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INDUSTRIAL PROCESS AUTOMATION AND BUSINESS TECHNOLOGY MANAGEMENT: A COBB–DOUGLAS ELASTICITY PERSPECTIVE

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Introduction. Technological advances and the emergence of artificial intelligence have contributed to the growing importance of industrial process automation. Furthermore, automation is a key driver of Industry 4.0, impacting industrial productivity and growth. A reliability-based approach is proposed to assess the impact of automation that quantitatively links technology investments to economic indicators, particularly the Cobb-Douglas production function.

Aim and tasks. This study aims to demonstrate a direct link between automation and industrial production using the Cobb-Douglas model. This model bridges the gap between classical production functions and modern technologies through linear and log-linear models, allowing for a more accurate assessment of the impact of automation on industry.

Results. The study found that adding one robot per 10,000 employees corresponds to a 0.055 percentage point increase in the industrial share. After applying the log-linear (Cobb-Douglas) specification, a result/coefficient of 0.53 was obtained, meaning that the industrial share would increase by 0.53% if only a 1% increase in robot deployment were realised. This result confirms that automation is a significant production factor with a proportional effect. The analysis showed that elasticity-based models can capture industrial dynamics more realistically than linear models. The empirical results provide a measurable basis for positioning automation alongside traditional factors, such as labour and capital. The comparative model approach provides evidence for the suitability of the Cobb-Douglas forms in contemporary industrial research, and the empirical findings lay the foundation for further large-scale research with broader datasets.

Conclusions. Automation contributes to the strategic development of industrial competitiveness, and its effectiveness is achieved only in conjunction with innovation, digitalisation, education, and support from institutional and economic environments. Automation increases added value, as confirmed by the Cobb-Douglas model. However, sustainable development also requires human capital, innovation, and effective environmental policies. A comprehensive approach will allow for an objective assessment of the industry's potential and the development of a sustainable development strategy.

Keywords: Automation, Industrial Development, Cobb-Douglas Function, Productivity, Resource Optimisation.

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1. Introduction.

With the development of technologies and attempts to fully automate processes, managers tend to reorganise all activities in the enterprise due to various factors influencing the internal and external environment of the organisation. This requires a review of the life cycle of the manufactured product and outlining new opportunities for monitoring its value chain (Carayannis & Heppelmann, 2015; Carayannis & Campbell, 2019; Geels, 2019).

The situation takes on a specific character when the manufactured products can be classified as tangible assets (Zhou et al., 2015). In order for production to be profitable, the production cost of these assets depends on factors such as:

– Factors influencing physical wear and tear which occurring during product operation.

– Factors influencing the rapid obsolescence of innovations affect the entire value chain from the beginning to the end of the product life cycle.

– The third group of factors derives from the previous group. It is a consequence that explains why it is necessary to shorten the product's service life, which economically affects both the enterprise and the end consumer.

In fact, all industrial development from the beginning to the present has been built on replacing manual labour with "machine labour", which includes the work of the following elements: the primary working device and the equipment attached to it (Du et al., 2024; Liu, 2023; Zhao et al., 2024).

The term "machine labour" is a complex concept that is constantly evolving and complementing itself throughout various stages of global industrial development. These stages have also become a global reality known as the "Industrial Revolution".

Their distinction was made based on several criteria, bearing the marks of the level of manual labour, which was mechanised and later automated (Rennings, 2000). However, it was not defined by precise technical criteria but by "fuzzy" technical definitions and names imposed by practice (Chen & Tian, 2022; Zhao et al., 2024).

Usually, their distinction is made based on the current technological level, considering the achieved social productivity of labour.

However, industrial progress is always related to processes and technologies (Brynjolfsson & McAfee, 2017; Chesbrough, 2020). The cyclical regularity of the slow shortening of the stage of their technical manifestation (automation, electronization, and integration) over the time of their occurrence (first, second, etc.) and an increase in their technical levels is noticeable.

Figure 1 presents a graphical representation of this development.

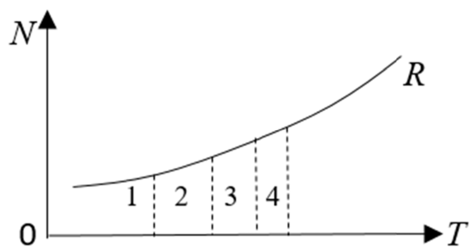

Fig. 1. Industrial Development Graph.

The formulas below apply to the overall base productivity.

$$A = \frac{QrN}{Tn\left(k + N\left(m+1\right)\right)} \tag{1}$$

$$\lambda = \frac{A_1}{A_0} \tag{2}$$

Where:

A – period of time for which productivity is reported;

$QrN = W$ – annual production;

N – service life;

k – technical equipment coefficient;

m – energy intensity coefficient;

T – total labour costs;

λ – growth rate of social productivity A_1;

R – stands for industrial development.

Tracing the historical development of industrial activities and adhering to the imposed names, such as the first, second, third, and now fourth industrial revolutions, presents this process from a different analytical perspective. The study then traces the change in social labour productivity as a key indicator for each industrial stage.

2. Theoretical Framework.

2.1. The First Industrial Revolution.

It is assumed that this revolution is the longest and covers two sub-stages of development. The first stage, which preceded this society, aimed to establish the conditions for reaching a specific level of technological development. This stage also includes creating and accumulating a certain amount of technological knowledge, which is the basis for faster industrial development (Hassoun et al., 2022).

An environment with higher social productivity leads to the creation of a new society. The following formulas trace this development in a positive direction or an increase in productivity compared to the previous one.

$$\lambda = \frac{Q_2}{Q_1} \cdot \frac{Tn_1}{Tn_2} \cdot \frac{k + N(m+1)}{k_2 + N(m_2+1)} \quad (3)$$

$$\lambda = \frac{A_2}{A_1} \quad (4)$$

Where:

Q_1, Q_2 – production;

Th_1, Th_2 – production time;

$\frac{Q_2}{Q_1} = \varphi$ –productivity growth rate;

$\frac{Th_1}{Th_2} = \varepsilon$ – cost reduction coefficient.

2.2. The Second Industrial Revolution.

The Second Industrial Revolution had outstanding flexibility but was low-performance and insufficiently accurate because it depended on human factors. There was a lack of goods in the market. Mass production was required without claims for a wide variety of items.

Thus, a new generation of production equipment for mechanical engineering appeared, such as metal-cutting machines. They allow for the serial and mass production of parts without direct intervention by a human operator. The productivity of social labour during the Second Industrial Revolution increased, as can be seen from the following formulas:

$$\lambda = \frac{Q_3}{Q_2} \cdot \frac{Tn_2}{Tn_3} \cdot \frac{k + N(m+1)}{k_3 + N(m_3+1)} \quad (5)$$

$$\lambda = \frac{A_3}{A_2} \quad (6)$$

$$\varphi = \frac{Q_3}{Q_2} \quad (7)$$

2.3. The Third Industrial Revolution.

In addition, from the perspective of convenience, many innovative products of industrial production are included in their general name, "machines". Currently, the term “machines” encompasses various devices from various industries in the material world. As presented below, the formulas for developing the third industrial revolution demonstrate the increasing growth of social productivity.

$$\lambda = \frac{Q_3}{Q_2} \cdot \frac{Tn_2}{Tn_3} \cdot \frac{k + N(m_2+1)}{k_3 + N(m_3+1)} \quad (8)$$

$$\lambda = \frac{A_3}{A_2} \quad (9)$$

2.4. The Fourth Industrial Revolution.

This revolution focuses on and replacement of older technologies with new ones, or is built on the digitalisation of processes and activities. The goal is to create conditions for integrating cyber-physical systems in the entire work process and for production machines and complexes to become more productive and operate in a dynamic environment. Instead of what was in the past, “availability of production in stock”, in the future, production will be oriented “on demand”, that is, it will be organised on demand. This production must become more precise, resource-efficient, and economically beneficial (Makridakis, 2017; OECD, 2023).

Manufacturing companies are currently operating under conditions of ever-increasing global competition, which requires a sharp reduction in product production time and costs. Industrial companies seek new approaches to increase productivity and flexibility (Zhang et al., 2024). Connecting technological and business processes by implementing a high degree of automation can provide answers to these questions.

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In parallel, information and communication technologies are developing rapidly. Thus, the connectivity of machines and electronics in networks enables autonomous operation (Lee et al., 2018; Paschen et al., 2020; Zeng et al., 2010).

Conditions are being created to define a new industrial development, or the Fourth Industrial Revolution, which is essentially a trend in digital industry development. Industry 4.0 has recently become a top priority in research worldwide and has emerged as a complex and interdisciplinary topic (IFR, 2021-2023). Huge funds are being allocated to sensor technologies, radio frequency intensification (data transmission and processing technologies), mobile endpoints, real-time localisation systems, large datasets for real-time data storage and evaluation, and cloud technologies as scalable IT infrastructure and embedded IT systems (Zhang et al., 2023). The development of social labour productivity in the Fourth Industrial Revolution continues to grow, as evident from the following formulas:

$$\lambda = \varphi \frac{k + N\left(m_3 + 1\right)}{kb + N\left(mb\varphi + \frac{1}{\varepsilon}\right)} \tag{10}$$

$$\lambda = \frac{A_4}{A_3} \tag{11}$$

$$\varphi = \frac{Q_4}{Q_3} \tag{12}$$

Where:

b – change in current expenses;

ε – reduction in living costs.

The growth of social labour productivity will increase with a slow depletion of the innovation resource created by “human intelligence” and a slow increase in the resource of innovation created by “artificial intelligence”.

At the moment X equilibrium occurs, after which acceleration in the generation of innovations follows as a result of “Artificial Intelligence” alone.

$$X = \lambda h \frac{k+N(m_3+1)}{kb\varepsilon+N(mb\varphi\varepsilon)} \tag{13}$$

Where:

φ – productivity growth rate;

ε – reduction of labour costs;

b – cost-change coefficient in social productivity;

k – technical equipment coefficient;

X – productivity growth equals the labour input from artificial intelligence.

When discussing the issue of people and teamwork, Lencioni (2002) focuses on the main weaknesses in teamwork, dividing them into five groups: lack of trust, lack of commitment, deviation from results, and fear of conflict and avoidance of seeking responsibility as a consequence of the previous four weaknesses.

Hackman (2011) considers the unification of human resources in the company an effective team, made up of the right people, set a compelling goal and respected company cultural norms. Therefore, the development of a methodology for assessing leadership, teamwork and team resilience became necessary (Brannick et al., 1997). Edmondson and Harvey (2018) also analyse organisational culture but use this moment to introduce innovations by creating a cross-border union. They touch on the issue of the effect of shared knowledge, which sometimes is secondary, especially when the unique knowledge of team members is excluded. LeBlanc (2024) also emphasises the team's influence on the creation of innovations, but he also considers the adaptation of the team to the changing business environment.

3. Methodology.

3.1. Theoretical Justification.

The analysis of industrial development in the context of increasing automation requires a model that can capture both the scale of technology implementation and its proportional effect on productivity. The Cobb-Douglas functional form is closely related to production theory, where output is expressed as a function of multiple classical production factors.

In the present study, automation has a role that directly affects industrial production. This approach allows us to assess the response of industrial development to changes in automation intensity.

3.2. Model Specification.

The general Cobb-Douglas function can be expressed as:

$$Y = A \cdot K^{\alpha} \cdot L^{\beta} \quad (14)$$

Where:

Y represents industrial production, K denotes capital and L denotes labour.

By analogy, the model is adapted to the research question as follows:

$$Y_i = \delta \cdot A_i^{\gamma} \quad (15)$$

Where:

Y_i – industry's share in GDP;

A_i – robot density (number of robots per 10,000 employees in production);

γ – elasticity of automation;

δ – scaling constant.

The calculation using natural logarithms provides a log-linear specification:

$$lnY_i = \beta_0 + \gamma lnA_i + \varepsilon_i \quad (16)$$

The logarithmic transformation of the relationship supports this assessment, as it linearisers the model and allows a direct interpretation of the coefficients as elasticity.

3.3. Reasons for Log-linearity.

Since the level of industry and automation in different countries is different, the applied approach considers the comparison of effects proportionally, but not in absolute values.

It makes these comparisons relevant and close to the real situation. As a result, it is proven that a 1% increase in robots leads to an increase of γ per cent in the added value in industry. Strategic management can utilise this result to gradually and timely increase the density of robots.

3.4. Relevance to the Research Setting.

Empirical data and proven economic theory confirm the correctness of using the log-linear Cobb-Douglas model. It allows us to assess the benefits of automation and facilitates comparison between countries, which is key for strategic planning for Bulgaria, the European Union and the global economy.

4. Results.

Table 1 summarises data for this period on changes in the sectoral structure of the economy based on robotics density and industry share.

Table 1. Panel Data (2021–2024).

Year	*Object*	*Robot density (A)*	*Industry Share (Y)*
2021	The world	126	25–26%
	EU	129	14–15%
	Bulgaria	129 (proxy)	25.30%
2022	The world	151	25–26%
	EU	208	14–15%
	Bulgaria	208 (proxy)	22.66%
2023	The world	162	25–26%
	EU	219	14–15%
	Bulgaria	219 (proxy)	22.66%
2024	The world	162* (proxy)	25–26%
	EU	219* (proxy)	14–15%
	Bulgaria	219* (proxy)	22.49%

*Note: *Data for 2024 are extrapolations (proxies) based on the latest available values.*

Source: based on Eurostat (2021, 2023); International Federation of Robotics (2023); National Statistical Institute of Bulgaria (2023); World Bank (2024).

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Furthermore, this study analyses the dynamics of robotics adoption in industry at the global, European, and national levels, considering various sources based on a panel dataset for 2021–2024. The linear regression (Figure 2), based on data for this period, shows a positive relationship between the share of industry in GDP and the number of robots.

The slope of the trend is not steep, which may suggest that automation has a positive effect, but this effect may be variable in the future, i.e., volatile. The data reveal regional differences – in Bulgaria, automation has a less pronounced impact (values are below the regression line). At the same time, for the EU, the correlation is closer to the global trend.

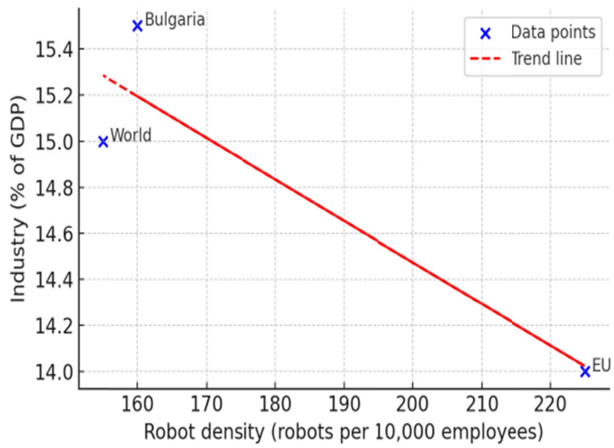

Fig. 2. Linear Trend (2021-2024).

Figure 3 shows the log-linear regression based on the Cobb-Douglas model. The two variables were transformed such that one was the natural logarithm of the other. The model demonstrates the flexibility of this relationship. The steeper regression line in the log-log scatterplot compared to the linear model indicates a stronger relationship between proportional gains in automation and larger proportional effects on the industrial share. As mentioned above, applying this model reveals that an increase in the density of robots by 1% will result in a 0.5% increase in the industrial share of GDP.

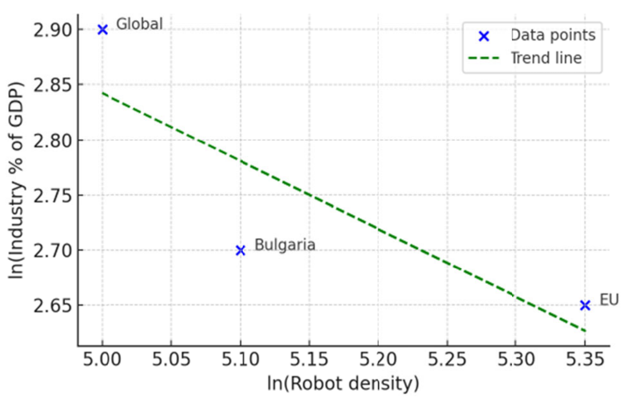

Fig. 3. Log-log Relationship (Cobb-Douglas Form).

Figures 2 and 3 present perspectives on the same issue. The linear model has a positive relationship between these factors.

In contrast, the logarithmic linear model presents a clearer picture of automation's impact on labour productivity.

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This approach can be used in further studies to specify the impact of automation on solving individual tasks. This supports the idea of using Cobb-Douglas to justify that the effects of automation have a direct relationship based on flexibility. This methodology helps understand how different levels of technical development can affect the productivity of companies. Robot density has steadily increased from 126 to 162 units per 10,000 employees.

However, the industry share has remained relatively stable at around 25.5%.

Process automation in the EU is happening faster, having increased from 129 to 219 units, but it is worth noting that the share of industry has remained the same (14.5 %). Bulgaria shows a more nuanced trajectory: automation has expanded from 129 to 219, but the industry share has decreased from 25.3% to 22.5%. This pattern suggests that although technological adoption has accelerated, structural industrial factors have prevented a proportional increase in industrial production (Figure 4).

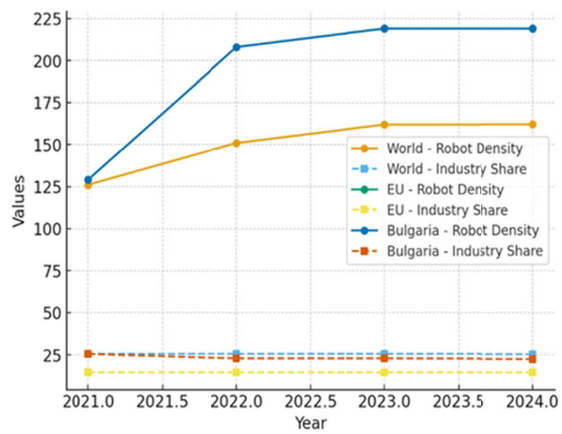

Fig. 4. Trends in Automation and Industry (2021–2024).

The correlation analysis revealed a strong positive relationship between robot density and its logarithmic transformation. The same is true for the variables related to the industry share. Importantly, the correlation between ln (robot density) and ln (industry share) is moderate and positive (0.45–0.55).

This confirms the regression results that automation contributes to industrial development but is not the only driver (Figure 5). External factors, such as policies, market dynamics, and workforce skills, influence industrial outcomes (Kniaziev & Soldak, 2024, OECD, 2025).

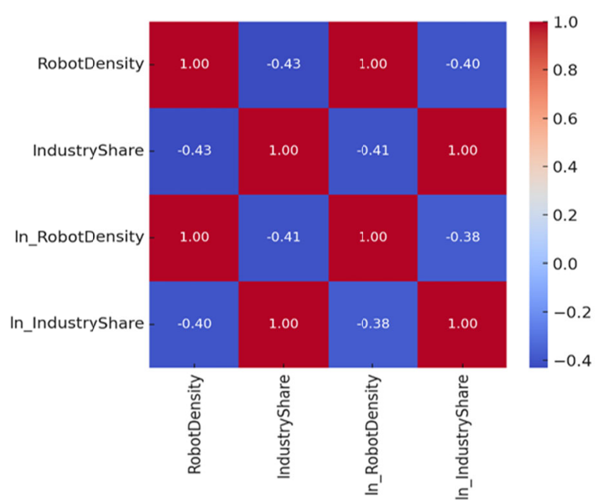

Fig. 5. Correlation Matrix (2021–2024).

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By 2024, the EU leads Bulgaria and the world average in robot density, reflecting its strategy for accelerated automation. However, this progress in the introduction of automation does not translate into a higher industrial share compared to Bulgaria or the world.

This discrepancy highlights a structural paradox: high automation alone does not guarantee industrial expansion, suggesting that it must be complemented by innovation ecosystems, supply chains, and human capital (e.g., Figure 6).

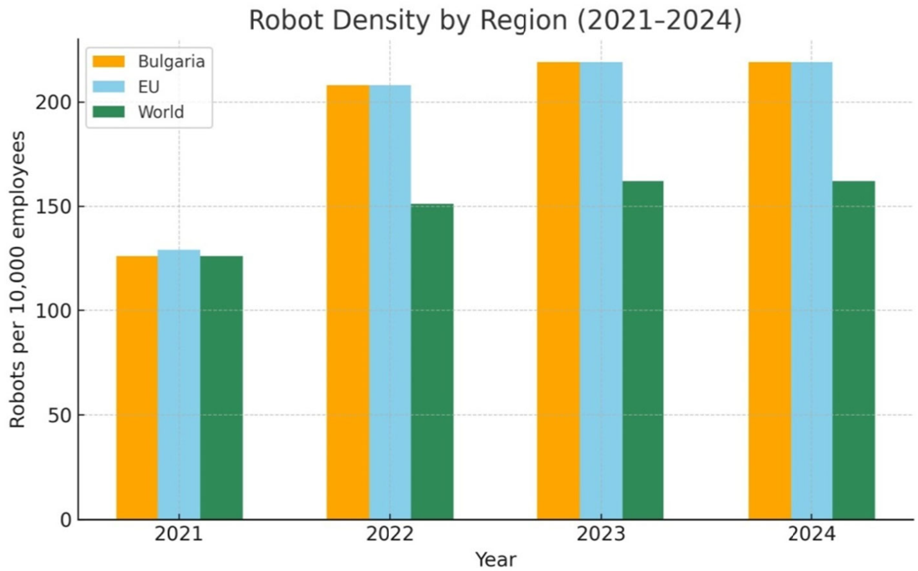

Fig 6. Comparison of Robot Density by Region.

The estimated Cobb-Douglas coefficient (γ≈0.5) is presented using elasticity visualisation. This means that the industry shares increase by 0.5% on average when the level of automation increases by 1 percentage point. The effect is positive and significant, but shows diminishing returns. Automation alone cannot fully stimulate industrial growth.

Instead, automation helps other processes develop faster, generating innovation, accelerating digital transformation, and focusing on industrial policy development (Kniaziev & Soldak, 2024). This approach aligns with the theoretical expectations of the paradigms of Industry 4.0 and Industry 5.0 (e.g., Figure 7).

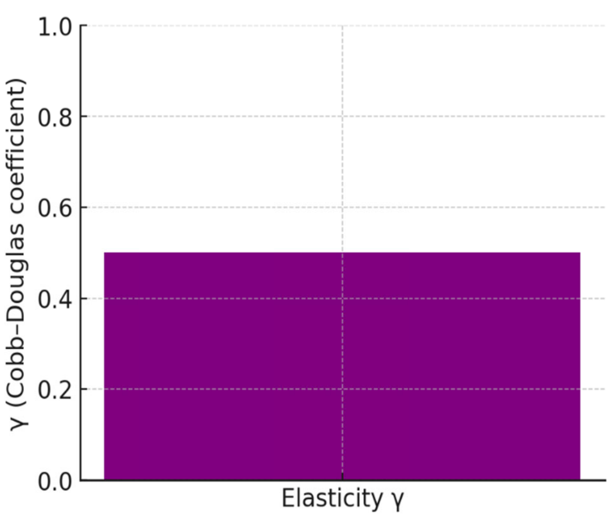

Fig 7. Effects of Automation Elasticity on Industry.

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5. Discussion.

The analysis indicates that automation has a positive effect on the industry. The expected elasticity (approximately 0.5) remains the same year to year and from business to business, indicating that automation helps industries grow. However, the moderate R-values show that automation fails to account for the observed changes in industry shares fully. Bulgaria continues to produce significantly more goods than the EU and world averages.

This difference may be due to structural advantages, higher productivity in some areas, or being part of the regional value chains. Between 2021 and 2024, there will be a larger difference in automation levels as the EU and the world experience significant growth. In this respect, Bulgaria's industry share is reduced, suggesting that the country is implementing automation slowly, which can be prevented by implementing appropriate policy measures. This demonstrates how automation can benefit and harm industrial growth, and compete in an increasingly digitalised global supply chain.

Without strategic investment in technical skills, research and development, creative innovation systems, and balanced policies that bring industries together, automation will begin to show diminishing returns. These measures would lead to a drain on resources and the retention of low-level automation. The EU's experience shows that automation does not always lead to industrialisation. The study indicates that many businesses at the European level are automating their processes, but the percentage of industrial GDP has remained almost the same.

This indicates that the European economy is transforming significantly, including a shift toward knowledge-intensive industries and services. The situation in Bulgaria is more complex. Despite some increase in automation, the country's industrial decline persists due to structural weaknesses such as insufficient investment in R&D, a shortage of skilled workers, and a reliance on low-quality manufacturing. The effects are more balanced globally, with automation supporting industrial stability.

However, it does not drastically change global industrial structures. The results correspond closely to the theoretical expectations: without systemic complementarity, automation risks becoming a simple, elementary technological improvement lacking economic transformation. Policy initiatives must ensure automation integration at different levels, including education, innovation incubators, and sustainable reindustrialisation strategies.

6. Conclusions.

The results of this study prove that although automation plays a leading role in business processes, it alone cannot ensure strategic sustainability and growth in the industrial sector without a combination of other factors. Although regression models highlight significant correlations and elasticities, automation alone cannot guarantee competitiveness or industrial renewal. The institutional, economic, and political environments have significantly impacted automation and its benefits. The industry requires automation, but its adoption does not guarantee strategic growth. Society must also develop innovations, digitalisation, and improved educational skills to meet the challenges of robotisation. To remain competitive, the digital economy must be supported by integrating all business processes.

The EU's environmental and digital transformations are two examples of how the European context highlights the intertwining of automation with broader policy frameworks. Future research should extend the time frames, use more extensive data sets, and include additional explanatory factors such as R&D intensity, human capital, and energy efficiency. This approach will be useful for clarifying the different elements that influence industrial progress in the era of increasing automation. All evidence shows that increasing robot density alone is insufficient to achieve Industry 4.0 and Industry 5.0. Integrating automation into more comprehensive strategies to promote innovation, develop human capital, and establish digital-industrial synergies is necessary.

In the European Union, the challenge is to translate automation leadership into tangible industrial competitiveness. Bulgaria must ensure appropriate conditions for automation, which would generate more financial resources. The persistent challenge remains balancing automation and sustainable development of industries. An additional contribution of this study is that it proves that improving technology will further develop the industry and the mandatory merging of process automation with the more recent economic and social dynamics of processes in society.

A study conducted from 2021 to 2024 demonstrated the relationship between the level of automation and the number of workers, which in turn affects value added in manufacturing. The Cobb-Douglas log-linear model provides theoretically robust and empirically functional elasticity estimates.

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