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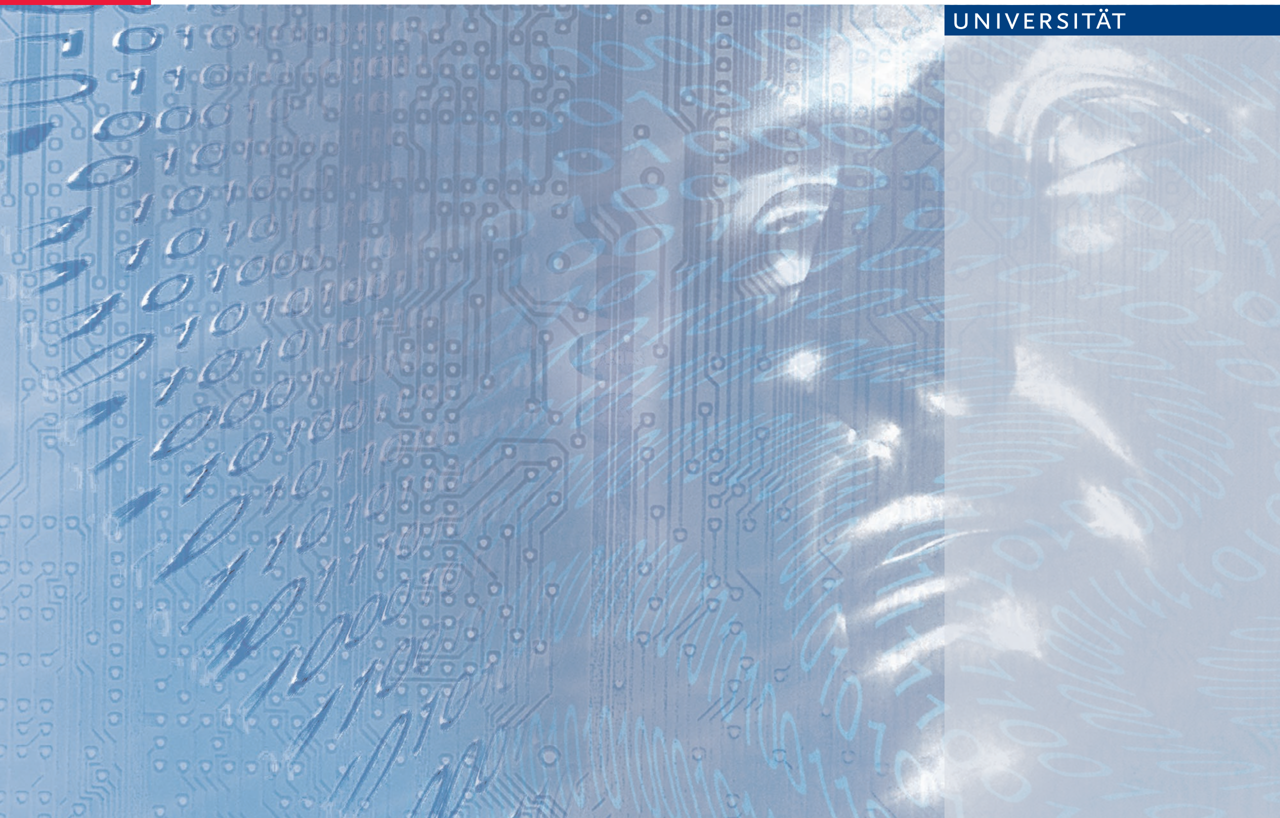

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Doucek Petr ■ Sonntag Michael ■
Nedomova Lea (Editors)

IDIMT-2025

ICT in Business: AI Everywhere?
Glory and Disgrace of AI

33rd Interdisciplinary
Information Management Talks
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Hradec Králové, Czech Republic

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UTILIZATION OF AI-DRIVEN MANUFACTURING TECHNOLOGIES: AN EMPIRICAL STUDY

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AI-driven technologies, Manufacturing companies, Managerial expectations, Utilization

Abstract

The article aims to identify the current and anticipated use of AI-driven manufacturing technologies in Slovak manufacturing companies. Building on a 2017 study by Závadský & Závadská, the research revisits and expands the original sample to 115 companies. The study examines the adoption and future expectations of 10 selected AI technologies through a structured survey of quality and production managers. Key findings show that 3D Printing, Predictive Maintenance Systems, Generative Design, and Supply Chain Optimization Systems are the most widely used. Digital Twins, Robotic Process Automation, and Collaborative Robots are the most anticipated. Predictive Maintenance, though widely used, has limited future growth potential. The data reveal the current state and trajectory of AI integration in manufacturing. Statistical tests confirm the sample's representativeness across industries. These partial results contribute to understanding AI's practical implementation and expected evolution in industrial settings.

1. Introduction

Artificial intelligence (AI) is rapidly transforming manufacturing processes, offering potential to improve productivity, quality, and responsiveness. While numerous studies have explored the theoretical capabilities of AI in industrial settings, there remains a research gap in empirical data on how AI-driven technologies are being practically adopted. Much of the existing literature is either focused on global trends or centered around high-profile multinational corporations, leaving limited insight into how large manufacturing companies in smaller economies are engaging with these technologies. This research seeks to address that gap by examining the real-world application and anticipated use of ten selected AI-driven manufacturing technologies within Slovak industrial enterprises. The study builds upon earlier research conducted in 2017 by Závadský & Závadská, which assessed managerial expectations regarding the future deployment of intelligent technologies. However, while that prior work focused on predictive expectations, the current research shifts toward empirical verification. The relevance of this research is twofold. For academia, it introduces a structured methodology for assessing current versus future adoption levels, which can be replicated or extended in other regions or sectors. For practitioners, particularly managers and decision-makers in manufacturing, the study provides evidence-based insights into peer behavior, technology trends, and areas of opportunity. The motivation for this research is grounded in the need to close the gap between AI's theoretical promise and its actual implementation on the shop floor. While terms like Industry 4.0, smart manufacturing, and digital transformation are widely used, there is still uncertainty about how these concepts translate into concrete action. By capturing both the current state and expected trajectory of AI technologies in manufacturing, this study offers a clearer picture of how industrial digitalization is unfolding in practice. This research is motivated by the lack of granular, country-specific evidence on AI deployment in manufacturing, the need for practical guidance for industrial managers, and the opportunity to enhance scholarly understanding of technology adoption dynamics. The findings are expected to support theoretical advancement and practical decision-making in the evolving landscape of AI-driven production systems. The main scientific objective of this research study is to determine how AI-driven manufacturing technologies are currently used and what the expectations of managers of large manufacturing companies are regarding the future use of 10 selected AI-driven manufacturing technologies. Based on the main research objective, we set the following research questions: RQa (Which AI-driven manufacturing technologies are most widely used today?); RQb (Which AI-driven manufacturing technologies are most anticipated by managers in the future?); and RQc (Which AI-driven manufacturing technologies have the most negligible potential for deployment in a sample of large manufacturing companies?).

2. Literature review

There are a large number of studies on AI-driven technologies that are applied not only in manufacturing processes. It was challenging to identify a set of AI-driven technologies that would provide answers to the research questions. Rojeid et al. (2022) highlight AI's growing impact on manufacturing, a shift also emphasized by Kumar (2017), who outlines its benefits for planning, resource allocation, and decision-making. Predictive maintenance is key, as Wan et al. (2021) and Tikhonov & Sazonov (2022) show AI's ability to forecast equipment failures. Waltersmann et al. (2021) highlight how AI enables flexible production lines, and Rojek & Mikołajewski (2024) point to its use in additive manufacturing. However, Antosz et al. (2020) mention data integration challenges, while Hassan et al. (2023) raise cybersecurity and workforce concerns. RPA's evolution is detailed by Bhardwaj et al. (2015), Madakam et al. (2019), Santos et al. (2020), and Mamede et al. (2022), stressing implementation hurdles. Hyun & Lee (2018) and Eulerich et al. (2023) point to RPA's limits and risks. Syed et al. (2020) discuss its shift toward intelligent automation. Zhang et al. (2023) show real-world use in finance, while Fernandez & Aman (2021) and Hofmann et al. (2020) highlight investment, maintenance, and ethical concerns. Digital Twins (DT) are explored by Tao et al. (2018), Horn & Mahadevan (2021), and Liu et al. (2021) for their predictive and modeling capabilities. Zheng et al. (2019) and Bhatti et al. (2021) show DT's industrial value. Mashaly (2021) and Yu et al. (2022) confirm its role in diagnostics and energy. Qi et al. (2021), Mihaita et al. (2022), and Hosamo & Imran (2022) emphasize broader applications and cybersecurity needs. Fuller et al. (2020) and Madni et al. (2019) discuss technical challenges. Based on the literature review, ten AI-driven technologies were selected for research purposes. Predictive Maintenance Systems (PMS) use machine learning to analyze data from equipment sensors, predicting when maintenance is needed before failures occur. This prevents unexpected downtimes, reduces repair costs, and extends the lifespan of machinery. It's crucial in high-volume manufacturing where even short disruptions can be costly. Computer Vision for Quality Control (CVQC) identifies defects on production lines in real time. It detects anomalies in shape, size, or texture with far greater accuracy and speed than human inspectors. This ensures consistent product quality, reduces waste, and prevents faulty items from reaching customers. Robotic Process Automation (RPA) enhanced with AI allows robots to handle repetitive, rule-based tasks autonomously. These systems free up human workers for higher-level duties, improve consistency, and speed up operations, especially valuable in sectors where precision and scalability are key. Digital Twins (DT) technology creates virtual replicas of physical assets and processes. With AI, manufacturers can simulate performance, test changes, and anticipate outcomes without disrupting actual production. This reduces risk and enhances strategic planning. Equipped with AI, Cobots (collaborative robots - CR) work safely alongside human operators on precision tasks like assembly or welding. They learn from human input and adapt to different roles, making production more flexible and efficient. AI-based supply chain optimization systems (SCOS) analyze massive data streams to optimize inventory, forecast demand, and improve logistics. These systems help minimize delays, reduce costs, and keep production aligned with market needs. Automated Guided Vehicles (AGV) with AI navigate factory floors independently, transporting materials without human oversight. Their ability to adapt routes in real time boosts safety and delivery efficiency, especially in dynamic environments. Natural Language Processing (NLP) for Human-Machine Interaction allows operators to control machines using natural language. This simplifies complex tasks, reduces training time, and improves accessibility on the shop floor. AI-driven generative design (GD) systems let manufacturers input design goals and constraints, then generate optimal solutions. This speeds up product development, fosters innovation, and creates designs that balance performance, cost, and manufacturability. Finally, AI-integrated 3D printing (3DP) enhances production speed, material efficiency, and part quality. By adjusting parameters in real time, AI ensures that each printed part meets specifications while reducing waste.

3. Methodology

The primary research method employed in this study is a structured survey administered to managers of large manufacturing companies operating in Slovakia. The survey was designed to capture both the current use and future expectations regarding ten selected AI-driven manufacturing technologies. This study builds on the foundation laid by an earlier investigation conducted in 2017 by Závadská & Závadský, which surveyed 44 companies to assess expectations surrounding the deployment of 14 intelligent technologies. In the current research, we aimed to revisit that original sample while expanding it to achieve broader representation and relevance. The same selection criteria were applied: each company had to qualify as a large manufacturing enterprise, defined by the Slovak Statistical Office, and be actively involved in production processes. Using this framework, we reached out to an additional group of quality and production managers, resulting in a total of 150 companies contacted. By the cut-off point for analysis in mid-February 2025, we received 115 complete responses, which form the basis of the current findings. These responses span a range of industries, and a Pearson chi-square test confirmed that the sample is representative of the national distribution of large manufacturing enterprises by sector. The research was conducted in three main phases: 1) Preparation Phase (November–December 2024); 2) Data Collection Phase (January–Mid-February 2025); and 3) Analysis Phase (Mid-February–March 2025). The questionnaire was concise but targeted, structured around the following key questions for both quality managers and production managers: “Which of the following AI-driven manufacturing technologies are currently in use in your company?” and “Which AI-driven manufacturing technologies does your company plan to implement shortly (e.g., next 3–5 years)?”.

For the research, we applied the Pearson representativeness test. As Table 1 shows, the research sample is representative. At a significance level of 0.05, we tested the sample according to 9 degrees of freedom because we examined enterprises from 10 types of industries. Since the achieved χ^2 value is lower than the statistical one, we conclude that the sample is representative, namely $\chi^2 = 2.695 < 3.320$, and where n_i is events observed in the sample, np_i is particular theoretical distribution at the level of statistical significance α for appropriate degrees of freedom (k-1), and k is the number of fitted parameters. According to the Slovak Statistical Office, the basic set consisted of 251 large manufacturing enterprises for selected industrial sectors.

Table 1. χ2-test due to the type of industry

Type of industry (SK NACE)	np_i		n_i			$(n_i-np_i)^2$
	No.	%	No.	%	$(n_i-np_i)^2$	$/np_i$
CA Manufacture of food products, beverages, and tobacco products	23	9.16	11	9.57	0.16	0.018
CE Manufacture of chemicals and chemical products	5	1.99	2	1.74	0.06	0.032
CF Manufacture of pharmaceuticals, medicinal chemicals, and botanical products	3	1.20	2	1.74	0.30	0.248
CG Manufacture of rubber and plastics products and other non-metallic mineral products	40	15.94	21	18.26	5.40	0.339
CH Manufacture of basic metals and fabricated metal products, except machinery and equipment	29	11.55	12	10.43	1.25	0.108
CI Manufacture of computer, electronic, and optical products	11	4.38	5	4.35	0.00	0.000
CJ Manufacture of electrical equipment	29	11.55	12	10.43	1.25	0.108
CL Manufacture of transport equipment	52	20.72	21	18.26	6.03	0.291
F Construction	11	4.38	8	6.96	6.63	1.512
H Transportation and storage	48	19.12	21	18.26	0.74	0.039
	251	100.00	115	100.00		$\chi^2 = 2.695$

Source: (authors)

For the research, we have established variables based on which we will be able to answer the research questions. These are the following research variables:

- AI_IT_abs = absolute number of managers from manufacturing enterprises where an AI-driven technology is used or planned to be used;
- AI_IT_rel = percentage of managers from manufacturing enterprises where an AI-driven technology is used or planned to be used;
- AI_IT_absA = absolute number of managers from manufacturing enterprises where an AI-driven manufacturing technology is used;
- AI_IT_absF = absolute number of managers who are expecting the use of AI-driven manufacturing technologies in the future;
- AI_IT_relA = percentage of managers from manufacturing enterprises where an AI-driven manufacturing technology is used;
- AI_IT_relF = percentage of managers who are expecting the use of AI-driven manufacturing technologies in the future;
- ΔFA = difference between future and actual utilization of an AI-driven manufacturing technology.

4. Results and Discussion

We asked managers in a sample of large manufacturing companies to select 5 AI-driven manufacturing technologies that they already use (AI_IT_absA) and plan to use in the future (AI_IT_absF). We calculated these two research variables' relative shares (AI_IT_relA; AI_IT_relF) in 115 businesses. We then calculated the difference between actual utilization and future managers` expectations as ΔFA. The total sum of relative shares (AI_IT_rel) speaks to AI-driven manufacturing technology's actual use and future use.

Table 2. AI-driven manufacturing technologies utilization

	AI_IT_abs	AI_IT_absA	AI_IT_relA	AI_IT_absF	AI_IT_relF	ΔFA	AI_IT_rel
RPA	67	24	20.87	43	37.39	16.52	58.26
DT	82	31	26.96	51	44.35	17.39	71.30
PMS	63	51	44.35	12	10.43	-33.91	54.78
CVQC	41	21	18.26	20	17.39	-0.87	35.65
CR	62	23	20.00	39	33.91	13.91	53.91
SCOS	48	37	32.17	11	9.57	-22.61	41.74
AGV	61	33	28.70	28	24.35	-4.35	53.04
NLP	31	9	7.83	22	19.13	11.30	26.96
GD	67	46	40.00	21	18.26	-21.74	58.26
3DP	87	54	46.96	33	28.70	-18.26	75.65

Source: (authors)

As Table 2 shows, the most used AI-driven manufacturing technologies are currently 3DP (46.96%), PMS (44.35%), GD (40.00%), and SCOS (32.17%). It answers the RQa: Which AI-driven manufacturing technologies are most widely used today?

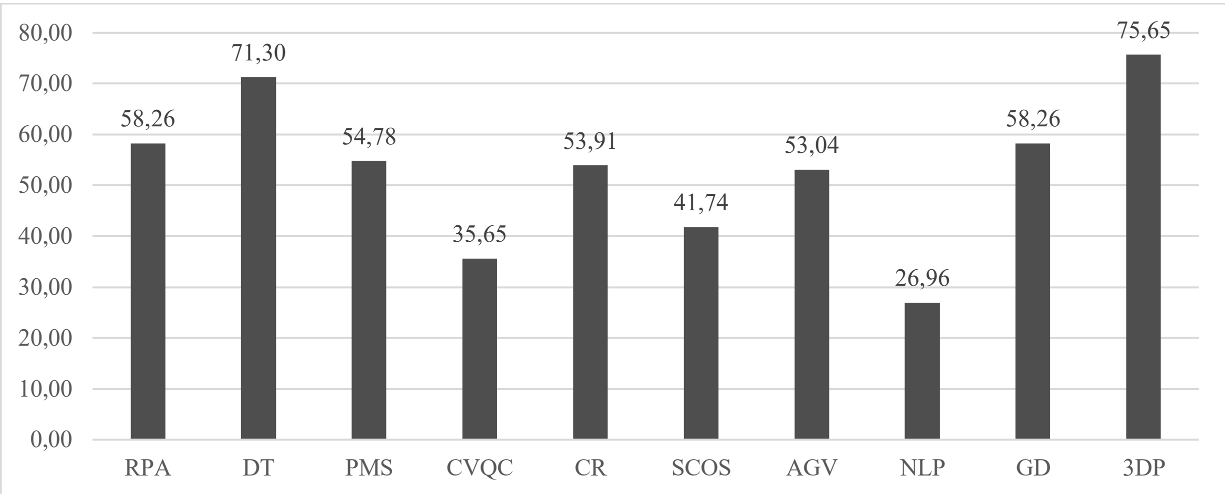

Figure 1. Prediction of the future AI-driven technologies utilization in total [%] Source: (authors)

The most expected AI-driven manufacturing technologies in the future are DT (17.39%), RPA (16.52%), CR (13.91%), and NLP (11.30%). Expectations are calculated as the difference between the current and future use of AI-driven manufacturing technology. This answers the research question RQb: Which AI-driven manufacturing technologies are most anticipated by managers in the future? The technologies with the most negligible growth potential, as they are already sufficiently used today, are PMS (33.91%), SCOS (22.61%), GD (21.74%), and 3DP (18.26%). This answers the research question RQc: Which AI-driven manufacturing technologies have the smallest potential for deployment in a sample of large manufacturing companies? However, if we add up the relative shares of current use and future use, Figure 1 shows which AI-driven technologies will be most used in the future. The research revealed clear patterns in the adoption and expected use of AI-driven manufacturing technologies. Among the ten examined, 3D Printing, Predictive Maintenance Systems, Generative Design, and Supply Chain Optimization Systems were identified as the most commonly used in the surveyed companies. These technologies are likely to lead due to their established practical benefits, relatively mature development, and tangible impact on operational efficiency. For instance, 3D Printing supports prototyping and customized production, Predictive Maintenance reduces downtime and maintenance costs, Generative Design enhances product innovation, and Supply Chain Optimization helps manage complexity and improve logistics performance. In contrast, technologies like Digital Twins, RPA, and NLP (though not yet widespread) show the highest increase in expected adoption. This trend reflects an interest in more advanced, integrated, intelligent systems. Digital Twins, for example, allow virtual replication of fundamental processes, enabling predictive analytics and real-time control. Their relatively low current use, paired with high future expectations, suggests growing awareness and improving readiness for implementation. Similarly, RPA is gaining attention as companies seek to automate repetitive, rule-based tasks, often in administrative or quality control processes. On the other hand, technologies such as Predictive Maintenance and 3D Printing show negative growth potential. This indicates that many companies that intended to implement them may have already done so, reaching a saturation point. These technologies have become standard tools rather than emerging innovations, especially in industries with high operational demands and mature digital infrastructures. These findings offer several practical implications for manufacturing enterprises. Companies can prioritize investment in Digital Twins, RPA, and Collaborative Robots to align with industry trends and remain competitive. Firms that have not yet adopted Predictive Maintenance or 3D Printing may need to assess why peers have integrated them successfully. Managers should also consider training and workforce adaptation strategies to support the transition toward these advanced technologies.

The research also highlights several limitations and barriers. First, the study itself is based on a partial dataset. Although the sample size is statistically representative, additional data could provide more robust insights and enable deeper analysis across specific sectors. Moreover, the focus on large companies may not fully reflect the experiences and challenges faced by small and medium-sized enterprises, which often lack the same resources and technological infrastructure. From the adoption perspective, several practical barriers persist. Implementation complexity, integration with legacy systems, high initial investment costs, and a shortage of skilled personnel continue to slow progress, especially for advanced solutions like Digital Twins and NLP. Concerns around cybersecurity and data governance also remain unresolved in many companies. Furthermore, the organizational mindset is a non-trivial factor: even when technologies are available and technically viable, resistance to change and limited digital maturity can delay or derail implementation.

5. Conclusion

This study offers a focused analysis of the current and expected use of AI-driven technologies in Slovak manufacturing, based on a survey of managers from large industrial companies. It explores ten specific technologies: Predictive Maintenance Systems, 3D Printing, Generative Design, Supply Chain Optimization Systems, Digital Twins, Robotic Process Automation (RPA), Collaborative Robots (Cobots), Computer Vision for Quality Control, Automated Guided Vehicles (AGVs), and Natural Language Processing (NLP). These technologies collectively form the backbone of AI-driven manufacturing transformation under the Industry 4.0 framework. The results suggest a maturing landscape where some technologies—particularly Predictive Maintenance, 3D Printing, Generative Design, and Supply Chain Optimization—have already seen broad adoption. These systems are now considered part of the operational core in many companies, contributing to greater efficiency, reduced downtime, and enhanced customization. However, their saturation also implies limited room for further expansion. Conversely, technologies such as Digital Twins, AI-enhanced RPA, Cobots, and NLP show strong potential for future deployment. These tools offer deeper integration, real-time responsiveness, and improved human-machine interaction, aligning with the evolving demands of intelligent, adaptive production environments. The findings suggest that future success will hinge not only on adopting new technologies but also on overcoming these organizational, technical, and human barriers. Companies must invest in workforce development, change management, and robust digital infrastructure to fully realize the benefits of AI-driven manufacturing. The technologies with the greatest growth potential will likely be those that offer not just innovation, but ease of integration, scalability, and clear returns on investment. In conclusion, while the road to full AI integration in manufacturing is still under construction, this study provides a directional map. It underscores that true transformation is a multidimensional effort, requiring not only technology adoption but strategic alignment, cultural readiness, and sustained investment. As new research expands the dataset and more companies move from pilot phases to scaled deployment, a clearer picture will emerge of how AI will ultimately redefine manufacturing performance.

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