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# Content

# Assessment of the impact of unemployment and GDP on the average wage and forecast of the average wase in the Czech Republic

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**Abstract**

The aim of this thesis was to evaluate the impact of unemployment and GDP on the average wage in the Czech Republic from 2011 to 2023 and to create a forecast for the average wage for the year 2024. Statistical methods including correlation and regression analyses were employed to assess the influence of unemployment and GDP on the average wage in the Czech Republic. The results revealed an inverse relationship between unemployment and the average wage, while GDP had a positive effect on the average wage. The forecast for the average wage in 2024 was 53,098 CZK, indicating continued growth. The research provided valuable insights for policymakers and other stakeholders. The main limitations of the study include the omission of additional factors such as changes in tax policy, inflation, and technological innovations, as well as reliance on historical data.

**Keywords:** Average wage, gross domestic product, unemployment, prognosis, regression

## Introduction

In the current economic environment, analyses and predictions of the average wage in the Czech Republic are of fundamental importance not only for economic policy and business decisions, but also for individuals and households. The dynamics of the average wage reflect the economic development of the country, social changes and the level of the population's standard of living. Therefore, it is crucial to understand the social demand for accurate and reliable prediction of the average wage and its importance for the economy and society as a whole. That is why I decided to focus on the forecast of the average wage in the Czech Republic and evaluate the factors that influence it.

Research conducted by Meixnerová & Krajnák (2020), which examined the impact of macroeconomic indicators such as GDP, unemployment, implicit tax rate on labor and consumer price index on minimum and average wages in the V4 countries, is one of the models for this work. Its conclusions support the importance of predicting the average wage and show that macroeconomic factors have a significant impact on this prediction. Another research indicating that long-term trends in the economy can affect the level of the average wage in the future is the analysis of the economic development of the Czech Republic by Bílková (2023). This provides us with additional context for predicting the average wage in the future. Another work focusing on a macroeconomic factor with an impact on the average wage is the research on the progressivity of personal income tax in the Czech Republic (Krajnák 2023). The structure of the tax system can have a significant impact on individual incomes and thus on the average wage in the country.

Society is not only the recipient of wages, but of course also a fundamental factor directly influencing the level of wages. It is not only about education, experience and development, but also about secondary social pressures on wage equality. It is precisely social policy that Turečková et al. (2022) focused on in their work. They used income inequality as an indicator for measuring the effectiveness of social policy. Their study can help me understand how social policies affect the structure of income and thus the level of the average wage.

Employers and employment as such are the third most important factor and, together with the already mentioned company and the state, the most influential factors on wages. At the same time, however, it is not true that the offer of a higher wage is the only motivation for a person to change jobs and thus increase wages. People evaluate jobs according to many factors. A look at the quality of employment and the fact that differences in wages are not the only factor in assessing the quality of employment was prepared by Ledic & Rubil (2021). This gap can affect the level of the average wage, because the quality of employment can influence individuals' decisions regarding their employment and remuneration - wages.

The aim of the work is to conduct a detailed assessment of the impact of unemployment and GDP on the average wage in the Czech Republic for the years 2011-2023 and to make a short-term forecast of the average wage in the Czech Republic for 2024.

In connection with the objective, the following research questions are set:

*VO1: What is the impact of unemployment and GDP on the average wage in the Czech Republic? The period 2011-2023 will be evaluated.*

*VO2: What will be the development of the average wage in the Czech Republic based on the influence of GDP and unemployment in 2024.*

## Methods and Data

**Date**

The source of data for Average Wages 2011-2023, GDP 2011-2023, GDP Forecasts 2024 and Unemployment 2011-2023 will be the Czech Statistical Office (CZSO, 2024). These data will be used to answer VO1 using analysis. Secondary data from the Ministry of Finance of the Czech Republic (Ministry of Finance of the Czech Republic, 2024) and their Macroeconomic Predictions – April 2024 will also be used. The source of the unemployment value will be the analysis by Zeman (2024) from the analysis published under the banner of the Institute for Politics and Society. As part of the data preparation for the analysis, a check will be made to ensure that no values are missing, outliers will be identified and the normality of the data will be verified. A Z-score will be calculated to detect outliers. Data for which the Zscore exceeds 2 or falls below –2 will be considered an outlier. The Zscore will be calculated as follows. The average of all values from one group (GDP, average wages, unemployment) will be calculated. The average is subtracted from the ordinal value and raised to the power. The exponentiation will create imaginary squares and also remove negative values. The average of the squares will be calculated and then the square root of the average of the squares. This will give the standard deviation. Using the standard deviation, it will be easy to calculate the Zscore by subtracting the average of the ordinal values from the ordinal value and dividing by the standard deviation. The result will be the Zscore. Values >2 and <-2 are considered outliers.

Table 1: Consolidated secondary data

| Year | GDP mil. | Average salary | Unemployment rate |
|---|---|---|---|
| 2024 | 7447243 | It will be predicted | 0.0320 |
| 2023 | 7344421 | 43341 | 0.0270 |
| 2022 | 6786742 | 40317 | 0.0220 |
| 2021 | 6108717 | 38277 | 0.0281 |
| 2020 | 5709131 | 36176 | 0.0255 |
| 2019 | 5791498 | 34578 | 0,0202 |
| 2018 | 5410761 | 32051 | 0,0225 |
| 2017 | 5110743 | 29638 | 0,0289 |
| 2016 | 4796873 | 27764 | 0,0395 |
| 2015 | 4625378 | 26591 | 0,0505 |
| 2014 | 4345766 | 25768 | 0,0611 |
| 2013 | 4142811 | 25035 | 0,0695 |
| 2012 | 4088912 | 25067 | 0,0698 |
| 2011 | 4062323 | 24455 | 0.0672 |

Source: Own processing according to Czech Statistical Office and Ministry of Finance of the Czech Republic.

**Methods**

The normality of the data will be verified in the R software. It provides a wide range of statistical tests and graphs that allow you to examine the distribution of the data. Using the Shapiro-Wilk test to verify the normality of the data. The significance level will be set at n and $\alpha$ = 10%. Hypotheses will be set

H 0 - the assumption of normality of the data is met and H1 - the assumption of normality of the data is not met.

As part of the exploratory analysis, histograms of quantities will be compiled, which will allow a distribution and trend graph to be displayed. The basic visualization will be followed by a correlation analysis between the individual indicators. Average wage x unemployment, average wage x GDP, HPD x unemployment. Excel software and Spearman's correlation coefficient will be used to determine the correlation. The output will be coefficients ranging from 1 to –1, where strong positive correlations will be closer to +1, strong negative correlations closer to -1, and weak correlations closer to 0. These coefficients will be interpreted to answer VO1. The coefficients will also be needed to predict the average wage in 2024, but they will be different coefficients than those obtained from Spearman's correlation analysis. The correlation coefficients will show the strength of the influence and whether the influence is positive or negative. A regression analysis will be performed in Excel, which will provide us with coefficients suitable for regression for the year 2024. These coefficients will express the rate at which the quantities increase or decrease. These coefficients will be used in a linear regression with the formula

$$Y=\beta 0 +\beta 1\ X1 +\beta 2\ X2 +\epsilon, \tag{1}$$

where:

Y = average salary 2024,

β0 = will be the value of the average wage at zero HPD and zero unemployment, i.e. zero,

β1 will be the coefficient for unemployment vs average wage in 2024 from the regression analysis,

X1 will be the predicted unemployment in 2024,

β2 will be the coefficient for GDP x average wage in 2024 from the regression analysis,

X2 will be the predicted GDP in 2024.

Y will be the answer to VO2.

The expected results are an inverse relationship between unemployment and average wage, a conversion relationship between GDP and average wage. The expected result is also the predicted growth of the average wage for the year 2024.

## Results

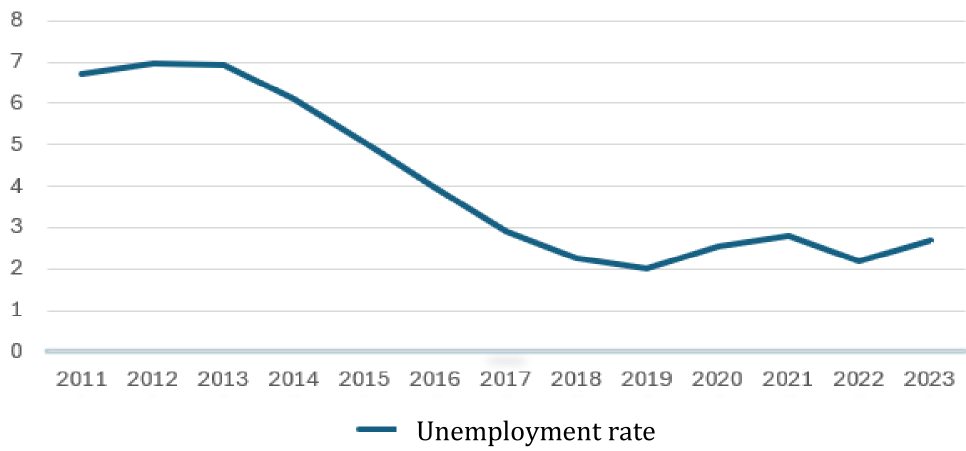
For secondary, it is confirmed that all necessary values are obtained and none are missing. 2012-2023 for GDP, unemployment and average wage. Also 2024 for GDP and unemployment. All necessary data are ready.

Outlier identification. It is performed for each of the variables separately. The values for the period 2011-2023 are averaged. The average is subtracted from each value in the series and raised to the power. The standard deviation is calculated using the average of the obtained values. Furthermore, the average initial value is subtracted from the initial value of the variable for each year and divided by the standard deviation. It is found that the only outlier deviating from the range of -2 to 2 zscore is the GDP of 2023 with a zscore of 2.05.

The normality of the data is verified in the R software for each variable separately using the Shapiro-Wilk test. For GDP, the resulting p-value is 0.3132, for unemployment the p-value is 0.01466 and for the average wage the p-value is 0.1351. Normality is met for GDP and the average wage when their p-value is higher than 0.1, which is the established significance level $\alpha = 10\%$. Unemployment does not meet the normality of the data and for rejecting H0„the assumption of normality of the data is met". H1„the assumption of normality of the data is not met" is not rejected.

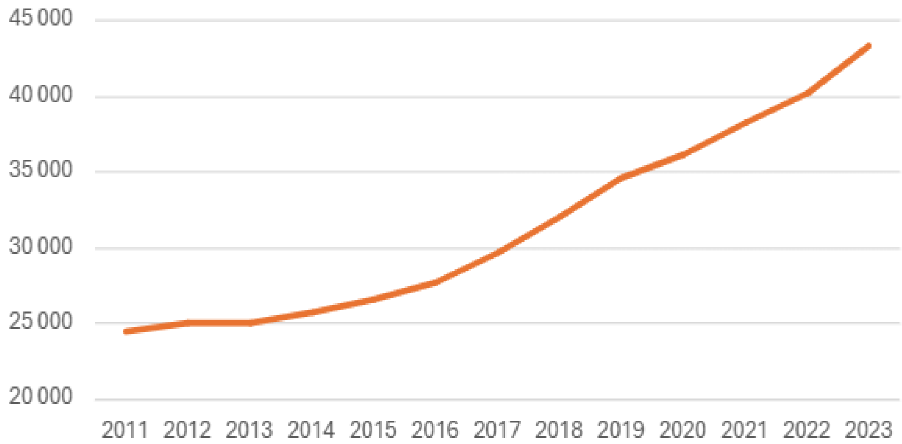
Exploratory analysis. Graphs of quantities are compiled for the research period 2011-2023.

Figure 1: Unemployment rate in the Czech Republic 2011 – 2023



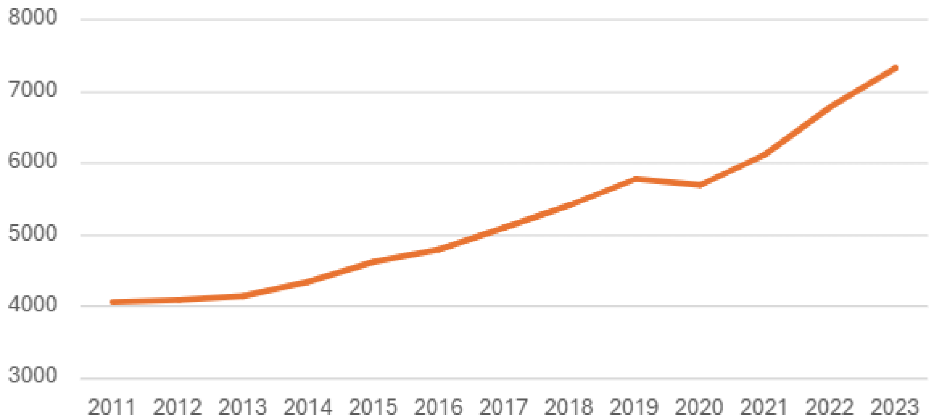

Source: Own processing.

Figure 2: Average wage in the Czech Republic 2011 - 2023




Source: Own processing.

Figure 3: Gross domestic product of the Czech Republic 2011 - 2023




Source: Own processing.

Correlation analysis. To use Spearman's rank correlation coefficient, ranks are first prepared in Excel for individual values of quantities using the RANK function. In other words, for each value of a given quantity, the order that the value would take if the values were compared according to size is determined. Each value is given its rank in the row of its quantity and it is important to maintain the order of the ranks, according to the order of the initial values. The KORREL function is then used for all combinations of rank rows. That is, GDP vs. average wages, where the correlation coefficient is rounded to 0.989. GDP vs. unemployment, the correlation coefficient is -0.863. The last correlation coefficient is average wages vs. unemployment, which is -0.841.

Table 2: Processed data with assigned ranks

| Year | GDP million | GDP Rank | Average salary | Rank average salary | Unemployment rate | Unemployment rate |
|---|---|---|---|---|---|---|
| 2024 | 7,447,243 | XXX | XXX | XXX | 0.0320 | XXX |
| 2023 | 7344421 | 1 | 43341 | 1 | 0.0270 | 9 |
| 2022 | 6 786742 | 2 | 40317 | 2 | 0.0220 | 12 |
| 2021 | 6 10871 | 3 | 38277 | 3 | 0,0281 | 8 |
| 2020 | 5 5709131 | 5 | 36176 | 4 | 0,0255 | 10 |
| 2019 | 5 5791498 | 4 | 34578 | 5 | 0,0202 | 13 |
| 2018 | 5410761 | 6 | 32051 | 6 | 0,0225 | 11 |
| 2017 | 5110743 | 7 | 29638 | 7 | 0,0289 | 7 |
| 2016 | 4796873 | 8 | 27 764 | 8 | 0,0395 | 6 |
| 2015 | 4625378 | 9 | 26591 | 9 | 0,0505 | 5 |
| 2014 | 4345766 | 10 | 25 768 | 10 | 0,0611 | 4 |
| 2013 | 4142811 | 11 | 25035 | 12 | 0,0695 | 2 |
| 2012 | 4088912 | 12 | 25067 | 11 | 0,0698 | 1 |
| 2011 | 4062323 | 13 | 24455 | 13 | 0.0672 | 3 |

Source: Own processing.

Table 3: Coefficients obtained by correlation analysis

| Coefficients | | |
|---|---|---|
| GDP x Wage | GDP x Unemployed | Salary x Unemployment |
| 0.989 | -0.863 | -0.841 |

Source: Own processing.

Regression analysis. First, it is necessary to determine the coefficients for the final linear regression. A separate regression analysis in Excel is used to determine the coefficients. The columns contain data on average wages in absolute values, GDP in absolute values (not in billions or millions), and unemployment rates, where the units of numbers are whole percentages (so the shapes of the numbers are 2.7 2.2 2.81, etc., not 0.0027 0.022, etc.). The integrated Regression function in the Data and Data Analysis tab is used. The area of average wage data for the years 2011-2023 is marked in the input area Y. The columns of GDP and unemployment for the years 2011-2023 are marked in the input area X. The Labels checkbox is checked and the regression result is generated on a new sheet of the workbook.

Table 4: Regression result in Excel

| **Regression statistics** | |
|---|---|
| Multiple R | 0.987238448 |
| Reliability value R | 0.974639753 |
| Set reliability value R | 0.969004143 |

| | |
|---|---|
| Error page value | 992.9988116 |
| Observation | 12 |

| | Difference | SS | World Cup | F | Significance F |
|---|---|---|---|---|---|
| Regression | 2 | 341059861.8 | 170529930.9 | 172.9430678 | 6.58705E-08 |
| Residue | 9 | 8874419.759 | 986046.6399 | | |
| Total | 11 | 349934281.6 | | | |

| | Coefficients | Error page value | t Stat | P-value | Lower 95% | Upper 95% | Lower95.0% | Upper 95.0% |
|---|---|---|---|---|---|---|---|---|
| Limit | -6478.261055 | 5151.963651 | -1.257435319 | 0.240243992 | -18132.81253 | 5176.29042 | -18132.81253 | 5176.29042 |
| 7.34442E+12 | 6.97644E-09 | 7.57661E-10 | 9.207870137 | 7.08059E-06 | 5.2625E-09 | 8.69039E-09 | 5.2625E-09 | 8.69039E-09 |
| 2.7 | 357.2796527 | 333.2534499 | 1.072095886 | 0.311581923 | -396.592026 | 1111.151331 | -396.592026 | 1111.151331 |

Source: Own processing in MS Excel SW.

Two coefficients are obtained in rows, where it is known that the first row is the coefficient for the first column of the input area X and the second row is the coefficient for the second column. The coefficients 0.0000000069644 for GDP and the coefficient 357.2796527 for unemployment are obtained. The coefficients are inserted into the final linear regression equation for the forecast of the average wage for the year 2024. I insert the values into the formula:

$$Y=\beta 0 +\beta 1\ X1 +\beta 2\ X2. \quad (2)$$

Where:

Y = average salary 2024,

β0 = is the value of the average wage at zero HPD and zero unemployment, i.e. zero,

β1 is the coefficient for GDP vs average wage in 2024 from the regression analysis, i.e. $6.97644 \times 10^{-9}$

X1 is the predicted GDP for 2024, i.e. 7,447,242 million

β2 is the coefficient for unemployment x average wage in 2024 from the regression analysis, i.e. 357.2796527

X2 is the predicted unemployment rate for 2024, which is 3.2%. It is entered as 3.2 because the coefficient was calculated with absolute values.

$Y = 6.97644 \times 10^{-9} \times 7{,}447{,}242{,}000{,}000 + 357.2797 \times 3.2$. The result is 53098.53202. (CZK)

## Discussion

*Research question 1: What is the impact of unemployment and GDP on the average wage in the Czech Republic?*

Research has shown that there is a significant relationship between unemployment, GDP and average wages. Correlation analysis revealed a negative relationship between unemployment and average wages, meaning that as unemployment falls, average wages rise. This result is consistent with the theory that higher unemployment reduces pressure on wage growth because more people are competing for the same job. A positive relationship was found between GDP and average wages, suggesting that a growing economy supports wage growth. This result is consistent with the expectation that economic growth leads to higher productivity and profits, which in turn allows firms to pay higher wages.

*Research question 2: What will be the development of the average wage in the Czech Republic based on the influence of GDP and unemployment in 2024?*

The predicted average wage for 2024 was determined based on a regression analysis of data from 2011-2023. The model predicted that the average wage in 2024 would be CZK 53,099 . This estimate was based on historical unemployment and GDP trends.

Current data from March 2024 from the Czech Statistical Office show that the average wage is CZK 46,013. This means that the prediction is very close to the reality that has developed so far, which confirms the reliability of the model used. The deviation may be caused by short-term economic fluctuations or specific sectoral changes that were not included in our model. An upward deviation could also be caused by the GDP outlier identified by Zscore in 2023, where the value deviated from the upward trend.

The research results are in line with the conclusions of Meixnerová & Krajňák (2020), who also confirmed that macroeconomic factors such as GDP and unemployment have a significant impact on the average wage. In addition, the conclusion of the research study by Sokolová & Mohelská (2023) confirms that the level of the average wage can vary depending on regional differences, which may be another factor that could explain the small deviation between the predicted and actual wage.

Omran & Bilan's (2024) research on the relationships between foreign direct investment, unemployment, and GDP in Egypt supports our conclusions by showing how macroeconomic factors can influence wages across countries. Although this research focuses on a different region, similar mechanisms are at work in the Czech Republic.

## Conclusion

The aim of this work was to conduct a detailed assessment of the impact of unemployment and GDP on the average wage in the Czech Republic for the years 2011-2023 and to make a short-term forecast of the average wage in the Czech Republic until

2024. The aim of the work was achieved using statistical analysis and regression models, which allowed us to examine the relationships between macroeconomic indicators and the average wage.

The analysis used historical data on average wages, unemployment and GDP. It was found that unemployment has an inverse relationship with average wages, which confirms the theoretical assumptions that with increasing unemployment, average wages fall. GDP has a positive effect on average wages, which is in line with the expectation that economic growth leads to wage increases.

The resulting average wage forecast for 2024 was CZK 53,098. The current average wage as of March 5, 2024 is CZK 46,013, indicating continued growth. This result indicates that the models and methods used were effective and reliable. The predicted increase is therefore approximately CZK 10,000, which is in line with the current development, which has already recorded an increase of over CZK 2,000 in the first two months and part of March.

The impact of unemployment and GDP on average wages: The analysis showed that unemployment has a negative impact on average wages, while GDP has a positive impact. These conclusions are consistent with economic theory and confirm the results of previous studies.

Average wage forecast: The short-term forecast for 2024 was CZK 53,098, which is higher than the current average wage as of March 5, 2024 (CZK 46,013), but given the growth rate in the first two months and part of March, the predicted increase is realistic.

Comparison with other authors: The results of this work are in line with the research of Sokolová & Mohelská (2023) on the determinants of job satisfaction and Prokopyev (2023) on the differences between the average wage in metropolitan areas and rural areas. The findings of this work also confirm the conclusions of the studies of Meixnerová & Krajňák (2020) on the strong correlation of the average wage with macroeconomic factors.

Correlation analysis and theory generally argue that there is an inverse relationship between unemployment and average wages, meaning that higher unemployment should lead to lower average wages, other things being equal. This relationship is based on the assumption that higher unemployment increases the supply of labor, which puts downward pressure on wages.

However, the regression analysis revealed a positive coefficient for unemployment, suggesting that even the increased unemployment rate actually led to an increase in average wages. This result may be initially surprising, but there are several possible explanations. One is that the theoretical inverse relationship between unemployment and wages only holds above a certain level of unemployment. If the unemployment rate is low (for example, below 5%), a slight increase in it can have the opposite effect on wages.

This situation can occur when the labor market is very tight and employers are forced to increase wages to attract and retain qualified workers, even if unemployment is rising slightly. Therefore, if the increase in the unemployment rate does not change the fact that the unemployment rate remains low, the effect of unemployment on wages can still be positive. This may be important for understanding the specific conditions of the Czech labor market during the analyzed period.

Limited factors: The model does not take into account some other factors that could affect the average wage, such as changes in tax policy, inflation, or technological innovation.

Dependence on historical data: The model is based only on historical data and assumes that future trends will be similar to past ones. Unexpected economic shocks or significant structural changes could jeopardize the accuracy of predictions.

Regional differences: The model does not take into account regional differences that may affect the average wage. As Prokopyeva (2023) shows, average wages can vary considerably between metropolitan and rural areas.

Seasonal fluctuations: This work does not take into account seasonal fluctuations that can affect short-term changes in average wages. Only annual values are taken into account.

Availability of secondary data: The methodology requires that secondary data on GDP and unemployment predictions be available, which may be a limitation if they are unavailable or of low quality.

This work provides valuable insights into the relationship between unemployment, GDP, and average wages in the Czech Republic. Our findings may be useful for economic policymakers, entrepreneurs, and other stakeholders interested in wage developments and economic trends.

## References

BALL, L., MAZUMDER, S. 2019. The non-puzzling behavior of median inflation. Online. *National Bureau of Economic Research*

BÍLKOVÁ, D. 2023. The Czech Republic's economy since the 1990s and its development forecasts: Selected macroeconomic indicators. *Engineering Economics*, 34(4), 370–383. https://doi.org/10.5755/j01.ee.34.4.27427

BIVENS, J., MISHEL, L. 2015. Understanding the historic divergence between productivity and a typical worker's pay: Why it matters and why it's real. Online. *Economic Policy Institute*. https://www.epi.org/publication/understanding-the-historic-divergence-between-productivity-and-a-typical-workers-pay-why-it-matters-and-why-its-real/

BIVENS, J., MISHEL, L. 2015. Understanding the historic divergence between productivity and a typical worker's pay: Why it matters and why it's real. Online. *Economic Policy*

*Institute*. https://www.epi.org/publication/understanding-the-historic-divergence-between-productivity-and-a-typical-workers-pay-why-it-matters-and-why-its-real/

BLANCO-ARANA, M. C. 2023. Public housing as a policy tool in the autonomous communities: An empirical analysis for the period 2008–2022. *Journal of Business Studies. Second Era*, pp. 91–108. https://doi.org/10.17561/ree.n2.2023.7852

BLANCHARD, O. 2016. The Phillips curve: Back to the '60s? *American Economic Review*, 106(5), 31–34. https://doi.org/10.1257/aer.p20161103

CLERK, P. 2021. The dynamics of unemployment and inflation in New Keynesian models with two labor margins. *Journal of Money, Credit and Banking*, 53(2–3), 301–332. https://doi.org/10.1111/jmcb.12768

CZECH STATISTICAL OFFICE. 2021. Employment, unemployment – time series. Online. https://www.czso.cz/csu/czso/zam_cr

CZECH STATISTICAL OFFICE. 2024. Gross domestic product expenditure method (current prices). Online. https://apl.czso.cz/pll/rocenka/rocenkavyber.makroek_vydaj

CZECH STATISTICAL OFFICE. 2024. Wages, labor costs – time series. Online. Prague: CZSO. Data on average wages and unemployment for the years 2011–2023. https://www.czso.cz/csu/czso/pmz_cr

CZECH STATISTICAL OFFICE. 2024. Wages, labour costs – time series. Data on average wages for the years 2011–2023. Online. https://www.czso.cz/csu/czso/pmz_cr

DARMO, Ľ., NOVÁK, M., LISÝ, J. 2020. Relationship between foreign direct investment inflow and unemployment in the Slovak Republic. *Politická ekonomie*, 68(4), 443–461. https://doi.org/10.18267/j.polek.1289

DAVID, H., KATZ, L. F., KEARNEY, M. S. 2008. Trends in U.S. wage inequality: Revising the revisionists. *The Review of Economics and Statistics*, 90(2), 300–323. https://doi.org/10.1162/rest.90.2.300

DAVID, H., SALOMONS, A. 2018. Is automation labor share-displacing? Productivity growth, employment, and the labor share. *Brookings Papers on Economic Activity*, 2018(1), 1–63. https://doi.org/10.1353/eca.2018.0001

DUDA, D., TUREČKOVÁ, K., BURYOVÁ, I., KUBALOVÁ, R. 2022. Maternity benefit: Comparison of systems and financing in V4 countries. *Eastern Journal of European Studies*, 13(Special issue), 141–163. https://doi.org/10.47743/ejes-2022-SI08

EUROPEAN CENTRAL BANK. 2017. Assessing labor market slack. Online. *ECB Economic Bulletin*, Issue 3. https://www.ecb.europa.eu/pub/economic-bulletin/html/eb201703.en.html

EUROPEAN CENTRAL BANK. 2017. Assessing labour market slack. Online. *ECB Economic Bulletin*, Issue 3. https://www.ecb.europa.eu/pub/economic-bulletin/html/eb201703.en.html

EUROPEAN CENTRAL BANK. 2018. Wage dynamics network: Final report. Online. *ECB*

*Occasional Paper*, No. 201. https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op201.en.pdf.

EUROPEAN COMMISSION. 2019. Labour market and wage developments in Europe: Annual review 2019. Online. Luxembourg: Publications Office of the European Union. https://ec.europa.eu/social/main.jsp?catId=738&langId=en&pubId=8240

GRINEVICA, L., RIVZA, B. 2018. Economic costs of youth unemployment in the European Union. *Proceedings of the International Scientific Conference "Economic Science for Rural Development"*, pp. 299–305. https://doi.org/10.22616/ESRD.2018.098

CHANG, J.-J., HUNG, L.-W., PENG, S.-K. 2023. (De)unionization, trade, unemployment, and wage differentials. *Southern Economic Journal*, 90(1), 121–155. https://doi.org/10.1002/soej.12647

INTERNATIONAL LABOUR ORGANIZATION. 2019. Global wage report 2018/19: What lies behind gender pay gaps. Online. Geneva: ILO. https://www.ilo.org/global/publications/books/WCMS_650553/lang--en/index.htm

INTERNATIONAL MONETARY FUND. 2018. World economic outlook: Cyclical upswing, structural change. Online. Washington, D.C.: IMF. https://www.imf.org/en/Publications/WEO/Issues/2018/03/20/world-economic-outlook-april-2018

INTERNATIONAL MONETARY FUND. 2019. World economic outlook: Growth slowdown, precarious recovery. Online. Washington, D.C.: IMF. https://www.imf.org/en/Publications/WEO/Issues/2019/03/28/world-economic-outlook-april-2019

KRAJŇÁK, M. 2020. Is personal income tax on dependent activity in the Czech Republic progressive? *Politická ekonomie*, 68(5), 534–553. https://doi.org/10.18267/j.polek.1295

KURTOVIC, S., MAXHUNI, N., HALILI, B., KRASNIQI, B. 2021. The asymmetric effect of foreign direct investment on the net average wages of Southeastern European countries. *Journal of Applied Economics and Business Research*. ISSN 1927-033X. https://www-webofscience-com.ezproxy.techlib.cz/wos/woscc/full-record/WOS:000715748800001

LEDIĆ, M., RUBIL, I. 2021. Beyond wage gap, towards job quality gap: The role of inter-group differences in wages, non-wage job dimensions, and preferences. *Social Indicators Research*, 155(2), 523–561. https://doi.org/10.1007/s11205-021-02612-y

MEIXNEROVÁ, L., KRAJŇÁK, M. 2020. Macroeconomic time series affecting the minimum and average wages of V4 countries. *E+M Ekonomie a Management*, 23(4), 4–22. https://doi.org/10.15240/tul/001/2020-4-001

NKIKABAHIZI, C., CHERUIYOT, W., KIBE, A. 2022. Chaining Zscore and feature scaling methods to improve neural networks for classification. *Applied Soft Computing*, 123. https://doi.org/10.1016/j.asoc.2022.108908

OECD. 2017. Employment outlook 2017. Online. OECD Publishing.

https://www.oecd.org/employment-outlook/2017/

OECD. 2018. Good jobs for all in a changing world of work: The OECD jobs strategy. Online. OECD Publishing. https://www.oecd.org/employment/jobs-strategy/

OECD. 2019. Under pressure: The squeezed middle class. Online. OECD Publishing. https://www.oecd.org/social/under-pressure-the-squeezed-middle-class-689afed1-en.htm

OMRAN, E. A. M., BILAN, Y. 2024. Foreign direct investment and unemployment in Egypt. *Montenegrin Journal of Economics*. ISSN 1800-5845. https://www-webofscience-com.ezproxy.techlib.cz/wos/woscc/full-record/WOS:001124805800004

PATEL, D. P. C., CHOGA, I. 2018. Determinants of youth unemployment in South Africa. In: *Proceedings of the 9th Economics and Finance Conference, London*. International Institute of Social and Economic Sciences. ISBN 9788087927533. https://doi.org/10.20472/EFC.2018.009.016

PÍCL, M. 2018. The impact of the minimum wage on unemployment in the Czech Republic. In: *12th International Days of Statistics and Economics*. https://www-webofscience-com.ezproxy.techlib.cz/wos/woscc/full-record/WOS:000455809400139

PROKOPYEV, E. A. 2023. The average wage in the North-West Federal District: An assessment of territorial disparities on a settlement level. *Regionology*, 31(2), 335–356. https://doi.org/10.15507/2413-1407.123.031.202302.335-356

RISTANOVIĆ, V. 2023. Background of the unemployment in the Euro Area. *Economy of Regions*, pp. 1110–1120. https://doi.org/10.17059/ekon.reg.2023-4-12

SOKOLOVÁ, M., MOHELSKÁ, H. 2023. Development of the average gross wage as a determinant of job satisfaction in the Czech Republic in comparison with Germany, Austria and Poland. *Transformation in Business and Economics*, 19(3c), 603–617. https://www-webofscience-com.ezproxy.techlib.cz/wos/woscc/full-record/WOS:000630908700013

TKÁČOVÁ, A., GAVUROVÁ, B., MELASOVÁ, K., SNOPKO, P. 2022. Unemployment in the context of minimum wage concept in Slovakia. *Entrepreneurship and Sustainability Issues*, 10(1), 395–407. https://doi.org/10.9770/jesi.2022.10.1(21)

TUTKYSHBAYEVA, S., ZAKIROVA, A. 2024. Analysing IoT digital education: Fostering students' understanding and digital literacy. *International Journal of Engineering Pedagogy (iJEP)*, 14(4), 4–23. https://doi.org/10.3991/ijep.v14i4.45489

ÜLKER, E. D., ÜLKER, S. 2019. Unemployment rate and GDP prediction using support vector regression. In: *Proceedings of the 1st International Conference on Advanced Information Science and System*. New York, NY, USA: ACM, pp. 1–5. ISBN 9781450372916. https://doi.org/10.1145/3373477.3373494.

ZEMAN, M. 2024. Outlook for the Czech economy in 2024. Online. *Institute for Politics and Society*. https://www.politikaspolecnost.cz/wp-content/uploads/2024/01/Outlook-for-the-Czech-Economy-in-2024_IPPS_Martin-Zeman.pdf.

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# Analysis of the relationship between selected renewable energy and non-renewable resources

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**Abstract**

The aim of this paper is to determine the dependence between the installed capacity of wind power plants and annual CO2 production, as well as between coal energy use and CO2 production. Pearson and Spearman correlation methods are used for the analysis based on the normality of data, which was tested using the Shapiro-Wilk test of normality. The results show a negative correlation between the capacity of wind power plants and CO2 production in Belarus, Russia, and Norway, while in Spain and Germany, the correlation is positive. Furthermore, a positive correlation between coal energy use and CO2 production is found in the Czech Republic, Poland, Austria, Portugal, Italy, Greece, and Denmark, which aligns with expectations. Conversely, a negative correlation is found in Ireland and Lithuania, which may indicate more efficient energy use. Limitations are identified in the form of different correlation tests, which may partially distort the results. This work contributes to research in the field of energy and can be useful for the development of political and energy plans.

**Keywords:** Wind energy, angular energy, renewable energy, non-renewable energy, CO2

## Introduction

Coal-fired power plants emit hazardous substances and heavy metals into the air. For example, in Chinese coal-fired power plants, values of heavy metals such as arsenic, copper, lead, zinc and others have been measured, where the soil around the power plants is moderately to heavily polluted with heavy metals (Hu et al, 2021), which have a very negative impact on the environment, especially if water supplies are contaminated with heavy metals. At that point, the water becomes undrinkable for humans and its long-term consumption has many negative side effects. Such as liver failure, kidney damage, stomach and skin cancer, mental problems and negative effects on the reproductive system. As for the impact on the environment, here we can talk about changes in geological and geochemical processes and the hydrological properties of streams will also change. Heavy metals can be extracted from water streams in several ways, but these processes tend to be expensive and cause secondary pollution (Zhang et al., 2023). Of course, soil and water pollution are not the only problems related to coal-fired power plants, another one is air pollution, which according to research (Zhang et al., 2022) has an impact on neurobehavioral disorders in children living in places where the air is polluted by coal-fired power plants. The overall issue of coal-fired power plants, as a representative of a non-renewable energy source, is complex, as as such they emit many harmful substances into the environment, which negatively affect both residents in the vicinity of the power plants, and nature and the environment itself.

The need to address this issue becomes more urgent after discovering that only 13.9% of energy comes from renewable sources and the very basis of the global energy system currently consists of 81% coming from power plants that use solid fuels as fuel, which, as already mentioned, have a very negative impact on both residents in the vicinity of the power plant and the environment itself. Of this 81%, 31.5% are oil-fired power plants, 22.8% are natural gas-fired power plants and 26.8% are the aforementioned coal-fired power plants. The remaining 4.9% of energy comes from nuclear power plants.

Otherwise, there are representatives of renewable energy sources, such as wind, photovoltaic, hydro, biogas power plants, where their integration into various sectors such as agriculture would enable their sustainable energy operation and at the same time reduce energy costs for farmers (Majeed et al., 2023). In relation to the economic indicator of unemployment, the transition to so-called green energy would have a small positive impact (Swain et al, 2022). Of course, renewable sources also have a certain negative impact on the environment. In the case of wind and photovoltaic power plants, there is a problem of their spatial requirements. This problem is partially solved by placing wind power plants on the water surface, and photovoltaic power plants often use the multifunctionality of the land, so the land can serve as a source of electricity or as pasture for livestock. These and similar ideas may reduce the issue of spatial requirements in the future, but this leads me to the topic of other ecological phenomena caused by renewable energy sources. For example, according to a study (Maclaurin et al. 2022), hundreds of thousands of bats die annually in North America due to the operation of wind farms. Despite all the above facts, it should be noted that renewable energy sources will eventually run out, i.e. they will run out. And this leads us to the conclusion that it is necessary to develop the use of renewable energy sources, which is also increasingly important for securing the energy future.

The aim of the work is to determine the dependence between the level of carbon dioxide emissions and the capacity of installed wind energy. As a selected type of renewable energy in the countries of the European Union for the period 2010-2022 and to determine the dependence between the use of coal energy and the level of CO2 for the period 2008-2022. To meet the set goal, two research questions were set:

*VO1: Is there a relationship between CO2 levels and wind energy use in the EU between 2010 and 2022?*

*VO2: Is there a relationship between CO2 levels and energy use from wind energy in the EU between 2008 and 2022?*

## Methods and Data

**Data**

The investigation of the first research question (RO1) will be based on data obtained from the global Our database World in Data. Specifically, data on the installed capacity of wind farms will be drawn from (Installed wind energy capacity) and annual CO2 emissions (Annual CO2 emissions) from the Our database World in Data. The countries selected for the analysis include Germany, Spain, Russia, Belarus and Norway. These countries were chosen due to their different locations, renewable energy positions and economic sizes. The analysis will be conducted over the period 2010 to 2022.

For the second research question (VO2), data from the global Our database will also be used. World in Data. From articles on the Energy Mix, from which coal consumption data will be obtained. We will extract annual CO2 emissions data from (Annual CO2 emissions) for countries such as Poland, Austria, Czech Republic, Denmark, Greece, Italy, Lithuania, Portugal and Ireland. Coal energy consumption data will be converted into percentage equivalents within the total coal consumption in Europe, while data on tonnes of CO2 emissions will be converted into percentage equivalents within the total CO2 emissions production in Europe. Such an approach will allow comparing the contribution of individual countries to total coal consumption and CO2 emissions in Europe.

**Methods**

For the first research question, content analysis will be used. Next, correlation analysis will be used, where we first convert the data obtained from ta Mw into their percentage equivalents from installed wind energy sources and total global CO2 production. Subsequently, we transfer these data to the analytical program RStudio, where, through the packages, ggplot2, tidyr and dplyr Hmisc and corrplot will create visualizations of correlation coefficients between the mentioned data.

First, you will need to import the extracted data from the Our database. Wordl in Data and convert it to data frame.

Figure 1: How to transfer data to RStudio

```
Mydata2 <- data.frame(
  Belarus_CO2 = c(0.00188, 0.00179, 0.0018, 0.00183, 0.0018, 0.00166, 0.00165, 0.00167, 0.0017, 0.00168, 0.00171, 0.00166, 0.00159),
  Belarus_wind = c(0, 0, 0, 0, 0, 0, 0.0001, 0.0002, 0.0002, 0.0002, 0.0002, 0.0001, 0.0001),
  Russia_CO2 = c(0.05, 0.0489, 0.0491, 0.0467, 0.0463, 0.0465, 0.0459, 0.0461, 0.0464, 0.0463, 0.047, 0.0469, 0.0447),
  Russia_wind = c(0, 0, 0, 0, 0, 0, 0, 0, 0.0001, 0.0002, 0.0013, 0.0024, 0.0025),
  Norway_CO2 = c(0.00146, 0.00128, 0.00126, 0.00127, 0.00127, 0.00128, 0.00126, 0.00124, 0.00123, 0.00116, 0.00111, 0.0011, 0.0011),
  Norway_wind = c(0, 0, 0, 0, 0, 0, 0, 0.0002, 0.0003, 0.0005, 0.0055, 0.0061, 0.0057),
  Spain_CO2 = c(0.00081, 0.00081, 0.00079, 0.00071, 0.00072, 0.00076, 0.00074, 0.00076, 0.00073, 0.00068, 0.00061, 0.00063, 0.00065),
  Spain_wind = c(0.1142, 0.0978, 0.1067, 0.0765, 0.0655, 0.0551, 0.0489, 0.0449, 0.0415, 0.0412, 0.0367, 0.0338, 0.0326),
  Germany_CO2 = c(0.02246, 0.0218, 0.02206, 0.02238, 0.0224, 0.0225, 0.02264, 0.02165, 0.01995, 0.01913, 0.01746, 0.01832, 0.01794),
  Germany_wind = c(0.1485, 0.1303, 0.1154, 0.1115, 0.1106, 0.107, 0.1059, 0.1082, 0.1039, 0.0979, 0.085, 0.0774, 0.0738)
```

Source: Developed by the author in RStudio.

In the second step, a test of data normality will be performed using the Shapiro normality test and we will specify the correlation methods for normality and non-normality, where for normality we will use Spearman correlation analysis and for non-normality we will use Pearson

Figure 2: Shapiro's normality test

```
check_normality <- function(co2_data, wind_data, country) {
  co2_test <- shapiro.test(co2_data)
  wind_test <- shapiro.test(wind_data)
  cat("Country:", country, "\n")
  cat("Shapiro-Wilk Test for CO2: W =", co2_test$statistic, "p-value =", co2_test$p.value, "\n")
  cat("Shapiro-Wilk Test for Wind: W =", wind_test$statistic, "p-value =", wind_test$p.value, "\n\n")

  use_spearman <- (co2_test$p.value < 0.05 | wind_test$p.value < 0.05)
  correlation_method <- if (use_spearman) "spearman" else "pearson"

  return(correlation_method)
```

Source: Developed by the author in RStudio.

We then define the names of the countries under study.

Figure 3: Definition of the name of the monitored countries

```
countries <- c("Belarus", "Russia", "Norway", "Spain", "Germany")
```

Source: Developed by the author in RStudio.

In the penultimate step, we define the items for the correlation and run it using the cor command. We then use the print command to generate the correlation coefficients and the methods that were used.

Figure 4: Method of performing correlation analysis

```
for (country in countries) {
  co2_data <- Mydata2[[paste0(country, "_CO2")]]
  wind_data <- Mydata2[[paste0(country, "_wind")]]
  method <- check_normality(co2_data, wind_data, country)
  correlation_value <- cor(co2_data, wind_data, method = method)

  correlations[correlations$Country == country, "Correlation"] <- correlation_value
  correlations[correlations$Country == country, "Method"] <- method
}

print(correlations)
```

Source: Developed by the author in RStudio.

When generating correlation coefficients using the print command, it is evident that Spearman's correlation analysis was used for all countries, which indicates the normality of the data for all countries.

Figure 5: Generated pie analyses with correlation methods for VO1

```
> print(correlations)
  Country Correlation   Method
1 Belarus  -0.4812201 spearman
2  Russia  -0.2179980 spearman
3  Norway  -0.9219593 spearman
4   Spain   0.8209398 spearman
5 Germany   0.6593407 spearman
```

Source: Developed by the author in RStudio based on data from OWD 2024.

In the last step, we use the corrplot command to create a visualization of the correlation coefficients for the monitored countries (see Results).

Figure 7: Method for creating a correlation visualization using the corrplot command

```
cor_matrix <- matrix(correlations$Correlation, nrow = 1, ncol = length(countries))
colnames(cor_matrix) <- paste0(countries, "_CO2")
rownames(cor_matrix) <- "Correlation_with_Wind"
# Vizualizace korelační matice
corrplot(cor_matrix, method = "color", addCoef.col = "black", tl.col = "black", tl.srt = 45,
         title = "Correlation between CO2 and Wind for each Country", mar = c(0,0,2,0))
```

Source: Created by the author in RStudio.

For the second research question, we will also use content analysis and transfer the edited data to the analytical program RStudio, where we will perform a correlation analysis in the same way as for the first research question and subsequently generate a visualization of the correlation coefficients.

The only difference between the methods in the first and second research questions is the correlation methods used, as in the first VO all data were normal, so we used only Spearman's correlation analysis, but in the second research question the data were both normal and non-normal, so we used both Spearman's and Pearson's correlation analysis.

Figure 8: Generated pie analyses with correlation methods for VO2

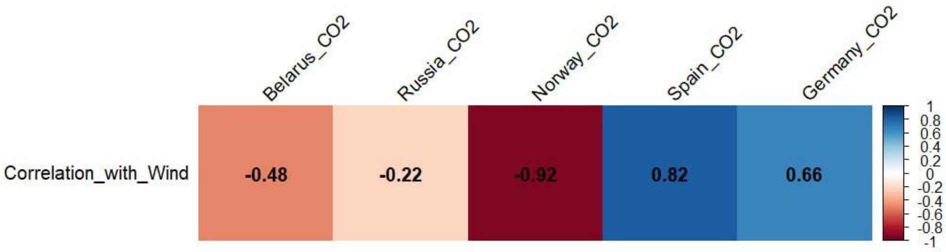
```
    Country Correlation   Method
1   Czechia   0.2358572  pearson
2    Poland   0.9107534  pearson
3   Hungary   0.4005402 spearman
4   Ireland  -0.1784496  pearson
5  Portugal   0.7559871  pearson
6 Lithuania  -0.2056883 spearman
7     Italy   0.6079961  pearson
8    Greece   0.2923768 spearman
9   Denmark   0.9908565  pearson
```

Source: Developed by the author in RStudio based on data from OWD 2024.

## Results

Based on the research questions, a visualization of correlation coefficients is created in the analytical program RStudio. The first visualization includes data on the percentage of installed wind energy capacity in given countries from all over the world and the percentage of CO2 production in these countries. We have chosen Belarus, Russia, Norway, Spain and Germany as the selected countries in the years 2010 to 2022.

Figure 9: Visualization of correlation coefficients for VO1

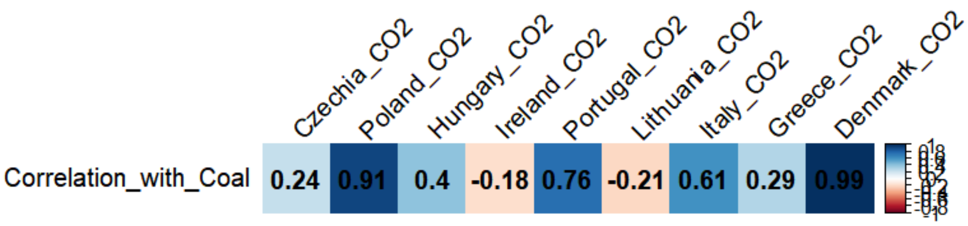



Source: Developed by the author in RStudio based on data from OWD 2024.

These results show the correlations between CO2 emissions and wind energy use in different countries. Norway has the highest negative correlation (-0.92), followed by Belarus (-0.48) and Russia (-0.22). On the other hand, Spain (0.82) and Germany (0.66) have high positive correlations. These data show how wind energy use affects CO2 emissions in different countries.

The second visualization of correlation coefficients worked from data regarding the percentage of angular energy use in given countries out of the total angular energy use in Europe and the percentage of CO2 emissions production in given countries out of the total CO2 emissions production in Europe in the years 2008 to 2022.

Figure 10: Visualization of correlation coefficients in VO2




Source: Developed by the author in RStudio based on data from OWD 2024.

These results show the correlations between CO2 emissions and coal consumption in different European countries. The highest positive correlations are found in Poland (0.91) and Denmark (0.99), indicating a strong dependence of CO2 emissions on coal. The negative correlations are found in Ireland (-0.18) and Portugal (-0.21), indicating that CO2 emissions in these countries are not so dependent on coal. The other countries have the following correlations: Czech Republic (0.24), Hungary (0.4), Lithuania (0.61), Italy (0.29) and Greece (0.61), indicating a slight to moderate dependence between CO2 emissions and coal consumption.

## Discussion

*VO1: There is a relationship between CO2 levels and wind energy use in the EU between 2010 and until 2022?*

The correlation analysis between CO2 emissions and installed wind power capacity for individual countries brings interesting results. For Belarus, Russia and Norway, all negative correlation strengths were measured (Belarus -0.481, Russia, -0.218, Norway -0.922), where in Russia the influence of wind power capacity on CO2 production is very weak. In Belarus, this influence is slightly stronger, but still not very strong. While in Norway we can observe a very strong influence of wind power capacity and CO2 production. On the other hand, in Spain and Germany we can observe a positive correlation (Spain 0.821, Germany 0.659), where in Spain a very strong positive correlation was measured, which means that in this country with increasing wind power capacity, CO2 production increases. In Germany we can observe the same phenomenon, but with less strength.

Overall, we can say that these relationships vary across countries, which may be due to various local factors and policies that may play a crucial role in this case.

One important factor why these results are so different in individual countries may stem from the already mentioned works by Kuang et al. (2022) and Kaffine et al. (2020), which dealt with the intermittency of wind energy and its impact on CO2 emissions. Based on their works, I tried to expand knowledge on this issue with this work.

*VO2: Is there a relationship between CO2 levels and energy use from coal-fired power plants in the EU between 2008 and 2022?*

Correlation analysis was used to examine the relationship between coal energy use and CO2 production. The most visible phenomenon is that seven out of nine countries studied showed a positive correlation coefficient, which in itself may indicate the possibility of a positive relationship between coal energy use and CO2 production, but the research found that in Ireland and Lithuania the correlation coefficient was in negative units. Although in both cases it is a weak negative correlation (Ireland -0.178, Lithuania -0.206), this suggests that in these countries there is a possibility of a negative impact of coal energy use on CO2 levels. These results can be attributed to several factors, such as alternative energy sources, efficient use of produced energy, etc. On the other hand, strong and very strong positive correlations were found in Poland, Denmark and Portugal (Poland 0.911, Denmark 0.991, Portugal 0.756), indicating that in these countries the use of angular energy has a positive effect on CO2, which is in line with public expectations, as angular energy is often associated with high CO2 emissions.

However, it is important to mention that different correlation methods were used for the correlation (see Data and Methods) due to differences in normality it was necessary to use Pearson correlation analysis and Spearman correlation analysis, which differ in that Spearman correlation analysis takes into account the order of values and Pearson correlation analysis takes into account linear relationships between variables. This may lead to different results.

In this study, I follow up on the research of Iqbal et al. (2022) and; which dealt with the relationship between the use of renewable energy sources and CO2 emissions. Iqbal et al. (2022) suggests that the growth of renewable energy production may have different impacts on CO2 emissions depending on individual factors and management effectiveness. At the same time, Thakuri et al. (2021) examine the relationship between CO2 production and economic growth, providing insights into policies and measures to reduce CO2 emissions. These studies provide context for our analysis of the relationship between energy use from coal-fired power plants and CO2 emissions in EU countries, allowing us to better understand the factors influencing CO2 emissions in the energy sector.

## Conclusion

The first research question examined the relationship between carbon dioxide emissions and installed wind power capacity in the European Union countries from 2010 to 2022. Correlation analysis revealed that there are different relationships between the two variables in different countries. For example, in Spain and Germany we observed a positive correlation, while in Belarus, Russia and Norway we recorded a negative correlation. These differences suggest that local factors and policies may play a key role in the impact of wind power capacity on CO2 production in individual countries.

In the second part of our analysis, we looked at the relationship between coal use and CO2 levels in the EU between 2008 and 2022. Here again, we found mixed results across countries. While we identified a positive correlation in Poland, Denmark and Portugal, we found a weak negative correlation in Ireland and Lithuania. These results suggest that coal use has a different impact on CO2 emissions depending on the specific conditions in the countries concerned. Overall, our analysis has provided valuable insights into the relationship between renewable and non-renewable energy use and CO2 emissions in the European Union. This study extends the findings of existing research and highlights the importance of further investigating this issue in the context of combating climate change and finding sustainable energy solutions.

However, it should be noted that our analysis has certain limitations. One of the main limitations is the possible inaccuracies in data collection and the use of different methods, due to the different normality of these data. Furthermore, due to the complex factors in the energy sector, some relationships may be distorted or insufficiently taken into account. Despite these limitations, this work provides useful insights for further research in the field of energy and the environment. Its results could serve as a basis for the formulation of policies and measures aimed at reducing CO2 emissions and promoting sustainable development in the energy sector.

In conclusion, this work provides important information on the relationship between the use of different types of energy and CO2 emissions in the European Union.

## References

ABDALLAH, L., EL-SHENNAWY, T. 2020. Evaluation of CO2 emission from Egypt's future power plants. *Euro-Mediterranean Journal for Environmental Integration*, 5(3). https://doi.org/10.1007/s41207-020-00184-w

ALNEMER, H. A., HKIRI, B., TISSAOUI, K. 2023. Dynamic impact of renewable and non-renewable energy consumption on CO2 emission and economic growth in Saudi Arabia: Fresh evidence from wavelet coherence analysis. *Renewable Energy*, 209, 340–356

AMER, E. A. A. A. et al. 2024. Impacts of renewable and disaggregated non-renewable energy consumption on CO2 emissions in GCC countries: A STIRPAT model analysis. *Heliyon*, 10(9)

APERGIS, N. et al. 2023. Investigating the association among CO2 emissions, renewable and non-renewable energy consumption in Uzbekistan: An ARDL approach. *Environmental Science and Pollution Research*, 30(14), 39666–39679

ASIF, M., NAWAZ, S., KHAN, M. 2022. Hybrid energy systems: A step forward towards energy sustainability. *Renewable and Sustainable Energy Reviews*, 153, 111–132. https://doi.org/10.1016/j.rser.2022.112150

BALCILAR, M., USMAN, O., IKE, G. N. 2023. Operational behaviours of multinational corporations, renewable energy transition, and environmental sustainability in Africa: Does the level of natural resource rents matter? *Resources Policy*, 81. https://doi.org/10.1016/j.resourpol.2023.103344

BALI SWAIN, R., KARIMU, A., GRÅD, E. 2022. Sustainable development, renewable energy transformation and employment impact in the EU. *International Journal of Sustainable Development & World Ecology*, 29(8), 695–708. https://doi.org/10.1080/13504509.2022.2078902

BOEHRINGER, C., RUTHERFORD, T. F., SANDSMARK, M. 2020. The economic and environmental benefits of renewable energy. *Energy Economics*, 87, 104725. https://doi.org/10.1016/j.eneco.2020.104725

BOZKAYA, Ş., ONIFADE, S. T., DURAN, M. S., KAYA, M. G. 2022. Does environmentally friendly energy consumption spur economic progress: Empirical evidence from the Nordic countries? *Environmental Science and Pollution Research*, 29(54), 82600–82610. https://doi.org/10.1007/s11356-022-23452-4

HU, Y., YOU, M., LIU, G., DONG, Z. 2021. Characteristics and potential ecological risks of heavy metal pollution in surface soil around coal-fired power plant. *Environmental Earth Sciences*, 80(17). https://doi.org/10.1007/s12665-021-09887-x

HUSSAIN, H., MAHMUD, S., AHMAD, Z. 2023. Renewable energy and energy security: The role of solar and wind energy in stabilizing energy markets. *Energy Policy*, 169, 113195. https://doi.org/10.1016/j.enpol.2022.113195

CHOWDHURY, A. T., ISLAM, S., ROY, S. 2021. Technological advancements in renewable energy storage systems: A review. *Energy Reports*, 7, 902–915. https://doi.org/10.1016/j.egyr.2021.07.012

IQBAL, S., WANG, Y., SHAIKH, P. A., MAQBOOL, A., HAYAT, K. 2022. Exploring the asymmetric effects of renewable energy production, natural resources, and economic progress on CO2 emissions: Fresh evidence from Pakistan. *Environmental Science and Pollution Research*, 29(5), 7067–7078. https://doi.org/10.1007/s11356-021-16138-w

KAFFINE, D. T., MCBEE, B. J., ERICSON, S. J. 2020. Intermittency and CO2 reductions from wind energy. *The Energy Journal*, 41(5), 23–54. https://doi.org/10.5547/01956574.41.5.dkaf

KUANG, Z., CHEN, Q., YU, Y. 2022. Assessing the CO2-emission risk due to wind-energy uncertainty. *Applied Energy*, 310. https://doi.org/10.1016/j.apenergy.2022.118615

KUO, Y., MANEENGAM, A., PHAN THE, C., BINH AN, N., NASSANI, A. A. et al. 2022. Fresh evidence on environmental quality measures using natural resources, renewable energy, non-renewable energy and economic growth for 10 Asian nations from CS-ARDL technique. *Fuel*, 320. https://doi.org/10.1016/j.fuel.2022.123914

LI, B., HANEKLAUS, N. 2021. The impact of fossil fuel consumption and renewable energy on CO2 emissions in China: An asymmetric analysis. *Sustainable Development*, 29(5), 706–718. https://doi.org/10.1002/sd.2366.

LI, B., HANEKLAUS, N. 2021. The role of renewable energy, fossil fuel consumption, urbanization and economic growth on CO2 emissions in China. *Energy Reports*, 7, 783–791. https://doi.org/10.1016/j.egyr.2021.09.194

MACLAURIN, G., HEIN, C., WILLIAMS, T., ROBERTS, O., LANTZ, E. et al. 2022. National-scale impacts on wind energy production under curtailment scenarios to reduce bat fatalities. *Wind Energy*, 25(9), 1514–1529. https://doi.org/10.1002/we.2741

MAJEED, Y., KHAN, M. U., WASEEM, M., ZAHID, U., MAHMOOD, F. et al. 2023. Renewable energy as an alternative source for energy management in agriculture. *Energy Reports*, 10, 344–359. https://doi.org/10.1016/j.egyr.2023.06.032

NI, X., WANG, Z., AKBAR, A., ALI, S. 2022. Natural resources volatility, renewable energy, R&D resources and environment: Evidence from selected developed countries. *Resources Policy*, 77. https://doi.org/10.1016/j.resourpol.2022.102655

RAJBHANDARI, R., SHRESTHA, S., KHATRI, P. 2023. Global cooperation for renewable energy development: A case study of the South Asian region. *Journal of Renewable and Sustainable Energy*, 15(1), 013202. https://doi.org/10.1063/5.0090247

SHAHBAZ, M., RAGHUTLA, C., ARIF, I. 2022. The dynamic links between renewable energy, technological innovation, and CO2 emissions: Insights from advanced panel techniques.

*Journal of Cleaner Production*, 370, 133333. https://doi.org/10.1016/j.jclepro.2022.133333

SIMONSEN, M., AALL, C., WALNUM, H. J., SOVACOOL, B. K. 2022. Effective policies for reducing household energy use: Insights from Norway. *Applied Energy*, 318. https://doi.org/10.1016/j.apenergy.2022.119201

THAKURI, S., KHATRI, S. B., THAPA, S. 2021. Enflamed CO2 emissions from cement production in Nepal. *Environmental Science and Pollution Research*, 28(48), 68762–68772. https://doi.org/10.1007/s11356-021-15347-7

YILDIRIM, E., ONAY, O., ADAR, H. 2023. International trade and renewable energy: A pathway to global energy transition. *Renewable and Sustainable Energy Reviews*, 169, 112979. https://doi.org/10.1016/j.rser.2022.112979

ZHANG, C. H., SEARS, L., MYERS, J. V., BROCK, G. N., SEARS, C. G. et al. 2022. Proximity to coal-fired power plants and neurobehavioral symptoms in children. *Journal of Exposure Science & Environmental Epidemiology*, 32(1), 124–134. https://doi.org/10.1038/s41370-021-00369-7

ZHANG, P., YANG, M., LAN, J., HUANG, Y., ZHANG, J. et al. 2023. Water quality degradation due to heavy metal contamination: Health impacts and eco-friendly approaches for heavy metal remediation. *Toxics*, 11(10). https://doi.org/10.3390/toxics11100828

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# Emission allowances and environmental impact

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## Abstract

The aim of the work was to analyse the mechanism of emission allowance trading within the European Union and to assess its impact on the environment. The period chosen was from 2014 to 2021. The aim was to determine whether changes in emission allowance prices affected the level of greenhouse gas emissions and to assess whether there is a linear relationship between the price of emission allowances and the level of emissions. The validity of this relationship was examined using content analysis and regression analysis. The results of the regression analysis indicated a moderately strong positive linear relationship between the variables, which indicates that if the price of emission allowances increases, the level of emissions tends to decrease and vice versa. In the monitored period, the prices of emission allowances increased, while greenhouse gas emissions tended to decrease. The lowest prices of allowances were recorded in 2014–2017 due to their surplus, while since 2019 prices have increased due to a limitation of their quantity in circulation. The analysis showed that emissions trading has a significant impact on reducing emissions and supports investment in cleaner technologies. The biggest limitation of the work was the variability of external factors, such as economic changes and political measures, that influenced the research.

**Keywords:** Emission allowances, emissions trading, European Union, CO2 emissions, regression analysis

## Introduction

The Earth's climate is changing at a rapid pace, and each of us plays a key role in the products we buy, the electricity we use, the ways in which manufacturing units produce toxic waste, release carbon dioxide and other harmful greenhouse gases, all of which lead to global warming. It also has a serious impact on our environment and economy, affecting both future and current generations. To combat the problem of global warming, the UNFCCC includes the Kyoto Protocol, which is a universal agreement between countries and commits them to setting universally binding emission reduction targets (Tripathi, 2020).

Emissions trading within the European Union has affected European industrial companies since 2005. Companies have to choose a strategy to minimize the costs associated with emission allowances given the constantly changing conditions of the system and the volatile price of allowances, which makes this decision very difficult. Moreover, increasing pressure on society from policy makers is aimed at increasing the efficiency of the system and increasing the price of emission allowances (Zapletal, 2019).

On the contrary, Lin, BQ et al. (2020) stated that the problems of excessive CO2 emissions and global warming caused by human activities are more binding than we thought. Measures such as carbon taxes and emissions trading schemes, which include mechanisms to mitigate emissions, are being used to address these problems.

The Emissions Trading System (ETS) has long been seen as a promising tool for regulating massive carbon emissions from energy-intensive industries. However, it remains unclear whether the ETS can achieve emission mitigation without disrupting economic activity in specific sectors in emerging markets (Quan et al. 2023).

The European Union Emissions Trading System (EU ETS) was created to reduce greenhouse gas emissions. Companies that produce carbon emissions must manage the associated cash flows by buying or selling carbon allowances. In addition, future carbon prices could influence a company's decision to invest in decarbonization technology, García et al. (2020) reported.

The aim of this work is to analyse the mechanism of emission trading within the European Union and to assess its impact on the environment. The target will be set from 2014 to 2021.

In connection with the objective, the following research questions are set:

*VO1: What is the real impact of emission trading on the environment in the European Union?*

*VO2: What are the environmental impacts of emissions trading from 2014 to 2021?*

## Methods and Data

### Date

To answer the first research question regarding the impact of emission trading on the environment in the European Union, data from the Trading website will be used.

economics (Trading economic, 2024), European Council (European Council, 2024), Eurostat (Eurostat, 2024).

The data will be monitored and recorded in a table in MS Excel. The subject of monitoring will be the price of emission allowances for individual years, expressed in Czech crowns. The impact of CO2 on the environment will also be evaluated. The overall impact of emission allowances will be described. The obtained data will be projected into graphs. The monitored period will cover the years 2014 to 2021. Data on emission allowances will be obtained from the website Climate Facts (Climate Facts, 2024).

These data also follow up on the second research question, which focuses on assessing the environmental impacts of emissions trading from 2014 to 2021.

**Methods**

To answer both research questions, regression analysis will be used to analyze the actual impact of emissions trading on the environment. Regression analysis will identify potential relationships between emissions trading and various environmental indicators, such as air quality, greenhouse gas emissions, or climate change.

To answer the research questions, a linear regression model will be used, which allows the prediction of the value of the dependent variable based on the values of the independent variables. The least squares method will be used to estimate the parameters of this model.

The following formula is used to calculate the parameters of a linear regression model using the least squares method:

To estimate the regression equation:

$$\hat{Y} = b_0 + b_1X_1 + b_2X_2 + \cdots + b_kX_k \tag{1}$$

To estimate the regression coefficients:

$$b_1 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{2}$$

$$b_0 = \bar{Y} - b_1\bar{X} \tag{3}$$

$\hat{Y}$ is the predicted environmental value,

$b_0$ is the estimate of the intercept (constant)

$b_1, b_2, \ldots, b_k$ are estimates of the regression coefficients

$X_1, X_2, \ldots, X_k$ are the values of emission allowances or other relevant factors,

Y is the state of the environment

$\bar{X}$ is the average of the emission allowance values,

$\bar{Y}$ is the average of the environmental state

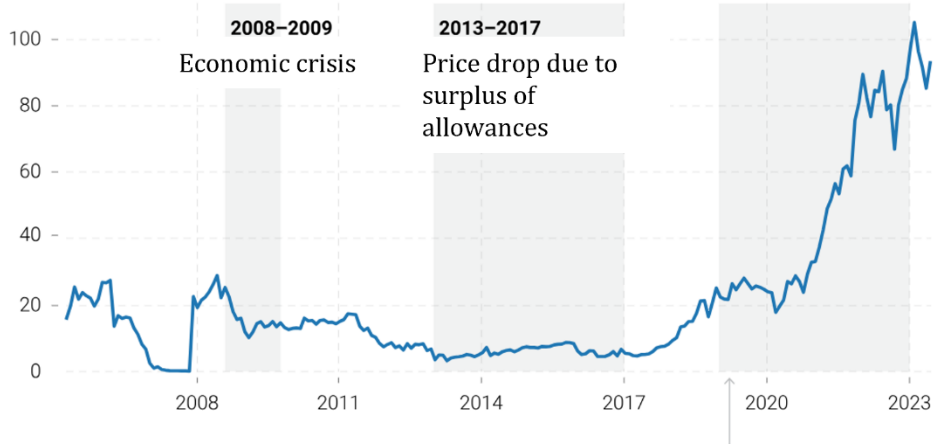
n is the number of observations

The calculation will be performed in Excel using data and data analysis and a regression analysis formula.

## Results

The data shown here is from 2014–2021.

Figure 1: Development of the price of emission allowances in euros




Source: Trading economics.

Figure 1 shows the development of emission allowances from 2008 to 2023. The data was obtained from the Climate Facts website. The data was recorded in European currency. The figure shows the maximum value of emission allowances in 2023. In the years 2013-2017, the price of allowances fell due to their surplus. Since 2019, the price of emission allowances has increased due to a decrease in their quantity in circulation.

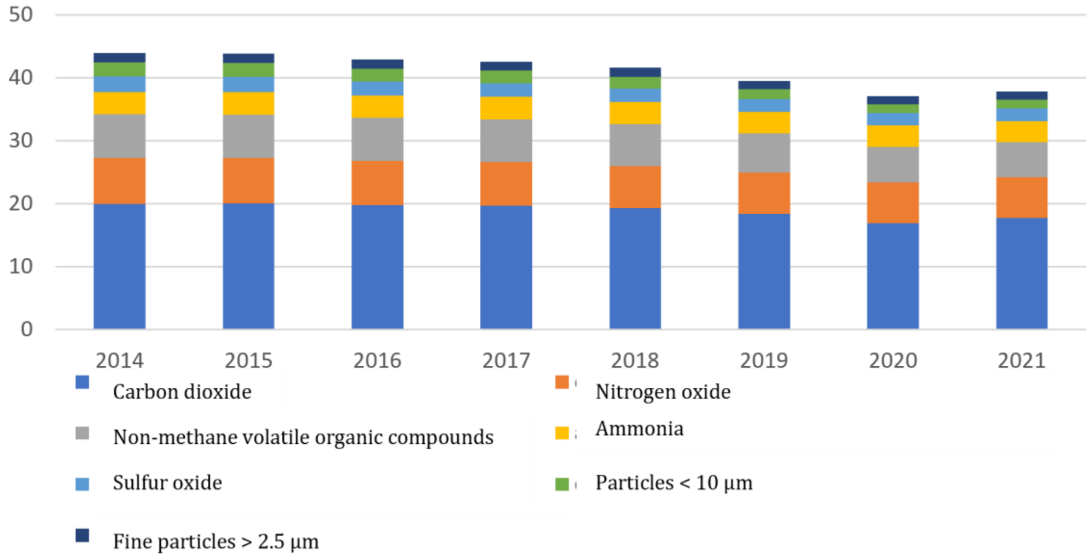
Table 1: Volume of emission allowance prices

| Year | Volume in billion CZK |
|---|---|
| 2014 | 2.08 |
| 2015 | 1.97 |
| 2016 | 1.8 |
| 2017 | 1.7 |
| 2018 | 1.6 |
| 2019 | 1.7 |
| 2020 | 1.6 |
| 2021 | 1.9 |

Source: Own processing.

Table 1 shows the volume of emission allowances in the European Union in individual years from 2014 to 2021. The data is recorded in billions of Czech crowns. It can be seen from the table that the lowest volume was in 2018 and the highest in 2014. The volume is also decreasing because not as many allowances are issued for fees anymore, some are even valid without fees.

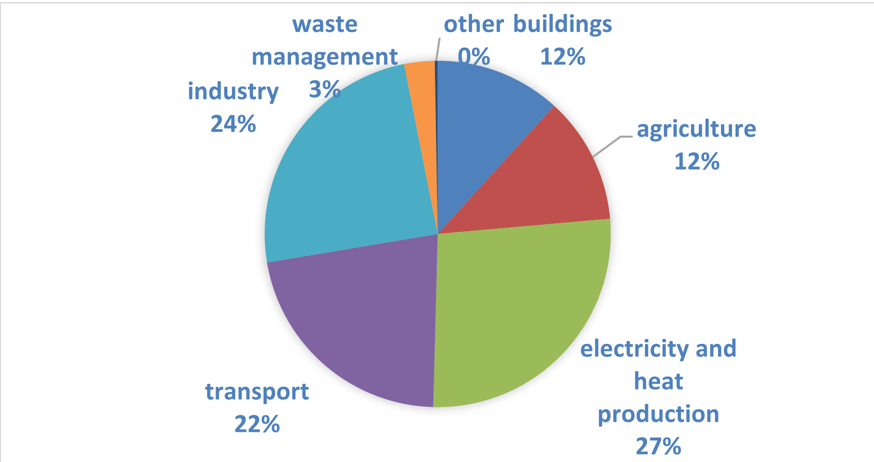
Figure 2: Air pollutant emissions from 2014-2021




Source: Own processing (Eurostat).

Figure 2 shows emissions of air pollutants from 2014-2021. Data on individual types of emissions are obtained from the Climate Facts website. From the chart, we can identify 7 individual substances that occur in the European Union. As can be seen from the chart, over the past few years, it can be observed that individual emissions are decreasing, except for a small jump in 2021.

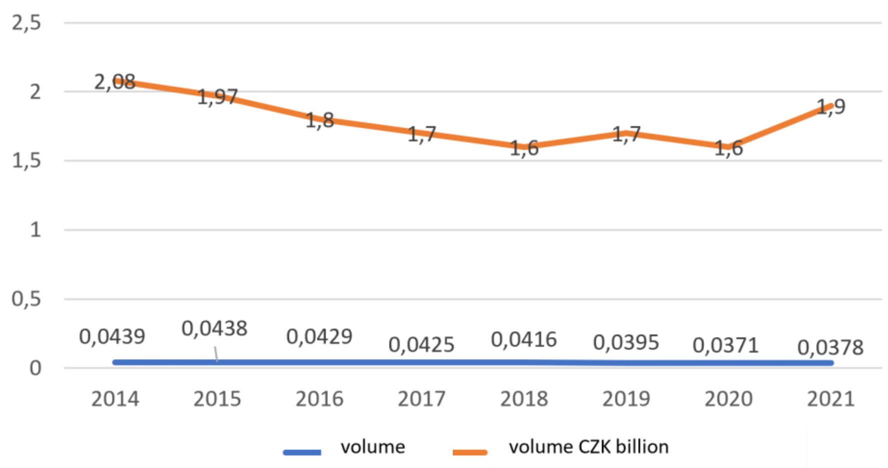
Figure 3: Greenhouse gas emissions in the EU by sector




Source: Own processing (Climate Facts).

Figure 3 shows greenhouse gas emissions in the European Union by sector. It shows 7 sectors, which show in percentage terms how harmful each sector is to Europe. The most polluting sector is electricity and heat production, followed by industry, which is also quite harmful to the environment.

Figure 4: Comparison of emissions and emission allowances




Source: Own processing.

Figure 4 shows the volume of emission allowances in Czech crowns and the volume of emissions in the air. This is all focused on the European Union. The period from 2014-2021 is shown here. From the graph we can see that the volume of individual emissions is not as high as the volume in crowns.

Table 2: Regression analysis calculation

| **Regression statistics** | |
|---|---|
| Multiple R | 0.49625 |
| Reliability value R | 0.246264 |
| Set reliability value R | 0.120642 |
| Average value error | 0.165102 |
| Observation | 8 |

Source: Own processing.

Table 2 contains the results of the regression analysis. The analysis was created in Excel. The data used were the volume of emission allowances and the volume of emission allowance prices in billions of crowns. This regression analysis provides information about the relationship between two variables. The multiple R, which measures the strength and direction of the linear relationship between the variables, was calculated to be 0.496, indicating a moderately strong positive linear relationship. The reliability value of R reaches 0.246, which represents the square of the correlation between the observed and predicted values, while the set reliability value of R is 0.120, which means that 12% of the variability of the explained variable can be explained by the modeled factors.

Table 3 Further calculation of regression analysis

| ANOVA | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Difference | SS | World Cup | F | Significance of F | | | |
| Regression | 1 | 0.053436 | 0.053436 | 1.960351 | 0.211006 | | | |
| Residue | 6 | 0.163551 | 0.027259 | | | | | |
| Total | 7 | 0.216988 | | | | | | |
| | Coefficients | Average value | t Stat | P-value | Lower 95% | Upper | Lower | Upper |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | error | | | | 95% | 95.0% | 95.0% |
| Limit | 0.449161 | 0.962107 | 0.466851 | 0.657077 | -1.90503 | 2.803353 | -1.90503 | 2.803353 |
| File X 1 | 32.68524 | 23.34451 | 1.400125 | 0.211006 | -24.4367 | 89.80721 | -24.4367 | 89.80721 |

Source: Own processing.

This part of the table contains the results of the analysis of variance (ANOVA) and the coefficients of the regression analysis. The variance is evaluated for the difference between the regression and the residuals, the total difference, and their significance. The regression shows that the model has explanatory power, but is not statistically significant ($F = 1.960$, $p = 0.211$). The regression coefficients describe the relationship between the independent variable (X) and the dependent variable (Y). The t-values, together with their significance (p-value), indicate the statistical significance of the relationship between X and Y. In this case, none of the coefficients are statistically significant.

## Discussion

Based on the results obtained, we can answer the research questions:

*VO1: What is the real impact of emission trading on the environment in the European Union?*

Based on the research, it can be assessed that the trading of emission allowances in the European Union has a significant impact on the environment. The analysis of the data shows that the price of emission allowances tends to influence the emission level, through the mechanism of market forces. The falling prices of allowances in the years 2013-2017 led to a surplus of allowances and a subsequent drop in the price, which was associated with higher emissions. On the contrary, since 2019, when the number of allowances in circulation was limited and the prices of allowances began to increase, emissions have started to decrease.

The data also suggests that the volume of emission allowances in circulation is linked to the volume of emissions, and that reducing the volume of allowances can lead to a reduction in emissions. The graphs and tables show that while emissions are decreasing, the volume of allowances to regulate them is decreasing, which can still reduce emissions if properly implemented and managed.

It can therefore be confirmed that emissions trading in the European Union has a positive impact on the environment, through the regulation of emissions and the encouragement of investment in cleaner technologies.

Dimos et al. (2020) examined the effects of capping on the price of allowances and the power of the financial sector in ETS trading. Their analysis provided useful insights into the mechanisms that influence the price of emission allowances and financial market dynamics within the ETS.

*VO2: What are the environmental impacts of emissions trading from 2014 to 2021?*

According to the analysis carried out as part of this study, the environmental impacts of emissions trading in the European Union from 2014 to 2021 were examined.

During the monitored period, the price of emission allowances showed a significant change. There were periods when prices decreased due to a surplus of allowances, and, conversely, periods when prices increased due to a decrease in the number of allowances in circulation. The maximum value of emission allowance prices was recorded in 2023.

The volume of emission allowances in the EU also showed changes. The lowest volume was recorded in 2018 and the highest in 2014. The trend shows a decreasing volume of allowances due to a smaller number of newly issued allowances and the cancellation of some valid ones. Emissions of air pollutants over the monitored period showed a slight decrease, with the exception of a small increase in 2021. The regression analysis performed as part of the work provided information on the relationship between the volume of emission allowances and their prices. It turned out that there is a moderately strong positive linear relationship between these two variables.

It can be said that trading in emission allowances in the EU has complex impacts on the environment, whether through pricing mechanisms, the volume of allowances or the emissions of air pollutants.

Fernandez et al. (2018), their study assessed the effectiveness of the EU-ETS in reducing greenhouse gas emissions and provided key insights for further optimization and implementation of economic mechanisms in the field of emissions regulation.

## Conclusion

The aim of this work was to analyse the mechanism of emission allowance trading within the European Union and to assess its impact on the environment. The target was set from 2014 to 2021. Based on the analysis carried out, it can be stated that the objective of the work was met.

This study conducted extensive research aimed at analyzing the mechanism of emission allowance trading within the European Union and assessing its impact on the environment in the period from 2014 to 2021. Based on the knowledge and analysis obtained, the work will examine possible strategies for improving and optimizing this instrument with regard to environmental protection and sustainable development.

Content analysis and regression analysis were used in this work. These analyses were used for both research questions. Content analysis and regression analysis methods were used to identify the relationships between emission trading and the environment.

The first part of the thesis provides an overview of the development of emission allowance prices over the years. Figure 2 shows that since 2019, the price of emission allowances has increased, which was caused by a decrease in their quantity in circulation.

The volume of emission allowances within the European Union was also monitored in individual years. Table 1 shows that the volume of allowances decreased, which was mainly caused by a decrease in the issuance of new allowances and invalid allowances.

The following section analyses emissions of air pollutants in the period 2014-2021. Figure

2 shows that emissions of these substances have gradually decreased, with the exception of 2021, when there was a moderate increase.

Another analysis focused on greenhouse gas emissions in the European Union by sector. Figure 3 shows that industry and electricity and heat production account for the largest share of emissions.

Subsequently, a comparison was made between the volume of emission allowances and the volume of emissions. Figure 4 shows that the volume of emission allowances in Czech crowns is much higher than the volume of emissions, which may be the result of various factors, including the reduction of emissions within the EU.

Finally, a regression analysis was performed to identify the relationship between emission allowance trading and environmental indicators. The results of the regression analysis (Table 2) show that there is some connection between emission allowance trading and the state of the environment, but this connection is not completely significant.

Overall, it can be said that the work achieved its goal and provided a comprehensive view of the impact of emission allowance trading on the environment in the European Union.

The recommendation for further research is to continue monitoring the emissions trading mechanism after 2021 and to analyse its long-term environmental impacts. It would also be appropriate to increase the frequency of data collection in order to capture a wider range of factors influencing the emissions trading market. A higher frequency of data collection could lead to more accurate and detailed conclusions. The results of this work can be used, for example, to predict the future development of the emissions trading market and its impact on the environmental policy of the European Union.

## References

AI, H., TAN, X., ZHOU, S., ZHOU, Y., XING, H. 2023. The impact of environmental carbon regulation emissions: Evidence from China. *Economic Analysis and Policy*, 80, 1067–1079. https://doi.org/10.1016/j.eap.2023.09.032

ALBITAR, K., BORGI, H., KHAN, M., ZAHRA, A. 2023. Business environment innovation and CO2 emissions: The moderating role of environmental governance. *Business Strategy and the Environment*, 32(4), 1996–2007. https://doi.org/10.1002/bse.3232

CLIMATE FACTS. Online. https://faktaoklimatu.cz/

DAI, Y., WU, H., PAN, H., LUO, L. 2023. The manufacturers' strategy selection of carbon emission reduction and pricing under carbon trading policy and consumer environmental awareness. *Frontiers in Environmental Science*, 11. https://doi.org/10.3389/fenvs.2023.1120165

DIMOS, S., EVANGELATOU, E., FOTAKIS, D., MANTIS, A., MATHIOUDAKI, A. 2020. On the impacts of allowance banking and the financial sector on the EU Emissions Trading System. *Euro-Mediterranean Journal for Environmental Integration*, 5(2).

https://doi.org/10.1007/s41207-020-00167-x

DU, S., QIAN, J., LIU, T., HU, L. 2020. Emission allowance allocation mechanism design: A low-carbon operations perspective. *Annals of Operations Research*, 291(1–2), 247–280. https://doi.org/10.1007/s10479-018-2922-z

EUROPEAN COUNCIL. Online. https://www.consilium.europa.eu/cs/infographics/air-pollution-in-the-eu/#0

EUROSTAT. Online. https://ec.europa.eu/eurostat/databrowser/view/env_air_emis__custom_8249852/default/bar?lang=en

FERNÁNDEZ FERNÁNDEZ, Y., FERNANDEZ LÓPEZ, M., GONZÁLEZ HERNÁNDEZ, D., OLMEDILLAS BLANCO, B. 2018. Institutional change and environment: Lessons from the European emission trading system. *Energies*, 11(4). https://doi.org/10.3390/en11040706

GARCÍA, A., JARAMILLO-MORÁN, M. A. 2020. Short-term European Union allowance price forecasting with artificial neural networks. *Entrepreneurship and Sustainability Issues*, 8(1), 261–275. https://doi.org/10.9770/jesi.2020.8.1(18)

CHOUDHURY, T., KAYANI, U. N., GUL, A., HAIDER, S. A., AHMAD, S. 2023. Carbon emissions, environmental distortions, and impact on growth. *Energy Economics*, 126. https://doi.org/10.1016/j.eneco.2023.107040

LIN, B., JIA, Z. 2020. Can carbon tax complement emission trading schemes? The impact of carbon tax on economy, energy and environment in China. *Climate Change Economics*, 11(3). https://doi.org/10.1142/S201000782041002X

MEI, T., LIU, J., GUO, J., SIANO, P., JIN, X. 2022. Allocation of emission allowances considering strategic voting. *Energy Economics*, 114. https://doi.org/10.1016/j.eneco.2022.106262

MILANÉS-MONTERO, P., PÉREZ-CALDERÓN, E., DIAS, A. I. 2021. GHG emissions performance: Alternatives accounting approaches for the European Union. *Prague Economic Papers*, 30(1), 37–60. https://doi.org/10.18267/j.pep.761

QUAN, Y., DUAN, M. 2023. Emission reductions, industrial competitiveness, and spillover effects under China's regional emission trading systems: Evidence from the iron and steel sector. *Journal of Environmental Management*, 344. https://doi.org/10.1016/j.jenvman.2023.118481

RICKELS, W., PROELSS, A., GEDEN, O., BURHENNE, J., FRIDAHL, M. 2021. Integrating carbon dioxide removal into European emissions trading. *Frontiers in Climate*, 3. https://doi.org/10.3389/fclim.2021.690023

SATO, M., RAFATY, R., CALEL, R., GRUBB, M. 2022. Allocation, allocation, allocation! The political economy of the development of the European Union Emissions Trading System. *WIREs Climate Change*, 13(5). https://doi.org/10.1002/wcc.796

TRADING ECONOMICS. Online. https://tradingeconomics.com/commodity/carbon.

TRIPATHI, A. 2019. Carbon credit management and strategies to combat GHGs emission: An overview of the carbon market. *Indian Journal of Economics and Development*, 15(4). https://doi.org/10.5958/2322-0430.2019.00081.7

ZAPLETAL, F. 2019. Impacts of emissions trading on a company under uncertain multi-period environment. *Fuzzy Information and Engineering*, 11(3), 241–256. https://doi.org/10.1080/16168658.2020.1853992.

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# Oil price trends and their prediction using the ARIMA model

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**Abstract**

The price of oil is an extremely volatile commodity, the prediction of which is complex, but crucial for the stability of the global economy and the energy market. The aim of this work was to evaluate the development of the oil price over the past 25 years and to create a prediction model for estimating its price until 2030. For this purpose, the ARIMA method was used, applied to the time series of WTI oil prices obtained from the EIA database. Statistical tests of stationarity, autocorrelation and subsequent differentiation of the data were performed to correctly set the model. The result was a successful prediction of the future price development of oil with an expected range of 60–90 USD per barrel, with the ARIMA (2,1,1) model demonstrating a good ability to capture both historical trends and cyclical fluctuations. The contribution of the work was the creation of a reliable tool for economic planning in the energy sector. The research is limited by the fact that it does not take into account all external factors, such as geopolitical events or technological progress.

**Keywords:** Prediction, oil, ARIMA method, data stationarity, volatility, economics, energy

## Introduction

Oil plays a key role in the global economy, accounting for one-third of global energy consumption. Despite its importance for policymaking and economic development, oil price prediction remains challenging due to its complexity and erratic price trends. Although a significant amount of research has been conducted to improve forecasts using external factors, machine learning, and deep learning, only a few studies have used hybrid models to improve prediction accuracy. (Kim & Jang, 2023) . Investments in the oil industry are usually associated with a high level of risk due to uncertainty caused by economic factors. Typical factors include oil and gas prices, interest rates, operating costs, and capital expenditures. In addition, investment risk increases with increasing offshore exploration, production, and production activities. Therefore, accurate prediction of economic factors is crucial for the oil and gas industry to make better strategic decisions with minimized risk (Naderi et al., 2019).

OPEC+, composed of the Organization of the Petroleum Exporting Countries (OPEC) and non-OPEC oil-producing countries, has a significant influence on the global oil market. However, the current literature lacks a comprehensive application of this factor in oil price prediction, mainly due to the complexity of measuring such political evolutions (Li et al., 2024).

High inflation targets continue to pose a challenge for macroeconomic stabilization policies in developing economies. Oil prices are considered a significant factor influencing inflation. Given the high and volatile international oil prices, the question of the relationship between inflation and oil prices, and its impacts on economic welfare, has become a crucial empirical issue (Ayisi, 2021) . Oil product prices respond to changes in oil prices with varying speed or intensity. The public perceives this as a relatively rapid response of oil product prices to increases in oil prices, as opposed to their adjustment when oil prices fall. If this asymmetric price transmission is present, it is a direct consequence of the behavior of entities in the energy sector that exploit oil price fluctuations to the detriment of customers. Although the existing literature is quite extensive, it is still predominantly focused on developed countries (primarily the US), with research findings showing significant differences (Cipcic, 2021).

The ongoing Russian-Ukrainian conflict has also had a significant impact on global energy dynamics, which has subsequently weakened the functional capacity of economies around the world (He, 2024) . Conflict caused worry regarding the stability of the global energy sector , given that Russia is a large player in this industry , produces and exports oil and natural gas gas all over world (Kot et al., 2024).

The aim of the thesis is to evaluate the development of oil prices over the last 10 years and to predict oil prices until 2030.

In connection with the objective, the following research questions are set:

The price of oil has experienced significant fluctuations since 2015, affecting the global economy. Examining these developments helps to understand the factors influencing the oil market and makes it easier to predict future prices.

*VO1: How has the price of oil developed from 2000 to the present?*

Oil price prediction is crucial for the economy, energy and investment decisions. Given the market instability, it is important to evaluate current economic indicators to better estimate the development of oil prices over the next 5 years.

*VO2: How will the price of oil develop over the next 5 years?*

The price of oil is one of the most important indicators of the global economy. Understanding these factors is crucial as it allows us to better predict price changes and make strategic decisions.

*VO3: What factors most significantly influence the development of oil prices?*

## Methods and Data

The data used in this research comes from the Energy database Information Administration (EIA, 2024), which provides historical oil price data. Specifically, this will be a time series of data from January 15, 2000 to December 15, 2024. This data is monthly and contains historical WTI (West Texas Intermediate) crude oil prices in US dollars per barrel. The data will be used to apply the ARIMA method to predict future oil price developments based on historical values. All data are freely available and were checked for missing or anomalous values before being used for analysis.

AutoRegressive Inverse Model (method will be used for data analysis. Integrated Moving Average), which is often used for time series prediction. The goal is to use historical oil price data to create a model that will be able to predict future oil price developments. Before using the ARIMA model, basic statistics such as mean, median, mode, standard deviation, and variance will be calculated, which will allow a better understanding of the data structure.

The ARIMA model will be applied using RStudio, a powerful data analysis environment in the R language. Using the forecast package, an ARIMA model will be created that will be optimized for the best results based on historical data. The result will be a model capable of predicting oil prices based on a time series. The ARIMA model is defined by the following formula: (Hyndman & Athanasopoulos, 2018):

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \qquad (1)$$

where:

- $Y_t$ is the value of the time series at time ttt,
- $\alpha$ is a constant (intercept),
- $\phi_i$are the parameters of the autoregressive part of AR,
- $\theta_j$ are the parameters for the moving average MA,
- $\epsilon_t$ is the error (residual) at time ttt,
- $p$is the order of the autoregressive part,
- $q$is the order of the moving average.

Before using the ARIMA model, a check for stationarity of the data will be performed, which is a key condition for the correct application of this model. In case the data are not stationary, they will be subjected to differentiation. The Dickey-Fuller test is commonly used to test for stationarity. It has the following hypothesis: (Hamilton, 1994)

- $H_0$ (null hypothesis): The time series has a unit root (is not stationary).
- $H_1$ (alternative hypothesis): The time series does not have a unit root (it is stationary).

If the p-value of this test is greater than 0.05, the data is considered nonlinear and will need to be adjusted (differentiated).

Another important formula in time series analysis is the differentiation model for achieving stationarity. If the time series is not stationary, differentiation is used to remove trends: (Hyndman & Athanasopoulos, 2018):

$$\Delta Y_t = Y_t - Y_{t-1} \tag{2}$$

where:

- $\Delta Y_t$ is the first differentiation of the time series in time$t$
- $Y_t$ is the value of the time series at time
- $Y_{t-1}$ is the value of the time series at the previous time point$t - 1$

If the first differentiation is not sufficient to achieve stationarity, a second differentiation can be performed: (Hyndman & Athanasopoulos 2018):

$$\Delta^2 Y_t = \Delta Y_t - \Delta Y_{t-1} \tag{3}$$

where:

- $\Delta^2 Y_t$ *je d*reverse differentiation of a time series in time$t$
- $\Delta Y_t$ *je p*smooth differentiation of a time series in time$t$
- $\Delta Y_{t-1}$ *je první* differentiation of a time series in the previous time$t - 1$

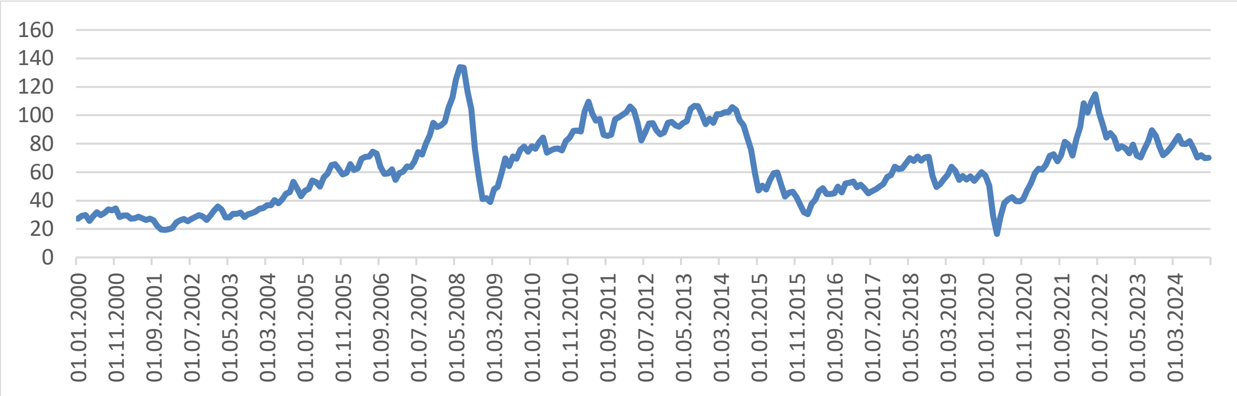
Next, the model will be optimized automatically using the auto.arima () function, which will select the best parameters for the model. Subsequently, oil prices for the next 5 years (until 2030) will be predicted and displayed on the graph.

The analysis is expected to result in a robust model that is capable of providing reliable oil price predictions based on historical trends. The results of this analysis will then be used to answer the research questions and fulfill the research objectives.

## Results

A table was created to process historical data, from which the following graph (Figure 1) was created in RStudio, which shows the development of the oil price in the period between 2000 and 2024. As this Graph 1 shows, the price of oil has undergone significant changes over the past few decades. After a stable period in the early 2000s, when the price of oil fluctuated around 20-30 USD per barrel, there was a significant increase in the years 2004-2008, when the price rose to more than 140 USD per barrel. This growth was followed by a significant decrease in 2008 and a subsequent recovery in the years 2010-2014. After 2014, the price of oil fell below 30 USD per barrel again. In 2020, the price of oil experienced a historic decline, when short-term contracts even had negative values. In recent years, since approximately 2021, the price of oil has stabilized between $50 and $100 per barrel, with occasional fluctuations.

Figure 4: WTI oil price development in 2000-2024

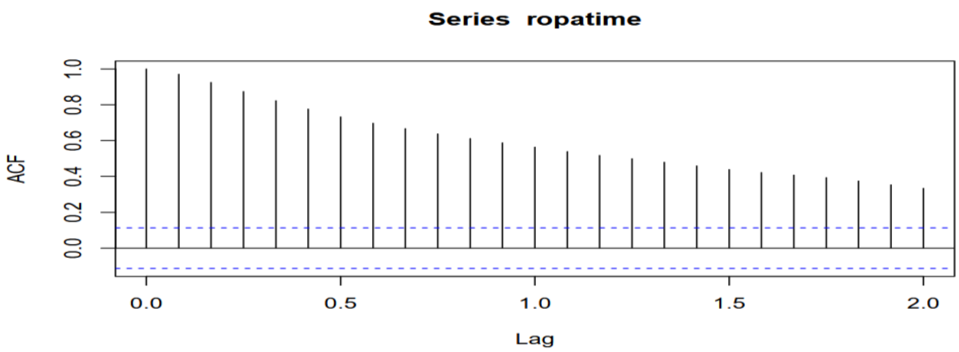



Source: Own processing based on data from Energy Information Administration (EIA,2024).

Next, the data was entered into RStudio, where ACF (autocorrelation) and PACF (partial autocorrelation) testing was performed.

The ACF (Figure 2) shows how the values of a time series depend on their previous values (lags). It is evident from this chart that for lower lags the autocorrelation is significant, but as lags increase the correlation decreases rapidly. This result suggests that the data show some dependence between the values, but this dependence weakens rapidly, which could mean that the data are not fully stationary, but that they are gradually leveling out.

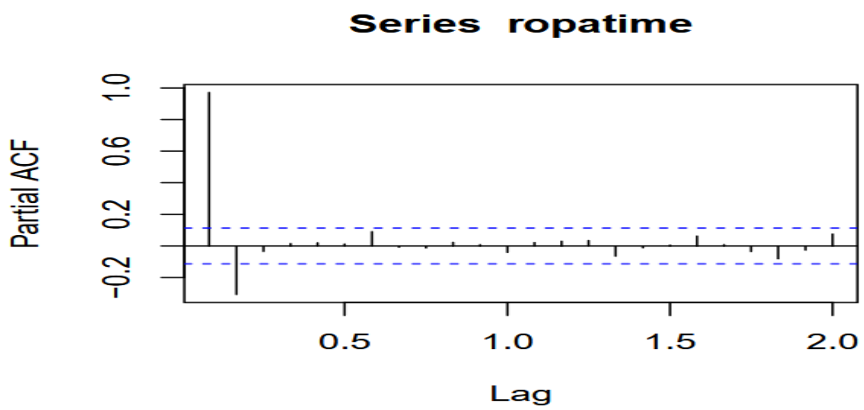
Figure 2: ACF of the original time series




Source: Own processing using RStudio.

The PACF (Figure 3) chart shows the partial autocorrelation, which measures the correlation between values at a time and their lagged values after removing the effect between previous lags. In this chart, we see that the values are mostly below the statistical significance threshold (blue lines), which means that there is no strong correlation between the values after cleaning up the effect of previous values.

Figure 3: PACF of the original time series




Source: Own processing using RStudio.

Based on these plots, it can be concluded that the data shows some autocorrelation, but after removing it (in the PACF), the values are not strongly correlated. This suggests that the data is not ideally stationary, but shows some weak autocorrelation.

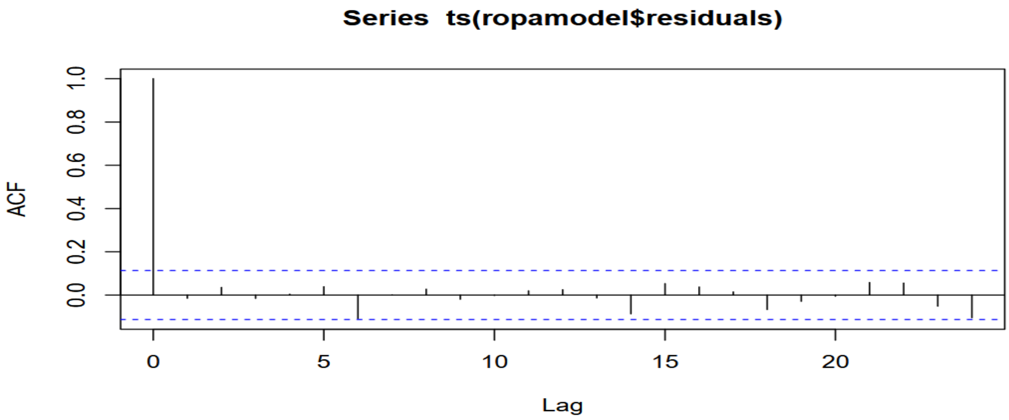
It was also carried out Augmented Dickey-Fuller (ADF) test. The ADF result indicates that the data is not stationary. The ADF test statistic was -2.4843, which indicates some degree of dependence between the values in the time series. However, the p-value of the test is 0.3721, which is higher than 0.05, and means that we cannot reject the null hypothesis that the time series has a unit root. This indicates that the data is non-stationary.

Thanks to these results, we know that the time series shows some trend or structure that causes a dependence between values over time. Therefore, to use this data in modeling, it is necessary to make adjustments so that the time series becomes stationary and can be properly analyzed and used for predictions.

After applying differentiation to the data to make it stationary, further stationarity checks were performed using ACF and PACF.

The ACF plot (Figure 4) shows that after differentiation, the autocorrelation is very weak and most of the values are below the statistical significance threshold (blue lines). This indicates that the model has estimated the structure of the time series well and the residuals do not contain any strong patterns.

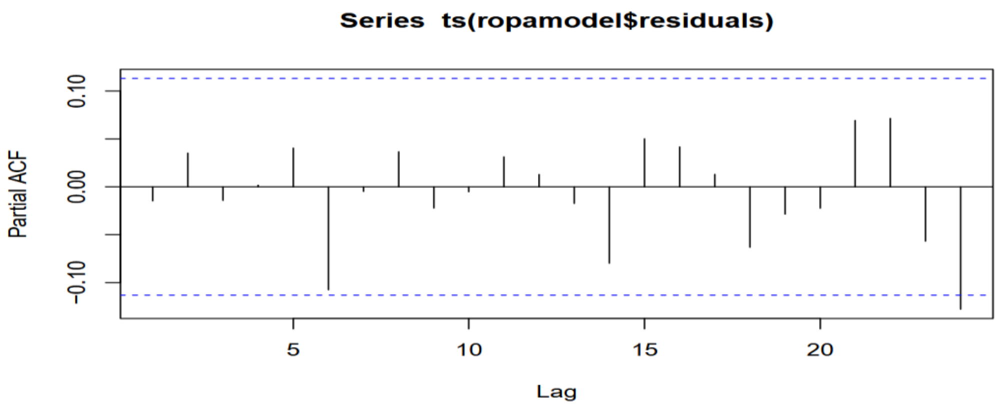
Figure 4: ACF adjusted time series




Source: Own processing using RStudio.

The PACF plot (Figure 5) shows that after removing the influence of previous lags, only a weak partial autocorrelation remains, confirming that the model adequately captures the structure of the data and no strong patterns remain. The data are stationary after differentiation. Based on these analyses, the ARIMA (2,1,1) model was recommended.

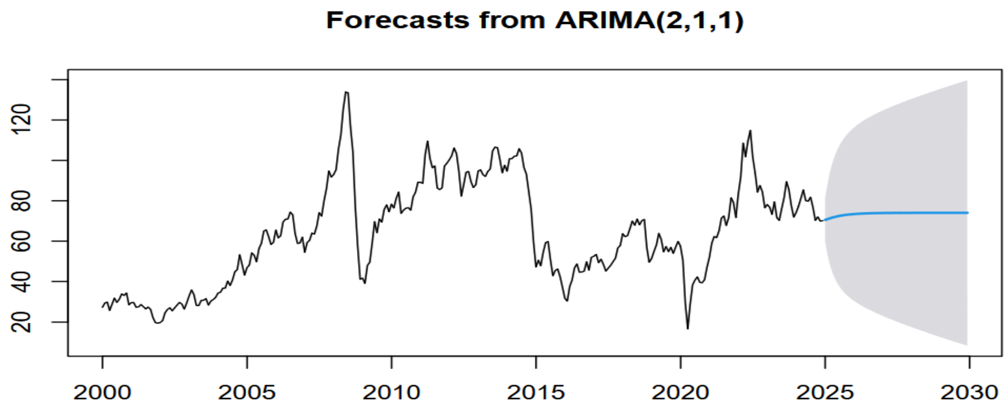
Figure 5: PACF adjusted time series




Source: Own processing using RStudio.

The final forecast for the WTI oil price was then made using the ARIMA (2,1,1) model. Figure 6 shows the historical oil price values along with the predicted future development up to 2030. The blue line shows the predicted values, while the grey area around this line shows the confidence interval of the prediction, which means the range in which the actual values are expected to move. The ARIMA (2,1,1) model is able to capture the main trend and cyclical fluctuations in the historical data, but the prediction into the future is burdened with some uncertainty, as seen in the form of a grey shadow. The model provides an estimate of the future development of the oil price, which should, however, be taken with caution due to the possibility of changes in external factors affecting the oil market.

Figure 6: Oil price forecast until 2030




Source: Own processing using RStudio.

Finally, a Box- Ljung test was performed to check whether the residuals show autocorrelation. This test is used to determine whether the remaining values after applying the model are random or whether there are any patterns in them that would indicate that the model was not properly fitted. The first result, where X- squared = 0.99601, df = 5 and p-value = 0.9629, indicates that the p-value is very high, which means that there is no significant autocorrelation in the residuals. Therefore, it can be said that the residuals are random and the model captures the data structure well. The second result with X- squared = 8.5349, df = 15 and p-value = 0.9006 again confirms that the p-value is very high, which means that the residuals do not show any significant autocorrelation.

Overall, these results confirm that the ARIMA (2,1,1) model is well-fitted and that the residuals are random. This suggests that the model captures the dynamics of the data well and can be considered reliable for predictions.

## Discussion

*VO1: How has the price of oil developed from 2000 to the present?*

The development of the price of oil from 2000 to the present shows significant fluctuations, which is clearly visible from the historical price trends, as shown in the graph of the price of WTI oil. In the period between 2000 and 2008, the price of oil was stable, moving in the range of 20-30 USD per barrel. This stable development was characterized by relatively low demand and the absence of major geopolitical or economic shocks that could fundamentally affect prices on the oil market. However, in the years 2004-2008, there was a significant increase in the price, which rose to more than 140 USD per barrel. This growth was supported by strong global economic growth, especially in emerging economies such as China, which demanded more and more oil, and also contributed to the growth of speculative activities in commodity markets. After the peak in 2008, the price fell dramatically, which was related to the global financial crisis. The decline in oil prices at the beginning of the financial crisis was the result of a sharp economic slowdown, which led to a decline in demand for oil. This decline continued in 2020, when the world faced the COVID-19 pandemic, which led to an unprecedented decline in demand and oil prices. This year, the price of oil even briefly fell into negative values on futures markets due to excess supply and loss of demand. This development clearly shows the high volatility in the oil market and significant sensitivity to global economic and political factors. After a period of crises, from 2016 to the present, the price of oil has gradually increased, stabilizing between 50-100 USD per barrel, with occasional fluctuations. This trend is mainly attributed to the recovery of the global economy after the crisis and the growth in demand, as well as the decision of OPEC and other producers to limit production, which helped stabilize the market. However, this stabilization is subject to a certain degree of uncertainty, not only due to geopolitical factors (such as OPEC+ policy decisions), but also due to environmental and technical changes in the way of extraction, such as the increasing extraction of shale oil in the USA. This development is in line with the findings of Naderi et al. (2019), who observed similar fluctuations and trends when using the ARIMA model to analyze historical oil price data. Their study shows that even with the help of traditional statistical methods such as ARIMA, it is possible to capture long-term cyclical fluctuations and major crisis events that affect oil prices, which confirms the validity of the ARIMA model for this type of prediction.

*VO2: How will the price of oil develop over the next 5 years?*

The forecast of oil prices for the next 5 years using the ARIMA (2,1,1) model suggests that oil prices will continue to show volatility. The predicted price range is between 60-90 USD per barrel, reflecting the historical fluctuations that have been recorded in previous years. This price interval is consistent with the trend of the last decade, when the oil price has stabilized between 50-100 USD per barrel, with occasional fluctuations caused by geopolitical factors, changes in demand and OPEC+ decisions. This prediction is consistent with the research of Naderi et al. (2019), who used a similar ARIMA model to predict oil prices on a monthly basis. Their study showed that forecasts based on the ARIMA model are able to accurately capture long-term trends, although there is some uncertainty in the case of unexpected changes in the market, such as geopolitical conflicts, pandemics or new extraction technologies. As in their research, our 5-year forecast shows that price volatility will continue to be present, but the ARIMA model provides a solid framework for estimating these price changes if the market continues to trend similarly to the past. It is important to note that while the ARIMA model provides useful predictions, it is still sensitive to changes in external factors. Forecasts for longer time horizons are therefore subject to a higher degree of uncertainty.

*VO3: What factors most significantly influence the development of oil prices?*

Several key factors influencing the price of oil can be identified, including geopolitical factors (such as the Russia-Ukraine conflict), economic indicators (inflation, interest rates) and OPEC+ decisions. For example, in 2008, the oil price fell sharply after the outbreak of the global financial crisis. The same thing happened again in 2020, when the oil price even went negative. This decline was, on the contrary, a consequence of reduced demand caused by the global pandemic and worldwide lockdown. In the literature, authors such as Kim & Jang (2023) focus on the complex effects of various factors using a hybrid model, which also includes OPEC political factors. The analysis focused on historical data and macroeconomic indicators, but in the future, the accuracy of the prediction could be improved by including specific political and economic factors, as shown by Kim & Jang and Li et al. (2024). The prediction could therefore be enriched with factors that influence the price of oil but which were not included in this research.

This research used the ARIMA model, which is a widely used method for time series analysis. The results in terms of modeling historical data and predicting oil prices show similar developments to the studies of Naderi et al. (2019) and others who used ARIMA or other machine learning methods. A significant finding was that even using the ARIMA method, it was able to capture historical trends and cyclical fluctuations, which is consistent with similar studies. When comparing this prediction with machine learning methods such as LSTM (Abdulrahim et al., 2025), it can be said that even ARIMA provides solid predictions, although modern machine learning models may show better performance for some types of data.

## Conclusion

The aim of this work was to analyze the development of oil prices over the last 25 years and to predict its price until 2030. For this purpose, the ARIMA (AutoRegressive Inverse Matrix) method was used. Integrated Moving Average), which is known for its ability to model time series and predict future values based on historical data.

The oil price forecast to 2030 suggests that the price will continue to show significant volatility, ranging between 60 and 90 USD per barrel. This price range reflects not only historical trends, but also current uncertainties and fluctuations in the global oil market. The ARIMA model was able to capture the main long-term trend as well as cyclical fluctuations that are typical for the market for this commodity.

Although the model shows good predictive ability based on historical data, its results are subject to a significant degree of uncertainty. This uncertainty mainly arises from external factors that the model cannot directly include or accurately predict. These factors include, in particular, geopolitical events, such as the ongoing war in Ukraine, which has significantly disrupted global oil supply chains and caused instability in the markets. This conflict has an impact on oil production, exports and prices, and although it is not possible to simply incorporate it into the ARIMA model, it should be taken into account as a key element influencing future price developments. Other key factors are OPEC+ decisions on production volumes, which have a direct impact on the supply of oil on the market and can cause sharp price fluctuations. In addition, economic factors such as changes in global demand, inflation, interest rates or technological innovations in mining and alternative energy sources also play a role. These factors often act in a complex way and can significantly shift the price trajectory.

The ARIMA model is therefore an effective tool for monitoring and predicting oil prices based on available historical data and allows capturing basic patterns in the data. However, due to the inability to include some dynamic and unpredictable external influences, it is necessary to interpret the results with caution and in the context of current events on the world market.

Overall, it can be stated that the objective of the work was met, as it was possible to build a reliable statistical model that provides valuable insight into the likely development of oil prices in the coming years. This model can serve as a useful tool for decision-making in the energy sector and for planning, however, to increase the accuracy of the prediction, it would be appropriate to incorporate a wider range of factors in the future, including geopolitical indices, macroeconomic indicators and technological changes, or to use more modern machine learning methods.

However, it should be mentioned that the main limitation of this study may be that the ARIMA model, although effective for time series prediction, does not take into account all external factors that can fundamentally affect oil prices, such as political events or changes in extraction technology. Another limitation is that predictions for a longer time horizon are always burdened with a higher degree of uncertainty, which is clearly visible in the prediction graph, where the gray area represents the confidence interval.

In the future, it would be useful to explore other predictive methods, such as machine learning methods, and compare them with classical statistical models such as ARIMA. Furthermore, it would be possible to incorporate a wider range of external factors into the model that can better explain fluctuations in the oil market.

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## References

AYISI, R. K. 2021. The asymmetry effect of oil price changes on inflation, and the welfare implication for Ghana. *African Journal of Economic and Management Studies*, 12(1), 55–70. https://doi.org/10.1108/AJEMS-01-2020-0009

GAO, S., LEI, Y. 2017. A new approach for crude oil price prediction based on stream learning. *Geoscience Frontiers*, 8(1), 183–187. https://doi.org/10.1016/j.gsf.2016.08.002

HE, K., E., J. 2024. Potential formation mechanism and prediction of crude oil price based on underdetermined independent component analysis. *Petroleum Science and Technology*, 1–22. https://doi.org/10.1080/10916466.2024.2408437

HE, Y. 2024. Unraveling the economic echoes: The Russo-Ukrainian conflict's influence on South Korean macroeconomic stability – Insights from the energy sector. *Sage Open*, 14(4), 21582440241287296. https://doi.org/10.1177/21582440241287296

JHA, N., KUMAR TANNERU, H., PALLA, S., HUSSAIN MAFAT, I. 2024. Multivariate analysis and forecasting of the crude oil prices: Part I – Classical machine learning approaches. *Energy*, 296, 131185. https://doi.org/10.1016/j.energy.2024.131185

KIM, G. I., JANG, B. 2023. Petroleum price prediction with CNN-LSTM and CNN-GRU using skip-connection. *Mathematics*, 11(3), 547. https://doi.org/10.3390/math11030547

KOT, S., PIONTEK, B., KHALID, B. 2024. The economic shockwaves of the Russia-Ukraine conflict and energy sources prices—The impact on international energy markets. *Acta Montanistica Slovaca*, 29(2), 353–366. https://doi.org/10.46544/AMS.v29i2.10

LI, J., HONG, Z., YU, L., ZHANG, C., REN, J. 2024. Do OPEC plus policies help predict the oil price: A novel news-based predictor. *Helion*, 10(14), e34437. https://doi.org/10.1016/j.heliyon.2024.e34437

LIN, H., SUN, Q. 2020. Crude oil prices forecasting: An approach of using CEEMDAN-based multi-layer gated recurrent unit networks. *Energies*, 13(7), 1543. https://doi.org/10.3390/en13071543

LIU, J., ZHAO, X., LUO, R., TAO, Z. 2024. A novel link prediction model for interval-valued crude oil prices based on complex network and multi-source information. *Applied Energy*, 376, 124261. https://doi.org/10.1016/j.apenergy.2024.124261

NADERI, M., KHAMEHCHI, E., KARIMI, B. 2019. Novel statistical forecasting models for crude oil price, gas price, and interest rate based on meta-heuristic bat algorithm. *Journal of Petroleum Science and Engineering*, 172, 13–22. https://doi.org/10.1016/j.petrol.2018.09.031

SHIN, H., HOU, T., PARK, K., PARK, C.-K., CHOI, S. 2013. Prediction of movement direction in crude oil prices based on semi-supervised learning. *Decision Support Systems*, 55(1), 348–358. https://doi.org/10.1016/j.dss.2012.11.009

SOHRABI, P., DEHGHANI, H., RAFIE, R. 2022. Forecasting of WTI crude oil using combined ANN-Whale optimization algorithm. *Energy Sources, Part B: Economics, Planning, and Policy*, 17(1), 2083728. https://doi.org/10.1080/15567249.2022.2083728

US ENERGY INFORMATION ADMINISTRATION (EIA). Monthly crude oil prices. [online]. [cit. 2025-05-20]. Available from: https://www.eia.gov/

YANG, H., ZHANG, Y., JIANG, F. 2019. Crude oil prices forecast based on EMD and BP neural network. *2019 Chinese Control Conference (CCC)*, 8944–8949. https://doi.org/10.23919/ChiCC.2019.8866586

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# Inflation forecast with oil price forecast

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**Abstract**

The aim of the work was to map the development of the inflation rate in the Czech Republic and oil prices on world markets in the period from January 2020 to March 2024, and in connection with this development, to create a forecast of the development of the inflation rate in the Czech Republic and oil prices on world markets in the following period, i.e. from April to December 2024. Another aim was to compare both quantities, or rather their development, and to determine whether the inflation rate in the Czech Republic is influenced by the price of oil on world markets. The chosen method for determining the forecasts of the development of both quantities was linear regression. Quantitative content analysis was used to obtain data. The values of the inflation rate and oil prices were subsequently also expressed graphically for better clarity. From May 2022 to August 2022, the inflation rate ranged from 16% to 18%. The price of Brent oil in the same period ranged between CZK 2,374 and CZK 2,613.70. In both cases, it was a sharp increase compared to 2020. Although the curves of both quantities showed a similar trend, a detailed comparison subsequently showed that the price of oil on world markets does not have a direct connection with the inflation rate in the Czech Republic, although it certainly influences it to some extent in certain periods. Both the inflation rate in the Czech Republic and the price of Brent oil on world markets will have a slightly increasing trend until the end of 2024, but will not return to their highs from the summer of 2022. The most significant limitation of this work was the factor of the Russian-Ukrainian conflict, which caused large fluctuations in values, which could have distorted the actual relationship between the two quantities.

**Keywords:** Inflation, oil price, linear regression, inflation rate development, forecast

## Introduction

According to Alsuhaili, the higher inflation rate and Panigrahi (2023) have a greater negative impact on the country's financial development, while GDP growth reduces this impact. Many external factors influence the level of inflation. The study by Nguyen et al. (2020) shows that exchange rate and oil shocks have also been significant factors recently. The growth of the money supply and output is also not negligible. These findings have profound implications for the formulation of monetary policy and price stability.

The increase in inflation has a significant impact on the economy and purchasing power of households, with the lowest income and socially weaker groups of the population and seniors being most affected, whose nominal wages and pensions (if not valorized) are devalued. Inflation also affects the economic performance of companies - if inflation decreases, then the profit of companies will constantly increase, on the contrary, if the inflation rate increases, the total profit will continuously decrease (Padiyar, 2023).

Higher inflation rates also reduce the value of deposits and loans, and higher inflation expectations lead firms to increase prices, demand for loans, and reduce employment and capital (Coibion et al., 2020). In this situation, the national central bank has a significant position, as its measures can influence inflation, both positively and negatively. Although it is an independent institution that determines the country's monetary policy, it is subject to some influence and in many cases also under political pressure, especially from left-wing governments that are trying to implement a looser monetary policy.

The Covid-19 pandemic has increased inflation and unemployment worldwide, prompting national central banks to implement measures to mitigate their impacts (Long, et al., 2022). Another negative impact on inflation developments not only in the Czech Republic was the Russian invasion of Ukraine, which began in February 2022. A study conducted on the basis of data from the Czech Statistical Office showed the extent to which the European financial system is sensitive to external shocks that occur during significant inflationary changes (Vochozka et al., 2023).

Since the inflation rate is one of the most important macroeconomic indicators and its level is an important aspect for price formation, wage and interest rate setting, as well as for pension valorization, it is necessary to predict its development in the upcoming period, usually in the following calendar year.

The aim of this work is to forecast the development of inflation in the Czech Republic in 2024 in connection with the development of oil prices on world markets.

In connection with the objective, the following research questions are set:

*VO1: How will the expected inflation rate in the Czech Republic develop in 2024?*

*VO2: What is the expected development of oil prices on world markets in 2024?*

## Methods and Data

### Data

In order to answer the first research question, quantitative content analysis of data will be used, namely from data available on the website of the Czech Statistical Office. Here, the Inflation, consumer prices tab will be searched, and then the Inflation – types, definitions, tables section will be searched. In this section, only data from Part 2 will be used (https://www.czso.cz/ csu / czso / mira_inflace). Here, the inflation rate is expressed as the increase in the consumer price index to the same month of the previous year and expresses the percentage change in the price level in the reported month of the given year compared to the same month of the previous year. It is therefore the achieved price level that excludes seasonal effects by always comparing the same months. From the table in this section, data for individual months in the period 1/ 2020 – 3 /2024 will be used, which will be entered into a table in MS Excel and subsequently visualized in the form of a graph.

As a basis for answering the second research question, a content-based quantitative analysis of data from the Kurzy.cz website will also be used as a basis for answering the second research question, where the commodity Oil, more precisely Brent Oil, will be specified in the Commodities section. Here, in the Brent Oil history section, the table lists oil prices for individual calendar years, and data for the period 1/2020 – 3/2024 will be used for the analysis. It will therefore be necessary to click on the given year in order to obtain data for individual months (https://www.kurzy.cz/komodity/ropa-brent-graf-vyvoje-ceny/historie-czk-1barel). It will also be necessary to specify the currency, in this case CZK, for 1 barrel. The Average data will be used from the data offered. The values will be recorded in a table in MS Excel. Subsequently, this data will also be converted into a graph.

### Methods

To evaluate research questions 1 and 2, a regression method will be used, which will allow us to examine the relationship between two variables, one of which is the independent variable x and the other the dependent variable Y, assuming that both variables are continuous.

The conditions of the regression model are as follows:

$$Y_1 = \beta_0 + \beta_{1.xi} + e_i \tag{1}$$

Where:

1. $E(e_i) = 0$ for each i=1, 2, …., n
   the mean value of the random component is zero
2. $D(e_i) = \sigma^2$ for each i=1, 2, …., n
   the variance of the random component is constant
3. $Cov(e_i e_j) = 0$ for each $i \neq j$, where i, j = 1, 2, … n
   the covariance of the random component is zero
4. Normality: The random components ei have a normal distribution for i = 1, 2, …, n.

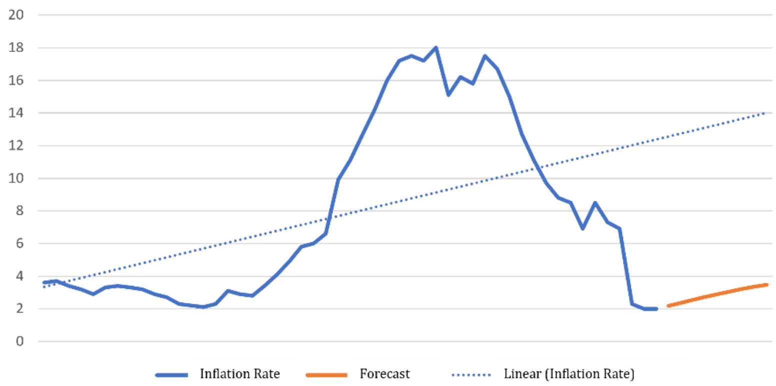
5. The regression parameters β 1 can take on arbitrary values
6. The regression model is linear in parameters

The existence of a linear relationship between two quantities is determined by answering the question whether the slope β 1 is equal to zero. If the answer is positive, it means that the slope of the adjustment line differs from zero only by chance, so the relationship between the monitored variables is not linear. Otherwise, it will be a linear relationship. The conditions of the linear regression model will need to be verified within the framework of the regression analysis, which will confirm or refute the connection between the price of oil and the inflation rate. At the same time, based on the calculation performed, it will be possible to predict the development of both variables in the next period of 2024.
Data from the content analysis of the development of the oil price and the inflation rate in the period 1/2020 - 3/2024 will be used as input data for the calculation.

## Results

Both the price of oil and the inflation rate were monitored for one calendar month, from January 2020 to April 2024. The source data with the price of oil and the inflation rate were included in the Annexes chapter.

Figure 1: Development of the inflation rate (in %)

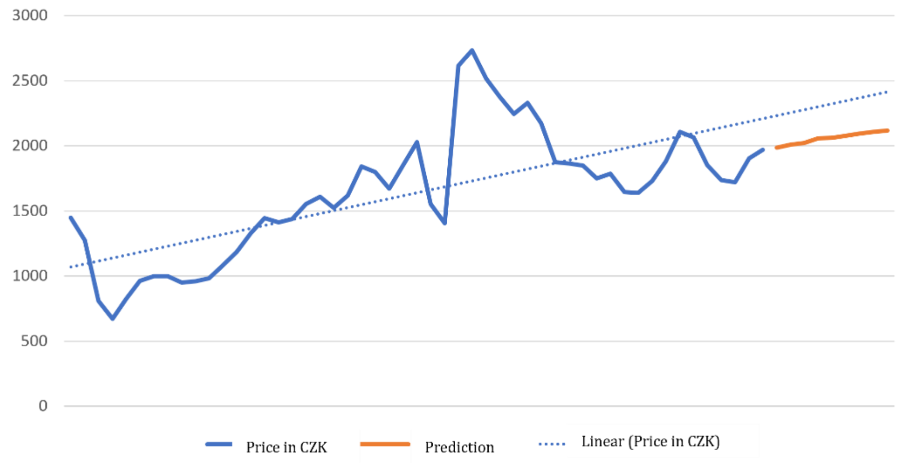



Source: Author.

Figure 1 shows the development of the inflation rate in the period from January 2020 to March 2023. Inflation was monitored in percentages, using the values from the second part of the table, where the inflation rate is expressed as the increase in the consumer price index compared to the same month of the previous year and expresses the percentage change in the price level in the reported month of the given year compared to the same month of the previous year. The low inflation rate is evident throughout 2020, when it averaged around 2.24%. In April 2021, its value increased slightly to 3.1%, but immediately decreased again. In July 2021, it rose to 3.4%, and from this month onwards, only an increase followed, which gradually accelerated, with inflation reaching a record rate of 18% in September 2022. In April 2023, a significant decrease to 12.7% was recorded, which then continued until February 2024, when the inflation rate stopped at

2%. The prediction for the period April - December 2024 shows an increasing trend, which, however, will no longer reach the extreme values of 2022 and will stick to the average monthly value of 2.87%.

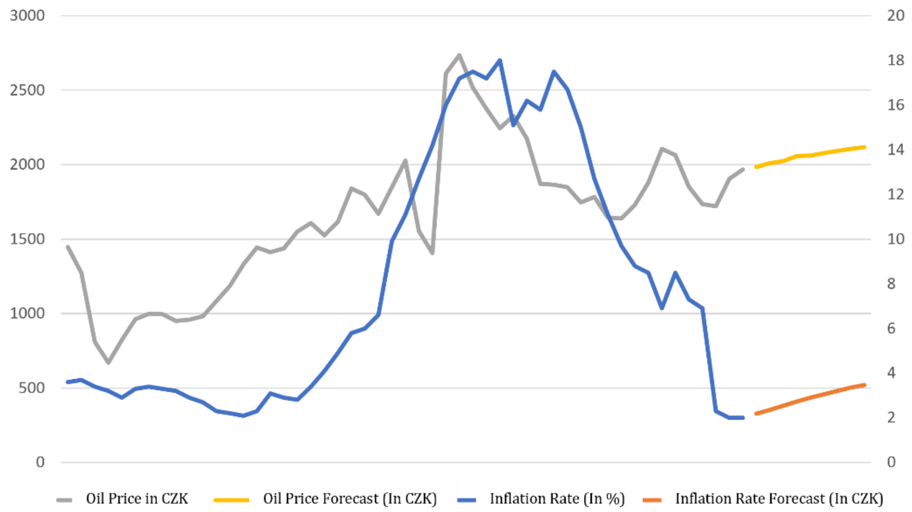
Figure 2: Brent oil price development (in CZK per barrel)




Source: Author.

Figure No. 2 shows the development of the price of Brent crude oil in the period from January 2020 to March 2023. The price was monitored in Czech crowns and in the unit of measure barrel, and the Average values were considered. The data was taken from the website kurzy.cz (kurzy.cz, 2024). The graph shows the lowest price in April 2020, when it was 669.86 CZK per barrel. Then the price gradually increased. In April 2022, there was a rapid decline, but immediately the price began to rise again, and in June 2022 it reached its maximum with a value of 2734.7 CZK per barrel. Subsequently, there was a gradual decline again, but the price did not return to its initial values. Based on the linear regression method, the development of the price of this commodity in the subsequent periods of 2024 was predicted - i.e. from April to December. According to this forecast, the price of oil will tend to continue to rise slightly in the following period, exceeding CZK 2,000 per barrel in May and remaining at an average value of CZK 2,059.23 per barrel until the end of the year.

Figure 3: Comparison of inflation and oil price developments




Source: Author.

Both data on the development of the inflation rate and the development of Brent oil prices were included in graph number 3 in order to compare whether there is a relationship between the two variables, i.e. whether the development of oil on world markets has an impact on the development of inflation in the Czech Republic. In April 2020, both variables showed a decrease, while in May 2020 the price of oil increased slightly, while the inflation rate, on the contrary, decreased. Until the end of 2020, identical and opposite trends continued. Already in February 2021, the price of oil increased significantly to CZK 1,330 per barrel compared to CZK 1,185 in January, while the inflation rate, on the contrary, decreased by 0.1%. Until December 2021, the inflation rate increased slowly, while the price of oil rose more steeply. In January and February 2022, both variables had the same upward trend. In April 2022, the price of oil fell sharply, while the inflation rate continued to rise steeply. From November 2022 to June 2023, the price of oil fell, but the inflation rate alternately rose and fell. Then, until March 2024, both variables had completely opposite development trends. From a comparison of the curves of both variables, it can be concluded that the price of oil on world markets does not have a direct connection with the inflation rate in the Czech Republic, although it certainly influences it to some extent in some periods.

## Discussion

Based on the results obtained, it is possible to answer the following research questions*:*

*VO1: How will the expected inflation rate in the Czech Republic develop in 2024?*

In the case of this research question, quantitative content analysis of data was used, based on data available on the website of the Czech Statistical Office. The first month monitored was January 2020, when the inflation rate in the Czech Republic was 3.6%. Until July 2021, there was an alternating slight increase and decrease in the inflation rate in the range of up to 3.4%. However, in August 2021, there was an increase to 4.1% and until the end of

2021, the inflation rate was only increasing, reaching its maximum in September 2022, at 18%, which was an increase of 400% compared to January 2020. After that, there was an initially fluctuating decline to the current value of 2% in March 2024. Using the regression method, an estimate of the development of the inflation rate until the end of 2024 was determined, with its values continuing to range between 2 and 3.5%.

The study by Nguyen et al. (2020) examined the impact of exchange rate and oil shocks on inflation rates. For this reason, another research question examined the development of oil prices on global markets to assess the actual impact on inflation rates.

*VO2: What is the expected development of oil prices on world markets in 2024?*

To answer this research question, it was necessary to obtain data using quantitative content analysis. The source was the website www.kurzy.cz. At the beginning of the monitored period, i.e. in January 2020, the price of one barrel of Brent crude oil was CZK 1447.5, then there was a gradual decrease to the price of CZK 823.29 per barrel. However, in June 2020, there was a sharp increase in the price, and this growth had an upward trend with small fluctuations in the following months. The price reached its maximum in May 2022, when it was CZK 2734.7 per barrel, which was an increase of almost 89% compared to January 2020. From July 2022, the price gradually decreased until June 2023, when it reached the level of CZK 1638.8 per barrel. Until September 2023, the price rose again, but from October 2023 there was a gradual decline to CZK 1,968.9 per barrel in March 2024. The regression analysis shows that the price per barrel of Brent crude oil will have a slightly increasing trend in the following months of 2024, but will no longer reach the maximum of May 2022.

## Conclusion

The aim of the work was to map the development of the inflation rate in the Czech Republic and the price of oil on world markets in the period from January 2020 to March 2024, and in connection with this development, to create a forecast of the development of the inflation rate in the Czech Republic and the price of oil on world markets in the following period, i.e. from April to December 2024. Another aim was to compare both quantities, or rather their development, and to determine whether the inflation rate in the Czech Republic is influenced by the price of oil on world markets. The aim of the work was met.

From May 2022 to August 2022, both the inflation rate and the price of oil were at their maximum values, with inflation ranging from 16% to 18%, which was an increase of approximately 400% compared to the beginning of the monitored period in January 2020. The price of Brent oil in the same period ranged between CZK 2,374 and CZK 2,613.70, which was an increase of an average of 89% compared to January 2020. Both quantities were undoubtedly significantly influenced by the Russian aggression in Ukraine in the given period, which began in February 2022 and from May to August 2022 had the strongest impact on global economic development, including inflation and the price of oil.

It was found that both the inflation rate curve and the oil price curve had a similar, but not entirely identical, course in the monitored period. A detailed comparison subsequently revealed that the price of oil on world markets has no direct connection with the inflation rate in the Czech Republic, although it certainly influences it to some extent in some periods.

Regarding the development of the inflation rate in the Czech Republic and the price of Brent oil on world markets in April - December 2024, the result of the linear regression was the finding that both quantities will have a similarly slightly increasing trend in this period. The price of Brent oil will not return to its 2020 lows or attack the summer 2022 highs, but will fluctuate around CZK 2,000 per barrel until the end of 2024. In contrast, the inflation rate in the Czech Republic already returned to its 2020 value in January 2024 and will maintain the current trend of between 2% and 3.5% until the end of 2024.

The most significant limitation of this work was the factor of the Russian-Ukrainian conflict, which caused large fluctuations in values, which could have distorted the true relationship between the two quantities.

For this reason, follow-up research and monitoring of the further development trend of both quantities in the coming years is recommended, especially in connection with global socio-political developments.

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## References

ALSUHAILI, L. K., PANIGRAHI, S. K. 2023. Investigating the relationship between inflation and financial development: Evidence from Saudi Arabia. *2023 International Conference on Sustainable Islamic Business and Finance (SIBF)*, Bahrain, 159–163. https://doi.org/10.1109/SIBF60067.2023.10380099

COIBION, O., GORODNICHENKO, Y., ROPELE, T. 2020. Inflation expectations and firm decisions: New causal evidence. *The Quarterly Journal of Economics*, 135(1), 165–219. https://doi.org/10.1093/qje/qjz029

ČESKÝ STATISTICKÝ ÚŘAD [Czech Statistical Office]. Míra inflace [Inflation rate]. [online]. 2024. Available from: https://www.czso.cz/csu/czso/mira_inflation [cit. 2024-06-01].

HAILEMARIAM, A., SMYTH, R., ZHANG, X. 2019. Oil prices and economy policy uncertainty: Evidence from a nonparametric panel data model. *Energy Economics*, 83, 40–51. https://doi.org/10.1016/j.eneco.2019.06.010

KOROLEVA, E., KOPEYKIN, M. 2022. Understanding of macro factors that affect yield of government bonds. *Risks*, 10(8). https://doi.org/10.3390/risks10080166

KURZY.CZ. Ropa Brent – historie cen (CZK/1 barel) [Brent crude oil – price history (CZK/1 barrel)]. 2024. Available from: www.kurzy.cz/komodity/ropa-brent-graf-vyvoje-ceny/historie-czk-1barel [cit. 2024-06-01].

LIAO, Q., YANG, L., LIM, E. J. 2023. A bibliometric and content analysis of marketing-finance interface research from 1986–2021. *Journal of Business & Finance Librarianship*, 28(4), 278–301. https://doi.org/10.1080/08963568.2023.2263984

LONG, H., CHANG, C.-P., JEGAJEEVAN, S., TANG, K. 2022. Can central bank mitigate the effects of the COVID-19 pandemic on the macroeconomics? *Emerging Markets Finance and Trade*, 58(9), 2652–2669. https://doi.org/10.1080/1540496X.2021.2007880

OLUGBENGA ADARAMOLA, A., DADA, O. 2020. Impact of inflation on economy growth: Evidence from Nigeria. *Investment Management and Financial Innovations*, 17(2), 1–13. https://doi.org/10.21511/imfi.17(2).2020.01

PADIYAR, S. V. S., VANDANA, SINGH, S. R., SINGH, D., SARKAR, M. et al. 2023. Three-echelon supply chain management with deteriorated products under the effect of inflation. *Mathematics*, 11(1). https://doi.org/10.3390/math11010104

PHAM, T. A. T., NGUYEN, T. T., NASIR, M. A., DUC HUYNH, T. L. 2023. Exchange rate pass-through: A comparative analysis of inflation targeting & non-targeting ASEAN-5 countries. *The Quarterly Review of Economics and Finance*, 87, 158–167. https://doi.org/10.1016/j.qref.2020.07.010

SARKAR, A., GUCHHAIT, R., SARKAR, B. 2022. Application of the artificial neural network with multithreading inside an inventory model under uncertainty and inflation. *International Journal of Fuzzy Systems*, 24(5), 2318–2332. https://doi.org/10.1007/s40815-022-01276-1

SHAPIRO, A. H., SUDHOF, M., WILSON, D. J. 2022. Measuring news sentiment. *Journal of Econometrics*, 228(2), 221–243. https://doi.org/10.1016/j.jeconom.2020.07.053

TOSUNI, G., MISINI, S. 2023. Economic performance of the countries in the Western Balkans. *Journal of Governance and Regulation*, 12(4), 8–21. https://doi.org/10.22495/jgrv12i4art1

VAN DINH, D. 2020. Comparison of the impact of lending and inflation rates on economy growth in Vietnam and China. *Banks and Bank Systems*, 15(4), 193–203. https://doi.org/10.21511/bbs.15(4).2020.16

VOCHOZKA, M., ŠKAPA, S., APANOVYCH, Y. 2023. Changes in real income of households in the Czech Republic due to the Russian invasion of Ukraine. *Entrepreneurship and Sustainability Issues*, 11(2), 37–53. https://doi.org/10.9770/jesi.2023.11.2(3)

VRONTOS, I. D., GALAKIS, J., PANOPOULOU, E., VRONTOS, S. D. Forecasting GDP growth: The economy impact of the COVID-19 pandemic. *Journal of Forecasting*. https://doi.org/10.1002/for.3072

XU, Z., MOHSIN, M., ULLAH, K., MA, X. 2023. Using econometric and machine learning models to forecast crude oil prices: Insights from economy history. *Resources Policy*, 83. https://doi.org/10.1016/j.resourpol.2023.103614

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# Appendix

## Appendix No 1

Figure 4: Brent crude oil price on world markets and inflation rate in the Czech Republic in the period January 2020 – March 2024, including the forecast of both quantities for the period April – December 2024

| Month | Inflation rate (in %) | Inflation forecast (in %) | Oil price (in CZK) | Oil price forecast (in CZK) |
|---|---|---|---|---|
| January 20 | 3.6 | | 1447.5 | |
| February 20 | 3.7 | | 1275.1 | |
| March 20 | 3.4 | | 809.08 | |
| April 20 | 3.2 | | 669.86 | |
| May 20 | 2.9 | | 823.29 | |
| June 20 | 3.3 | | 961.02 | |
| July 20 | 3.4 | | 999.3 | |
| August 20 | 3.3 | | 997.52 | |
| September 20 | 3.2 | | 950.02 | |
| October 20 | 2.9 | | 959.42 | |
| November 20 | 2.7 | | 981.13 | |
| December 20 | 2.3 | | 1083.9 | |
| January 21 | 2.2 | | 1185 | |
| February 21 | 2.1 | | 1330 | |
| March 21 | 2.3 | | 1445 | |
| April 21 | 3.1 | | 1411.2 | |

| | | | | |
|---|---|---|---|---|
| May 21 | 2.9 | | 1436.7 | |
| June 21 | 2.8 | | 1551.7 | |
| July 21 | 3.4 | | 1606.9 | |
| August 21 | 4.1 | | 1524.5 | |
| September 21 | 4.9 | | 1617 | |
| October 21 | 5.8 | | 1840.6 | |
| November 21 | 6 | | 1797.3 | |
| December 21 | 6.6 | | 1670.8 | |
| January 22 | 9.9 | | 1848.6 | |
| February 22 | 11.1 | | 2028.2 | |
| March 22 | 12.7 | | 1552.9 | |
| April 22 | 14.2 | | 1406.4 | |
| May 22 | 16 | | 2613.7 | |
| June 22 | 17.2 | | 2734.7 | |
| July 22 | 17.5 | | 2516.7 | |
| August 22 | 17.2 | | 2374 | |
| September 22 | 18 | | 2243.9 | |
| October 22 | 15.1 | | 2328.4 | |
| November 22 | 16.2 | | 2173.4 | |
| December 22 | 15.8 | | 1872.6 | |
| January 23 | 17.5 | | 1865.2 | |
| February 23 | 16.7 | | 1847.8 | |
| March 23 | 15 | | 1747.8 | |
| April 23 | 12.7 | | 1783.8 | |
| May 23 | 11.1 | | 1645 | |
| June 23 | 9.7 | | 1638.8 | |
| July 23 | 8.8 | | 1729.2 | |
| August 23 | 8.5 | | 1880.5 | |
| September 23 | 6.9 | | 2106.7 | |
| October 23 | 8.5 | | 2063.8 | |
| November 23 | 7.3 | | 1852.6 | |
| December 23 | 6.9 | | 1735.7 | |
| January 24 | 2.3 | | 1719.9 | |
| February 24 | 2 | | 1904.3 | |
| March 24 | 2 | | 1968.9 | |
| **April 24** | | **2.180877828** | | **1985,19881** |
| **May 24** | | **2.363034814** | | **2009.61153** |
| **June 24** | | **2.546091837** | | **2022.8121** |
| **July 24** | | **2.725314807** | | **2058.30684** |
| **August 24** | | **2.897375116** | | **2061.8525** |
| **September 24** | | **3.055874191** | | **2077.31704** |
| **October 24** | | **3.208722003** | | **2092.93104** |
| **November 24** | | **3.349344609** | | **2106.92104** |

Source: Author.

*Littera Scripta, 2025, Volume 18, Issue 1*

# Foresight into Predictive Maintenance Integration: The Economic Role of Digitalization in Automotive Industry

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**Abstract**

This study investigates the economic and operational impacts of predictive maintenance integration in the context of digital transformation within the Slovak automotive industry. The purpose is to evaluate how the adoption of condition monitoring systems (CMS) and real-time data technologies contributes to enhancing production efficiency and financial performance, while supporting the strategic objectives of digital innovation at the enterprise level. The research employs a mixed-methods approach, combining quantitative and qualitative statistical analysis of secondary data obtained from the international ORBIS database. The dataset includes financial and operational indicators from selected Slovak automotive enterprises, analyzed across periods before and after the implementation of predictive maintenance solutions. These indicators function as proxies for digital maturity, operational resilience, and innovation performance. A historical and conceptual review of maintenance strategies and digitalization trends is also provided to contextualize the analysis. The findings reveal that predictive maintenance systems, supported by advanced analytics and user-friendly CMS interfaces, lead to measurable improvements in production continuity, reduced failure rates, and enhanced return on assets. The integration of digital tools enables more timely interventions and decentralized decision-making by maintenance staff, fostering a shift from reactive to proactive operational models. These outcomes demonstrate the broader strategic potential of predictive maintenance as a component of digitally enabled innovation systems. The originality of this study lies in its focus on a regionally specific and sectoral application of Industry 4.0 technologies, contributing empirical evidence on how predictive maintenance influences firm-level economic performance. It offers valuable insights for both policymakers and industrial stakeholders regarding the alignment of technological foresight, digital investment strategies, and science, technology, and innovation (STI) policy in manufacturing-intensive economies.

**Keywords:** Predictive maintenance; information technology management;

information system development; digitalization; automotive industry; condition monitoring systems (CMS)

## Introduction

The rapid expansion of digitalization has become a defining characteristic of contemporary economic and business environments, influencing the way enterprises operate, compete, and sustain growth (Dabbous et al., 2023). As businesses increasingly rely on digital technologies to optimize processes, develop innovative solutions, and enhance productivity, the role of financial indicators in guiding and assessing digital transformation has gained significant attention (Verhoef et al., 2021). Financial indicators serve as essential tools for evaluating the efficiency, profitability, and sustainability of digital investments, ensuring that organizations can navigate the complexities of digital adoption while maintaining financial stability (Martinez-Pelaez et al., 2023). However, despite the increasing importance of financial metrics in corporate decision-making, there remains a substantial research gap in understanding the direct relationship between financial performance and digital transformation. As stated by Peretz-Andresson et al. (2024), one of the most pressing challenges businesses face in the digital age is ensuring that digital transformation efforts yield tangible financial benefits while minimizing risks. Investments in digital infrastructure, technological advancements, automation, cloud computing, artificial intelligence, and cybersecurity require significant financial commitments (Jada & Mayayise, 2024). Without a comprehensive assessment of financial indicators, businesses risk inefficient resource allocation, increased debt burdens, and miscalculated return on investment.

Nonetheless, technological advancements have a profound impact on daily life, introducing innovations that improve efficacy across sectors, particularly in manufacturing. It is imperative to adopt contemporary technologies to enhance competitiveness, reduce costs, and optimize processes. Petkovski et al. (2022) assert that sustainability constraints necessitate that enterprises manufacture high-quality products at a low cost and with minimal environmental impact. Maintenance is essential for guaranteeing the quality of products, and contemporary strategies have transitioned from reactive to predictive approaches. Digitalization facilitates the early detection and prediction of issues, thereby enhancing operational efficiency through planned maintenance. Predictive maintenance utilizes real-time sensor data to anticipate potential issues, thereby facilitating proactive interventions. The effective utilization of predictive tools frequently necessitates the availability of scarce specialized specialists, despite their advantages (Ledmaoui et al., 2025). Operational efficiency is a critical determinant of organizational competitiveness, particularly in industries reliant on complex machinery and systems. Predictive maintenance, driven by advanced digital technologies, has emerged as a transformative approach to minimize unplanned downtimes, reduce maintenance costs, and optimize resource utilization. By leveraging digital tools such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics, predictive maintenance enables real-time monitoring, accurate failure prediction, and timely intervention (Murtaza et al., 2024). This integration of digitalization into maintenance strategies not only enhances operational reliability but also aligns with Industry 4.0 principles, fostering data-driven decision-making and sustainable practices (Kans & Campos, 2024). Moreover, the integration of predictive maintenance with digitalization fosters a proactive maintenance culture, moving away from traditional reactive or scheduled approaches. This shift not only reduces the financial and operational burden of unexpected failures but also enhances equipment lifespan and energy efficiency. As organizations increasingly adopt smart sensors and cloud-based platforms, they gain access to predictive insights, enabling strategic decision-making and the alignment of maintenance activities with broader organizational goals (Al-Sharafi et al., 2023). The confluence of digitalization and predictive maintenance represents a significant step toward achieving operational resilience and sustainable performance in an ever-evolving industrial landscape (Rame et al., 2024).

This study aims to empirically investigate the relationship between digitalization, specifically through the implementation of predictive maintenance systems, and financial performance in the Slovak automotive industry. It focuses on assessing the economic impact of predictive maintenance by conducting a comparative statistical analysis of key financial and operational indicators before and after its implementation. The research is situated within the broader context of Industry 4.0 and seeks to introduce condition monitoring systems (CMS) specifically adapted for the Slovak industrial environment. The originality of the study lies in its context-specific application of digital maintenance technologies and its integration of financial performance evaluation with technological foresight. While existing research has largely emphasized the technological dimensions of predictive maintenance, this study extends the discourse by examining the financial outcomes of digital interventions within a defined regional and sectoral setting. It contributes novel empirical evidence by linking digital tools with traditional financial metrics to evaluate the effectiveness of digital transformation strategies in manufacturing. A significant research gap exists in understanding how predictive maintenance influences financial and operational performance within post-transition economies, particularly in Central and Eastern Europe. The literature remains limited in its exploration of the interplay between digital innovation, maintenance practices, and economic performance at the firm level. Furthermore, few studies have addressed how condition monitoring systems can be operationalized to empower non-specialist personnel in data-driven environments. This research addresses these shortcomings by delivering a foresight-oriented, data-driven analysis that not only demonstrates the strategic value of predictive maintenance but also informs STI governance, digital policy, and innovation management practices in industrial settings.

The structure of the paper is as follows: The Literature Review provides an overview of the most pertinent and recent studies in the field. The Methodology section outlines the research sample, and the analytical techniques employed in the study. The Results section presents and explains the key findings, which are then compared with international data in the Discussion. Finally, the Conclusions summarize the main findings, highlight both theoretical and practical contributions, discuss the study's limitations, and propose directions for future research.

## Literature review

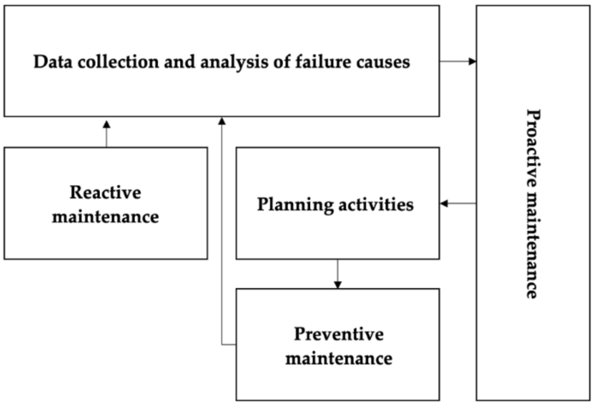
Digitalization is reshaping industrial practices by enabling smarter, more efficient, and data-driven operations. In the automotive sector, predictive maintenance has emerged as a key application of digital technologies, offering the ability to monitor equipment conditions in real time, predict potential failures, and schedule interventions before breakdowns occur (Arena et al., 2022). This proactive approach reduces unplanned downtime, optimizes resource use, and extends the lifecycle of critical assets. Predictive maintenance relies on a range of digital tools, including sensor networks, machine learning algorithms, and cloud-based platforms, which together support continuous monitoring and intelligent decision-making (Fordal et al., 2023). As enterprises increasingly integrate these technologies, predictive maintenance is becoming an essential element of modern asset management and operational excellence, closely tied to broader trends in automation, connectivity, and sustainable industrial performance (Allioui & Mourdi, 2023).

The quality of a product or service is guaranteed by the functionality and reliability of equipment, which are provided by maintenance actions and processes. Maintenance guarantees operability and faultlessness by promptly restoring equipment to operational condition and reducing repair expenses (Souto, 2022). The world is currently undergoing Industry 4.0, the fourth industrial revolution and the digital transformation of business. The challenge has been to balance the increasing demand for commodities from limited natural resources with the desire to minimize environmental and social consequences since the 18th century (Ghobakhloo, 2020). The digital revolution, which is associated with Industry 4.0, was initiated by the first computers. The most significant advancements that lie ahead include the Internet of Things, integrated systems, smart technologies, and fully automated production. Technology implementation speed and adaptability are essential due to the fact that components and machines acquire and share data in real time (Poor et al., 2019). With each industrial revolution in technology, socioeconomics, and culture, maintenance management undergoes modifications. Reactive equipment maintenance has been replaced by predictive equipment maintenance. Companies are now prioritizing risk and cost reduction rather than solely addressing issues. Regular maintenance was necessary for the operation of basic tools and machinery. Predictive and preventive maintenance were not known, and maintenance was considered a secondary job that was only useful during breakdowns from 1960 to 1980 (Ozgur-Unluakin et al., 2019). The technicians were lubricants and concentrated on repair. With the increasing complexity of tools, maintenance necessitated specialization. Production is currently dependent on maintenance (Dui et al., 2023). Speedy failure recovery and operability are essential for technological system maintenance. The optimization and planning of maintenance are essential for the reduction of production costs. Clear maintenance expectations are essential for effective planning. Problem solutions are subordinate to prevention and downtime reduction. Technical systems must be efficient, dependable, and secure (Zhong et al., 2021). Reactive maintenance is a response to events, typically failures. This maintenance technique, which is the oldest, is employed for equipment that has minimal impacts on production in terms of availability, safety, and quality. Machines are only maintained under this approach when they malfunction. Staff may be compelled to operate within time constraints, which could jeopardize their safety, as a result of the unplanned downtime associated with this approach. In order to mitigate workplace hazards, maintenance professionals must comprehend the interplay between machines, humans, and the workplace. Significant financial resources are required to sustain a substantial spare parts inventory (Mooi et al., 2020).

During the second industrial revolution, productivity escalated and machine complexity increased. Preventive maintenance was implemented as a result of the increasing cost of failure (Saihi et al., 2023). In order to prevent malfunctions, preventive maintenance is implemented according to a predetermined schedule (Ansari et al., 2023). A scheduled operation that is designed to maintain functionality by identifying, avoiding, or mitigating component or equipment degradation. It is primarily conducted in areas that are considered reliable (Friederich & Lazarova-Molnar, 2024). There are two primary categories of preventive maintenance: schedule for Maintenance which adheres to a performance or cycled time strategy. The disadvantage of this maintenance is that recurrent activities are typically estimated rather than determined by the condition of the equipment. Additional faults and additional expenses may result from the assembly and disassembly of machine parts and components. And secondly, vondition-based maintenance when equipment is maintained solely when performance deviates, thereby increasing its efficiency (Han et al., 2021). This innovative maintenance method enhances production cost efficiency by integrating data-driven analysis with reactive and preventive maintenance. It aims to identify and resolve contamination, misalignment, incorrect machine lubrication, and other issues that may result in failures (Hardt et al., 2021). Equipment monitoring, restoration, and retirement are established through proactive maintenance. The prevention of failure entails the identification of the underlying causes and the implementation of corrective measures in accordance with the results of the analysis (Figure 1). It entails the identification of mechanical malfunctions and the emphasis on the underlying causes rather than the symptoms. Proactive maintenance employs a methodical approach to evaluate the productivity of equipment and implement corrective measures to guarantee its dependability throughout its lifespan (Scaife, 2024).

The fourth industrial revolution is predictive maintenance. This is the most sophisticated maintenance technique. Data is collected and monitored from equipment sensors to facilitate predictive maintenance. These sensors concentrate on temperature, vibrations, and noise (Ucar et al., 2023).

Figure 1: Proactive maintenance scheme




Source: Own elaboration.

The analysis of production data is necessary to identify patterns and anticipate potential issues in order to prevent equipment failure. It is crucial to incorporate comprehensive data collection and analysis in order to identify patterns and anomalies. Predictive data and alerts from regression analysis, as well as real-time equipment monitoring, are indispensable (Aminzadeh et al., 2025). Sensors, IoT, big data, networks, cloud computing, mobile networks, and Wi-Fi are all necessary components of Industry 4.0 predictive maintenance. Maintenance roles have also undergone modifications. Companies are now required to employ engineers, data analysts, and experienced maintenance personnel. Predictive maintenance data is expanding as companies accumulate data on asset condition, asset utilization, maintenance history, and other assets associated with the monitored machine, including internal and external assets, as well as environmental data. In the process of digitalizing maintenance, reactive repairs and manual records are replaced by digital solutions. Industrial digitalization and Industry 4.0 entail the integration of digital technologies into all business operations (Nagy et al., 2023). Digitalization is a process that enhances productivity by automating and streamlining maintenance, thereby reducing downtime. The use of data and analytical tools to anticipate failures and plan repairs, thereby preventing unanticipated outages. Analytical tools enhance the lifespan of equipment and enhance maintenance planning, and thus, reducing operational and maintenance costs. Digital systems mitigate accidents by monitoring equipment in real time (Kliestik et al., 2024). However, the equipment in numerous manufacturing plants is outdated and unprepared for the Internet of Things.

## Methods and Data

Predictive maintenance is one of the obstacles to the successful implementation of Industry 4.0. It is regarded as essential by numerous automotive companies as a means of preventing errors and expediting production. The content of this section of the paper is a brief description of the dataset of analyzed enterprises of the automotive industry in Slovakia, which were investigated before and after the implementation of predictive maintenance. The ORBIS database, which is the world's largest database with a focus on private company financials based on fundamental economic principles, was employed in the analysis. This database was used to find the financial data of enterprises in the period 2018-2023 with the focus on those entities where the structured questionnaire was realized (April – June 2023). The dataset consists of 62 enterprises operating in the sector NACE C (code 29) with the following firm specific features: 8.1% micro, 24.2 % small, 43.5 medium-sized and 24.2% large enterprises; 50 % private limited, 40.3 % public limited and 9.7 % general partnership enterprises. The objective is to evaluate the understanding of predictive maintenance and its potential consequences. Table 1 summarizes the basic financial information about the analyzed dataset of enterprises (in thousand euros).

The consequences of the COVID-19 pandemic and worsen financial and economic status of enterprises are evident. There was a sharp decline in the development of crucial financial indicators in 2021 and 2022 (as indicated in the Table 1) when the production was severely disrupted as factories were forced to shut down temporarily due to government-imposed lockdowns, health and safety concerns, and supply chain interruptions. Global shortages of critical components, particularly semiconductors, further exacerbated the situation, delaying production and reducing output. In addition, demand for new vehicles plummeted during the initial phases of the pandemic due to economic uncertainty and reduced consumer spending, further straining the industry. These challenges not only affected production volumes but also had ripple effects on employment in the sector and the broader economy, given the industry's pivotal role in Slovakia's GDP and export revenues. Despite these difficulties, the industry has shown resilience, with recovery efforts focused on improving supply chain resilience, adopting digitalization, and transitioning toward electric vehicle production to align with evolving global market demands. However, one of the mapped indicators, operating expenses, has been increasing since 2021. The detail analysis in the enterprises proved, that most of the expenses were given to the implementation of predictive maintenance systems, which proved to be highly important for this sector, automotive industry, during the COVID-19 pandemic. With the pandemic causing frequent disruptions to production schedules, reduced workforce availability, and strained supply chains, predictive maintenance became a critical tool for ensuring operational efficiency and minimizing downtime (which is also proved on a dataset of Slovak enterprises). Predictive maintenance systems, allowed manufacturers to monitor equipment in real-time, anticipate failures, and schedule maintenance proactively.

Tab. 1: Basic financial information of the dataset

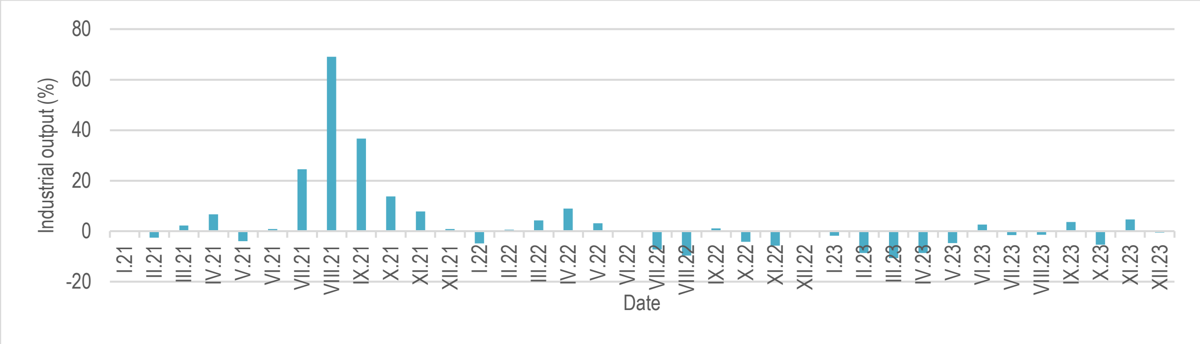
| | **Stock 2018** | **Stock 2019** | **Stock 2020** | **Stock 2021** | **Stock 2022** | **Stock 2023** |
|---|---|---|---|---|---|---|
| Mean | 3496,03 | 3793,65 | 3539,02 | 898,37 | 1220,10 | 1284,53 |
| Median | 766,76 | 718,50 | 623,47 | 223,82 | 345,08 | 308,17 |
| Std. deviation | 5971,25 | 6484,00 | 6005,79 | 1561,18 | 2242,07 | 3347,94 |
| | **TOAS 2018** | **TOAS 2019** | **TOAS 2020** | **TOAS 2021** | **TOAS 2022** | **TOAS 2023** |
| Mean | 30477,18 | 30830,90 | 32135,89 | 18147,71 | 19032,03 | 19339,63 |
| Median | 4353,53 | 3874,42 | 4421,65 | 5594,11 | 6422,28 | 6074,86 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Std. deviation | 56769,36 | 59321,87 | 62477,97 | 46451,67 | 45432,94 | 44615,65 |
| | **NCLI 2018** | **NCLI 2019** | **NCLI 2020** | **NCLI 2021** | **NCLI 2022** | **NCLI 2023** |
| Mean | 5822,57 | 6018,35 | 6114,68 | 3891,10 | 3515,34 | 3574,46 |
| Median | 356,94 | 394,35 | 415,01 | 313,20 | 320,13 | 367,19 |
| Std. deviation | 18975,21 | 19378,79 | 18779,24 | 10193,39 | 9630,91 | 9457,45 |
| | **CULI 2018** | **CULI 2019** | **CULI 2020** | **CULI 2021** | **CULI 2022** | **CULI 2023** |
| Mean | 11569,84 | 11323,21 | 11979,02 | 6339,02 | 7041,91 | 6530,94 |
| Median | 2620,06 | 2095,82 | 1940,71 | 2793,56 | 3418,73 | 3142,60 |
| Std. deviation | 20493,01 | 19640,35 | 22241,69 | 16348,62 | 15774,81 | 14938,26 |
| | **EBIT 2018** | **EBIT 2019** | **EBIT 2020** | **EBIT 2021** | **EBIT 2022** | **EBIT 2023** |
| Mean | 1695,87 | 1802,49 | 1772,62 | 412,95 | 963,56 | 1367,01 |
| Median | 164,69 | 140,54 | 207,53 | 407,33 | 318,98 | 774,49 |
| Std. deviation | 4643,52 | 4382,71 | 4226,63 | 1588,29 | 2051,30 | 2805,30 |
| | **OPEX 2018** | **OPEX 2019** | **OPEX 2020** | **OPEX 2021** | **OPEX 2022** | **OPEX 2023** |
| Mean | 7099,85 | 7435,55 | 6949,85 | 8705,41 | 9534,30 | 11643,90 |
| Median | 1233,86 | 1437,26 | 1609,37 | 1702,22 | 1797,96 | 1652,74 |
| Std. deviation | 12281,33 | 11646,72 | 10398,43 | 14146,46 | 16089,74 | 28240,65 |
| | **SHFD 2018** | **SHFD 2019** | **SHFD 2020** | **SHFD 2021** | **SHFD 2022** | **SHFD 2023** |
| Mean | 13084,77 | 13489,34 | 14042,20 | 7917,59 | 8474,78 | 9234,22 |
| Median | 1259,91 | 1327,08 | 1233,89 | 1525,15 | 1720,60 | 2445,14 |
| Std. deviation | 27144,40 | 27318,30 | 29029,74 | 27665,73 | 27517,14 | 27215,03 |
| | **Sales 2018** | **Sales 2019** | **Sales 2020** | **Sales 2021** | **Sales 2022** | **Sales 2023** |
| Mean | 48732,81 | 50261,54 | 43260,50 | 12395,27 | 15412,05 | 16643,88 |
| Median | 6026,88 | 5981,02 | 5000,96 | 9045,72 | 11178,72 | 11422,08 |
| Std. deviation | 124622,62 | 130685,70 | 114234,06 | 10865,90 | 12949,63 | 13162,54 |

Source: Own elaboration.

This was particularly valuable during periods of limited access to facilities and reduced staff capacity, as it enabled maintenance tasks to be optimized, reducing the risk of unexpected breakdowns that could further disrupt production. In Slovakia's automotive industry, where production efficiency and continuity are vital, the ability to predict and prevent equipment failures helped mitigate the financial and operational risks posed by the pandemic. By reducing unscheduled downtime and improving resource allocation, predictive maintenance systems supported manufacturers in maintaining output levels despite external challenges. Additionally, the adoption of such systems aligned with broader trends toward Industry 4.0, enabling companies to enhance their long-term resilience and competitiveness in a post-pandemic environment. That was also the reason why the qualitative analysis, in the form of a questionnaire, was applied to analyze and verify this trend with the key managers of enterprises within the dataset. For the overall assessment of this sector, it also very important emphasize the current state of production in the automotive sector. In the context of predictive maintenance, it is imperative to ensure that all standards, including internal ones, are in accordance with the international criteria and requirements that have been developed in collaboration with major global companies on international platforms. Thus, the initial focus is also on the general production of the automotive industry in Slovakia, defining the following values (Figure 2).

Figure 2: Slovak industrial production




Source: Own elaboration.

In 2023, Slovakia's industrial production experienced a 0.6 % decline, and the industry was spared from a more severe decline due to the country's robust automobile production. After a year in which the country's industry fluctuated between decline and occasional growth, this result is the result of the automobile industry's superior performance in 2023 compared to the previous year. This offset the decline in manufacturing that was observed in "two-thirds of the monitored sectors" over the past year. The Statistical Office's report (2024) underscored that the industry experienced a four-time year-over-year decline, the lowest in 15 years. This was also less than the declines in 2020 and 2022. Since 2018, the automobile industry has experienced the most significant year-over-year growth at 4.9 %. The production of electrical equipment also had a positive effect, resulting in a 7.4 % increase. The most significant negative impact was attributed to the 8.9 % decrease in the production of rubber and plastic products and the 22 % decrease in the production of computer products. It was also reported that output decreased by 3.1 % month-to-month and by 0.1 % year-over-year in December, which was the eighth month of decline in 2023. The overall year-on-year result was significantly influenced by the 20 % growth in the manufacturing of electrical equipment. The most substantial decreases were observed in the manufacturing of rubber and plastic products, which experienced a nearly 11 % decrease, and the manufacturing of machinery installation, which experienced a nearly 13 % decrease. In 2023, Slovak construction experienced a 1.1% year-over-year increase, resulting in the production of €7.1bn in works. It was also the lowest growth rate since 2009, primarily due to a 4.4% increase in new construction, reconstructions, and modernizations. The construction output experienced a 12.1% year-over-year decline in December, which was the most severe monthly result of 2023. Based on the abovementioned, the following methodological steps were followed to conduct the analysis:

1. The choice of enterprises operating in the sector NACE C, code 29, with full 6-year data history of financial parameter.

2. Calculation of annual average values of individual parameter to recognize the changes in the development of selected financial parameters.

3. The use on non-parametric Friedman test (as the normality of the dataset was not proved) to investigate whether groups of three or more repeated measurements differ from each other. The test was used to determine whether there are significant differences in selected financial parameters across individual years (2018-2023). If a significant difference exists, the p-value of the Friedman test will be below the significance level of 0.05, indicating that the financial parameter varies over the years (consequences of the pandemic are evident)

4. The structured interviews in the dataset of enterprises to assess the implementation of predictive maintenance systems and digital innovations in enterprises.

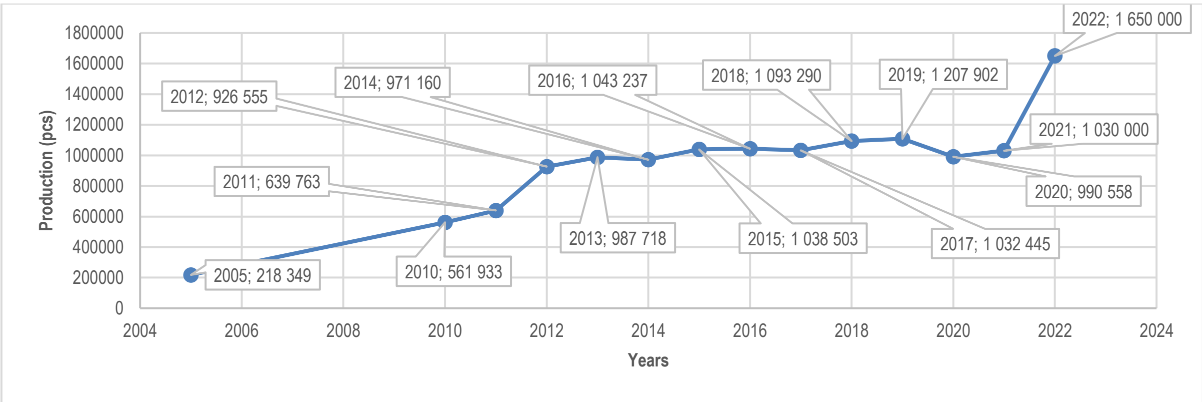
5. The summary of findings and recommendation for enterprises operating in the automotive industry.

## Results

The purpose of the study was to identify the current situation of predictive maintenance in the automotive sector, highlight opportunities for production growth using predictive maintenance, and identify current trends and future visions in the field of smart planning and predictive engineering. In Slovakia, the automotive industry has a long history and has emerged as the most significant sector and driving force of the economy. It has been a significant source of industrial innovation and foreign direct investment over the past three decades. Slovakia is one of the primary players in the global automotive industry. Its position has been further fortified by the world-class facility of Jaguar Land Rover and the recently announced Volvo plant, which is scheduled to commence production in 2026. Figure 3 summarizes the car production in the country over the last 20 years.

As mentioned in the methodological section of the paper, the average annual values of the critical financial parameters for the enterprises in the dataset were calculated. To determine the significant differences in the development of these parameters across the years 2018-2023, the Friedman test was applied; results are presented in Table 2.

Figure 3: Car production in Slovakia




Source: Own elaboration.

Tab. 2: Hypothesis test summary (time period 2018-2023)

| Null Hypothesis | Test | Sig. | Decision |
|---|---|---|---|
| The distributions of Stock are the same across the period | Related-Samples Friedman's Two-Way Analysis of Variance by Ranks | 0.063 | Retain the null hypothesis. |
| The distributions of TOAS are the same across the period | Related-Samples Friedman's Two-Way Analysis of Variance by Ranks | 0.036 | Reject the null hypothesis. |
| The distributions of NCLI are the same across the period | Related-Samples Friedman's Two-Way Analysis of Variance by Ranks | 0.125 | Retain the null hypothesis. |
| The distributions of CULI are the same across the period | Related-Samples Friedman's Two-Way Analysis of Variance by Ranks | 0.004 | Reject the null hypothesis. |
| The distributions of EBIT are the same across the period | Related-Samples Friedman's Two-Way Analysis of Variance by Ranks | 0.072 | Retain the null hypothesis. |
| The distributions of OPEX are the same across the period | Related-Samples Friedman's Two-Way Analysis of Variance by Ranks | 0.000 | Reject the null hypothesis. |
| The distributions of SHFD are the same across the period | Related-Samples Friedman's Two-Way Analysis of Variance by Ranks | 0.093 | Retain the null hypothesis. |
| The distributions of Sales are the same across the period | Related-Samples Friedman's Two-Way Analysis of Variance by Ranks | 0.000 | Reject the null hypothesis. |

Source: Own elaboration.

Even though the average values of these financial parameters show robust differences in the development across the analyzed years, the results of the Friedman test revealed, that in the case of shareholder´s funds, earnings before interests and taxes, non-current liabilities and stock the differences were not statistically significant. Vice versa, the statistically significant differences were observed with total assets, current liabilities, operating expenses and sales. In these cases, when the Friedman test is significant, post-hoc pairwise comparisons are required to determine which groups differ. These comparisons are typically performed using Dunn's test with Bonferroni correction. If the adjusted p-values are below the significance lever, the pairwise difference is statistically significant. The results indicate that the COVID-19 pandemic, had a tremendous effect on the development of this parameters, as 2020 and 2021 are the breaking points; the results of Dunn's test are presented in table 3 (only the statistically significant pairwise differences are portrayed).

Tab. 3: Pairwise comparison of samples

| Sample 1-Sample 2 | Test Statistic | Std. Error | Std. Test Statistic | Sig. | Adj. Sig. |
|---|---|---|---|---|---|
| TOAS 2020 – TOAS 2022 | -0.864 | 0.344 | -2.510 | 0.012 | 0.034 |
| TOAS 2020 – TOAS 2023 | -0.814 | 0.344 | -2.362 | 0.018 | 0.042 |
| CULI 2017 – CULI 2022 | -1.138 | 0.347 | -3.276 | 0.001 | 0.016 |
| CULI 2019 – CULI 2022 | -1.034 | 0.347 | -2.978 | 0.003 | 0.044 |
| OPEX 2018 – OPEX 2020 | 1.377 | 0.339 | 4.065 | 0.000 | 0.001 |
| OPEX 2018 – OPEX 2021 | 1.828 | 0.339 | 5.396 | 0.000 | 0.000 |
| OPEX 2018 – OPEX 2022 | 2.336 | 0.339 | 6.896 | 0.000 | 0.000 |
| OPEX 2018 – OPEX 2023 | 1.754 | 0.339 | 5.178 | 0.000 | 0.000 |
| OPEX 2019 – OPEX 2021 | 1.107 | 0.339 | 3.267 | 0.001 | 0.016 |
| OPEX 2019 – OPEX 2022 | 1.615 | 0.339 | 4.767 | 0.000 | 0.000 |
| OPEX 2019 – OPEX 2023 | 1.033 | 0.339 | 3.049 | 0.002 | 0.034 |
| Sales 2018 – Sales 2023 | -1.016 | 0.344 | -2,998 | 0.002 | 0.024 |
| Sales 2019 – Sales 2023 | -1.102 | 0.344 | -3.198 | 0.001 | 0.021 |
| Sales 2020 – Sales 2022 | -1.441 | 0.344 | -4.183 | 0.000 | 0.000 |
| Sales 2020 – Sales 2023 | -1.814 | 0.344 | -5.265 | 0.000 | 0.000 |
| Sales 2021 – Sales 2023 | 1.254 | 0.344 | 3.641 | 0.000 | 0.004 |

Source: Own elaboration.

It is evident that total assets, current liabilities, operating expenses, and sales play a crucial role in the effectiveness of predictive maintenance systems, particularly in capital-intensive industries, which is also the case of the Slovak automotive industry. Total assets determine the scale of investments in machinery and equipment, influencing the need for predictive maintenance to maximize asset utilization and lifespan. They also reflect the scale of a company's capital investments, particularly in machinery, equipment, and production facilities. The larger the asset base, the greater the need for predictive maintenance to ensure maximum equipment uptime, cost efficiency, and asset longevity. Companies with substantial fixed assets invest heavily in maintenance strategies to prevent costly failures and production halts (Li et al., 2014). Predictive maintenance becomes crucial in such environments as it allows organizations to shift from reactive or preventive maintenance to a proactive approach, reducing unnecessary maintenance costs and minimizing unexpected breakdowns. Current liabilities affect short-term financial flexibility, impacting a company's ability to invest in PMS without liquidity constraints. High level of current libilities can limit a company's financial flexibility, making it difficult to allocate funds for long-term investments in predictive maintenance systems. When an organization has a high level of current liabilities relative to its assets, it may prioritize urgent financial commitments over maintenance infrastructure improvements. This can lead to delayed adoption of predictive maintenance technologies, reliance on reactive repairs, and ultimately higher operational risks due to unplanned equipment failures. On the other hand, companies with low current liabilities have greater liquidity to invest in advanced maintenance technologies, enhancing their operational efficiency and reducing long-term costs associated with equipment failures (Ucar et al., 2024). Operating expenses include maintenance costs, making predictive maintenance essential for cost optimization and reducing unplanned downtime. Predictive maintenance plays a key role in optimizing these costs by minimizing unnecessary repairs, reducing energy consumption, and improving asset efficiency (Zhong et al., 2023). Traditional maintenance strategies, such as time-based preventive maintenance, often result in unnecessary part replacements or servicing of machinery that does not require immediate attention, leading to inflated maintenance budgets. In contrast, predictive maintenance reduces operating expenses by allowing organizations to perform maintenance only, when necessary, based on real-time data and predictive analytics (Arinze et al., 2024). Lowering maintenance costs while maintaining high equipment reliability is crucial for organizations aiming to improve profitability and achieve a competitive advantage in asset-heavy industries. Sales volume reflects production levels, where higher sales necessitate reliable equipment performance, increasing the importance of PMS in maintaining operational efficiency. Companies with high sales volumes must ensure continuous and efficient production, making predictive maintenance vital in preventing unplanned downtime that could disrupt supply chains and affect revenue generation (Zonta et al., 2020). When demand is high, any unexpected equipment failure can result in significant financial losses and reputational damage.

Conversely, businesses experiencing a decline in sales might attempt to cut costs, including maintenance expenditures, which can be risky if it leads to neglecting necessary predictive maintenance efforts. A balanced approach is needed to align maintenance strategies with market demand fluctuations while ensuring long-term equipment reliability. The COVID-19 pandemic significantly influenced the relevance of these financial indicators in predictive maintenance. Liquidity constraints due to economic uncertainty made companies more cautious about capital expenditures, leading some to postpone predictive maintenance investments despite their long-term cost-saving potential. Disruptions in sales and supply chains altered production schedules, affecting maintenance planning and asset utilization rates. Additionally, firms experiencing declining revenues faced pressure to cut operating expenses, sometimes reducing maintenance budgets, which paradoxically increased the risk of unexpected failures. Conversely, industries that saw demand spikes, had to intensify predictive maintenance efforts to sustain continuous operations. The pandemic underscored the necessity of PMS in ensuring resilience, minimizing unplanned downtime, and optimizing maintenance strategies amid financial and operational uncertainties.

Finally, based on these outputs, the structured interviews were conducted in all enterprises to focus on the implementation of Industry 4.0, particularly in the realm of digital innovations, such as predictive maintenance in the enterprise. The crucial findings can be summarized in the following way. The respondents unequivocally confirmed the critical role of predictive maintenance in Slovakia, particularly in the automotive and mechanical engineering sectors, as indicated by the initial question. It is imperative to remain informed about the most recent developments in Industry 4.0 and digitization, and to promptly and effectively integrate them into business operations. In general, it can be inferred that industrial enterprises prioritize this revolution and give it a significant amount of importance, as evidenced by their corporate culture and policies. The aforementioned companies are actively seeking and concentrating on the application of the Internet of Things connection, which will enable machines to communicate with one another more efficiently and quickly. This policy facilitates communication and cooperation on a distinct level, thereby enhancing the enterprise's intelligence and interconnectivity. Real-time synchronization and reception of a variety of requests, data, and instructions will be facilitated by the application of Cloud and Big Data technologies. Digitizing processes also speed up communication and eliminate excessive paper consumption. This approach can result in improved control, a reduced product error rate, and more efficient production processes. Moreover, the concept of the Industry 4.0 framework introduces a plethora of new systems and solutions that can and do achieve the desired outcomes for the business. This concept is essential for the company, particularly in the context of enhancing product quality, enhancing manufacturing efficiency, and reducing error rates. Innovations are especially important for large industrial companies, as they facilitate sustainable development. The company's innovative capabilities are further enhanced by collaboration and increased financial investments. The following advantages are associated with the concept: automation of production and logistics processes through the development of solutions, digital transformation of business structures, the establishment of partnerships with universities, technology companies, and government entities, the efficient administration of grants or subsidies. However, cybernetics and artificial intelligence are also critical technologies in this context, as they facilitate the continuous and efficient interaction between various components of the production process, as well as the real-time sharing and analysis of data. The enterprises uniformly confirmed that the core business category is the primary category in which processes are automated, indicating that predictive maintenance is essential. Core activities are the primary focus of automation in businesses, as they are essential for the creation of value and production. Automation is most frequently implemented in rough production, assembly lines that employ industrial robots, raw material processing, and specialized processes that necessitate high precision and repeatability. Laser welding is an example of a process that can be performed with or without additional material and guarantees the quality and strength of welded joints. The implementation of PMS may have very positive effects, as confirmed by enterprises, especially in the field of the lowest machine error rates, and the highest number of cars produced annually. Another important point is the use of sensors in manufacturing processes. Complex monitoring of multiple processes simultaneously is necessary for automotive companies, which are leaders in the number of sensors used, to guarantee quality, safety, and efficiency. Sensors are utilized throughout the production process in the automotive sector, including the verification of individual components, the monitoring of assembly lines, and the testing of the final product. These sophisticated systems facilitate the faster detection of defects, the optimization of manufacturing processes, and the overall enhancement of production line performance. The implementation of sensors in production is contingent upon the industry type, technical readiness, and the company's objectives in automation and digitalization, as evidenced by the varying levels of sensor usage. Predictive maintenance is highly effective; however, it is also financially demanding. Nevertheless, the advantages of this approach outweigh the disadvantages of the increased expenses that come with the acquisition of new methodologies and programs.

## Discussion

PMS (predictive maintenance system) is indispensable for the reliability and efficiency of industrial systems. Industry 4.0 technologies, including IoT, big data, and machine learning, have stimulated predictive maintenance in the automotive, energy, and manufacturing sectors (Rahman et al., 2023; Achouch et al., 2022). PMS is revolutionizing automotive production in Slovakia, where the automotive industry is essential to the economy, thereby enhancing efficiency and competitiveness (Torok, 2022). Organizations can optimize maintenance costs, extend asset lifespans, and reduce downtime by transitioning from preventive and reactive to predictive maintenance. In Slovakia's automotive industry, where production volumes are high and precision is critical, unplanned breakdowns can result in production delays, financial losses, and reputational damage (Valaskova et al., 2022). These hazards may be mitigated by PMS. Automotive manufacturers can anticipate component failure and promptly address it by monitoring equipment performance and utilizing historical data. Slovakia's automotive industry's global competitiveness is enhanced by the optimization of resource allocation, the transition from reactive to condition-based maintenance, and the streamlining of production processes (Arena et al., 2022). The automotive industry has experienced a decrease in unplanned downtime as a result of predictive maintenance. In automotive manufacturing, assembly lines are intricate and employ numerous interconnected machines, which can result in catastrophic unplanned downtime (Murtaza et al., 2024; Poliak et al., 2022). It causes delays in deliveries, reduces production, and disrupts the supply chain. Volkswagen, Kia, and Peugeot must reduce downtime in Slovakia to satisfy international market demands and production objectives. Slovak automotive manufacturers can enhance production efficiency and reduce operational costs by proactively addressing equipment failures (Kovacova et al., 2022). Another advantage of predictive maintenance is the extension of the lifespan of manufacturing equipment. In order to operate efficiently, automotive production necessitates costly machinery, including robotic arms, conveyor belts, and automated systems (Moleda et al., 2023). Mechanical wear, misalignment, and lubrication failure are identified through predictive maintenance prior to their development into costly repairs or equipment replacement (Jiminez et al., 2020). By proactively addressing these issues, the lifespan of machinery can be extended, thereby reducing the need for replacement and repair. This enhances the global competitiveness of Slovakian automakers, which are essential to the economy, by reducing their long-term costs (Halliouli et al., 2023). Predictive maintenance is challenging to implement in the automotive industry, despite its advantages. PMS necessitates substantial investments in data analytics platforms, condition monitoring systems, and sensors (Mallioris et al., 2024). This can impede the operations of smaller Slovak manufacturers or those operating on a limited budget. The quality and quantity of data are also factors that influence predictive maintenance. The advantages of PMS may be compromised by inaccurate data and predictions. Consequently, Slovakian organizations must implement technology that is capable of accommodating the intricate requirements of automotive manufacturing and to establish robust data collection and analysis processes (Llopis-Albert et al., 2021). PMS systems must also consider data privacy and cybersecurity when employing cloud-based platforms and connected devices to monitor and store asset data. As a result of sensitive intellectual property, production designs, and operational strategies, automotive security breaches could result in substantial operational and financial losses (Siraparapu and Azad, 2024). The automotive industry in Slovakia is increasingly interconnected with global supply chains, necessitating that manufacturers prioritize cybersecurity to safeguard their systems. Machine learning and artificial intelligence are essential components of Slovakia's automotive industry's predictive maintenance future. It is expected that these technologies will be crucial in enhancing the precision and dependability of predictive models, thereby enabling manufacturers to more accurately predict failures. In order to optimize maintenance operations, PMS can be integrated with other Industry 4.0 technologies, such as digital twins and augmented reality (Juracka et al., 2024). By establishing real-time virtual replicas of production systems, manufacturers can improve the efficacy of their maintenance decisions and gain a more profound understanding of asset health. In Slovakia's automotive sector, predictive maintenance has the potential to enhance asset management, optimize maintenance costs, and reduce downtime (Nagy et al., 2025). Although cybersecurity, cost, and data quality must be addressed, the advantages of PMS, such as increased efficiency, reduced costs, and extended equipment life, outweigh the disadvantages. PMS will become an indispensable component of Slovakia's contemporary manufacturing strategies as technology continues to develop, thereby enhancing the automotive sector's global leadership, operational efficiency, and competitiveness (Ramos and Ruiz-Galvez, 2024).

## Conclusion

This investigation simulated an automotive enterprise analysis, with a particular emphasis on predictive maintenance within the Slovak automotive sector. The study proves that total assets, current liabilities, operating expenses, and sales are critical financial parameters influencing the adoption and effectiveness of predictive maintenance systems. Total assets determine the scale of investment in maintenance technologies, current liabilities affect financial flexibility, operating expenses shape cost-efficiency strategies, and sales impact production demands and maintenance priorities. The COVID-19 pandemic underscored the importance of predictive maintenance by revealing vulnerabilities in traditional maintenance approaches and highlighting the need for financial resilience and digital transformation. Organizations that strategically invested in predictive maintenance before the pandemic gained a competitive advantage, maintaining operational efficiency despite economic uncertainties. Moving forward, businesses must balance financial constraints with long-term maintenance optimization, leveraging data-driven maintenance strategies to ensure resilience, cost savings, and sustainable growth. The findings of this analysis indicate that PMS enhanced production efficiency and decreased equipment failures. This investigation demonstrates that predictive maintenance can enhance the performance of the Slovak automotive industry when executed efficiently and accurately. By utilizing real-time data to proactively address maintenance needs, companies can reduce unexpected breakdowns, extend the lifespan of machinery, and enhance cost-effectiveness. This research demonstrates that Slovak automotive companies have the potential to implement predictive maintenance and underscores the significance of data-driven maintenance strategies in the contemporary industrial sector. The automotive industry will be equipped with the necessary tools to compete on a global scale as a result of the significant potential of artificial intelligence and machine learning in predictive maintenance. One of the key limitations in studying predictive maintenance systems in Slovakia, particularly in the automotive sectors, is the scarcity of historical and real-time data from various enterprises. These may not have the same level of data digitization or IoT sensor infrastructure as in more technologically advanced countries, limiting the availability and quality of data for effective PMS implementation. While Slovakia has a growing industrial sector, especially in automotive, the adoption of advanced predictive maintenance technologies may still be in early stages. Many small and medium-sized enterprises may lack the financial resources or technical expertise to invest in state-of-the-art maintenance technologies. As a result, the study might face challenges in assessing the impact and effectiveness of PMS across diverse industries with varying levels of technological readiness.

The adoption of predictive maintenance systems requires a cultural shift within organizations, moving from reactive or preventive maintenance to data-driven, proactive strategies. In Slovakia, certain industries may have strong traditions of reactive maintenance practices or resistance to technological change, which could limit the willingness of companies to fully integrate predictive maintenance systems. Given that the study focuses on specific industry and enterprises, there might be a limited sample size or focus on only certain regions. The variability in industrial sectors and geographical differences might skew results and limit the scope of conclusions that can be drawn for the broader population. While predictive maintenance systems have the potential to significantly enhance operational efficiency in Slovakia's industrial sectors, several limitations hinder their widespread adoption and implementation, including data availability, financial constraints, and organizational barriers. Future research in Slovakia should focus on overcoming these challenges by addressing technological integration, data standardization, cost-benefit analysis, human factors, and sustainability considerations. By tackling these research challenges, Slovakia can foster a more robust and resilient industrial landscape, leveraging predictive maintenance technologies to drive economic growth and technological advancement in the post-pandemic era.

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## References

ACHOUCH, M., DIMITROVA, M., ZIANE, K., SATTARPANAH KARGANROUDI, S., DHOUIB, R., IBRAHIM, H., ADDA, M. 2022. On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. *Applied Sciences*, 12(16), 8081. doi: https://doi.org/10.3390/app12168081

ALLIOUI, H., MOURDI, Y. 2023. Exploring the Full Potentials of IoT for Better Financial Growth and Stability: A Comprehensive Survey. *Sensors*, *23*(19), 8015. doi: https://doi.org/10.3390/s23198015

AL-SHARAFI, M.A., IRANMANESH, M., AL.EMRAN, M., ALZAHRANI, A.I., HERZALLAH, F., JAMIL, N. 2023. Determinants of cloud computing integration and its impact on sustainable performance in SMEs: An empirical investigation using the SEM-ANN approach. *Heliyon*, 9(5), e16299. doi: https://doi.org/10.1016/j.heliyon.2023.e16299

AMINZADEH, A., SATTARPANAH KARGANROUDI, S., MAJIDI, S., DABOMPRE, C., AZAIEZ, K., MITRIDE, C., SÉNÉCHAL, E. 2025. A Machine Learning Implementation to Predictive Maintenance and Monitoring of Industrial Compressors. *Sensors*, 25(4), 1006. doi: https://doi.org/10.3390/s25041006

ANSARI, I.A.; BAJAJ, V.; MAŠÍN, I., JANDURA, P. 2023. IoT for Industry 4.0: Performance Monitoring in Manual Production. *Advanced Signal Processing for Industry 4.0. 2*, 1-29. doi: https://doi.org/10.1088/9780750356589

ARENA, F., COLLOTTA, M., LUCA, L., RUGGIERI, M., TERMINE, F. G. 2022. Predictive Maintenance in the Automotive Sector: A Literature Review. *Mathematical and Computational Applications*, *27*(1), 2. doi: https://doi.org/10.3390/mca27010002

ARINZE, CH., ISONG, V., DAUDU, D., ADEFEMI, D., ADEDAYO, D. 2024. Predictive maintenance in oil and gas facilities, leveraging ai for asset integrity management. *International Journal of Frontiers in Engineering and Technology Research*, 6, 16-026. doi: https://doi.org/10.53294/ijfetr.2024.6.1.0026

DABBOUS, A., BARAKAT, K.A., KRAUS, S. 2023. The impact of digitalization on entrepreneurial activity and sustainable competitiveness: A panel data analysis. *Technology in Society*, 73, 102224. doi: https://doi.org/10.1016/j.techsoc.2023.102224

DUI, H.; LIU, M.; SONG, J., WU, S. 2023. Importance Measure-Based Resilience Management: Review, Methodology and Perspectives on Maintenance. *Reliability Engineering & System Safety*, 237(1), 109383. doi: https://doi.org/10.1016/j.ress.2023.109383

FORDAL, J.M., SCHJØLBERG, P., HELGETUN, H., SKJERMO, T.O., WANG, Y., WANG. C. 2023.

Application of sensor data based predictive maintenance and artificial neural networks to enable Industry 4.0. *Advances in Manufacturing,* 11, 248–263. doi: https://doi.org/10.1007/s40436-022-00433-x
FRIEDERICH, J., LAZAROVA-MOLNAR, S. 2024. Reliability assessment of manufacturing systems: A comprehensive overview, challenges and opportunities. *Journal of Manufacturing Systems*, 72, 38-58. https://doi.org/10.1016/j.jmsy.2023.11.001
GHOBAKHLOO, M. 2020. Industry 4.0, digitization, and opportunities for sustainability. *Journal of Cleaner Production*, 252, 119869. doi: https://doi.org/10.1016/j.jclepro.2019.119869
HALLIOUI, A., HERROU, B., KATINA, P. F., SANTOS, R. S., EGBUE, O., JASIULEWICZ-KACZMAREK, M., SOARES, J. M., MARQUES, P. C. 2023. A Review of Sustainable Total Productive Maintenance (STPM). *Sustainability*, 15(16), 12362. doi: https://doi.org/10.3390/su151612362
HAN, X., WANG, Z.,, XIE, M., HE,. Y, LI, Y., WANG., W. 2021. Remaining useful life prediction and predictive maintenance strategies for multi-state manufacturing systems considering functional dependence. *Reliability Engineering & System Safety*, 210, 107560. doi: https://doi.org/10.1016/j.ress.2021.107560
HARDT, F., KOTYRBA, M., VOLNA, E., JARUSEK, R. 2021. Innovative Approach to Preventive Maintenance of Production Equipment Based on a Modified TPM Methodology for Industry 4.0. *Applied Sciences*, 11(15), 6953. doi: https://doi.org/10.3390/app11156953
JADA, I., MAYAYISE, T.O. 2024. The impact of artificial intelligence on organisational cyber security: An outcome of a systematic literature review. *Data and Information Management*, 8(2), 100063. doi: https://doi.org/10.1016/j.dim.2023.100063
JIMINEZ, V.J., BOUHMALA, N., GAUSDAL, A.H. 2020. Developing a predictive maintenance model for vessel machinery. *Journal of Ocean Engineering and Science*, 5(4), 358-386. doi: https://doi.org/10.1016/j.joes.2020.03.003
JURACKA, D., NAGY, M., VALASKOVA, K., NICA, E. 2024. Meta-Analysis of Innovation Management in Scientific Research: Unveiling the Frontier, *Systems, 12*, 130. doi: https://doi.org/10.3390/systems12040130
KANS, M., CAMPOS, J. 2024. Digital capabilities driving industry 4.0 and 5.0 transformation: Insights from an interview study in the maintenance domain. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(4), 100384. doi: https://doi.org/10.1016/j.joitmc.2024.100384
KLIESTIK, T., KRAL, P., BUGAJ, M., DURANA, P. 2024. Generative artificial intelligence of things systems, multisensory immersive extended reality technologies, and algorithmic big data simulation and modelling tools in digital twin industrial metaverse. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 19(2), 429–461. doi: https://doi.org/10.24136/eq.3108
KOVACOVA, M., NOVAK, A., MACHOVA, V., CAREY, B. 2022. 3D Virtual Simulation Technology, Digital Twin Modeling, and Geospatial Data Mining in Smart Sustainable City Governance and Management. *Geopolitics, History, and International* Relations, 14(1), 43–58. doi: https://doi.org/10.22381/GHIR14120223

LEDMAOUI, Y., EL MAGHRAOUI, A., EL AROUSSI, M., SAADANE, R. 2025. Review of Recent Advances in Predictive Maintenance and Cybersecurity for Solar Plants, *Sensors*, 25(1), 206. doi: https://doi.org/10.3390/s25010206

LI, CH., DONG, H., CHEN, S. & YANG, Y. 2014. Working Capital Management, Corporate Performance, and Strategic Choices of the Wholesale and Retail Industry in China. *The Scientific World Journal*, 1(1), 15. doi: https://doi.org/10.1155/2014/953945

LLOPIS-ALBERT, C., RUBIO, F., VALERO, F. 2021. Impact of digital transformation on the automotive industry. *Technological Forecasting and Social Change*, 162, 120343. doi: https://doi.org/10.1016/j.techfore.2020.120343

MALLIORIS, P., AIVAZIDOU, E., BECHTSIS, D. 2024. Predictive maintenance in Industry 4.0: A systematic multi-sector mapping. *CIRP Journal of Manufacturing Science and Technology*, 50, 80-103. doi: https://doi.org/10.1016/j.cirpj.2024.02.003

MARTÍNEZ-PELÁEZ, R., OCHOA-BRUST, A., RIVERA, S., FÉLIX, V. G., OSTOS, R., BRITO, H., FÉLIX, R. A., & MENA, L. J. 2023. Role of Digital Transformation for Achieving Sustainability: Mediated Role of Stakeholders, Key Capabilities, and Technology, *Sustainability*, *15*(14), 11221. doi: https://doi.org/10.3390/su151411221

MOLĘDA, M., MAŁYSIAK-MROZEK, B., DING, W., SUNDERAM, V., MROZEK, D. 2023. From Corrective to Predictive Maintenance—A Review of Maintenance Approaches for the Power Industry, Sensors, 23(13), 5970. doi: https://doi.org/10.3390/s23135970

MOOI, E.; RUDD, J., DE JONG, A. 2020. Process innovation and performance: the role of divergence. *European Journal of Marketing*, *54*(4), 741-760. doi: https://doi.org/10.1108/EJM-02-2018-0110

MURTAZA, A.M., SAHER, A., ZAFAR, M.H., MOOSAVI, S.K.R., AFTAB, M.F., SANFILIPPO, F. 2024. Paradigm shift for predictive maintenance and condition monitoring from Industry 4.0 to Industry 5.0: A systematic review, challenges and case study. *Results in Engineering*, 24, 102935. doi: https://doi.org/10.1016/j.rineng.2024.102935

NAGY, M., FIGURA, M., VALASKOVA, K., LĂZĂROIU, G. 2025. Predictive Maintenance Algorithms, Artificial Intelligence Digital Twin Technologies, and Internet of Robotic Things in Big Data-Driven Industry 4.0 Manufacturing Systems. *Mathematics*, 13(6), 981. doi: https://doi.org/10.3390/math13060981

NAGY, M., LĂZĂROIU, G., VALASKOVA, K. 2023. Machine intelligence and autonomous robotic technologies in the corporate context of SMEs: Deep learning and virtual simulation algorithms, cyber-physical production networks, and Industry 4.0-based manufacturing systems. *Applied Sciences*, 13(3), 16-81. doi: https://doi.org/10.3390/app13031681

ÖZGÜR-ÜNLÜAKIN, D., TÜRKALI, B., KARACAÖRENLI, A., ÇAĞLAR AKSEZER, S. 2019. A DBN Based Reactive Maintenance Model for a Complex System in Thermal Power Plants. *Reliabilita Engineering & System Safety,* 190, 106505. doi: https://doi.org/10.1016/j.ress.2019.106505

PERETZ-ANDETSSON, E., TABARES, S., MIKALEF, P., PARIDA, V. 2024. Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach. *International Journal of Information Management*, 77, 12781. doi: https://doi.org/10.1016/j.ijinfomgt.2024.102781

PETKOVSKI, I., FEDAJEV, A., BAZEN, J. 2022. Modelling Complex Relationships Between Sustainable Competitiveness and Digitalization. *Journal of Competitiveness*, *14*, 79–96. doi: https://doi.org/10.7441/joc.2022.02.05

POLIAK, M., JURECKI, R., BUCKNER, K. 2022. Autonomous Vehicle Routing and Navigation, Mobility Simulation and Traffic Flow Prediction Tools, and Deep Learning Object Detection Technology in Smart Sustainable Urban Transport Systems. *Contemporary Readings in Law and Social* Justice, 14, 25–40. doi: https://doi.org/10.22381/CRLSJ14120222

POOR, P., ZENISEK, D., BASL, J. 2019. Historical Overview of Maintenance Management Strategies: Development from Breakdown Maintenance to Predictive Maintenance in Accordance with Four Industrial Revolutions. *Proceedings of the International Conference on Industrial Engineering and Operations Management, Pilsen, Czech Republic*. doi: https://doi.org/2-s2.0-85079502932

RAHMAN, M.S., GHOSH, T., AURNA, N.F., KAISER, M.S., ANANNYA, M., HOSEN, A.S.M.S. 2023. Machine learning and internet of things in industry 4.0: A review. *Measurement: Sensors*, 28, 100822. doi: https://doi.org/10.1016/j.measen.2023.100822

RAME, R., PURWANTO, P., SUDARNO, S. 2024. Industry 5.0 and sustainability: An overview of emerging trends and challenges for a green future. *Innovation and Green Development*, 3(4), 100173. doi: https://doi.org/10.1016/j.igd.2024.100173

RAMOS, M.R., RUIZ-GALVES, M.E. 2024. The transformation of the automotive industry toward electrification and its impact on global value chains: Inter-plant competition, employment, and supply chains. *European Research on Management and Business Economics*, 30(1), 100242. doi: https://doi.org/10.1016/j.iedeen.2024.100242

SAIHI, A., BEN-DAYA, M., AS'AD, R. 2023. Underpinning Success Factors of Maintenance Digital Transformation: A Hybrid Reactive Delphi Approach. *International Journal of Production Economics,*. 255, 108701. doi: https://doi.org/10.1016/j.ijpe.2022.108701

SCAIFE, A. D. 2024. Improve predictive maintenance through the application of artificial intelligence: A systematic review*. Results in Engineering*, 21, 101645. doi: https://doi.org/10.1016/j.rineng.2023.101645

SIRAPARAPU, S.R., AZAD, S.M.A.K. 2024. Securing the IoT Landscape: A Comprehensive Review of Secure Systems in the Digital Era. *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, 10, 100798. doi: https://doi.org/10.1016/j.prime.2024.100798

STATISTICAL OFFICE. 2024. *STAT Data*. Available on: https://statdata.statistics.sk/public/ui/dc/domov/data-view (Accessed on 31. January 2025).

SOUTO, J. E. 2022. Organizational creativity and sustainability-oriented innovation as drivers of sustainable development: overcoming firms' economic, environmental, and social sustainability challenges. *Journal of Manufacturing Technology Management*, *33*, 805-826. doi: https://doi.org/10.1108/JMTM-01-2021-0018

TÖRÖK, L. 2022. The contribution of the Visegrad four automotive industry to economic growth. Journal of International Studies, 15(1), 90-103. doi: https://doi.org/10.14254/2071-8330.2022/15-1/6

UCAR, A., KARAKOSE, M., KIRIMÇA, N. 2024. Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends. *Applied Sciences*, 14(2), 898. doi: https://doi.org/10.3390/app14020898

VALASKOVA, K., NAGY, M., ZABOJNIK, S., LĂZĂROIU, G. 2022. Industry 4.0 wireless networks and cyber-physical smart manufacturing systems as accelerators of value-added growth in Slovak exports, *Mathematics*. 10(14), 24-52. doi: https://doi.org/10.3390/math10142452

VERHOEF, P.C., BROEKHUIZEN, T., BART, Y., BHATTACHARYA, A., DONG, J.Q., FABIAN, N., HAENLEIN, M. 2021. Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889-901. doi: https://doi.org/10.1016/j.jbusres.2019.09.022

ZHONG, D., XIA, Z., ZHU, Y., DUAN, J. 2023. Overview of predictive maintenance based on digital twin technology. *Heliyon*, 9 (4), 12. doi: https://doi.org/10.1016/j.heliyon.2023.e14534

ZHONG, R., XU, X., KLOTZ, E., NEWMAN, S.T. 2021. Intelligent Manufacturing in the Context of Industry 4.0: A Review. Engineering, 3, 616–630. doi: https://doi.org/10.1016/J.ENG.2017.05.015

ZONTA, T., DA COSTA, C.A., DA ROSA RIGHI, R., DE LIMA, M.J., DA TRINDADE, E.S., LI, G.P. 2020. Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, 150, 106889. doi: https://doi.org/10.1016/j.cie.2020.106889

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# TRIC: Assessing Intellectual Capital as a Driver of Strategic Transformation

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**Abstract**

This article introduces a new theoretical model called TRIC 1.0 (Transformation-Related Intellectual Capital), designed to assess organizational readiness for complex strategic transformations. A comparable model has not yet been published. The originality of the model lies in the unconventional clustering of intellectual capital components into identifiable, assessable, and developable bundles (dimensions). The TRIC 1.0 model addresses a gap in evaluating intellectual capital in manufacturing companies with project management during or before transformation. It was developed in two steps: literature review and qualitative research through a three-month participatory observation in a manufacturing organization. The author acted as an HR manager, enabling direct insight into behaviours, attitudes, and organizational dynamics. The research methodology combined participatory ethnographic observation, critical incident analysis, and micro-narratives. The model supports a 360-degree feedback approach, in which departments evaluate themselves and each other across ten dimensions. This approach enables mapping of organizational readiness and identifying barriers and opportunities for transformation.

**Keywords:** Intellectual capital, company transformation, change, assessment, strategy

## Introduction

Throughout the history of research, Intellectual Capital (IC) has been viewed as a source of competitive advantage that is difficult to replicate, with its significance in the knowledge economy continuously increasing (Lentjusenkova, 2020). In financial terms, IC can be broadly equated with the difference between an organization's market value and its book value.

IC is traditionally and predominantly divided into three main components: Human Capital – the knowledge and skills of employees (tacit knowledge), their motivation, and their relationship to work. Structural Capital – strategies, processes, information systems and the data they contain, organizational structure, corporate culture, patents and innovations, product models, manuals and instructions, policies (explicit knowledge). Relational Capital – relationships with customers, suppliers, and other stakeholders, company reputation, and brand strength (Dmitrović et al., 2017; Crema et al., 2016).

Over five decades of IC studies, researchers' focus has gradually evolved alongside the demands of the global economy and organizations. Dumay et al. (2013) identified three major streams in IC research:

The first stream dealt with defining IC itself, its nature and structure. In this early era of "grand theories," numerous models emerged, and IC gained attention from both scholars and managers.

The second phase focused primarily on the quantitative and financial valuation of IC and its reporting. Although there has been a gradual shift away from the "accounting approach" to IC, transparent IC reporting remains of interest among financial managers and shareholders, according to Richard Petty (2008). Dumay et al. (2013) noted that many authors still remain caught in this "reporting loop".

The third phase of research analyses the impact of IC and its components on value creation, financial performance, and organizational competitiveness. Numerous studies have confirmed the positive influence of IC on organizational outcomes. For example, José Sánchez-Gutiérrez (2016), in a study of 420 SMEs in Mexico, demonstrated a positive relationship between the level of IC and competitiveness. The VAIC (Value Added Intellectual Coefficient) model assesses IC using ratio indicators of the efficiency of its components (Iazzolino et al., 2014). The modified version, MVAIC (Modified Value-Added Intellectual Coefficient), confirmed a statistically significant impact of IC on the financial performance of 953 Chinese manufacturing firms (Xu et al, 2022). Recent research in Brazilian companies has also confirmed the strong influence of IC on sustainable value creation, using both the IC-index and MVAIC methodology (Dias Jordão, 2024).

At the same time, IC models are being developed as managerial tools for strategic development and for enhancing organizational competitiveness. One example is the AMIC model (Assessment and Management of Intellectual Capital), which analyses the relationship between IC and value creation (Grimaldi, 2015). In this study, the components of IC (so-called value drivers) were assessed in 2010, followed by targeted development activities. A repeat study in 2011 demonstrated an increase in the AMIC index.

Despite this clear evolution, a static, assessment-oriented approach still dominates the literature, with IC divided into historically stabilized components (HC, SC, RC), and IC thinking structured in terms of causes and effects. Future development should therefore move toward models that focus more on flow the creation of knowledge and its transformation into value (what the organization does) rather than on stock, as measured in value terms (what the organization has) (Dumay et al., 2013).

Similarly, Edvinsson (2013) abandoned the view of IC as a “measurable quantity” and emphasized the need for organizations to remain open to external sources of knowledge and to build alliances for shared growth.

A completely new approach to IC assessment is introduced by Dumay (Dumay et al., 2012), who advocates for a bottom-up narrative method of evaluating IC levels. Selected employees critically comment on the IC evaluation results obtained through one of the models. According to Dumay, this allows organizations to gain more detailed contextual insights while simultaneously enhancing employees’ self-awareness and empowerment.

Further development could be enriched by focusing on core competencies and core capabilities instead of the traditional IC components. While the conventional components are suitable for assessment, they are difficult to manage strategically in isolation, as they typically form interconnected "bundles" of qualities that cannot generate value on their own. For instance, innovation emerges at the intersection of human, structural, and relational capital, but in assessment models, it is reported under the structural capital component (Martí et al., 2023).

However, IC is not only a source of value and wealth for an organization in the present moment. It is also and primarily a driving force for organizational renewal and development in a changing world. Ongoing and incremental changes in processes, products, organizational structure, and culture are often initiated in response to market demands, managerial intuition, or partial analyses of internal and external environments. Such changes may be challenging, but they do not pose a critical burden on the organization, as intentions can be iteratively adjusted and refined without significant losses.

However, when an organization stands at the very beginning of a complex strategic transformation, it is necessary to assess its overall systemic readiness for a multitude of interconnected changes across all dimensions of the organizational system. Such a transformation, if it fails in any system dimension, may result in serious and difficult-to-repair damage both financial and in terms of employee trust or organizational reputation among customers. This article introduces a new model TRIC 1.0 (Transformation-Related Intellectual Capital) for evaluating IC before and during an ongoing organizational transformation.

## Methods and Data

This study employed grounded theory methodology as conceptualized by Strauss and Corbin (Binder et al, 2010) which is particularly suited for generating theory from complex and evolving organizational settings. Grounded theory allows for an iterative and inductive approach where data collection and analysis proceed in cycles, enabling theoretical constructs to emerge directly from the empirical data.

The author of the article spent three months in a Czech manufacturing organization in the role of HR manager. During this time, he participated in shopfloor management meetings, leadership and departmental sessions, employee training, negotiations with external partners, performance reviews, problem-solving workshops, and organizational changes. He also conducted dozens of informal and formal interviews with employees from all organizational levels, departments, and professional roles.

Research data were collected using qualitative, ethnographically inspired methods: participatory ethnographic observation in a natural setting, critical incident analysis, and micro-narratives. The sample consisted of 61 employees selected via purposive sampling to ensure diversity in age, gender, seniority, and professional background. Participants were drawn from various departments, including production, quality assurance, engineering, logistics, finance, project management, and senior leadership. Their positions ranged from frontline operators to department heads.

Based on an initial literature review, a proto-TRIC model was drafted, consisting of four preliminary dimensions:

- Future orientation ("knowing where to")
- Employee engagement ("knowing why")
- Knowledge sharing and collaboration ("knowing how")
- Relationships with external partners ("knowing with whom")

The coding process followed grounded theory principles and was conducted manually by the author without the use of specialized software. Initial open coding yielded these four proto-dimensions. As data saturation increased, further iterations of axial and selective coding were employed, eventually refining and expanding the framework into a structured set of ten final dimensions that form the TRIC model. This development was guided by the constant comparative method and focused on identifying recurring patterns of behaviour, perceptions, and knowledge flows relevant to organizational transformation.

In line with Strauss and Corbin's vision of grounded theory as both a creative and scientific process, the TRIC model represents an empirically grounded yet theoretically robust response to the challenges of measuring intellectual capital in transformative settings.

# Results

### Proposal of the New Theoretical Model TRIC 1.0

The studied organization is a manufacturing company with more than 30 years of history, whose managerial philosophy remains stuck in the 1990s. Its organizational culture is characterized by strong control, limited willingness to collaborate across departments, and a suboptimal mix of serial and custom production with outdated and inefficient processes and immature project management. The company holds a weak position in relation to both customers and suppliers. While its employees are stable and technically competent, they lack broad T-shaped knowledge and experience. The current workforce includes 450 core employees and 70 agency workers. The turnover for the most recent year was CZK 1.5 billion. However, the company reported a loss due to old contracts and a decline in turnover from the previous CZK 2.1 billion.

Despite this unfavourable situation, the foreign headquarters has set an ambitious vision to transform the production plant into a flagship of the corporate group, with double the turnover and full competencies in product development, manufacturing, and sales, including to automotive customers.

Embarking on a complex strategic transformation of this organization without a thorough readiness analysis is risky. Without such an in-depth assessment, the organization may remain unaware of what it does not know or cannot do and of what or who stands in the way of successful change.

The TRIC 1.0 model was developed to provide a qualitative assessment of organizational readiness for transformation, as well as to enable continuous monitoring of progress and early warning of potential failure. The resulting TRIC 1.0 model monitors ten aspects associated with the change process, each evaluated from three perspectives: What resources are available, what practices are in place, what results are being achieved.

This structure enables a more dynamic view of intellectual capital not only as a "stock" but also as a "flow" – processes.

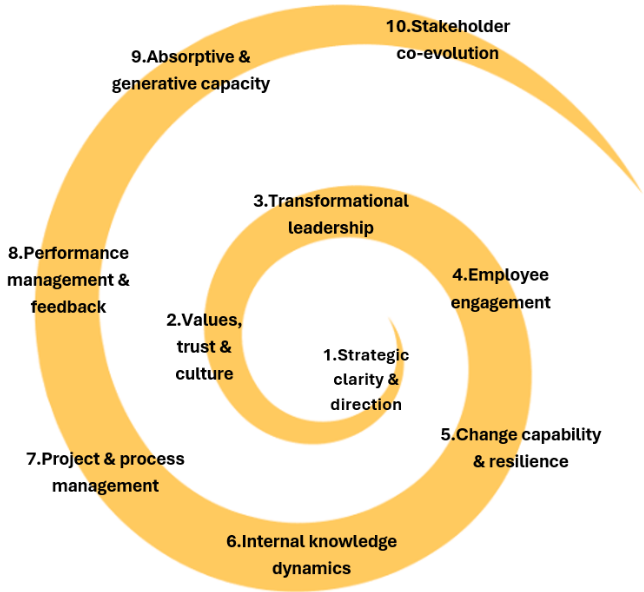
Table 1: Overview of the 10 Dimensions of the TRIC 1.0 Model and Their Association with Intellectual Capital Components

| Dimension | Human capital | Structural capital | Relational capital |
|---|---|---|---|
| 1.Strategic clarity & direction | x | x | |
| 2.Values, trust & culture | x | | |
| 3.Transformational leadership | x | | |
| 4.Employee engagement | x | | |
| 5.Change capability & resilience | x | x | |
| 6.Internal knowledge dynamics | x | x | |
| 7.Project & process management | x | x | |
| 8.Performance management & feedback | x | x | |

| | | | |
|---|---|---|---|
| 9.Absorptive & generative capacity | x | | x |
| 10.Stakeholder co-evolution | x | x | x |

Source: Own processing.

Figure 1: Spiral shape of the TRIC 1.0 model




Source: Own processing.

The spiral visually represents the iterative and systemic nature of organizational transformation—rather than progressing linearly, organizations revisit similar themes repeatedly, each time at a higher level of maturity. Each of the ten TRIC dimensions emerges with varying intensity across different phases of change. This reflects principles of circular causality and adaptive learning, where insights in one area influence and enrich others. The assessment process itself follows an iterative structure, as respondents revisit the dimensions multiple times to gradually deepen their understanding and refine their responses.

**Strategic clarity & direction**

The first dimension of the TRIC 1.0 model is the definition of direction and target vision. However, a colorful presentation of the vision and strategy is not sufficient. What is essential is a real plan based on facts and a thorough analysis of the current state.

One useful approach is “strategic design,” which contributes to organizational transformation by enabling a deeper understanding of the rationale for change. During the transformation process, signals of potential failure or, conversely, unplanned opportunities will emerge. Abductive competencies allow for the timely recognition of such signals. A participatory approach engages various employee stakeholder groups, thereby fostering understanding, acceptance, and shared ownership of the transformation vision. Together with creative leadership, abductive competencies and a participatory approach provide a solid foundation for successful transformation (Giraldo et al., 2023).

| **Resources: >>>** | **Processes: >>>** | **Results:** |
|---|---|---|
| Strategy, mission, vision, plans, internal and external analysis, benchmarking | Participatory planning, involvement of key employees, transparent and systematic communication | Employee understanding and alignment with strategic intentions, degree of employee involvement in strategic initiatives, stability of decision-making processes |

**Values, trust & culture**

Articulating a changing corporate culture while simultaneously involving employees in the change are common variables addressed during cultural transformation. In practice, attention is paid selectively to specific elements of the company culture: those that are functioning well and should be preserved, and those that are dysfunctional or outdated and should be changed.

Ernst Graamans et al. (2021) highlight the risk of vague statements, which cannot serve as a foundation for change, and differentiate between: Agreements – unwritten rules about what is considered right, Customs – long-standing norms and automatisms, Arrangements – formal and informal structures and procedures

A lack of trust can lead to transformation failure. When employees do not trust their leaders, and managers, in turn, rely too heavily on their own solutions and do not trust their people, it creates an atmosphere of doubt and fear. As a result, senior leadership may not receive accurate information about the actual progress of change.

It is not enough for employees to merely “buy into” the change they must be actively involved in co-creating it. (Rousseau et al., 2022)

| **Resources: >>>** | **Processes: >>>** | **Results:** |
|---|---|---|
| Company values, rituals, work environment, shared stories, interpersonal behavior | Deliberate culture shaping, reflection and feedback on behavior, storytelling, employee involvement in shaping the culture | Mutual trust, cohesion, inclusivity, understanding of values, willingness to absorb change |

## Transformational leadership

Transformational leadership is a key ingredient in the development of employee competencies and innovative capabilities, and it helps create a "winning" culture within the organization during periods of change (Guha et al., 2025).

Numerous studies have confirmed the positive impact of transformational leadership on various organizational aspects, including organizational and employee performance, interpersonal collaboration, lean management, enhanced knowledge sharing, and innovativeness (Agazu et al., 2025).

One of the dimensions of transformational leadership is creative leadership, which together with an innovation-friendly climate affects employees' innovative behavior. This means making work engaging, stimulating new ideas, creating a psychologically safe environment for innovation, inspiring through vision, encouraging diverzity of thought, facilitating collaboration, and supporting the implementation of new ideas (Pinghao et al., 2022).

Research on the influence of mindfulness in successful change management has shown that systemic perception, present-moment awareness, inquisitive and intentional reactions, and holistic acknowledgment support successful transformation. The most significant elements were: Systemic perception – the leader's ability to see interconnections, the relationships between system components, and understand broader implications of decisions. Inquisitive response – an open, curious, and non-judgmental approach to change rather than automatic defensive reactions (Higgs et al., 2024).

| **Resources: >>>** | **Processes: >>>** | **Results:** |
|---|---|---|
| Management team, personal integrity, training in change management, experience in leading transformations, psychologically safe environment | Respectful dialogue with employees, walk the talk, active listening, coaching, empowering, decision-making transparency, emotional support | Employee trust in leadership, ability to lead in uncertainty, alignment of leadership on direction and balanced energy investment in the transformation |

**Employee engagement**

Implementing changes during a transformation requires managers to adopt a respectful approach toward each employee, taking into account their individual personality. Based on employees' attitudes toward change, they can be categorized into five types (Miziara, et al., 2025). These varying levels of engagement reflect differences in roles, age, seniority, and personal attitudes. An experienced manager adjusts their leadership style to the employee's typology, thereby avoiding unnecessary misunderstandings and conflicts.

Despite the different ways in which employees approach change, maintaining engagement requires that all employees without exception receive clear information about the details and purpose of the change, specific instructions, goals, and expectations from leadership, as well as the opportunity to give feedback and safely express their views on ongoing changes without fear of consequences (Skiba, 2021).

| **Resources: >>>** | **Processes: >>>** | **Results:** |
|---|---|---|
| Communication channels, visualization, system for recognizing exceptional effort | Listening to feedback, addressing employee requests, acting with respect, engagement surveys | Employee stability, engagement index and survey participation rate, pride in the company and its results |

**Change capability & resilience**

The success of transformation depends on: Clarity of goals, Adaptive change planning, Transparent communication, Involvement of company leadership, and Utilization of knowledge from past experiences (Miziara et al., 2025).

The evidence-based change framework is a compelling alternative to models such as Kotter and ADKAR. The authors focus on the following key processes: Goal setting, Vision communication, Fairness and justice, Transition structures, Feedback and redesign, Ongoing learning (Rousseau et al., 2022).

| **Resources: >>>** | **Processes: >>>** | **Results:** |
|---|---|---|
| Change management tools (Kotter's model, ADKAR), change leaders, employee capacity for implementing change | Planning, coordination, reflection, iterative adaptation, change communication, progress recognition, integration of new standards into the system, training | Acceptance of changes, coherent organizational movement forward, implementation of new processes |

**Internal knowledge dynamics**

Effective sharing of tacit knowledge among employees and teams (knowledge management) plays a significant role in organizational learning and creates both financial and non-financial value for the organization, enabling it to differentiate itself from competitors (Alzoubi, 2022).

Equally important is the transformation of tacit knowledge into explicit, tacit into tacit, and explicit into explicit knowledge. These knowledge transfers are captured in the SECI model: socialization (tacit to tacit), externalization (tacit to explicit), combination (explicit to explicit), and internalization (explicit to tacit) (Nonaka et al., 1995).

A prerequisite for open knowledge sharing, particularly of tacit knowledge, is a culture of trust among colleagues and leadership acceptance of initial mistakes that may occur during implementation and innovation (Kucharska et al., 2024).

To enable effective learning from mistakes (lessons learned) in project teams, discipline, appropriate IT tools, and an understanding of the purpose of knowledge sharing are necessary (Doskočil, 2019).

For an organization, knowledge is a rare, non-replicable, and irreplaceable asset that is "dispersed in the minds of employees" (knowledge-based view of the firm) (Bagis, et al., 2025). Therefore, organizations seek to encourage employees to share knowledge. Intrinsic motivation stems from internal drivers such as loyalty, prestige, and self-actualization, whereas extrinsic motivation responds to external incentives like rewards, recognition, and promotion.

| **Resources: >>>** | **Processes: >>>** | **Results:** |
|---|---|---|
| IT infrastructure, internal documentation, tools for community-based knowledge sharing, coaches and mentors, opportunities for informal knowledge exchange | Knowledge sharing across teams, lessons learned, knowledge codification, informal knowledge exchange | Speed and accuracy of knowledge sharing, satisfaction with interdepartmental collaboration, number of active knowledge communities |

**Project & process management**

A manufacturing organization with predominantly process-oriented management, focused on efficient resource utilization, may perceive the project-based approach, which emphasizes customer satisfaction, as a foreign element. In this component of the model, we focus on the maturity of project management (e.g., IPMA, Patzak et al., 2012), the clarity of procedures and responsibilities, and the alignment between process and project approaches.

| Resources: >>> | Processes: >>> | Results: |
|---|---|---|
| Project management system (Project Management Office), ERP, APS, competencies in project management, lean competencies | Designing new and optimizing existing processes, implementing lean methods, training, measuring process efficiency, alignment of process and project management | Achievement of plans and budgets, process and project management maturity, number of successfully optimized processes, defined interface between projects and processes |

**Performance management & feedback**

The Performance Management System (PMS) is an important tool in both operational and strategic management, as it enables the integration of qualitative and quantitative metrics. However, since PMS is often heavily focused on measuring short-term efficiency and goal achievement, it may come into conflict with change management, which requires a long-term perspective, flexibility, and creativity. Therefore, during a transformation, it is necessary to seek an acceptable balance between the present and the future, between perfect efficiency and "strategic slack" in the form of experimentation and the search for optimal solutions (Lewandowski, et al., 2021).

| Resources: >>> | Processes: >>> | Results: |
|---|---|---|
| KPIs, dashboards, internal audits, reward system, performance management process, HR policy | Goal setting, performance measurement, reporting, regular feedback, active use of recognition systems | Alignment between strategy and departmental goals, employee satisfaction with feedback, KPI fulfillment rate |

**Absorptive & generative capacity**

Effective change management requires continuous organizational learning from the external environment through four key steps: 1. Identification and acquisition of knowledge, 2. Assimilation of knowledge, 3. Transformation of knowledge, 4. Exploitation of knowledge. Effective knowledge absorption enhances both innovative performance and organizational competitiveness. (Acklin, 2013; Chang, et al., 2023).

| Resources: >>> | Processes: >>> | Results: |
|---|---|---|
| R&D, universities, benchmarking, external consultants, customers, suppliers | Mentoring, creation of knowledge databases, knowledge collaboration with customers and suppliers | Number of innovations, increase in knowledge database entries, customer satisfaction with technical expertise |

**Stakeholder co-evolution**

It is advantageous for organizations to engage in strategic partnerships with their suppliers and customers in the development of products and services. Studies have shown that strong relational capital between supplier and buyer acts as a catalyst for collaborative effectiveness, positively influencing the product's quality and cost, and enabling the relationship to extend far beyond the limits defined by the contract (Prajogo et al., 2021).

| **Resources: >>>** | **Processes: >>>** | **Results:** |
|---|---|---|
| CRM, effective strategies for developing relationships with customers and key suppliers, competent key account and commodity managers | Co-development of solutions with customers, active collection of customer feedback, supplier development | Level of customer loyalty and satisfaction, cost of complaints, supplier involvement in innovation, success rate in negotiating commercial terms with customers |

**Methodology of evaluation using TRIC 1.0**

The goal of assessment using the TRIC 1.0 model is to evaluate an organization's readiness for transformation, identify risks and barriers than continuously monitor its development. Employees from each department will be purposefully selected to represent different groups based on age, gender, seniority, and professional background.

Initially, the selected employees will be trained to ensure they understand the purpose of the assessment and are familiar with the terminology and methodology.

During semi-structured interviews, respondents will be asked to evaluate both their own department and other departments in all dimensions. Their responses will then be coded and recorded in an evaluation matrix, gradually forming a comprehensive organizational map in which weaknesses, barriers, and opportunities become visible.

The interview results will provide a multi-perspective mutual evaluation of each department across all dimensions of the model. This approach can be compared to a 360-degree feedback design.

## Discussion

This article represents the first step in developing a new model for assessing transformational intellectual capital. It was created for the needs of a manufacturing company that is at the beginning of a complex transformation for which it is clearly unprepared. The proposed TRIC model, in its current version 1.0, aims to help the company identify the main obstacles and weaknesses that could hinder or even prevent the transformation. Therefore, the model is not intended to be universally applicable in this form. After subsequent research steps are completed, version 2.0 will be proposed for broader use. However, the target group will remain medium and large engineering manufacturing companies with project-based order management.

10 dimensions are result of several iterations in clustering key topics which appeared during research. Some of them are specific for this company, because of history, some could be general for all companies in sector and in such situation.

As mentioned, the main limitation of this paper lies in the fact that it is based solely on research conducted within a single organization, where ethnographically inspired, participatory qualitative inquiry took place. The next direction of research will focus on the first use of the TRIC 1.0 in the studied company. In parallel detailed development of the model, validation of its dimensions, and determination of their weights will be proceed.

Another limitation of the article lies in the fact that the author held the role of HR manager, which may have influenced the observed behaviours and employee reactions. This risk was mitigated through informal behaviour, respect, empathy, and discretion. The information was verified from multiple sources and situations.

The final "product" will be model TRIC 2.0 suitable for medium and large manufacturing companies with project management which need to assess their readiness for complex changes.

## Conclusion

This article introduces a new model TRIC 1.0 for assessing Intellectual Capital (IC). It addresses a research gap in the evaluation of IC in manufacturing companies with project-based management, particularly in the pre-transformation phase or during complex change.

The model was developed in two stages: through a literature review and qualitative research conducted in a manufacturing company.

Although based on the traditional IC structure, the model logically clusters individual qualities into coherent bundles that can be clearly identified, assessed, and developed within the organization. Departments evaluate each other in a manner like 360-degree feedback, ensuring multi-perspective evaluation of each dimension across all organizational units.

The model not only fills a research gap but also provides practical support for organizations to better prepare for complex transformations and to define targeted development activities for successful change implementation.

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## References

ACKLIN C., 2013. Design management absorption model: A framework to describe and measure the absorption process of design knowledge by SMEs with little or no prior design experience. *Creativity and Innovation Management*, 22(2), 147–160. doi: https://doi.org/10.1111/caim.12022

AGAZU B. G., KERO C. A. & DEBELA K. L., 2025. Transformational leadership and firm performance: a systematic literature review. *Journal of Innovation and Entrepreneurship*, 14, 59 pp. doi: https://doi.org/10.1186/s13731-025-00476-x

ALZOUBI M. O., ALROWWAD A. & MASA'DEH R., 2022. Exploring the relationships among tacit knowledge sharing, communities of practice and employees' abilities: the case of KADDB in Jordan. *International Journal of Organizational Analysis*, 30(5), 1132–1155. doi: https://doi.org/10.1108/IJOA-11-2020-2480

BAGIS M., YOLCU T., KURUTKAN M. N., YILMAZ A., AYKAÇ Ö. S., ÖZKAYNAR K. & GÜRLER G., 2025. Intrinsic and extrinsic knowledge-sharing motivations as microfoundations of marketing capabilities and firm performance. *Journal of Knowledge Management*. doi: https://doi.org/10.1108/JKM-11-2024-1317

BINDER, M. and EDWARDS, J.S., 2010. Using grounded theory method for theory building in operations management research: A study on inter-firm relationship governance. International Journal of Operations & Production Management, 30(3), pp.232–259. https://doi.org/10.1108/01443571011024610.

CHANG K.-C., JIANG Y., HUANG C., XIONG X., CHEN Z., LAI Y.-C. & CHAI K.-C., 2023. The enterprise's external knowledge acquisition capability and technological diversification: From the perspective of intellectual property strategy. *Frontiers in Psychology*, 13, 1093362. doi: https://doi.org/10.3389/fpsyg.2022.1093362

CREMA M. & VERBANO C., 2016. Managing intellectual capital in Italian manufacturing SMEs. *Creativity and Innovation Management*, 25, 408–421. doi: https://doi.org/10.1111/caim.12074

DMITROVIĆ V., SIMEUNOVIĆ B. & KNEŽEVIĆ S., 2017. Establishing a system for intellectual capital measuring and reporting. Ministry of Finance of the Republic of Serbia.

DOSKOČIL R. & LACKO B., 2019. Root cause analysis in post project phases as application of knowledge management. *Sustainability*, 11, 1667. doi: https://doi.org/10.3390/su11061667

DUMAY J. & GARANINA T., 2013. Intellectual capital research: a critical examination of the third stage. *Journal of Intellectual Capital*, 14(1), 10–25. doi: https://doi.org/10.1108/14691931311288995

DUMAY J. & ROSLENDER R., 2013. Utilising narrative to improve the relevance of intellectual capital. *Journal of Accounting & Organizational Change*, 9(3), 248–279. doi: https://doi.org/10.1108/JAOC-07-2011-0034

GALLEGO G. & CALDERON-HERNANDEZ G., 2023. The contribution of strategic design, as intellectual capital, to organizational transformation. *Journal of Organizational Change Management*, 36(4), 541–560. doi: https://doi.org/10.1108/JOCM-06-2022-0163

GRAAMANS E., TEN HAVE W. & TEN HAVE S., 2021. Against the current: Cultural psychology and culture change management. *Culture & Psychology*, 27(2), 325–343. doi: https://doi.org/10.1177/1354067X21993789

GRIMALDI M., CRICELLI L. & ROGO F., 2015. Assessment and management of intellectual capital: a single case study on the construction and implementation of an IC index. *Knowledge and Process Management*, 22(4), 235–249. doi: https://doi.org/10.1002/kpm.1479

GUHA S., RABBY S. K. M. H., CHOWDHURY S. R. & JULEE S. A., 2025. Enhancing employee innovation capabilities through high-involvement HRM: mediating role of knowledge sharing and transformational leadership. *Future Business Journal*, 11, 59. doi: https://doi.org/10.1186/s43093-025-00482-1

HIGGS M. & ROWLAND D., 2024. Is change all in the mind? A study of leader mindfulness, leader behaviours in implementing change. *Journal of General Management*, 49(2), 146–162. doi: https://doi.org/10.1177/03063070221107130

IAZZOLINO G., LAISE D. & MIGLIANO G., 2014. Measuring value creation: VAIC and EVA. *Measuring Business Excellence*, 18(1), 8–21. doi: https://doi.org/10.1108/MBE-10-2013-0052

JORDAO R. V. D., AVELAR E. A. & LÚCIO M. A., 2024. The role of intellectual capital in the sustainable value creation of Brazilian listed companies. *Journal of Accounting & Organizational Change*. doi: https://doi.org/10.1108/JAOC-07-2024-0220

KUCHARSKA W. & BEDFORD D., 2024. The KLC Cultures' synergy power, trust, and tacit knowledge for organizational intelligence. *The Electronic Journal of Knowledge Management*, 22(2), 18–35. doi: https://doi.org/10.34190/ejkm.22.2.3554

LEWANDOWSKI R. A. & CIRELLA G. T., 2023. Performance Management Systems: Trade-off between implementation and strategy development. *Operations Management Research*, 16, 280–295. doi: https://doi.org/10.1007/s12063-022-00305-4

LENTJUŠENKOVA O. & LAPINA I., 2020. An integrated process-based approach to intellectual capital management. *Business Process Management Journal*, 26(7), 1833–1850. doi: https://doi.org/10.1108/BPMJ-03-2019-0101

MARTÍ J. M. V. et al., 2023. Advancing the intellectual capital theory: some ways forward. *In Proceedings of the 24th European Conference on Knowledge Management*, pp. 1399–1409.

MIZIARA T., PINTO J. D. S., SIGAHI T. F. A. C., DE MORAES G. H. S. M., RAMPASSO I. S., ZANON L. G. & ANHOLON R., 2025. Critical factors of change management in small- and medium-enterprises: an exploratory study using the best–worst method in the Brazilian context. *International Journal of Organizational Analysis*. doi: https://doi.org/10.1108/IJOA-06-2024-4586

NONAKA I. & TAKEUCHI H., 1995. The Knowledge-Creating Company: How Japanese companies create the dynamics of innovation. *Oxford University Press*. ISBN 978-0-19-509269-1.

PATZAK G. & RATTAY G., 2012. Project Management: Guideline for the management of projects, project portfolios, programs and project-oriented companies. Linde Verlag GmbH. ISBN 978-3-7094-0289-4.

PETTY R., RICCERI F. & GUTHRIE J., 2008. Intellectual capital: a user's perspective. *Management Research News*, 31(6), 434–447. doi: https://doi.org/10.1108/01409170810876035

PHILLIPS J. & KLEIN J. D., 2023. Change Management: From theory to practice. *TechTrends*, 67, 189–197. doi: https://doi.org/10.1007/s11528-022-00775-0

PRAJOGO D., MENA C. & CHOWDHURY M., 2021. The role of strategic collaborations and relational capital in enhancing product performance – a moderated-mediated model. *International Journal of Operations & Production Management*, 41(3), 206–226. doi: https://doi.org/10.1108/IJOPM-05-2020-0256

ROUSSEAU D. M. & TEN HAVE S., 2022. Evidence-based change management. *Organizational Dynamics*, 51, 100899. doi: https://doi.org/10.1016/j.orgdyn.2022.100899

SANCHEZ-GUTIERREZ J. M., MEJIA-TREJO J., VARGAS-BARRÁZA J. A. & VAZQUEZ-AVILA G., 2016. Intellectual capital, impact factor on competitiveness: manufacturing industry SMEs in Mexico. *Measuring Business Excellence*, 20(1), 1–11. doi: https://doi.org/10.1108/MBE-12-2015-0059

SKIBA Ł., 2021. Managing employee engagement in the reality of organisational changes. *Polish Journal of Management Studies*, 24(1). doi: https://doi.org/10.17512/pjms.2021.24.1.21

XU J. & LI J., 2022. The interrelationship between intellectual capital and firm performance: evidence from China's manufacturing sector. *Journal of Intellectual Capital*, 23(2), 313–341. doi: https://doi.org/10.1108/JIC-08-2019-0189

YE P. Y., LIU L. & TAN J., 2022. Creative leadership, innovation climate and innovation behaviour: the moderating role of knowledge sharing in management. *European Journal of Innovation Management*, 25(4), 1092–1114. doi: https://doi.org/10.1108/EJIM-05-2020-0199

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