation of the marketing information system provided new classes of data. Sigma has acquired the ability to analyse data and operate in real time. The challenges of managing data between channels were addressed before the implementation of a consistent customer base.

Data management issues and challenges continue to emerge: the plethora of repositories and high analytical needs mean that data integration processes are faced with two options:

1. Fast data integration, but in the current architecture; deepening technological debt.
2. Change in data architecture and the implementation of data management methods. This extends the implementation of data integration projects but significantly improves quality and data management.

The IT director clearly indicates that he is closer to the second approach, which aims to increase the analytical maturity of IT. The considered direction of data integration is virtual, external integration. From an architectural perspective, it appears to be a compromise between data silos and full integration at the physical level. Sigma management identifies this stage as temporary before the organisation moves to a full data-driven architecture.

The IT department decided to develop the demand forecasting system in a new hybrid, lambda architecture (Figure 1). The architecture involves the production of data both in batch and in real time (speed layer). An important aspect of Sigma is the use of virtual integration based on metadata.

User access

Project A (2017)

Access to data for business users had two dimensions: the scope of data and the analytical competencies of individual analysts. For example, a sales manager points that raw data are of little value, and only the knowledge flowing from the data provides a measurable advantage: ”First, we are not interested in the data about customers' lifestyle, hobbies, whether he is an athlete or not. We do not pay so much attention to this type of information. Rather, it is more valuable to know about what the customer potentially wants to buy and when [...]. On the other hand, a barrier [...] or a challenge that we just have is the lack of appropriate technologies, and the inability to create many customer segments”. Another respondent pointed to the issues of competencies and analytical support: ”Today, in order to generate a customer segment, I need an analyst who knows SQL and R. This analyst will prepare data and another person prepares an appropriate email template. And that should just be an on-going process, and the tools that we have in the company today are not suitable for commissioning such a series of personalised shipments on many segments”.

Although knowledge about customers is Sigma's key value and constitutes its competitive advantage, the scale of the company's operations significantly hinders the effective manual adjustment of the offer to the customer. This was indicated by one of the managers responsible for sales and marketing: ”... on TV we can buy an advertisement that will be seen by 3–4 million people, of which I think that 10 percent of these customers, that is, about 300,000 are interested in a product in our category. Well, for us, a big optimisation would be that we could only reach these 300,000, and not up to 3 million, because the cost of the TV ad is significant. If we are able to personalise this advertisement, we will be significantly ahead as a company, and we will save on this type of advertisement ”.

Sigma had the right data in the data warehouse, however, the level of IT tools offered was not entirely consistent with the competencies of business users. Relatively simple analyses and reports required the involvement of the IT staff, which significantly extended the reporting time.

Project B (2021)

This dimension of big data capabilities has undergone particular changes and developments. The analytical competencies built during the implementation of the marketing system have been expanded. The analytical team has been expanded to include several data science specialists. The increase in competencies, combined with the increase in demand for AI-based solutions, forces IT to use specific IT solutions. In particular, the use of innovative data analysis methods, such as deep learning or reinforced learning, requires investment in IT infrastructure.

The direction of data access development is architecture based on many technologies. This approach to analytics provides users with access to many categories of data: raw data, processed data and external data that are not available in the repositories.

Data reliability

Project A (2017)

Data reliability was examined in Sigma in two areas. The first issue covers marketing consents. The consent defines the possibilities of contacts with the customer as well as the customer data management policy. The client can express a different level of consent in each channel. The high concern about these issues stems from the fact that Sigma contacts its customers through many channels (shops, websites, phones, mobile applications, etc.). In most channels, the data are declared by customers, which makes it difficult to establish data consistency and unambiguity. For example, a client can register on the website as John Smith, providing an e-mail *john.smith@gmail.com*, and at the same time, he can register by phone as John Smith, with the e-mail address *jsmith@hotmail.com*. For each form of contact (phone, e-mail, etc.) the customer agrees (or not) to

Table 3. Data management gaps identified in Sigma in 2021

Management level	Business department	IT department
Top management	Inconsistent business definitions. No formal data ownership.	Data redundancy, hard to measure data quality.
Middle management	Lack of knowledge about what data are available in the data warehouse and reports.	No documentation about data processing and data model. It takes a long time to introduce new people to the project.
Operations management	There are no tools to analyse data that are not available on reports.	The increasing number of tables and data marts in the data warehouse. The data are delivered quickly, but the system is becoming increasingly difficult to maintain.

Source: own study

data processing, marketing communication, etc. That is why the quality of the collected data and ensuring their integration are so important.

The second issue concerns the use of data in the marketing process. In this area, the quality tolerance for high flexibility and speed data was higher. During the pilot phase of the marketing system project, the business users agreed to a slightly lower quality and completeness of data, to speed up the implementation of the project.

Project B (2021)

There is no common approach to data quality monitoring, either actively or passively. Due to legal conditions, the quality of personal data and marketing consent are maintained at a high level. Other domains are exposed to redundancy and incomplete data. Business departments clearly identify their needs in the domain of data quality:

1. The need to know that the data are up-to-date.
2. The need to define the source of the data and their meaning – this perspective is common among recipients of predefined reports.
3. What data are stored in repositories; how complete are these data and what rules were used to load the data into a specific table.
4. The need to build a feature store that manages features (variables) for machine learning models.

Sigma has implemented a number of data-based IT tools. Reporting is provided periodically based on the SQL database and static reports. Reports are generated on the basis of dedicated date marts. Each business area has a correlating area in the data warehouse. The environment is characterised by high flexibility and very good time-to-market. However, issues related to business definitions and data consistency are becoming a challenge. For example, different departments define the concept of sales differently. The sales division defines sales as ordered goods, finance as invoiced, accounting invoiced but relevant returns and corrections. However, sales are understood differently by the department responsible for the instalment sale. These issues indicate the need to implement data governance practices.

Conclusions

The state of big data capabilities in Sigma has changed over time as follows:

- Infrastructure flexibility has not changed significantly. This capability turns out to be a key success factor for data-driven projects.
- Data integration has increased over time. Initially, data integration was performed ad-hoc and physical data integration was only available for selected data classes. The increase in maturity was achieved through the development of data warehouse and the application of technology to virtual integration.
- User access has increased significantly. New business needs and new data sources forced the use of ad-hoc data analysis tools, programming languages (e.g. Python) and implementation of advanced analytics and machine learning. However, this area generated technological and organisational debt in the area of data governance.
- Data reliability – has not changed significantly. The key data areas are of high quality. However, issues emerged, related to data consistency, business definitions and data glossary management.

Due to the qualitative nature of the study, it is impossible to generalise the results to all organisations, but it is possible to formulate guidelines for other organisations that are at a similar level of maturity. Practical recommendations that can be drawn from the study include:

- The flexibility of data infrastructure has proven to be a key capability that has allowed Sigma to achieve higher analytical maturity over five years.
- The integration of IT systems is not a crucial limitation. When AI systems quickly adapt to business conditions, users are using them without the need to know how the systems are integrated. However, when changes in the data infrastructure are implemented slowly, users turn to different data sources to gather the needed information. In this scenario, users need to know how the systems are interconnected.
- When implementing the subsequent components of data architecture, data governance practices

should be implemented in parallel. Despite the fact that gaps in data governance are identified by the IT department, business departments are influenced indirectly by the technological debt in this area. (Table 3).

In weighing the results of this study, several limitations should be considered. First, the applied research method (case study) does not allow for generalisation of the research results to other organisations (Flyvbjerg, 2011). However, this method allowed for deep tracing of the processes related to the adoption of big data capabilities in the organisation. Second, the differentiation of areas in the organisation was relatively small. The author focused on the processes related to finance, sales, and marketing (and IT), which does not reflect the overall use of information within the organisation. In particular, the areas of logistics and distribution seem to the author to be an especially interesting cases of the use of artificial intelligence to shape competitive advantage.

The directions of further research result from the limitations of this study. Performing a quantitative study would be interesting and would allow the development of general practices for data science managers in organisations. Additionally, a comparative case study for several organisations in the industry could shed light on the formulation of AI initiatives.

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Zdolności dynamiczne big data: Studium przypadku

Streszczenie

Systemy oparte na sztucznej inteligencji wpływają na branżę i umożliwiają wdrażanie nowych modeli biznesowych. Celem artykułu jest opracowanie modelu dynamicznych zdolności big data, które przyczyniają się do efektywnego wykorzystania technik sztucznej inteligencji w procesach biznesowych. W artykule przedstawiono studium przypadku w dużej firmie z branży handlu detalicznego oraz realizację dwóch projektów opartych na algorytmach sztucznej inteligencji: systemu wspierającego marketing bezpośredni oraz systemu prognozowania popytu. Wyniki badania wskazują, że zidentyfikowane zdolności zwiększają szanse powodzenia projektów opartych na sztucznej inteligencji. Istotnym wnioskiem, który płynie z badania, jest to, że zdolność infrastruktury danych organizacji do szybkiego reagowania na nowe potrzeby biznesowe okazała się podstawą powodzenia projektów opartych na AI.

Słowa kluczowe

zdolności big data, AI, big data, studium przypadku, zdolności dynamiczne