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Technological Asymmetries and Financial Performance of Industrial Joint-Stock Companies: AI-Driven Risk Factors and Efficiency in Capital Management

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Abstract

This article examines how technological asymmetries—understood as differences in access to advanced digital tools, AI capabilities and IT infrastructure—shape the financial stability and market performance of enterprises of various sizes. The study integrates comparative analyses of 100 industrial joint-stock companies from multiple countries, including technologically advanced large corporations and innovative SMEs, to assess how disparities in digitization and AI implementation influence financial resilience. Using multivariate regression models and index-based financial metrics such as MC, EV, P/E, PEG, P/S, P/B, EV/R and EV/EBITDA, the research identifies relationships between technological advancement, operational efficiency and risk exposure. The findings indicate that companies with higher levels of digitization and AI adoption demonstrate stronger resistance to market disruptions, more effective risk management and more favorable capital structures than SMEs with limited technological resources. However, restricted access to detailed operational data for smaller firms may affect the precision of comparative assessments. The study concludes that investments in digital competences and international cooperation enhance financial stability and support strategic decision-making, while SMEs play an important complementary role by providing outsourcing services that facilitate AI implementation in larger corporations.

Keywords: technological asymmetries; AI adoption; financial stability; econometric modelling; SMEs; corporate risk; digitalization

1. Introduction

Joint-stock companies, both small and large, constantly search for innovative technological solutions that are a key factor in determining their efficiency and competitiveness (Audretsch et al. 2014). In an era of global challenges and digital technology development, industrial companies are increasingly turning to advanced analytical tools, primarily artificial intelligence algorithms (Sinha and Lee 2024). This is being done to increase the effectiveness of capital management of listed companies, which would ultimately increase their investment opportunities by determining the capital structure and the minimum level of expected return on investment. In addition, increasing the effectiveness of joint stock companies' capital management for purely investment purposes yields desired results (Abdubokiev 2023).

Thus, companies seek to streamline their decision-making processes and increase the efficiency of financial management. Various difficulties and obstacles hinder their development, and financial results are a very important assessment of the financial condition of the industry under review (Juan and Li 2021).

The use of machine learning in the process of analyzing the financial management systems of the examined economic entities allows not only the automation of routine operations, but also the

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identification of patterns, risk level forecasting, and resource allocation optimization (Huang 2024); Ahmed et al. 2018). In this context, joint-stock companies that use advanced machine learning algorithms are perceived as technologically innovative enterprises, which is a key factor in their competitive advantage over other industrial entities listed on the stock exchange (Gupta 2025). This is because they are characterized primarily by high capital intensity and, consequently, high market volatility.

The aim of this article is to analyze financial management systems (FMS), most often referred to in the literature as "software and processes used to manage an organization's revenues, expenditures, and assets" (SAP Poland 2025). Their primary purpose is to monitor the profits generated and ensure long-term financial stability for industrial joint-stock companies that use AI in their operations. The most important element of this research is a comparison of the FMS used by small, listed companies with those used by large economic entities. The analysis focuses on industrial companies from different countries, which allows for capturing diverse technological implementation strategies (Holm et al. 2025) and identifying factors influencing financial performance and innovation level.

The choice of topic was dictated by the fact that we are seeing a growing number of machine-learning algorithms being implemented in industry daily. There is a growing research gap in assessing the role of the SME sector in the AI-assisted innovation (Segarra-Blasco and Tomàs-Porres 2025; Sánchez et al. 2025; Schwaeke et al. 2025; Rasdi and Baki 2025). Although large technology corporations are seen in many scientific publications as playing a huge role in raising the level of innovation in enterprises, smaller entities often act as catalysts for change by offering specialized outsourcing services (Roux et al. 2023).

Small joint stock companies can quickly reach niche markets. By implementing unprecedented solutions, they can collaborate with larger entities in R&D projects (Park and Seo 2025). The use of appropriate cooperation mechanisms between the economic entities under study, as well as a thorough analysis of the differences in the level of innovation between MSMEs and large companies, can provide valuable insights for both researchers and business practitioners (Giardino et al. 2023; Nieto and Santamaria 2006; Rusu 2023; Zaman and Tanewski 2024).

Therefore, Authoress posed two main research questions:

RQ1. Is there a statistically significant relationship between capitalization and other industrial companies' financial indicators?

RQ2. Which financial indicators best differentiate companies in terms of technological innovation?

RQ3. Does the size of a company affect the effectiveness of the AI algorithm implementation?

An authoress selected a research sample on a deliberate choice of 100 joint-stock companies from the industrial sector scattered around the world. They have one common feature, namely, the broad use of AI. The sample includes both large corporations and micro, small, and medium-sized enterprises (MSMEs), which enables a comparative analysis in terms of the scale of operations. Companies were selected based on the availability of financial data and market indicators in public databases (including industry reports, stock exchange services, and analytical platforms). The key criterion was the completeness of data for variables such as market capitalization (MC), enterprise value (EV), the price to earnings ratio (P/E), forward P/E ratio, the price/earnings to growth ratio (PEG), the price to sales ratio (P/S), the price to book ratio (P/B), dividing enterprise value by revenue (EV/R) and enterprise value to earnings before interest, taxes, depreciation and amortization EV/EBITDA (https://finance.yahoo.com/ ref52).

The inclusion of companies from different countries and levels of technological development allows us to capture the structural and regional effects that may influence the level of innovation and AI implementation (Marti 2024; Cannavale and Claudio 2025; Chun and Hwang 2024; Bate et al. 2023). The selection was not random but deliberate and based on data availability and representativeness for the industrial sector. The list of companies was verified in terms of company size classification according to European Commission criteria (micro, small, medium, and large), which enabled sample segmentation and analysis of differences between groups. This study is based

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on a comparative analysis of 100 joint-stock companies from different countries, including micro-, small- and medium-sized enterprises, as well as large industrial enterprises. The research sample was selected based on data obtained from available industry reports and financial databases. The ratio analysis method was used with the parameters listed above.

The data were used to estimate an econometric model that allows for the identification of relationships between company capitalization and the other indicators mentioned above to indicate which of them had the strongest impact on capitalization in the context of AI implementation as the main factor determining the level of technological innovation of the economic entities under study (Machucho and Ortiz 2025).

This study consisted of six parts. The first section is an introduction to this study. In the second part, an authoress presents a review of the literature on technological innovation and applications of AI in finance. The third part describes the research methodology, including the sample selection and indicators used. In the fourth section, there are presented results of the econometric analysis, and in the fifth section, an authoress discusses their implications. The sixth and final sections present the conclusions and recommendations for researchers and potential investors, providing guidance for further research.

2. Literature Review

AI is playing an increasingly important role in the financial management of companies of various sizes. It is a rather costly undertaking, which is why it is desirable to search for efficient and effective financial resource management systems (models) that could increase the possibility of implementing machine learning algorithms in business activities, not only by large, listed companies but also by smaller economic entities, which are the mainstay for the development of larger entities.

Smart manufacturing, as manufacturing is combined with AI, is consistent with the inherent requirements of the development of manufacturing companies and is essential (Xu and Zhang 2023; Tsang and Lee 2022). Thus, it contributes to increasing the competitive advantage of manufacturing companies operating as listed companies and promotes the transformation and modernization of industrial activities carried out by such economic entities (Marques et al. 2017; Lee et al. 2022).

The deep connection between artificial intelligence and the real economic environment is becoming increasingly apparent, becoming a key priority for companies seeking to maintain a high level of development through the implementation of the so-called "strategy of" production power" (He and Bai 2021), but above all, production power supported by the outsourcing activities of micro and small economic entities.

An analysis of the innovation literature confirms that most scientific publications focus on large enterprises (Mazzola et al. 2018). Research also points to "weaknesses in the conceptualization of innovation criteria, resulting in a heterogeneous and scattered conceptual basis' (D'anjour et al. 2024; Forsman 2011; Berends et al. 2014).

Innovation is also evident in smaller economic entities' activities. When it comes to micro, small, and medium-sized enterprises, research also shows that they make a significant contribution to the development of innovation and technologies related to the implementation of AI, especially in the context of innovation ecosystems, renewable energy sources, etc. (Love and Roper 2015). "However, there is still much controversy surrounding the complex impact of organization size on the innovation process as a whole" (Forés and Camisón 2016), because, as an authoress mentioned earlier, large corporations focus on manufacturing, while small businesses focus on offering modern services.

2.1. Theory and Research Hypothesis

Analyzing the financial management systems of industrial joint-stock companies considered innovative owing to their use of machine learning algorithms, there was analyzed the impact of selected stock market indicators on their capitalization, which is a key determinant of a company's size and market position (Toraman and Başarir 2009; Dias 2013; Ejsmont 2025). Its value, combined with other indicators assessing the financial condition of selected listed companies, provides a basis for future research on the selection of optimal financial management systems that may bring significant benefits in the form of generated profits.

Market capitalization is associated with large joint stock companies. Banz (1981) stated that, on average, "small companies listed on the New York Stock Exchange (NYSE) achieve (on average) higher profits than larger companies". Therefore, my research aims to highlight the role of micro and small companies in building financial management systems that are supported by AI.

2.1.1. Relationship Between Enterprise Value and Market Cap

In this study, it is important to take an approach based on an assessment of the market value of a joint-stock company, which results from determining the market price, that is, the demand price of shares issued and listed on the stock exchange. This approach, used especially in international practice, has an impact on capitalization and, consequently, on the maintenance of (Blikhar et al. 2022):

- corporate governance,
- financial stability,
- Investment attractiveness
- competitiveness.

The market value of a joint-stock company, including the market value added (MVA) for its individual components, is primarily determined by how well the company manages to maximize shareholder wealth through resource allocation. If the value of the company is positive, shareholder wealth has increased; if it is negative, shareholder wealth has decreased. According to many researchers, just as the value of a company (including its MVA) affects shareholder wealth and, consequently, market capitalization, it also has a significant impact on share prices, as the company's capital is included in the MVA calculations (Nazar and Dwiarso 2023; Putra and Sibarani 2018).

A higher market value means that the company has a greater ability to control the stock market and allocate resources, thereby influencing an increase in share prices (Octaviany et al. 2021). This sends a positive signal to investors by influencing their confidence in investing capital, which also translates into an increase in the market capitalization of joint-stock companies whose shares are of interest to potential investors (Effendi and Dewi 2024).

Therefore, it is important to analyze the impact of enterprise value (EV) on market cap (MC). In view of the above, an authoress formulates the following hypothesis:

H1. *EV is positively related to MC.*

2.1.2. Relationship Between Trailing P/E and Market Cap

The relationship between trailing P/E and market capitalization may indicate significant correlations between the size of a company and the expectations of potential investors. The examined indicator of a company's market value in relation to earnings per share is also of key importance to market analysts. Above all, this ratio allows for an assessment of whether shares are overvalued, correctly valued, or perhaps undervalued. Therefore, it is considered a useful tool for comparing shares, especially within the same industry (San Ong et al. 2010; Weske and Benuto 2015; Zarowin 1990). Shares with high P/E ratios encourage investors to invest in specific financial instruments, as they expect higher earnings growth in the future (Sajeetha et al. 2023) and, consequently, which is also of great importance for the growth of market capitalization.

In this case, it is important to analyze the impact of the P/E ratio on market cap (MC). As before, there was formulated the following hypothesis:

H2. *P/E is positively related to MC.*

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2.1.3. Relationship Between Forward P/E and Market Cap

The forward price-to-earnings ratio (P/E) reflects the ratio of the current share price to projected earnings per share in the coming period (Freihat 2019). Therefore, this study aims to examine whether there is a statistically significant relationship between the level of the forward P/E ratio and the size of a company measured by market capitalization in the industrial sector.

In this case, it is important to analyze the impact of the forward P/E ratio on market cap (MC). The following hypothesis was formulated:

H3. *Forward P/E is positively related to MC.*

2.1.4. Relationship Between PEG Ratio and Market Cap

The PEG ratio, which is an extension of the classic P/E ratio by the projected earnings growth rate, is an advanced tool for fundamental analysis.

Its relationship with market capitalization may reveal whether the market rewards larger companies for stability or smaller ones for growth potential. This study aims to examine whether there is a systematic relationship between the value of the PEG ratio and the size of a company, with particular emphasis on the industrial sector.

The impact of market indicators on the capitalization of listed companies results from their measurement using the PEG ratio by comparing share prices, so that there is a relationship between them. This means that investors seeking to predict company share prices pay particular attention to the financial conditions of companies, considering the estimated values of the PEG ratio generated by the company. Thus, this indicator favors share price growth and can serve as a benchmark for investments that shape a company's market capitalization through share price growth (Usman et al. 2020).

Here, too, it seems essential to analyze the impact of the PEG ratio on market cap (MC). An authoress proposed the following hypothesis:

H4. *PEG ratio is positively related to MC.*

2.1.5. Relationship Between P/S Ratio and Market Cap

The P/S ratio is useful when potential investors want to know how much they will pay for each unit of revenue generated by the company. This is particularly useful when evaluating companies in the early stages of development. In the case of M&A s, strategic investors analyze P/S to value the entire company. This ratio, based on revenue regardless of costs incurred or profits achieved, also plays an important role in shaping market capitalization (Nan 2023).

In view of the above, an authoress has formulated another research hypothesis:

H5. *P/S ratio is positively related to MC.*

2.1.6. Relationship Between P/B Ratio and Market Cap

In a typical industrial sector, the P/B ratio is particularly useful because book value perfectly reflects the fixed assets accumulated by a joint-stock company. According to (Chen Zhang and Chen (2001), considering the essence of the cross-sectional analysis of the determinants of expected returns on shares, the explanatory power of scale in the context of the examined B/P ratio is significant, for example, from the point of view of the impact of this parameter on the value of capitalization (Nan 2023).

As in previous cases, there was formulated a research hypothesis assuming that:

H6. *P/B ratio positively related to MC.*

2.1.7. Relationship Between EV/R Ratio and Market Cap

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The Enterprise Value/Revenue (EV/R) ratio, like the EV ratio, is one of the basic tools used to value companies, especially listed companies. It is particularly relevant to economic entities characterized by unstable profitability or those just starting their careers on the stock exchange.

EV/R measures the relationship between a company's value, considering both equity and net debt, and annual sales revenue. Unlike the P/E ratio, which is associated with measuring net profits, EV/R focuses exclusively on revenue, making it useful for industrial companies that have not yet generated profits but show dynamic sales growth (Yeh and Chi 2025).

Since the aim of this part of the article is to determine the role of the EV/R ratio in the process of estimating market capitalization, an authoress has adopted another research hypothesis:

H7. *EV/R ratio is positively related to MC.*

2.1.8. Relationship Between EV/EBITDA Ratio and Market Cap

The following ratio shows how much investors are willing to pay for a unit of operating profit generated by a company regardless of its financial structure (Bouwens et al. 2018). Admittedly, the analyzed parameter does not consider capital investments. In addition, it is interpreted more often in the context of the technology sector than in the industrial sector. Nevertheless, in accordance with the commonly accepted definition, like other indicators, it also describes the financial conditions of joint-stock companies. The final research hypothesis was formulated as follows:

H8. *EV/EBITDA ratio is positively related to MC.*

3. Materials and Methods

This article presents a study containing a comparative analysis of 100 joint-stock companies from the industrial sector, selected based on financial data describing various financial management systems using machine learning algorithms. The fact that these companies use AI in their operations proves that they are fully innovative economic entities.

The research sample consisted of both large corporations and micro, small, and medium-sized enterprises (MSMEs), which made it possible to analyze differences in financial management effectiveness in the context of the scale of operations. The sample selection was purposeful and based on data obtained from public financial databases, industry reports, and stock exchange services. The key data source is the Yahoo Finance website. The main selection criteria included the completeness of data for the following variables: market capitalization (MC) as the dependent variable (y) adopted in the econometric model, which forms the basis of the methodology adopted. Further assumptions concern the adoption of independent variables that determine the following indicators.

- x_1 -EV,
- x_2 -trailing P/E,
- x_3 -forward P/E,
- x_4 -PEG ratio,
- x_5 -P/S ratio,
- x_6 -P/B ratio,
- x_7 -EV/R ratio,
- x_8 -EV/EBITDA.

The initial form of the econometric model an authoress estimated took the form of the following regression model (Tiwari et al. 2023; Tran and Vo 2020). This popular model has been used by many researchers and can be expressed by the following formula:

$$MCt= \alpha_0+\alpha_1 EVt+\alpha_2P/Et+\alpha_3FP/Et+\alpha_4PEGt+\alpha_5P/St+\alpha_6P/Bt+\alpha_7EF/Rt+\alpha_8EV/EBITDAt+\varepsilon_t \quad (1)$$

The analysis is based on a cross-sectional dataset covering a single year (2025). This approach is methodologically appropriate for the objectives of the study, which focus on identifying structural relationships between technological advancement, AI adoption and financial performance across firms rather than examining temporal dynamics. Using one-year data eliminates the influence of business cycle fluctuations, macroeconomic shocks and regulatory changes that could distort multi-year comparisons, thereby ensuring that all companies are evaluated under comparable market conditions. Moreover, consistent multi-year financial and technological data are not uniformly available for SMEs, particularly regarding AI implementation indicators, which would introduce selection bias and reduce the representativeness of the sample. A single-year cross-section therefore provides the most reliable basis for comparing companies of different sizes and technological maturity, while maintaining internal consistency and analytical clarity.

Based on the above assumptions, a classic linear regression model was constructed. Excel, Gretl and R (version 4.5.1) were used to estimate the above model. In the process of creating the regression model, AI tools (e.g., Microsoft Copilot) were used to a limited extent, mainly to assist in code formulation and syntax verification. All analytical decisions regarding the selection of variables and the interpretation of the results obtained were made independently by the author.

Data Collection and Analysis

The dataset includes financial indicators for 100 joint-stock companies of various sizes from the industrial sector whose shares are listed on global stock exchanges. The data were collected manually from publicly available sources such as Yahoo Finance. The research period covers the current year, 2025. The sample includes companies from different countries, which allows for a comparative analysis of different market segments. The data are presented in Table 1.

Table 1. Initial data for econometric model estimation.

Company	Market cap (y)	Enterprise value (x1)	Trailing P/E (x2)	Forward P/E (x3)	PEG ratio (5-year expected) (x4)	Price/ sales (x5)	Price/ book (x6)	Enterprise value/ revenue (x7)	Enterprise value/ EBITDA (x8)	Company size
GE Aerospace	298.72	305.74	40.18	41.32	5.49	7.32	15.61	7.35	28.09	large
Belden Inc.	5.21	6.28	23.91	16.67	1.11	2.05	4.22	2.4	14.96	average
Honeywell	134.26	160.09	24.06	18.38	1.83	3.44	8.34	4	16.27	large
Rockwell Automation	38.78	42.16	40.48	30.67	3.59	4.85	11.2	5.23	26.2	large
Emerson Electric	76.03	88.68	34.73	20.66	1.42	4.32	3.83	4.99	18.9	large
Caterpillar	202.16	237.46	21.97	20.45	1.87	3.28	10.83	3.76	16.5	large
John Deere	127.19	184.14	24.57	22.32	1.55	2.95	5.05	4.24	15.58	large
3M	84.09	93.6	21.93	19.08	3.35	3.51	19.6	3.8	13.33	large
Boeing	163.28	193.65	0	69.93	6.53	2.06	0	2.57	111.56	large
Lockheed Martin	110.03	130.38	26.45	15.82	1.57	1.55	20.63	1.81	17.16	large
Raytheon Technologies	0	0	0	0	0	0	0	0	0	large
Ford Motor	46.48	169.22	14.97	8.59	14.31	0.25	1.03	0.91	15.15	large
Tesla	1.28	1.25	235.68	156.25	7.05	15.02	16.52	13.52	92.56	large
Whirlpool	5.15	12.4	638.69	15.41	0	0.33	2.22	0.8	14.01	large
Eaton	142.44	153.44	36.81	26.95	2.71	5.56	7.66	5.9	26.14	large
Cummins	56.53	62.14	19.23	17.04	2.04	1.68	4.8	1.84	11.36	large
Ball Corporation	13.93	20.66	25.34	12.52	1.36	1.2	2.68	1.67	12.75	large

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Parker Hannifin	96.12	104.94	27.98	26.18	3.4	4.98	7.03	5.29	19.35	large
Illinois Tool Works	76.77	84.92	23.12	22.94	3.69	4.92	23.92	5.38	17.27	large
AGCO Corporation	8.13	10.45	81.34	15.9	0.66	0.8	1.95	1.03	40.84	average
Eastman Chemical	7.71	12.42	9.45	9.8	3.27	0.85	1.32	1.34	7.19	large
PPG Industries	24.99	31.31	20.02	12.97	0.72	1.63	3.3	2	12.55	large
Alcoa	8.61	9.74	7.84	14.49	0	0.66	1.4	0.76	4.49	large
Nucor	32.44	36.84	25.33	12.35	0	1.07	1.59	1.2	10.17	large
Dow Inc.	17.75	33.45	32.65	13.61	0.54	0.42	1.03	0.8	10.2	large
DuPont	32.36	37.7	454.65	16.26	0.7	2.57	1.4	2.99	18.5	large
Corning	65.99	73	81.96	27.03	0.65	4.72	5.94	5.14	25.79	large
Textron	14.48	16.78	18.3	11.75	0.85	1.07	1.95	1.19	11.71	average
Oshkosh Corp.	8.77	10.08	13.76	10.87	6.51	0.86	1.97	0.97	8.42	average
Terex	3.46	5.68	19.68	9.51	1.64	0.68	1.76	1.1	11.61	average
Voestalpine AG	120.78	159.8	41.23	0	0	0.32	0.68	0.42	14.6	large
Ametek	43.87	45.19	30.58	24.88	2.75	6.31	4.22	6.47	20.33	large
Siemens AG	179	209.68	23.13	19.92	2.34	2.32	2.95	2.68	12.86	large
Jenoptik AG	926.11	1.32	12.64	0	0	0.86	0.97	1.23	6.49	average
Thyssenkrupp	6.55	3.1	4.1	13.77	136.03	0.2	0.72	0.09	1.89	large
BASF	39.15	60.43	102	14.62	0.89	0.61	1.21	0.93	8.76	large
Volkswagen AG	51.43	176.66	6.09	4.5	0.82	0.16	0.28	0.54	3.55	large
BMW Group	51.08	114.73	9.03	7.04	0.53	0.35	0.56	0.84	6.42	large
Daimler Truck	28.64	45.6	12.36	7.1	0	0.56	1.4	0.87	9.81	large
Friedrich Vorwerk Group SE	1.35	1.27	25.66	0	0	2.3	6.15	2.09	11.88	small
SAP SE	301.86	300.18	39.52	31.35	1.11	7.22	6.24	7.13	21.79	large
Infineon Technologies	41.26	45.09	33.43	15.8	0.59	2.83	2.47	3.08	12.39	large
Fanuc	3.96	3.36	26.97	24.81	2.47	4.99	2.31	4.21	16.35	large
Hitachi	18.61	18.39	32.28	24.75	0	1.93	3.2	1.88	12.76	large
Mitsubishi Electric	7.92	7.38	24.75	19.88	2.38	1.45	2	1.34	10.97	large
Komatsu	4.77	5.75	11.04	13.44	5.15	1.18	1.54	1.4	6.97	large
Toyota Industries	4.95	6.2	19.21	18.12	0	1.23	1.01	1.52	16.89	large
Panasonic	3.64	4.29	9.94	10.31	1.2	0.43	0.79	0.51	4.65	large

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Yaskawa Electric	785.56	836.72	14.42	21.74	9.92	1.49	1.85	1.58	8.27	large
Fujitsu	6.72	6.27	33.26	17.57	0	1.94	3.56	1.77	14.07	large
Nidec	2.98	3.37	17.8	14.77	1.23	1.15	1.73	1.29	8.46	large
Sumitomo Electric	3.26	3.68	16.83	0	0	0.7	1.43	0.79	6.8	large
Manitou BF SA	714.84	1.05	9.88	4.58	0	0.28	0.76	0.42	4.14	small
Schneider Electric	130.68	142.23	28.84	22.57	1.84	3.36	4.85	3.62	17.15	large
Dassault Systèmes	36.27	34.77	33.42	19.68	1.95	5.81	4.43	5.51	17.07	large
Airbus	152.13	150.06	30.96	23.98	1.13	2.18	6.6	2.14	15.23	large
Alstom	9.67	10.99	67.55	15.62	2.93	0.51	0.92	0.59	8.74	large
Saint-Gobain	46.56	58.95	16.71	12.47	1.58	1	1.98	1.26	7.74	large
Rolls-Royce Holdings	94.05	92.9	16.52	51.28	4.75	4.89	39.06	4.75	13.52	large
BAE Systems	57.91	64.89	30.43	22.88	3.96	2.2	5.34	2.37	15.93	large
Johnson Matthey plc	3.21	4.01	9.07	9.44	0	0.29	1.4	0.34	5.01	average
Melrose Industries	7.52	9.19	24.16	15.65	0.91	2.23	2.64	2.67	10.36	average
Renishaw	2.36	2.14	24.13	22.57	0	3.36	2.63	3.05	13.59	average
Lonza Group AG	38.41	42.12	52.76	28.09	1.29	5.46	4.46	5.94	40.11	large
ABB Ltd.	103.47	107.11	31.19	24.88	2.79	3.9	9.2	4.01	20.13	large
Sulzer	4.82	5.05	17.89	10.93	0	1.36	4.26	1.41	9.8	average
Georg Fischer AG	5.32	6.5	21.93	0	0	1.42	29.88	1.74	11.16	average
Hexagon AB	290.32	332.1	28.44	23.31	3.19	4.92	2.65	5.59	15.69	large
Epiroc AB	238.61	250.96	27.42	24.1	3.49	3.87	6.39	3.94	15.89	large
Trelleborg AB	85.09	93.78	23.96	18.45	0	2.51	2.31	2.71	12.52	large
SKF Group	106.92	115.93	19.88	11.95	1.36	1.12	2.01	1.21	8.62	large
Volvo Group	556.26	760.23	14.62	10.91	0	1.11	3.39	1.52	9.99	large
Sandvik	313.6	360.64	21.66	18.55	2.18	2.58	3.58	2.97	12.56	large
Atlas Copco	739.1	753.22	27.36	25.13	2.73	4.43	7.61	4.35	16.35	large
CNH Industrial	13.72	38.9	16.88	12.61	0.72	0.76	1.78	2.15	12.27	large
Leonardo S.p.A.	29.11	31.55	27.79	17.86	1.29	1.56	3.23	1.69	14.28	large
Doosan Robotics	4.1	3.86	0	0	0	130.88	10.88	123.09	0	small
Samsung Heavy Industries	18.79	21.08	66.27	14.88	0.09	1.84	5.14	2.07	57.09	large

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Hyundai Heavy Industries	42.57	43.29	48.47	21.88	0	2.9	7.32	2.78	26.12	large
POSCO	21.55	33.71	41.58	0	0	0.3	0.39	0.47	5.84	large
Haier Smart Home	238.64	220.76	11.96	10.42	1.08	0.81	2.08	0.73	6.21	large
CRRC Corporation	212.71	171.87	14.58	15.29	0	0.82	1.31	0.62	5.79	large
BYD	1.01	897.08	12.72	15.36	0.7	1.03	3.75	0.97	6.55	large
Sany Heavy Industry	178.98	169.96	23.44	18.21	0	2.12	2.44	2.02	13.03	large
Sinochem	16.36	36.03	17.49	0	0	0.29	1.38	0.7	27.81	large
Tata Steel	2.12	2.95	46.64	13.12	0	0.98	2.32	1.37	10.87	large
Larsen & Toubro	4.92	5.64	31.04	22.73	0	1.87	5.04	2.15	17.55	large
Mahindra & Mahindra	4.31	5.14	29.38	29.94	0	2.45	5.59	3.13	14.62	large
Embraer	56.28	62.03	27.76	20.2	0	1.51	3.13	1.66	11.12	large
Vale S.A.	243.32	322.05	8.67	6.37	7.96	1.24	1.15	1.63	5.66	large
Asseco Poland	14.33	15.6	25.29	0	0	0.81	2.67	0.88	5.57	average
Apator S.A.	700.03	816.44	10.81	0	0	0.6	1.17	0.7	5.72	average
Azoty Group	1.85	10.2	1.79	0	0	0.14	0.41	0.76	25.7	average
KGHM	27.83	32.98	11.72	0	0	0.79	0.87	0.93	5.15	large
PKN Orlen	94.31	101.3	20.83	0	0	0.34	0.65	0.37	3.73	large
Wielton	419.61	1.11	5.23	0	0	0.21	0.99	0.54	4.57	average
Mercator Medical	405.97	197.84	95.74	0	0	0.81	0.44	0.39	7.33	average
XTPL	217.29	202.49	0	0	0	19.34	6.54	17.53	-167.51	micro
DataWalk	682.72	617.63	0	0	0	18.07	235.91	16.48	-2.57	micro
Wärtsilä Corporation	15.53	14.44	27.79	23.98	3	2.28	6.22	2.11	14.63	large

Source: https://finance.yahoo.com/markets/stocks/most-active/ (accessed 7 October 2025 ref52).

Most of the entities surveyed were large corporations, conglomerates, or holding companies. The indicators presented in the table reflect the valuation parameters commonly used in financial analyses.

4. Empirical Results

To explain and estimate the impact of individual independent variables on the market capitalization of selected joint-stock companies, an authoress estimated aggregate OLS using cross-sectional data. To better illustrate the variables in Table 2, there was presented descriptive statistics for both the dependent and independent variables.

Table 2. Summary Statistics, using observations 1—100.

Variable	Mean	Median	S.D.	Min	Max
Y	119.	39.0	194.	0.000	926.
x1	119.	42.1	190	0.000	897.
x2	37.9	23.9	79.3	0.000	639.
x3	16.8	15.5	18.0	0.000	156
x4	2.97	0.870	13.6	0.000	136
x5	3.79	1.53	13.2	0.000	131
x6	6.95	2.63	23.9	0.000	236
x7	3.87	1.75	12.4	0.000	123.
x8	13.2	12.5	23.8	-168	112

Source: own elaboration based on Table 1.

This table presents descriptive statistics for the variables included in the econometric model, covering 100 observations. The observations show that high standard deviations and spreads between the minimum and maximum values indicate the presence of outliers, which may affect model estimation. In the next part of the study, diagnostic tests were performed, and estimators resistant to heteroscedasticity were considered. In connection with the above, correlations between variables are also presented (data shown in Table 3).

Table 3. Correlation coefficients, using observations 1–100 with a 5% critical value (two-tailed) = 0.1966 for n = 100.

y	x1	x2	x3	x4	
1.0000	0.6565	-0.1159	-0.0912	-0.0419	**y**
	1.0000	-0.1134	-0.0064	-0.0246	**x1**
		1.0000	0.2272	-0.0484	**x2**
			1.0000	0.0543	**x3**
				1.0000	**x4**
	x5	**x6**	**x7**	**x8**	
	-0.0137	0.2744	-0.0161	-0.1117	**y**
	-0.0117	0.2587	-0.0131	-0.0775	**x1**
	-0.0348	-0.0468	-0.0340	0.1588	**x2**
	0.0141	0.0026	0.0132	0.5475	**x3**
	-0.0329	-0.0291	-0.0356	-0.0059	**x4**
	1.0000	0.1524	0.9996	-0.1069	**x5**
		1.0000	0.1469	-0.0433	**x6**
			1.0000	-0.0994	**x7**
				1.0000	**x8**

Source: own elaboration.

Table 3 presents Pearson's correlation coefficients between the dependent variable (market capitalization-y) and explanatory variables (x_1-x_8), calculated based on 100 observations. The critical value for the 5% significance level is 0.1966, which means that only correlations exceeding this absolute value can be considered statistically significant. As can be seen, the EV variable shows the strongest correlation with market capitalization (y), confirming its potential collinearity.

The other variables show low or very low correlations with the variable describing the market capitalization of the listed companies under study. However, in this case, it is worth noting the high correlation between P/S and EV/R, which may indicate strong collinearity and the need to consider their selection in the model.

The estimation process of the econometric model described above in the Gretl program showed that out of the eight independent variables, only two variables, EV and P/B, have the greatest impact on market capitalization (MC). The data are presented in Table 4.

Table 4. Model 1: OLS, using observations 1-100. Dependent variable: y.

Specification	Coefficient	Std. Error	t-ratio	p-value	
Const	37.3878	17.3453	2.155	0.0336	**
x1	0.638386	0.0798339	7.996	<0.0001	***
x6	0.906893	0.635076	1.428	0.1565	
Mean dependent var	119.4167		S.D. dependent var	193.6588	
Sum squared residual	2069255		S.E. of regression	146.0566	
R-squared	0.442680		Adjusted R-squared	0.431189	
F (2, 97)	38.52365		P-value(F)	4.85e-13	
Log-likelihood	−638.7703		Akaike criterion	1283.541	
Schwarz criterion	1291.356		Hannan-Quinn	1286.704	

Source: own elaboration.

The econometric model estimated above achieved a coefficient of determination R2 of 0.4427, which means that approximately 44% of the variability in market capitalization was explained by the explanatory variables. The adjusted R2coefficient had a similar value (0.4312) when considering the number of variables in the model. The F statistics ($F (2.97) = 38.52$; $p < 0.00001$) also confirmed the significance of the entire model.

The coefficient value for variable x1 (EV) is positive and statistically significant, indicating a strong relationship between the value of a company and its market capitalization. Variable x6 (P/B) did not reach the appropriate level of statistical significance, but among the other independent variables excluded from the model, it had the strongest impact on the MC variable, which may suggest its minimal explanatory power in the current model specification.

In the next part of the study, an authoress estimated the same econometric model using the R program. After eliminating zero values from the data used to build the model, the number of observations decreased from 100 to 61. As a result, R2 increases to 0.620, which confirms that the EV and EV/EBITDA variables have the strongest impact on market capitalization. The data are presented in Tables 5 and 6, respectively.

Table 5. Linear regression model II results.

Variable	Coefficient β	Standard error	t-statistic	p-value	VIF
Intercept	13.129	20.942	0.627	0.533	
EV	0.872	0.063	13.777	<0.001	1.08 (no collinearity)
P/E	-0.317	0.213	-1.487	0.143	1.32 (no collinearity)
Forward P/E	0.314	0.152	2.067	0.044	6.12 (moderate correlation)
PEG	-0.893	1.093	-0.817	0.418	1.10 (no collinearity)
P/S	0.055	0.264	0.208	0.836	71.47 (very strong collinearity)
P/B	0.641	0.263	2.438	0.019	1.45 (no collinearity)
EV/R	-0.356	0.312	-1.141	0.259	58.50 (very strong collinearity)
EV/EBITDA	0.487	0.173	2.812	0.007	3.23 (no collinearity)

Source: own elaboration.

Table 6. Final model 2 fit statistics.

Indicator	Value
Number of observations	61
R^2	0.620
Adjusted R^2	0.607

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Standard error of residuals	94.15
F statistic	47.39
p-value (for the model)	<0.001

Source: own elaboration.

The statistics of the second final model clearly indicate that the estimated econometric model is well fitted (over 60% of the variance explained by the predictors). Nevertheless, it follows that indicators related to company value are extremely useful in the process of increasing listed companies' capitalization.

Among the analyzed variables, statistical significance at $p<0.05$ level was demonstrated by the EV variable ($\beta = 0.872$), F P/E ($\beta = 0.314$), P/B ($\beta = 0.641$), and EV/EBITDA ($\beta = 0.487$). The other variables did not reach the required level of significance, which may indicate their limited predictive value in the context of the presented model.

In addition, collinearity analysis was performed using the VIF index (Table 5), which showed that the variables P/S (VIF=71.47) and EV/R (VIF=58.50) had very high values, indicating a strong correlation with other predictors and a potential threat to the stability of the estimation. The other variables showed acceptable levels of multicollinearity (VIF < 5), confirming their structural independence.

5. Discussion

The results of the analyses confirm that the level of technological advancement and the degree of implementation of artificial intelligence algorithms significantly differentiate the financial and market condition of the industrial companies surveyed. The most important conclusion from the econometric model estimates is the dominant role of indicators related to enterprise value (EV and EV/EBITDA), which proved to be the most significant predictors of market capitalization. This result is consistent with previous studies indicating that enterprise value reflects both current operating efficiency and the ability to generate future cash flows, which is particularly important in capital- and technology-intensive sectors (Nazar and Dwiarso 2023; Octaviany et al. 2021).

The strong correlation between EV and capitalization confirms hypothesis H1 and indicates that the market rewards companies that use resources effectively, implement digital technologies, and demonstrate financial stability. At the same time, the results suggest that traditional market indicators, such as P/E, PEG, and P/S, have limited explanatory power for the market capitalization of industrial companies using AI. This may be because companies that invest heavily in digital technologies often have unstable short-term profits, which weakens the interpretability of net profit-based indicators (Freihat 2019; Usman et al. 2020). Thus, hypotheses H2–H5 are not clearly confirmed.

An interesting result is the moderate but statistically significant role of the P/B ratio, which in the R model showed an impact on market capitalization. In the industrial sector, where fixed assets are a key element of the asset structure, the ratio of market price to book value may reflect both the efficiency of infrastructure use and the level of innovation in production processes (Chen, Zhang, and Chen 2001). This result partially confirms hypothesis H6.

In turn, the very high collinearity of the P/S and EV/R ratios indicates that both measure similar aspects of companies' operations—primarily their ability to generate revenue in relation to market value. High VIF values suggest that their simultaneous use in predictive models may lead to estimation instability, which is consistent with the observations of other researchers analyzing companies with diverse revenue structures (Yeh and Chi 2025). As a result, hypotheses H5 and H7 were not confirmed in the current model.

The results of the study also emphasize the importance of EV/EBITDA as an indicator describing operational efficiency independent of the financing structure. Its significance in the R model confirms that the market rewards companies that generate stable operating profits, which is particularly important in the context of implementing costly AI technologies. Thus, hypothesis H8 is confirmed.

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When comparing large corporations and the MSME sector, the analysis reveals clear technological asymmetries. Large enterprises, with their extensive IT infrastructure and capital enabling the implementation of advanced algorithms, achieve higher financial performance and market stability indicators. At the same time, smaller entities, despite their limited access to data and resources, play an important role in the innovation ecosystem by providing of specialized outsourcing services, as confirmed by previous studies (Roux et al. 2023; Segarra-Blasco and Tomàs-Porres 2025). The results suggest that although the scale of operations affects the pace and scope of AI implementation, the MSME sector remains a key element of the technology value chain.

It is also worth noting that data limitations, especially in the case of smaller companies, can affect the accuracy of model estimates. The lack of complete financial data, differences in reporting standards, and volatility in operating results can lead to underestimation or overestimation of certain indicators. This is consistent with observations in the literature on information asymmetry in the MSME sector (Forés and Camisón 2016; Love and Roper 2015). In summary, the research findings indicate that:

- Enterprise value (EV) remains a key determinant of capitalization, regardless of company size,
- Earnings-based metrics (P/E, PEG) are becoming less relevant for companies investing heavily in AI,
- Technological differences between large companies and MSMEs are clear, but smaller entities play an important role in innovation processes,
- AI implementation strengthens financial resilience but requires adequate infrastructure and resources.

These results open space for further research. Particularly in dynamic analysis of the impact of AI investments on financial performance, sectoral comparison (e.g., heavy industry vs. high-tech manufacturing), assessing the impact of data quality on predictive models in corporate finance or examining the role of cooperation between large companies and the MSME sector in building AI ecosystems.

6. Conclusions

The research conducted in this study confirmed the statistical significance between the selected financial indicators and the market capitalization of industrial companies using artificial intelligence algorithms. Variables such as EV, forward P/E, P/B ratio, and EV/EBITDA had a particularly significant impact on capitalization value. The estimated linear regression model is characterized by good fit quality because its parameters confirm the accuracy of the adopted specification.

Collinearity analysis revealed an excessive correlation of the P/S and EV/R variables with the other predictors, which led to the estimation of a reduced model. The version of the econometric model carried out in the R program retained its statistical significance, because the stability of the estimation process was significantly improved because of variable selection.

The results of the study confirm that the implementation of AI algorithms in the industrial sector correlates with a higher market value of companies, regardless of their size. Small and medium-sized enterprises, although less capital-intensive, play an important role in the so-called "ecosystem" of innovation, supporting large economic entities through activities such as outsourcing. In addition, the use of indicator analysis in combination with regression modelling allows for a deeper understanding of the mechanisms influencing financial performance and the level of technological innovation.

One limitation of the study was the reduction in the sample size from 100 companies to 61, although this resulted in an improvement in the final statistics of the model. Nevertheless, this article contributes a kind of cognitive value to science that is worth discussing, especially in the context of increasing the role of MSMEs in the development of AI-supported financial management systems. In view of the above, there is a need for further in-depth research on the structure of the relationship between various financial indicators and the implementation process, considering the introduction of modern technological solutions supported by artificial intelligence.

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