

Data Analysis in Polish Enterprises - The Use of Data Analysis in Making Strategic Decisions

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Abstract

Purpose. This article, based on both a literature review and empirical research, was prepared to assess the degree to which data analysis is used in strategic decision-making in Polish enterprises. Based on our own research, conducted in companies from various sectors and operating on various scales (from sole proprietorships to entities employing several hundred employees), it has also been attempted to assess how managers use data in decision-making processes and what barriers executives face.

Design/methodology/approach. The analyses and discussions presented in this article are grounded in two primary sources: a review of the relevant scientific literature and original empirical research. The empirical study was conducted via an online survey involving a total of 99 respondents, all of whom were entrepreneurs or managers. The research aimed to examine how analytical insight is utilized in strategic decision-making within Polish enterprises.

Practical implications/Originality/value. Empirical research indicates that the frequency and scope of data analysis, as well as the barriers encountered in conducting it, largely depend on company size. However, this does not mean that smaller business entities always conduct analyses less frequently or to a limited extent; large entities also face barriers to effective analytical insights. These studies demonstrate that data analysis in business is a multi-step process, complex even in organizations with adequate resources.

Findings. The study confirms that managerial competencies are the strongest predictor of data-driven decision-making, outperforming company size and AI adoption. Data quality perception was the only significant barrier, while firm size and market experience positively correlate with analytical intensity.

Keywords data, analysis, management, market competitiveness, data-driven organization

INTRODUCTION

Modern businesses operate in an environment of fierce competition, growing market dynamics, and significant environmental uncertainty, further exacerbated by globalization and the rapid development of digital technologies (Batko, Ślęzak, 2022). In this context, data analysis becomes an essential tool supporting managers in making sound, long-term business decisions. Data from, for example, accounting systems, Customer Relationship Management (CRM) databases, e-commerce platforms, and social media allows for the continuous monitoring of key performance indicators, customer behavior, and market trends in real time. By using analytical tools, managers can predict demand, optimize logistics processes, better allocate financial resources, and minimize investment risk. This means that strategic decisions are no longer based solely on subjective experience or intuition, but are instead based on objective and measurable premises, which in practice increases their effectiveness and reduces the possibility of costly errors (Weinert, 2019; Wiśniewski, 2013). This is linked to the concept of corporate marketing orientation, which requires managers to thoroughly understand customer needs, anticipate changes in their preferences, and quickly respond to competitive behavior, which can determine the success or failure of sales efforts (Łobaziewicz, 2019; Bieńkowska et al., 2017; Schlögl, 2007).

Data analytics tools enable advanced customer segmentation, offer personalization, real-time analysis of advertising campaign effectiveness, and the identification of the most profitable communication channels. This allows managers not only to spend marketing budgets more efficiently but also to increase customer satisfaction and loyalty. Data therefore allows for building a competitive advantage based on knowledge, precision, and speed, rather than haphazard decisions made based on intuition.

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The concept of a data-driven organization indicates that in a modern economy, business entities should treat data as a key strategic resource, comparable to human, financial, or technological capital – understood here as the totality of an organization's technical infrastructure, digital tools, and analytical systems that enable the collection, processing, and utilization of data in management processes (Szopa, Cyplik, 2020). This means that data cannot be viewed solely as reports for reporting purposes, but must become the foundation of daily management and a source of knowledge used at every level of the organization. Companies that consistently implement a data-driven decision-making culture achieve better financial results, adapt more quickly to changes in their environment, and implement product and process innovations more effectively (Batko, Ślęzak, 2022). From this perspective, data analysis is not merely a technical tool supporting managers, but the foundation of the entire management process within a company, enabling rational, flexible, and competitive action, which can be crucial for long-term market success (Łobaziewicz, 2019; Baran, 2021; Schlögl, 2007).

The topic of data analysis in enterprises is very popular in scientific literature, as confirmed by search results in the OpenAlex database. The general phrase "Data analysis in enterprises" yielded 72,310 results (according to a search on 2025-11-14). This number alone indicates that analytical insights are a cornerstone of contemporary research on management, economics, and digital technologies, and are closely linked to trends in the development of the information society. A clear and systematic upward trend is visible – the number of publications is growing year by year, particularly rapidly in the last decade, which correlates with the growing role of digitization and big data in business. The most frequently recurring research topics include the development of small and medium-sized enterprises in the context of digital marketing (3,098 papers), entrepreneurship research (1,909 papers), and big data and business intelligence analyses (1,627 papers). It's also worth noting that the largest number of publications comes from China (12,350), the United States (5,010), and Indonesia (4,907), demonstrating the global nature of interest in this topic and its importance in various economic systems*.

This paper aims to investigate the following hypothesis:

- H1: The frequency of using data in making managerial decisions is correlated with the size of the company (measured by the number of employees) and its experience in the market.
- H2: The extent to which particular data sources are used to make managerial decisions varies depending on the size of the enterprise and the length of time the entity has been operating in the market.
- H3: Management competencies are a stronger predictor of data-driven decision-making than company size or technological advancement alone.
- H4: Subjectively perceived barriers and beliefs about the quality of available data influence, to varying degrees, whether companies make data-driven management decisions.
- H5: Companies that already regularly analyze data in multiple areas (question 5) are more likely to increase their financial outlays on analytics in the future.

To empirically verify the formulated hypotheses, the following specific research objectives were established:

- Examining the relationship between the size of the enterprise measured by the number of employees and market experience and the frequency of data use in decision-making processes.
- Determining the impact of a company's size and market experience on the structure and diversity of data sources used.
- Comparison of the predictive power of managerial competencies against structural (company size) and technological factors in the context of implementing data-driven decisions.
- Analysis of the impact of perceived barriers and subjective assessment of data quality on the readiness of enterprises to use a data-driven approach.
- Identifying the relationship between the company's current level of analytical advancement and plans to increase financial outlays on analytical tools in the future.

While the relationships between firm size, market experience, and data-driven practices (H1, H2) are well-documented in developed Western or Asian economies, blindly applying these assumptions to Central and Eastern Europe risks overlooking critical context. The Polish enterprise landscape has followed a unique historical and structural path. Unlike in long-established economies, where business growth naturally leads to formalized and data-driven management, the growth of Polish SMEs remains deeply rooted in owner-centric, highly intuitive styles. In this environment, a company's size or age does not automatically guarantee advanced data practices; instead, these factors often hide significant internal differences in digital readiness and managerial culture. Therefore, re-examining these seemingly 'obvious' relationships in a major post-transformation economy is much more than a repetitive replication. It serves as a necessary reality check for global strategic management theories, testing whether international standards actually hold true when faced with a market characterized by uneven digitization, historical legacy, and more personal, intuition-based management styles.

* Search results in the Open Alex database can be found at: https://openalex.org/works?page=1&filter=title_and_abstract.search:Data+analysis+in+enterprises&group_by=publication_year,open_access.is_oa,primary_topic.id,authorships.countries,keywords.id (access date: 2025-11-14)

The theoretical foundation of this study draws on two complementary frameworks. First, the Resource-Based View (RBV) posits that sustained competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). In this context, data analytics capability constitutes a strategic resource, as its value is contingent not merely on technological infrastructure but on the human capital required to interpret and act upon analytical outputs. This perspective directly motivates the inclusion of managerial competencies as a key explanatory variable. Second, analytical maturity models – such as the Data Management Maturity Model (DMMM) or Gartner's Analytic Ascendancy Model – suggest that organizations progress through distinct developmental stages, from descriptive to predictive and prescriptive analytics (Cosic et al., 2015). Firm size and market experience, included as structural controls, serve as proxies for an organization's position along this maturity continuum.

THEORETICAL SCOPE

In the terms of the globalized, digitalized market economy of the 21st century, information has become one of the key resources of organizations, often surpassing traditional tangible assets. Competitive advantage is no longer determined solely by infrastructure, but rather by the ability to transform data into useful management knowledge. Access to reliable and structured data enables an efficient response to environmental volatility, strengthening market position and fostering growth in enterprise value (Klimecka-Tatar & Ingaldi, 2022).

What is crucial is not merely collecting information, but using it consciously in the decision-making process. Accumulating data without analysis and practical application creates no added value from the perspective of effective management. Sustainable advantage requires systematic quantitative analyses closely linked to the achievement of strategic goals (Cao & Duan, 2017). In a data-driven model, managerial decisions are directly justified by empirical data, shifting away from intuitive and subjective assessments that are fraught with cognitive bias (Surma-Syta & Majek, 2021; Noga, 2018). This transformation is organizational and cultural, constituting a prerequisite for functioning in a dynamic environment (Zimon, 2018).

Data should be treated as a strategic resource that determines competitive advantage, not merely a byproduct of operational activities. Data-driven management means making decisions based on verified analyses, which increases the rationality of actions. This enables more accurate trend forecasting, improved planning, and the optimization of financial and logistical processes. Systematic information processing enables the development of predictive models that support real-time management, increasing the organization's flexibility and ability to mitigate risk. Importantly, this approach is applicable both in large corporations and in the SME sector, supporting the development of a decision-making culture based on facts and verifiability, which strengthens the long-term stability of the enterprise (Surma-Syta & Majek, 2021; Cao & Duan, 2017; Noga, 2018).

From a strategic management perspective, data analysis is equally valuable. It allows for defining company development directions, assessing potential risks, and predicting market changes. It allows managers to base their decisions on facts, not just intuition. Long-term analyses based on historical data and forecasts facilitate investment planning and the selection of new markets. Data, therefore, becomes the foundation for creating a competitive advantage, enabling a better understanding of customer needs and more quickly adapting offerings to their expectations (Liu & Bell, 2019; Zimon, 2018).

Data analytics in enterprises is widely studied in the literature, and authors approach it from various perspectives – from the application of strategic tools in specific industries, through the development of big data technologies, to the implementation of modern decision support systems (Cao & Duan, 2017; Mehdi, 2018; Mandal, 2019).

Batko and Słężak (2022) focus on the healthcare sector, analyzing the potential use of big data, predictive analytics, and statistical analytics. This study demonstrates that data analysis supports decision-making processes related to clinical, administrative, and operational areas.

Noga (2018) examines innovative enterprises in various sectors, analyzing statistical methods such as the Pearson correlation coefficient and the Yule coefficient. He also highlights the importance of data analysis in strategy implementation and adaptation, focusing on industrial and service enterprises in Silesia, where they analyze the use of Business Intelligence (BI) systems and competitive analysis tools. The results show that business analytics supports forecasting, marketing, and strategic controlling.

Bieńkowska et al. (2017) analyze the industrial sector in Poland, focusing on the use of IT tools and Business Intelligence systems. Their study emphasizes the strategic controlling aspects of management.

Łobaziewicz (2019) addresses intelligent decision support systems in the IT, trade, and manufacturing sectors, highlighting the importance of ERP systems, Customer Relationship Management, and artificial intelligence in building competitive advantage.

Baran (2021) examines companies in Central Europe, highlighting the use of data integration in the context of environmental protection and corporate responsibility processes.

In the Polish context, it's certainly worth noting the 2025 report prepared by Algolytics, titled "Assessment of the Maturity of Polish Companies in the Area of Data Analysis and AI." This document largely covers the topic, providing a detailed source of knowledge on the level of implementation of analytical tools and artificial intelligence in Polish companies. The report's authors analyze, among other things, what barriers, according to respondents, stand in the way of effective data analysis, allowing for a better understanding of why some organizations, despite available technologies, fail to achieve the expected results.

On the other hand, the report, despite its high level of detail, does not distinguish between the specific data subject to analysis. While it generally refers to financial data, it does not delve into whether business entities analyze data on profitability, debt levels, or liquidity ratios, for example. This limitation makes the report a valuable source of knowledge on the state of implementation and organizational barriers, but it does not answer which data areas are crucial in the decision-making practices of Polish companies.

Enterprise data analysis is becoming a key tool supporting management in the modern economy. Its role goes beyond simple numerical summaries, as it enables the identification of patterns, relationships, and trends that are not visible with traditional situational assessment methods (Cheah et Wang, 2017; Gawin et Marcinkowski, 2017). In the area of operational management, this allows for ongoing process monitoring, the detection of inefficiencies, and improved resource management (Pech & Vrchota, 2020; Surma-Syta & Majek, 2021). Material flow analysis, for example, reduces downtime and warehousing costs (Lindgardt et al., 2009). Operational data provides information enabling rapid response to changing conditions, fostering operational flexibility and improving customer service quality (Mandal, 2019; Zimon, 2018).

A systematic search of the Scopus database using the query TITLE-ABS-KEY ("data-driven" AND "Poland" AND ("SME" OR "small and medium" OR "enterprises")) returned only 7 results, none of which directly addressed the relationship between firm size, managerial competencies, and data-driven decision-making practices in Polish enterprises. This strikingly low number confirms that the Polish context remains empirically underexplored in international scientific literature, despite Poland being one of the largest economies in Central and Eastern Europe and home to over one million registered business entities.

By contrast, a broader query – TITLE-ABS-KEY ("data-driven" AND ("SME" OR "small and medium" OR "enterprises")), limited to Business and Economics subject areas – yielded 828 unique publications, demonstrating that the topic is extensively studied in international contexts. The most cited works illustrate the thematic breadth of this field. Wang et al. (2016) examined big data analytics in logistics and supply chain management, demonstrating its potential to improve operational efficiency across industries. Choi et al. (2018) analyzed big data applications in operations management, highlighting the transformative role of analytics in production planning and resource allocation. Wu et al. (2023) investigated the role of competitive intelligence and dynamic capabilities in SME performance, showing that data utilization is a key driver of organizational adaptability. Shamim et al. (2020) focused on big data analytics capability and decision-making performance in emerging market firms, emphasizing the moderating role of governance mechanisms – a perspective particularly relevant to the Central European context.

Notably, the overwhelming majority of these 828 studies originate from Asian, North American, or Western European contexts. Research specifically addressing the conditions of post-transformation economies – characterized by a high share of micro and small enterprises, uneven digitization levels, and distinct managerial culture – remains scarce. This geographic and structural blind spot in the literature represents a clear research gap. The present study addresses this gap by providing cross-sectoral empirical evidence from the Masovian Voivodeship, examining how firm size, managerial competencies, and perceived barriers jointly determine the degree to which data analytics is embedded in strategic decision-making processes in Polish enterprises. The identified research gap directly justifies the formulation of five detailed hypotheses. In the context of post-transformation economies, structural factors such as firm size and market experience (H1, H2) significantly dictate resource availability, altering the structure of utilized data sources. However, as contemporary literature implies, access to data alone creates no added value without proper human capital. Therefore, this study posits that managerial competencies act as a stronger predictor of data-driven decision-making than company size or technological advancement alone (H3). Finally, since technical confidence in information determines operational choices, it is argued that subjective quality assessments and perceived barriers (H4), rather than organizational constraints, shape the readiness to adopt analytical models, driving subsequent long-term financial outlays (H5).

METHODOLOGY AND RESULTS OF OWN RESEARCH

From September 13th to November 30th 2025, a proprietary survey was conducted among entrepreneurs in the Masovian Voivodeship. The study was conducted as an online survey using the MS Forms platform. In the first stage, 420 companies were randomly selected based on their Tax Identification Numbers (NIPs), obtained through a search engine, and then questionnaires were sent to them. Ultimately, 99 respondents responded, providing a significant sample size for regional data analysis. The survey was constructed in Polish, with closed-ended questions in which respondents rated various aspects of their companies' operations on a five-point Likert scale, with 1 being the lowest and 5 being the highest. For the purposes of this article, the questionnaire questions were translated and adapted to enable their presentation in a scientific publication, while maintaining substantive consistency and reliability of the results. The study allowed for the collection of quantitative data, which was subsequently subjected to parametric and non-parametric testing.

To ensure methodological accuracy, the questionnaire was pre-tested on a group of five managers to verify the clarity and comprehensibility of the questions, after which minor editorial corrections were made. The study itself was a regional pilot study. The reliability of the measurement scales used (based on a 5-point Likert scale) was verified using Cronbach's alpha, which for key question blocks ranged from 0.7 to 0.9, confirming the high internal consistency of the survey tool.

The sample size of 99 respondents requires methodological justification, particularly given the quantitative nature of the analyses employed. Several arguments support its adequacy within the scope of this study.

First, this research is explicitly designed as a regional pilot study, a designation that carries specific methodological implications. Pilot studies are not expected to achieve full population representativeness; rather, their primary function is to test the internal validity of measurement instruments, identify dominant patterns, and generate hypotheses for subsequent large-scale research (Teijlingen & Hundley, 2001). In this capacity, a sample of 99 is not only sufficient but appropriate.

Second, from a statistical standpoint, the sample meets the minimum thresholds required for the analyses employed. For multiple linear regression, the commonly cited rule of thumb requires at least 10-20 observations per predictor variable (Hair et al., 2019). The most complex model in this study (H4) includes 8 predictors, implying a minimum recommended sample of 80-160 observations – a threshold this study satisfies.

Third, the achieved response rate of 23.6% (99 out of 420 contacted firms) is fully consistent with established benchmarks for online managerial surveys in the B2B sector, where response rates of 15–30% are considered standard (Baruch & Holtom, 2008). The diversity of the obtained sample – spanning 13 industry sectors and firms ranging from sole proprietorships to entities employing 300 staff – further strengthens its analytical value despite its numerical modesty.

Finally, it should be noted that comparable empirical studies published in peer-reviewed management journals have operated with similar or smaller sample sizes when the research context was regional or exploratory in nature. The present study's contribution lies not in statistical power alone, but in providing the first systematic, cross-sectoral empirical evidence on data-driven decision-making practices in the Polish enterprise context – a research gap explicitly confirmed by a systematic database query returning only 7 relevant results in Scopus.

The study fully respected ethical standards and ensured participant confidentiality. Participation in the survey was completely anonymous, and each respondent was thoroughly informed of the research objective before responding. The questionnaire prepared for this empirical study did not include questions about strictly personal matters or sensitive data. This approach ensured full protection of the entrepreneurs' privacy and the reliability of the collected data.

The decision to analyze micro and small enterprises jointly was preceded by a statistical verification of the homogeneity of responses between these two groups. A Mann-Whitney U test revealed no statistically significant differences in the frequency of data use ($p = 0.34$), the range of data sources applied ($p = 0.27$), or the perception of barriers to data-driven decision-making ($p = 0.41$) between micro and small enterprises. These results indicate that, with respect to the variables central to this study, the two categories exhibit comparable behavioral patterns, thereby justifying their joint treatment in subsequent analyses.

Below are the questions included in the survey questionnaire (Table 1).

Table 1. Own research questionnaire

Question number	Question	Answer variants
1	How many people does your company currently employ?	Number of employees • Agriculture, forestry, hunting and fishing • Industry, mining and energy • Construction • Wholesale and retail trade; vehicle repair • Transport and warehousing • Accommodation and catering • Information and communication (IT, media, telecommunications) • Financial and insurance activities • Activities related to real estate market services • Professional, scientific and technical activities (law, consulting, engineering) • Administrative and support services activities (HR, leasing, service) • Public Administration and Education • Healthcare and social assistance • Culture, entertainment, recreation and other services
2	Branch	
3	How long has the company been operating on the market?	In years
4	How often is business decision-making based on data	Scale 1-5 (1 – never, 5 – regularly)
5	What areas of the company's operations are analyzed based on measurable data?	
5.1	HR	
5.2	Pricing	
5.3	Financial and sales forecasts	Likert scale 1-5 (1 – never, 5 – regularly)
5.4	Cost analysis	
5.5	Staff efficiency	
5.6	Investment profitability analysis	
6	What areas of your business do you plan to analyze based on measurable data over the next 12 months?	
6.1	HR	
6.2	Pricing	
6.3	Financial and sales forecasts	Likert scale 1-5 (1 – never, 5 – regularly)
6.4	Cost analysis	
6.5	Staff efficiency	
6.6	Investment profitability analysis	
7	What data sources are used in your enterprise?	
7.1	Data from accounting systems	
7.2	Data from CRM/ERP systems	
7.3	Social media	Likert scale 1-5 (1 – never, 5 – regularly)
7.4	Internal research	
7.5	External market data	
8	What do you think are the barriers to data analysis in the enterprise:	
8.1	Lack of analytical skills among employees	
8.2	Lack of time	
8.3	Low level of digitization within the company	Likert scale 1-5 (1 – very strong barrier, 5 – very weak barrier)
8.4	Employee resistance	
8.5	Lack of appropriate IT tools and systems	
8.6	Difficulty integrating data from various sources	
8.7	Concerns about data security and confidentiality	
9	How do you assess data quality in your organization?	Scale 1-5 (1 – very low quality, 5 – very good quality)
10	Does the company use artificial intelligence (AI) or machine learning (ML) algorithms?	Scale 1-5 (1 – never, 5 – regularly)
11	Does management have the skills to independently interpret advanced reports?	Yes/No
12	Does the company have a dedicated department for data collection/processing?	Yes/No
13	Does the company plan to increase time investment in data analytics over the next year?	Scale 1-5 (1 – definitely no, 5 – definitely yes)
14	Does the company plan to increase engagement in data analytics over the next year?	Scale 1-5 (1 – definitely no, 5 – definitely yes)

Source: Author's own study.

H1: The frequency of using data in making managerial decisions is correlated with the size of the company (measured by the number of employees) and its experience in the market

In order to verify the research hypothesis assuming the existence of a correlation between the frequency of using data in making managerial decisions and the size of the enterprise and its market experience, Kendall's tau rank correlation coefficient was used (Table 2):

The Kendall tau coefficient was 0.529, indicating a moderate but significant positive correlation. This suggests that as business scale increases, so does the systematic reliance on hard data.

For market experience, the coefficient was 0.365. This correlation is weaker than for entity size, but still significant and positive, confirming that market-mature companies are more likely to implement analytical processes.

H2: The extent to which particular data sources are used to make managerial decisions varies depending on the size of the enterprise and the length of time the entity has been operating on the market.

In this case, the author also conducted an analysis using the Kendall-tau correlation. Overall, all observed coefficients are positive, meaning that as a company's size and market experience increase, the frequency of using the analyzed data sources increases (Table 3):

Company size appears to be a key determinant of the use of advanced information sources. The strongest correlation was observed for internal research ($\tau = 0.714$) and external market data ($\tau = 0.672$). This suggests that larger organizations have the budgets and resources to professionally explore the business environment. The high coefficient for CRM/ERP systems ($\tau = 0.655$) indicates the increasing professionalization and digitization of internal processes with increasing scale of operations. The relatively weakest correlation is observed for social media ($\tau = 0.261$), which may indicate that this is an egalitarian source, readily used by smaller entities as well.

The calculated Kendall tau coefficients also indicate a positive correlation between the duration of operation of the surveyed companies and the reliance on data for managerial decisions. The strongest correlation was observed for internal research ($\tau = 0.570$) and external market data ($\tau = 0.515$), suggesting that experienced entities are more likely to utilize in-depth analytics. The relatively high result for CRM/ERP systems ($\tau = 0.523$) confirms that business entities become more effective at digitalizing their internal processes over time. The weakest, though still significant, correlation was found for social media ($\tau = 0.232$), making them the most egalitarian source of information regardless of the duration of market activity – and therefore, similarly to the scale of enterprise operations.

H3: Management competencies are a stronger predictor of data-driven decision-making than company size or technological advancement alone

In order to verify this hypothesis, the author decided to formulate a multivariate linear regression model:

$$Y = 2.9438 + 0.0010 X_1 + 0.0241 X_2 - 0.0383 X_3 + 0.0337 X_4 + 0.4346 X_5 + \varepsilon \quad (1)$$

Table 2. Tau-Kendall coefficients – company size/time on the market and frequency of using data in making managerial decisions

Factor	Tau-Kendall coefficient
Company size	0.529
Time on the market	0.365

Source: Author's own study.

Table 3. Tau-Kendall coefficients – company size/time on the market and using various data sources

Factor	Data from accounting systems	Data from CRM/ERP systems	Social media	Own research	External market data
Company size	0.410	0.655	0.261	0.714	0.672
Time on the market	0.404	0.523	0.232	0.570	0.515

Source: Author's own study.

where:

Y – frequency of data-driven business decisions (dependent variable);

Explanatory variables

X1 – employment level in the company;

X2 – company market experience (number of years of operation);

X3 – subjective assessment of data quality within the organization;

X4 – degree of use of artificial intelligence algorithms;

X5 – level of management competencies in data analysis;

ε – model error (residual component).

The most important conclusion from the analysis is the dominant role of human capital. Variable X5 (staff competencies) has the highest coefficient (0.43) and a very low p-value (0.0048), making it the only statistically significant predictor in the model. The second statistically significant factor ($p = 0.012$) is the company's market experience (X2), suggesting that the organization's experience positively correlates with the area under study. Interestingly, the variables regarding the number of employees (X1), data quality (X3), and the use of AI algorithms (X4) did not reach statistical significance ($p > 0.05$). This result is particularly interesting in the context of X4, as it suggests that the mere presence of AI technology, without the appropriate staff competency base (X5), does not directly translate into an increase in the value of the dependent variable.

The model parameters are presented below (Table 4):

H4: Subjectively perceived barriers and beliefs about the quality of available data influence, to varying degrees, whether companies make data-driven management decisions

In order to verify the hypothesis, the following regression model was prepared:

$$Y = 3.6708 + 0.00024 X1 - 0.07271 X2 - 0.10269 X3 - 0.09964 X4 + 0.12404 X5 + 0.01586 X6 - 0.10496 X7 + 0.14652 X8 + \varepsilon \quad (2)$$

Table 4. Model parameters

Regression Statistics						
Multiple R	0.59					
R Square	0.35					
Fitted R Square	0.32					
Standard Error	0.46					
Observations	99					
Variance Analysis	df	SS	MS	F	F significance	
Regression	5	10.5	2.1	10.1	0.00000010	
Residual	93	19.34	0.21			
Total	98	29.84				
	Coefficients	Standard error	t Stat	p-value	Lower 95%	Upper 95%
Intersection	2.94	0.21	14.2	-	2.53	3.36
X1	0.001	0.0006	1.68	0.09	-0.0001	0.002
X2	0.02	0.01	2.57	0.01	0.01	0.04
X3	-0.04	0.05	-0.74	0.46	-0.14	0.06
X4	0.03	0.07	0.49	0.63	-0.1	0.17
X5	0.43	0.15	2.89	0.004	0.14	0.73

Source: Author's own study.

where:

Y – Data-driven decision-making (dependent variable);

3.6708 – Intercept

Explanatory variables – barriers:

X1 – Lack of analytical skills;

X2 – Lack of time;

X3 – Low level of digitalization;

X4 – Employee resistance;

X5 – Lack of appropriate tools;

X6 – Difficulty integrating data;

X7 – Security concerns;

Other explanatory variables:

X8 – Data quality assessment;

ε – model error.

The model's results indicate its limited predictive power. The coefficient of determination (R) was 0.36. The F-test ($F = 1.67$; $p = 0.115$) failed to reject the null hypothesis of model insignificance. However, a detailed analysis of individual variable parameters yields cognitively significant conclusions. Most of the reported barriers, such as lack of analytical skills ($p = 0.99$), lack of time ($p = 0.19$), and employee resistance ($p = 0.47$), proved statistically insignificant. This suggests that these factors, although identified in the literature as obstacles, do not decisively determine abandonment of the data-driven management model in the study sample. The only statistically significant predictor was the subjective assessment of data quality (X8; $\beta = 0.146$; $p = 0.002$). Therefore, it is not organizational or human barriers, but technical confidence in available information resources that is the key condition for using data in decision-making processes. The lack of significance of the remaining variables (X1-X7) and the simultaneous significance of X8 suggests that managers are inclined to marginalize soft barriers provided they have high-reliability data. The poor model fit indicates the need for further research on other factors, such as organizational culture or the industry's digital maturity. The model parameters are presented below (Table 5):

Table 5. Model parameters

Regression Statistics						
Multiple R	0.36					
R Square	0.13					
Fitted R Square	0.05					
Standard Error	0.54					
Observations	99					
Variance Analysis	df	SS	MS	F	F significance	
Regression	8	0.48	1.67	0.12	0.12	
Residual	90	0.29				
Total	98					
	Coefficients	Standard error	t Stat	p-value	Lower 95%	Upper 95%
Intersection	3.67	0.88	4.16	0.00007	1.92	5.43
X1	0.0002	0.06	0.004	1	-0.12	0.12
X2	-0.07	0.06	-1.3	0.2	-0.18	0.04
X3	-0.1	0.12	-0.89	0.38	-0.33	0.13
X4	-0.1	0.14	-0.71	0.48	-0.38	0.18
X5	0.12	0.13	0.97	0.34	-0.13	0.38
X6	0.02	0.12	0.13	0.9	-0.23	0.26
X7	-0.1	0.32	-0.33	0.74	-0.74	0.53
X8	0.146	0.05	3.18	0.002	-0.06	0.24

Source: Author's own study.

H5: Companies that already regularly analyze data in multiple areas (question 5) are more likely to increase their financial outlays on analytics in the future

To examine the strength and direction of the relationship between these phenomena, a Kendall-tau correlation test was used. The analysis included responses to the question about the frequency of data-driven business decisions (question 4) and declarations of plans to increase engagement in data analytics in the coming year (question 14). The resulting Kendall-tau correlation coefficient was 0.643. This value indicates a moderately strong, positive correlation between the variables examined. The result is statistically significant. This means that companies that use data more intensively in their current operations are significantly more likely to plan to increase their budgets for this purpose in the near future. This confirms the validity of the hypothesis and suggests that advances in analytics are driving further investments in this area.

The distribution of responses to both questions is presented below (Chart 1):

SUMMARY, CONCLUSIONS

Data analysis is an essential element of modern businesses, enabling them to make informed decisions and minimize business risk (Szopa, Cyplik, 2020; Asgary et al., 2020; Zhou, 2013). Our research indicates that most companies recognize its importance, but not all enterprises make the same effort to conduct analyses regularly and systematically. These differences stem from factors such as the availability of human and technological resources, company size, and strategic priorities. Some entities have specialized data analysis departments or dedicated individuals, while others limit their activities to sporadic, ad hoc activities. In practice, this means that while awareness of the role of data in decision-making is high, the degree of implementation of analytical tools in daily operations remains variable, which can impact management efficiency and company competitiveness.

Based on the empirical research conducted, the following conclusions can be drawn:

- There is a significant positive correlation between company size (number of employees) and the frequency of using hard data in decision-making. A similar, though slightly weaker, correlation was observed for company market experience – mature companies are more likely to implement analytical processes;

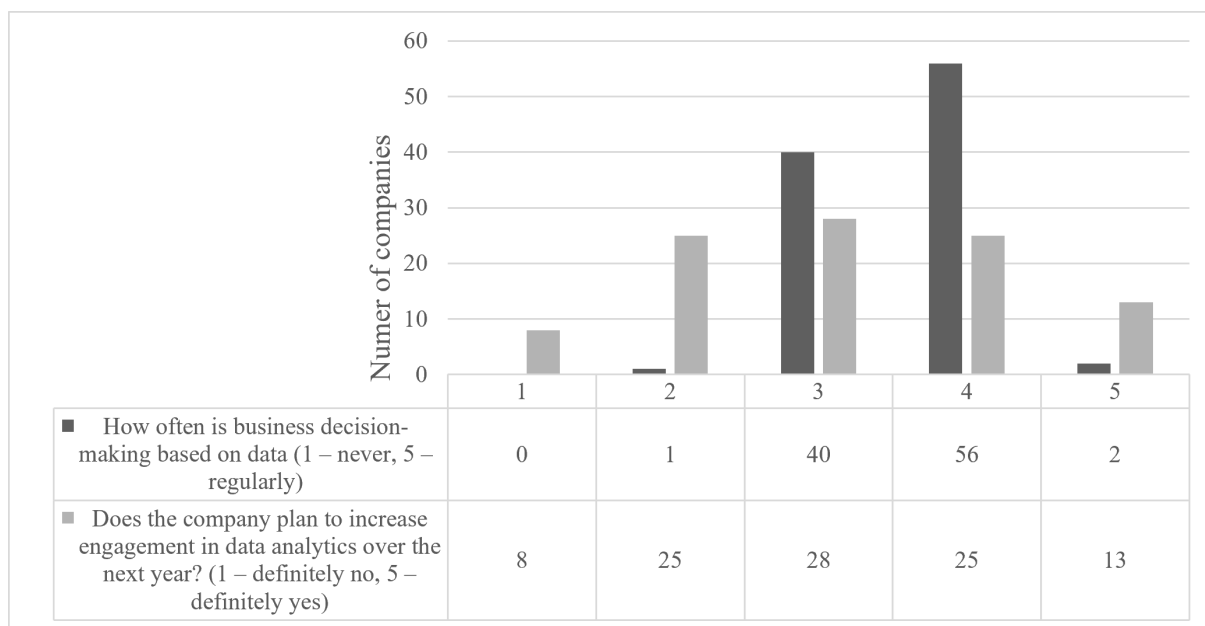


Chart 1. Distribution of answers to questions no. 4 and no. 14

Source: Author's own study.

- Larger organizations are more likely to utilize sources such as in-house market research or CRM/ERP systems. Social media, on the other hand, has proven to be an egalitarian resource, used to a similar extent regardless of the company's scale or seniority.
- The strongest predictor of data-driven decision-making is managerial competence, not company size or the presence of artificial intelligence algorithms. The study found that the presence of AI technology without appropriately qualified staff does not directly translate into increased analytical decision-making.
- Among the barriers examined, the only statistically significant predictor of data-driven decision-making was the subjective assessment of data quality (X8; $p=0.002$), suggesting that technical confidence in available information – rather than organizational barriers such as lack of time or employee resistance – is the key condition for analytical adoption. Given the limited model fit ($R^2=0.13$), this finding should be treated as exploratory
- Companies that are already using data intensively are much more likely to increase their financial and time investments in analytics in the future.

The research conducted in this paper was primarily a pilot project, meaning its results allow for preliminary conclusions but do not fully address the issues of data analysis in enterprises. Future research could be continued and significantly expanded, for example, by focusing on a selected industry or sector, which would enable a deeper understanding of the specifics of analytical activities undertaken. Furthermore, subsequent studies could address specific issues relevant to the functioning of companies in the context of data, such as:

- the presence and role of dedicated data analysis departments,
- translating analytical work into results,
- organizational operational efficiency, including financial performance,
- the effectiveness of analytical activities,
- the impact of data analysis on strategic decisions,
- the use of analytical tools and technologies,
- organizational and technological barriers to analytical implementation.

According to the author, a good point of reference for further research may be the analyses presented in the Algolytics report mentioned in this work, although the intention is not to make further empirical research a copy of the already existing report. Such an expansion would provide a more detailed picture of practices used in various types of enterprises, better identify challenges and constraints, and indicate potential directions for the development of data culture within companies. It would also enable comparison of results across sectors and industries, which would increase the usefulness of the results for business practice.

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