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Content

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

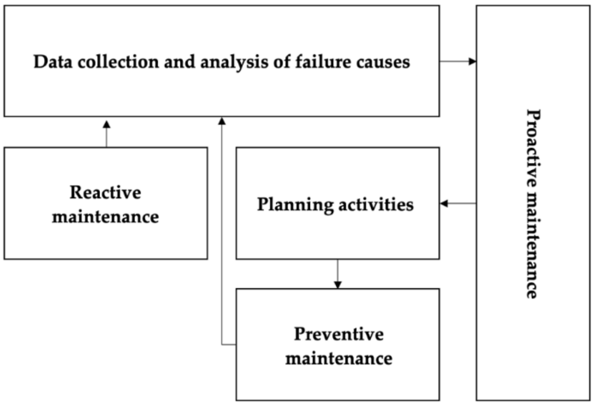
Digitalization is reshaping industrial practices by enabling smarter, more efficient, and data-driven operations. In the automotive sector, predictive maintenance has emerged as a key application of digital technologies, offering the ability to monitor equipment conditions in real time, predict potential 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

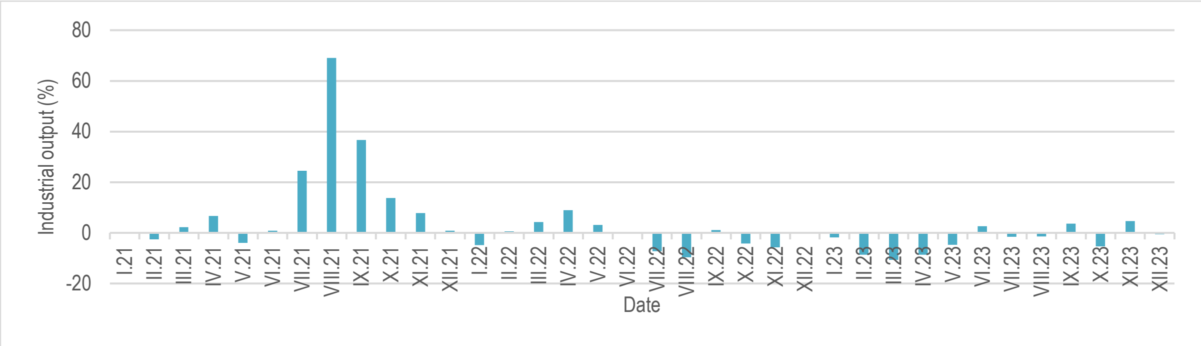
	Stock 2018	**Stock 2019**	**Stock 2020**	**Stock 2021**	**Stock 2022**	**Stock 2023**
Mean	3496,03	3793,65	3539,02	898,37	1220,10	1284,53
Median	766,76	718,50	623,47	223,82	345,08	308,17
Std. deviation	5971,25	6484,00	6005,79	1561,18	2242,07	3347,94
	TOAS 2018	**TOAS 2019**	**TOAS 2020**	**TOAS 2021**	**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.

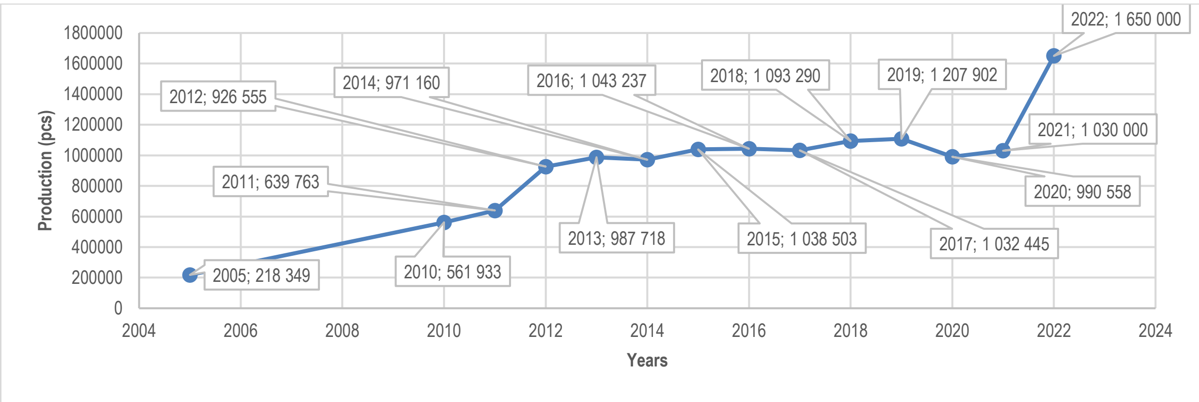
5. The summary of findings and recommendation for enterprises operating in the automotive industry.

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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