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Content

Content

Tomáš BALALA[1], Martin GAŠO[2], Vladimíra BIŇASOVÁ[3]

VIRTUAL REALITY IN EDUCATION: A COMPARATIVE OF ACADEMIC AND INDUSTRIAL CONTEXTS

Abstract

This article explores how virtual reality (VR) is used in the educational process in schools and industry. Contrary to first impressions, these two approaches in education are quite different. The main purpose of VR is to assist people in learning by transporting them into a specific environment. The article describes the specific applications of VR in both contexts. It highlights their common as well as distinct characteristics. As part of this study, the most common and best aspects of both approaches are identified.

Keywords: virtual reality (VR), industrial engineering education, academic training, immersive learning

1. INTRODUCTION

The constant rapid development of digital technologies is transforming the consumer market, product development, and manufacturing. Also, the environment of education and vocational training. Today, teachers and students can choose from a wide range of advanced technologies that have gradually become more widely adopted over the past two decades. Among these technologies, virtual reality (VR) is one of the most promising tools in the modern educational process. VR is primarily used to create immersive, experiential learning environments. Thanks to its ability to present users with real-world situations without the associated risks, it represents an ideal solution for a wide range of educational and training applications. [1, 2]

This opens a wide range of possibilities for applying VR in education. In general, the use of VR in education relies on the same underlying technology. However, its implementation in academic and industrial settings differs significantly. Universities focus primarily on long-term skill development, critical thinking, and a broad theoretical

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foundation. Industrial training, on the other hand, focuses on immediate performance improvement, specific procedural skills, measurable increases in productivity, and cost reduction. [3,4]

This form of difference raises an important question. Is it possible to systematically transfer knowledge from one field to another to improve educational outcomes? To answer this question, it is necessary to identify the common principles and fundamental differences between these two areas of application. At the same time, it is important to propose a framework that would identify and integrate the strengths of both contexts. [5]

2. LITERATURE REVIEW

A review of the literature and general interest reveals a relatively extensive body of scientific literature devoted to VR in education. In their meta-analysis, including 1,536 articles, Al-Ansi et al. (2023) documented the widespread application of augmented reality (AR) and VR in both educational institutions and industrial enterprises. During this review, they pointed out persistent differences between these two spheres of application. [6]

In educational institutions, compared to traditional lecture-based teaching, VR improves, for example, spatial thinking, increases student motivation, and enhances knowledge retention. Studies focused primarily on bachelor's and engineering education highlight the role of VR as a tool capable of making abstract concepts visible to students. This shifts the mode of knowledge acquisition from passive to active. As a result, students can actively interact with simulated machines, production lines, and logistics systems while learning the basic principles of how they work. At the same time, the primary goal of applying VR is not a quick return on investment. In this case, the application of VR aims to facilitate progress and convey necessary information in an effective, innovative, and interactive way. Thanks to VR, students do not have to leave their desks and can observe systems based on real-world models in a safe environment. [7, 8]

On the other hand, in the industrial sector, VR is used primarily because of its ability to train employees in hazardous or complex procedures without disrupting ongoing production. It can therefore be said that in the case of industrial VR implementation, the most common approach is a straightforward procedure and scenario designed to teach users repetitive tasks with the aim of saving costs in the real world. Zywicki et al. (2020) demonstrated that VR-based training in smart manufacturing environments led to measurable improvements in operator performance and a reduction in error rates. Xiong et al. (2024) further confirmed that manufacturing processes utilising VR in employee training has a positive impact on production efficiency in companies with high employee turnover. [9, 10]

Industrial practice shows there is not much room for experimentation with new technologies in full operation. On the other hand, in an educational setting, the scope for application is more flexible and focused on reflecting on the process or possible solutions. However, initial investments are often lacking, not only in the form of finances but also in the absence of implementation materials and technologies. [11, 12]

3. VR IN ACADEMIC EDUCATION AS A THINKING PLATFORM

Academic education using VR presents users and VR itself with a highly specific environment. In this environment, the level of the user's understanding of the information is observed. Similarly, it is observed whether the user reflects on and connects the information received with previously acquired knowledge. In an academic setting, VR represents more than just a mere visual experience. [3]

In this form, it becomes a platform for thinking, exploring and seeking new approaches and solutions. This highlights how traditional education often encounters the problem with abstraction. In such cases, however, they remain merely passive recipients of information while reading. VR seeks to remove this barrier of passivity. Instead of reading about workshop-style production, a student can participate directly as the workers. This transition from passive reception to active experience changes the user's perception of information and their understanding of that information. [7] Another significant advantage is that VR offers self-directed learning. Even without a mentor, students can acquire basic knowledge and gain opportunities for self-development. Among other things, this creates an alternative to individual learning spaces for collaborative thinking. Multiple students can share the same virtual environment (Fig. 1), address issues and discuss them regardless of physical distance. [13]

Fig. 1 The Collaborative World of Infinity EDU (exe, a. s., 2025)

VR in academic education represents a shift in the very philosophy of learning. This shift moves away from memorizing facts toward building understanding through experiencing scenarios and gaining hands-on experience. And this is precisely where the true potential of VR lies as a platform for thinking, collaboration, and generating new questions and perspectives on familiar facts.

4. VR IN INDUSTRIAL EDUCATION AS DRILLING PLATFORM

As noted, academic VR education serves primarily as a platform for critical thinking and conceptual understanding. In industrial training, VR education fulfils a completely different, yet equally important role. It becomes a platform for initial exposure to situations that the user will repeatedly encounter in the real world. In a way, it is a form of drill, that is, the repeated practice of skills until they become automatic. [13]

In addition to routine situations, irregular situations can also arise. In many industrial sectors, such as aviation, energy, mechanical engineering, and construction, both unusual and routine situations can lead to errors. In the worst-case scenarios, these errors can even cost human lives. The emphasis in VR training within industry is therefore not on understanding specific theory, but on flawlessly mastering specific procedures. Some of these must be performed under pressure. It is therefore excellent if people could test these procedures under conditions that are as realistic and safe as possible. VR ideally meets these conditions. We can therefore identify it as a training tool, as it allows for the unlimited repetition of dangerous, costly, or unique scenarios without any real risk, as can be seen in Fig. 2. [10, 13]

Fig. 2 An example of a safe learning environment for VR (exe, a. s., 2026)

This approach to training can be compared to that of experienced musicians. After a while, they no longer think about every single note. Similarly, an experienced technician doesn’t think about every step of the process and often acts instinctively in practice. VR training greatly aids this process by offering highly realistic environments with immediate feedback.

In a way, this process demonstrates how work standardisation works. Every employee goes through an identical training scenario under the same conditions. This allows for objective performance measurement and progress comparison. Companies can thus more effectively identify employees' weaknesses during the training process and address them in a targeted manner. It can therefore be said that VR in industrial training does not aim to develop critical thinking. Its goal is primarily to build reliable, automated skills that will hold up in the most demanding real-world situations.

5. CONCLUSION

After comparing these two perspectives on education using VR, the following conclusions can be drawn. Virtual reality has entered the world of education not as a temporary experiment, but as a technology with great potential to transform the educational process. This paper has demonstrated that, despite their apparent similarity, these are fundamentally different pedagogical philosophies, both of which are underpinned by a single technology.

The main and fundamental difference lies in the objectives of these two areas of education. In academic education, VR is used as a platform for thinking. It focuses primarily on building conceptual understanding and developing critical thinking and judgment. Finally, it seeks to impart the ability to apply knowledge in new, unpredictable situations. Industrial education, on the other hand, uses VR as a platform for systematic skill training. Here, the priority is precision, repeatability, and the automation of specific procedures. One of the major differences is the attitude toward error. In the academic environment, a mistake serves as a stimulus for reflection and deeper thinking, whereas in the industrial context, training is geared toward striving for its complete elimination. Despite these identified differences, there are also some overlaps and shared characteristics. Both approaches leverage one of the greatest strengths of VR technology to their advantage. It's about immersiveness, which is an engrossing and emotional VR experience. Other common overlaps include the ability to safely simulate environments inaccessible in traditional teaching and a higher level of student engagement compared to traditional methods. Challenges can also be classified among the common characteristics. The primary challenges remain the high cost of implementation, technical requirements, and the need for high-quality content. Currently, these obstacles are gradually being overcome by rapid technological development, falling equipment prices, and the integration of artificial intelligence into the content creation process.

Both areas of VR application suggest that the near future is unlikely to see a complete shift to VR-based instruction. Instead, it will likely involve a smart combination of traditional education and VR. At the same time, it would be beneficial if future VR applications designed for education catered to both academic and industrial training. Educational systems built in this way can combine deep understanding with automated skills. As a result, they will prepare students not only for common situations with the corresponding theoretical knowledge. Students will also gain access to more comprehensive training that will enhance their ability to handle unexpected situations. VR can thus be identified as a symbol of the transition from a world where knowledge is imparted to a world where it can be experienced.

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References

[1] PAÍS AMBROSIO, A. & RODRÍGUEZ FIDALGO, M. I. 2020. Past, present and future of Virtual Reality: Analysis of its technological variables and definitions. Culture & History Digital Journal, Vol. 9(1), pp. e010, DOI: doi.org/10.3989/chdj.2020.010

[2] ZEKEIK, H., CHAHBI, M., LAMARTI SEFIAN, M., BAKKALI, I. 2025. Augmented reality and virtual reality in education: A systematic narrative review on benefits, challenges, and applications. Eurasia Journal of Mathematics, Science and Technology Education, Vol. 21(9), pp. em2699, DOI: doi.org/10.29333/ejmste/16830

[3] STAREČEK, A., MATYS. M., BABEĽOVÁ, Z. G. 2025. Using Virtual Reality in the Real Process Simulation for Innovation of University Education. International Conference on Education Technology and Computers (ICETC), Barcelona, Spain, 2025, pp. 12-16, DOI: 10.1109/ICETC66579.2025.11387366

[4] ALFARO-VIQUEZ, D., ZAMORA-HERNANDEZ, M., FERNANDEZ-VEGA, M. Garcia-Rodriguez, J., Azorin-Lopez, J. 2025. Integrating Virtual Reality into Welding Training: An Industry 5.0 Approach. *Electronics*. Vol. *14*, pp. 1964, DOI: doi.org/10.3390/electronics14101964

[5] Thangavel, S. 2025. Revolutionizing Education Through Augmented Reality (AR) and Virtual Reality (VR): Innovations, Challenges and Future Prospects. SSRN, Vol. 8(1), pp. 1-28, DOI: doi.org/10.2139/ssrn.5195697

[6] AL-ANSI, M. A., JABOOB, M., GARAD, A., AL-ANSI, A. 2023. Analyzing augmented reality (AR) and virtual reality (VR) recent development in education. Social Sciences & Humanities Open, Vol. 8, pp. 100532, DOI: 10.1016/j.ssaho.2023.100532

[7] KRAJČOVIČ, M., GABAJOVÁ, G., FURMANNOVÁ, B., VAVRÍK, V., GAŠO, M., MATYS, M. 2021. A Case Study of Educational Games in Virtual Reality as a Teaching Method of Lean Management. Electronics, Vol. 10, pp. 838. https://doi.org/10.3390/electronics10070838

[8] SAYEG, G., AMADO-MORANCHEL, N., ACERO, A. (2024). Use of Virtual Reality to Improve Learning Experience on a Lean Manufacturing Course. 2024 ASEE Annual Conference & Exposition, pp. 13, DOI: 10.18260/1-2—48221

[9] ZYWICKI, K., ZAWADZKI, P., BUN, P., GORSKI, F. 2020. Employee Training in an Intelligent Factory Using Virtual Reality. IEEE Access, Vol. 8, pp. 135110–135117, DOI: doi.org/10.1109/ACCESS.2020.3010439

[10] XIONG, Y., LAM, H., KARIMI, S. 2024. The effect of virtual reality-enabled manufacturing practices on production efficiency. International Journal of Production Economics, Vol. 274, Art. 109288, DOI: doi.org/10.1016/j.ijpe.2024.109288

[11] WIEMER, T. & ROTHE, M. 2024. Comparing Augmented Reality in Industry and Technology Education: Exploring Teacher Views and Research Needs. Design and Technology Education, Vol. 29(2), pp. 380-393, ISNN: 1360-1431

[12] AKPAN, I. J. & OFFODILE, O. F. 2024. The Role of Virtual Reality Simulation in Manufacturing in Industry 4.0. Systems, Vol. 12(1), pp. 26, DOI: 10.3390/systems12010026

[13] Internal documents of exe, a.s., 2025

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APPLICATION OF ARTIFICIAL INTELLIGENCE IN 3D PRINTING

Abstract

Artificial Intelligence (AI) represents one of the most promising technologies for the future development of 3D printing. This paper provides a general overview of both technologies and explores the wide range of possibilities for their integration. AI can significantly improve design processes, optimize printing parameters, enhance quality control, reduce waste, and enable more intelligent and autonomous manufacturing systems. While many challenges still exist, the combination of AI and 3D printing offers potential for various industries including aerospace, automotive, and consumer goods. The paper discusses key application areas, benefits, and main obstacles on the path to wider implementation.

Key words: Artificial Intelligence, 3D Printing, Additive Manufacturing, Industry 4.0

1. WHAT IS ARTIFICIAL INTELLIGENCE

Artificial Intelligence is a branch of computer science focused on creating systems capable of performing tasks that typically require human intelligence. These tasks include learning from experience, recognizing patterns, making decisions, solving problems, and understanding natural language. Modern AI, particularly machine learning and deep learning, allows computers to improve their performance automatically through data without being explicitly programmed for every scenario.AI technologies range from simple rule-based systems to advanced neural networks that can process vast amounts of information and identify complex relationships. [1, 2]

2. WHAT IS 3D PRINTING

3D printing, also commonly referred to as additive manufacturing, is a modern production technology that creates physical three-dimensional objects by adding material layer by

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layer according to a digital 3D model. This approach fundamentally differs from traditional manufacturing methods, which are usually subtractive meaning they remove unwanted material from a larger block. The most widespread 3D printing technologies include Fused Deposition Modeling (FDM), Selective Laser Sintering (SLS), Stereolithography (SLA), and several others. One of the greatest advantages of 3D printing is the ability to produce highly complex geometric shapes, internal structures, and fully customized products that would be extremely difficult or even impossible to manufacture using conventional techniques. Moreover, additive manufacturing generally produces significantly less material waste. Despite its many benefits, current 3D printing still suffers from certain limitations such as process instability, variation in final product quality, relatively long optimization times, and dependence on operator experience. These challenges create a perfect opportunity for the application of artificial intelligence. [3, 4]

3. POTENTIALS OF ARTIFICIAL INTELLIGENCE IN 3D PRINTING

The integration of artificial intelligence into 3D printing technologies opens up a wide range of exciting new possibilities that can dramatically improve the entire production chain starting from the initial design phase, through parameter setting and the printing process itself, up to final quality inspection and post-processing. [3, 4]

3.1 Generative Design and Optimization

One of the most promising application areas is AI-powered generative design. While traditional design methods depend primarily on the knowledge and creativity of human engineers, artificial intelligence can automatically generate hundreds or even thousands of different design variants that perfectly meet specified requirements regarding weight, mechanical strength, cost, functionality, or aesthetic appearance. These advanced systems can create organic shapes and highly efficient lattice structures that are extremely difficult to design manually but are ideal for production using 3D printing technologies. Generative design tools based on genetic algorithms, neural networks, and other AI methods can explore vast design spaces in a very short time and propose solutions that achieve optimal balance between material consumption and product performance. This capability leads to lighter, stronger, and more material-efficient parts, which is particularly valuable in aerospace and automotive applications where every gram of weight matters [5].

3.2 Process Parameter Optimization

Correct setting of printing parameters such as nozzle temperature, printing speed, layer height, cooling intensity, and infill density is currently often based on personal experience and lengthy trial-and-error testing. Artificial intelligence can change this approach fundamentally. AI systems are able to analyze large historical datasets from previous successful and unsuccessful prints and then recommend or even automatically apply the optimal combination of parameters for any given material and geometric shape. This intelligent optimization can dramatically shorten the preparation phase, increase process repeatability, reduce the number of failed prints, and improve the overall mechanical properties of the final products. In the future, AI could continuously adjust parameters in real time during the printing process based on live sensor data. [6]

3.3 Quality Control and Defect Detection

Quality control represents another very important area with great potential for artificial intelligence. Modern computer vision systems combined with neural networks can monitor the printing process in real time using cameras and various sensors. These systems are capable of detecting common defects such as warping, layer shifting, poor interlayer adhesion, stringing, or material under extrusion almost immediately after they appear. Early detection allows the system to automatically pause printing, adjust critical parameters, or notify the operator, which leads to significant reduction in material waste and overall production costs. Such intelligent quality control can bring 3D printing technology much closer to the reliability standards required in professional and industrial applications [6].

3.4 Quality Control and Defect Detection

AI algorithms can also be very effectively used for predictive maintenance of 3D printers. By analyzing data from sensors, the system can predict when individual components (such as nozzles, belts, or heating elements) are likely to fail and recommend timely maintenance. This approach minimizes unexpected downtime and extends the lifetime of expensive equipment. Furthermore, artificial intelligence can optimize material consumption, accurately predict the amount of filament or powder needed for specific jobs, and even suggest suitable alternative materials that would provide better results for particular applications. [6, 7]

3.5 Smart and Autonomous Manufacturing

In the long term, the greatest vision is the creation of fully smart and autonomous 3D printing systems. Such advanced systems would be able to independently manage the whole production process from accepting a customer order, through automatic design optimization, best printing strategy selection, continuous process monitoring, to final quality verification and post-processing. These intelligent manufacturing cells would become a natural part of smart factories in the concepts of Industry 4.0 and especially Industry 5.0, where human workers and AI systems collaborate closely. Such development would enable faster, cheaper, and more flexible production of highly customized products even in small batches. [7]

4. CHALLENGES AND LIMITATIONS

Despite all the promising possibilities, there are still several important challenges and limitations that need to be solved before artificial intelligence can be widely and effectively implemented in 3D printing. The most significant one is the need for large amounts of high quality training data, which are often insufficient or not standardized in the field of additive manufacturing. Another problem is the great variety of different 3D printers, materials, and technologies, which makes it difficult to develop universally applicable AI solutions. Integration of AI systems with existing hardware and software can be technically complex and financially demanding, especially for smaller companies. In critical applications such as medicine or aerospace, the explainability of AI decisions plays a very important role. Finally, there is a noticeable skills gap many companies still lack personnel with sufficient knowledge in both 3D printing and artificial intelligence technologies. [6, 7]

5. CONCLUSION

The combination of Artificial Intelligence and 3D printing represents a very powerful technological synergy that has the potential to significantly transform modern manufacturing in the coming years. AI can effectively help overcome many current limitations of additive manufacturing and open the door to new levels of efficiency, customization, reliability, and innovation. Although we are still at the beginning of this promising integration, the rapid development of both fields indicates that intelligent 3D printing systems will gradually become common practice across many industries. Future efforts should focus on creating more user-friendly tools, improving data sharing between organizations, and developing hybrid solutions that optimally combine the strengths of artificial intelligence with human creativity and expertise. The possibilities are truly vast and those organizations that manage to successfully implement these advanced technologies will gain a significant competitive advantage in the global market.

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References

[1] EQUBAL, M. A. et al.: Machine learning in additive manufacturing: A comprehensive insight. International Journal of Lightweight Materials and Manufacture, 2025, 8(2), s. 264–284. DOI: 10.1016/j.ijlmm.2024.10.002.

[2] HASSAN, M. et al.: A review of AI for optimization of 3D printing of sustainable polymers and composites. Composites Part C: Open Access, 2024, 15, 100513. DOI: 10.1016/j.jcomc.2024.100513.

[3] UKWATHTHA, J.; HERATH, S.; MEDDAGE, D. P. P.: A review of machine learning (ML) and explainable artificial intelligence (XAI) methods in additive manufacturing (3D Printing). Materials Today Communications, 2024, 41, 110294. DOI: 10.1016/j.mtcomm.2024.110294.

[4] NASIRI, S.; KHOSRAVANI, M. R.: Machine learning in predicting mechanical behavior of additively manufactured parts. Journal of Materials Research and Technology, 2021. DOI: 10.1016/j.jmrt.2021.07.004.

[5] WESTPHAL, E.; SEITZ, H.: Machine learning for the intelligent analysis of 3D printing conditions using environmental sensor data to support quality assurance. Additive Manufacturing, 2022, 50, 102535. DOI: 10.1016/j.addma.2021.102535.

[6] ZHANG, X. et al.: Machine learning-driven 3D printing: A review. Applied Materials Today, 2024. DOI: 10.1016/j.apmt.2024.102306.

[7] ZHAO, H. et al.: Artificial intelligence powered real-time quality monitoring for additive manufacturing in construction. Construction and Building Materials, 2024, 429, 135894. DOI: 10.1016/j.conbuildmat.2024.135894.Results and Discussion.

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AI-DRIVEN DECISION SUPPORT IN ENTERPRISE INFORMATION SYSTEMS BASED ON PROCESS MINING AND WORKFLOW AUTOMATION

Abstract

The paper focuses on the integration of analytical methods, artificial intelligence, and workflow automation in enterprise information systems. The proposed model combines process mining, data mining, knowledge systems, and AI-driven decision support into a unified framework supporting operational decision-making. Particular attention is devoted to workflow automation as an execution layer enabling direct implementation of analytical outputs into enterprise processes. The proposed approach creates a continuous connection between enterprise data, analytics, decision-making, and automated operational actions in industrial environments.

Key words: augmented analytics, knowledge systems, industrial analytics, AI orchestration

1. INTRODUCTION

Enterprise information systems represent the fundamental infrastructure of modern industrial enterprises. ERP, MES, Business Intelligence, and IoT systems continuously generate large volumes of operational data. Despite the increasing availability of data, many enterprises are still unable to transform collected information into actionable knowledge supporting effective decision-making. This situation is frequently described as a "data-rich, insight-poor" environment. [9, 11]

The primary problem is not the absence of analytical tools, but the insufficient integration between individual layers of data processing. In many enterprises, analytics remains limited to dashboards and reports without direct implementation into operational

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processes. This issue is particularly significant in industrial environments where decisions must be performed rapidly and based on current information.

Current industrial engineering trends therefore focus on integrating analytical methods, knowledge systems, artificial intelligence, and workflow automation into unified decision support architectures. Among the most important analytical approaches are process mining and data mining, which enable enterprises to analyze processes and identify hidden patterns in operational data. [4, 5]

The objective of this paper is to analyze current approaches to enterprise data processing and propose an extended AI-driven decision support model integrating analytical, knowledge, and execution layers into a unified framework. The proposed model emphasizes the continuous connection between data acquisition, analytical processing, decision-making, and automated execution.

2. ENTERPRISE SYSTEMS AND ANALYTICS

Enterprise information systems such as ERP, MES, and Business Intelligence systems represent primary data sources in industrial organizations. ERP systems integrate economic and logistics processes, MES systems support production management, and Business Intelligence platforms provide analytical and visualization capabilities [2][3]. Together, these systems create a complex data environment enabling monitoring of enterprise activities in real time.

An important type of enterprise data is represented by event logs. Event logs contain information about executed activities, timestamps, and process entities, enabling reconstruction of real process behavior. These data are fundamental for process mining methodologies, which provide objective analysis of operational processes without requiring manual process modeling. [4]

Modern enterprises increasingly face the problem of data heterogeneity because operational data originate from multiple systems with different structures and formats. This challenge leads to the implementation of modern data architectures such as data fabric and data mesh approaches, enabling integrated and decentralized data management. [11]

The quality of enterprise data significantly influences analytical results. Incomplete or inconsistent data may produce incorrect conclusions and negatively affect decision-making processes. Therefore, enterprises must implement data quality management procedures including validation, cleansing, and standardization.

The analytical layer represents the connection between enterprise data and managerial information. Process mining enables analysis of real process execution, identification of process variants, and detection of deviations between expected and actual process behavior. [4] Process mining generally includes discovery, conformance checking, and enhancement approaches supporting process analysis and optimization.

Data mining complements process mining by identifying hidden patterns and predictive relationships within enterprise datasets. Descriptive, predictive, and prescriptive analytics enable historical analysis, prediction of future developments, and recommendation of optimal operational actions. [5, 6]

The combination of process mining and data mining enables enterprises not only to identify operational problems but also to analyze their causes and predict future process behavior. This integrated analytical approach provides a more comprehensive understanding of enterprise operations and supports more effective management.

Similar conclusions regarding integration of analytical approaches in industrial systems were presented in research focused on modeling and simulation of future manufacturing systems [8].

3. AI-DRIVEN DECISION SUPPORT AND WORKFLOW AUTOMATION

The development of artificial intelligence significantly changes how enterprise data are analyzed and utilized in decision-making processes. AI-driven decision support systems enable automated analysis of enterprise data and generation of recommendations without continuous human intervention. [9]

Augmented analytics represents an approach where analytical processes are supported by artificial intelligence technologies. This concept includes automation of data preparation, analytical processing, and interpretation of analytical outputs, reducing the time required to obtain relevant information. [10]

Another important aspect of AI implementation is explainability. Users must understand how analytical recommendations are generated; otherwise, trust in automated systems may decrease. For this reason, explainable AI approaches are becoming increasingly important in industrial environments. [9]

However, analytical and decision support systems alone do not guarantee practical implementation of decisions. Their effectiveness is limited unless they are connected with operational execution mechanisms. Workflow automation therefore represents a critical component of modern decision support architectures.

Workflow systems operate based on predefined rules determining system responses to operational events. In combination with analytical systems, workflow automation enables automatic identification of problems and execution of corrective actions without manual intervention. This approach reduces the time between problem identification and implementation of solutions while minimizing operational errors.

Workflow automation enables actions such as automatic notifications, task creation, escalation procedures, and enterprise system updates. Practical implementation can be realized using orchestration platforms such as n8n, which enable integration of data sources, analytical systems, artificial intelligence services, and execution mechanisms into unified workflows.

4. PROPOSED DECISION SUPPORT MODEL AND DISCUSSION

Based on the analysis of current enterprise information systems, a major limitation of existing solutions can be identified: insufficient integration between individual layers of enterprise data processing. Although enterprises often possess operational data and analytical tools, they frequently lack integration into unified decision support architectures enabling automated implementation of managerial actions.

The proposed model therefore integrates five interconnected layers: data layer, analytical layer, knowledge layer, decision layer, and execution layer. The data layer is responsible for acquisition and integration of operational information from ERP, MES, IoT, and enterprise databases. The analytical layer utilizes process mining and data mining methodologies for operational analysis and predictive modeling.

Outputs from the analytical layer are processed by the knowledge layer, which stores contextualized knowledge, historical data, analytical rules, and organizational experience. [11] The decision layer utilizes AI-driven decision support mechanisms and analytical models to generate recommendations and support managerial decisions under uncertain operational conditions.

The execution layer implements workflow automation mechanisms enabling realization of operational actions. This layer connects managerial decisions with enterprise operations through automatic task execution, notifications, and enterprise system updates. An important component of the proposed architecture is the feedback mechanism enabling continuous updating of enterprise data and analytical models.

The overall architecture of the proposed solution is illustrated in Fig. 1, which presents individual layers of the model and information flow between them.

The main advantage of the proposed model is elimination of fragmentation between analytical and operational systems. The model creates a continuous information flow from enterprise data acquisition to operational implementation of managerial decisions.

From a practical perspective, workflow automation represents one of the most important contributions of the proposed architecture. Many enterprises already utilize analytical tools; however, the absence of execution mechanisms significantly limits their practical benefits. Integration of workflow automation therefore represents a critical step toward fully operational AI-driven decision support systems.

Implementation of the proposed architecture requires high-quality enterprise data, interoperability between enterprise systems, and organizational readiness for automated decision-making. Additional limitations include technological complexity and the necessity of employee acceptance of AI-supported operational processes.

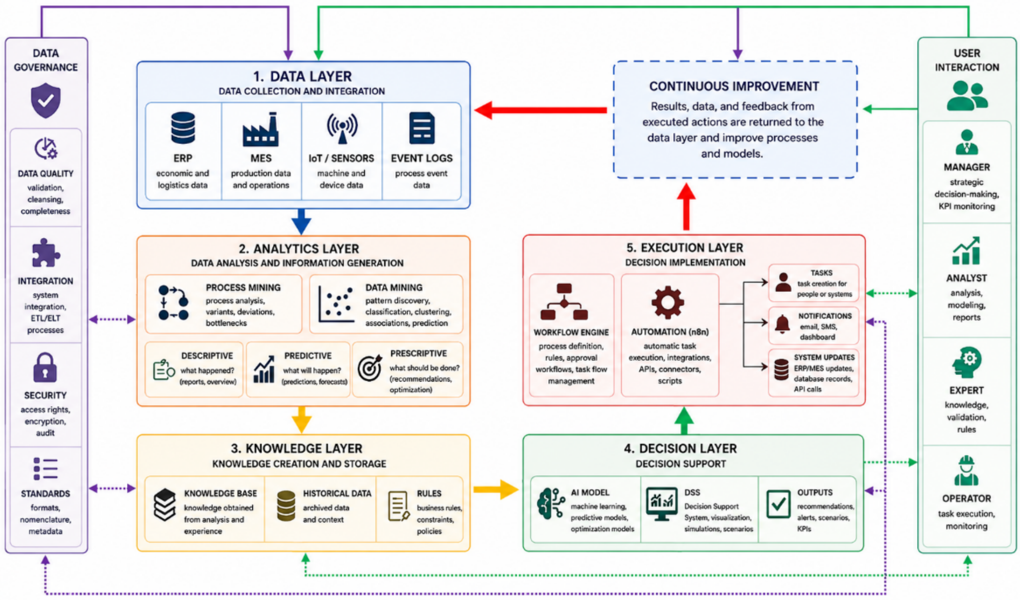

Fig. 1. Illustration of the proposed model and information flow between individual modules

5. CONCLUSION

Enterprise information systems generate extensive operational data whose effective utilization has become essential for modern industrial management. However, data availability alone is insufficient unless analytical processing, interpretation, and operational execution are properly integrated.

The paper presented an extended AI-driven decision support model integrating process mining, data mining, artificial intelligence, knowledge systems, and workflow automation into a unified enterprise architecture. The main contribution of the proposed model is the incorporation of workflow automation as an execution layer connecting analytical outputs with operational actions.

The proposed architecture enables continuous integration between enterprise analytics, managerial decision-making, and automated operational execution. This approach reduces the time between problem identification and corrective action implementation while improving enterprise responsiveness and operational efficiency.

Future research should focus on practical implementation of the proposed architecture, explainability of AI-based recommendations, and integration with smart manufacturing technologies.

Acknowledgement

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References

[1] DAVENPORT, T.; HARRIS, J.: Competing on Analytics. Harvard Business Press, 2007.

[2] GAO, T. et al.: Ten industrial software towards smart manufacturing. Journal of Manufacturing Systems, 2025. DOI: 10.1016/j.jmsy.2025.01.012.

[3] VAN DER AALST, W. M. P.: Process Mining: Data Science in Action. Berlin: Springer, 2016. ISBN 978-3662498507.

[4] BERRY, M.; LINOFF, G.: Data Mining Techniques. Wiley, 2011. ISBN 9780470650936.

[5] BASL, J. et al.: Inovace podnikových informačních systémů. Praha: Professional Publishing, 2011. ISBN 978-80-7431-045-4.

[6] BASL, J.; BLAŽÍČEK, R.: Podnikové informační systémy. Praha: Grada, 2008. ISBN 8024722795.

[7] TUFFÉRY, S.: Data Mining and Statistics for Decision Making. Wiley, 2011. ISBN 9780470688298.

[8] GRZNÁR, P. et al.: Modeling and Simulation of Processes in a Factory of the Future. Applied Sciences, 2020. DOI: 10.3390/app10134503.

[9] MADATHIL, A. et al.: Explainable AI in Smart Manufacturing. International Journal of Production Research, 2025. DOI: 10.1080/00207543.2025.2513574.

[10] REN, Y. et al.: AI Agents and Agentic AI in Manufacturing. Journal of Manufacturing Systems, 2025. DOI: 10.1016/j.jmsy.2025.08.017.

[11] ARDUIN, P.; GRUNDSTEIN, M.; SABROUX, C.: Information and Knowledge System. Wiley, 2015. ISBN 9781848217522.

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UTILIZATION OF PROCESS MINING AS A SUPPORTING TOOL FOR DIGITAL IMPROVEMENT OF BUSINESS PROCESSES

Abstract

Digital transformation has significantly increased the availability of process data generated by enterprise information systems. However, many organizations still fail to systematically utilize these data for continuous process improvement. This paper proposes a conceptual framework integrating process mining with Lean Six Sigma and Kaizen principles. The framework connects data-driven analysis, DMAIC methodology, and implementation mechanisms to support sustainable process improvement. The paper also formulates implication propositions and highlights the potential integration of process mining with simulation models and digital twins in lean logistics systems.

Keywords: process mining; Lean Six Sigma; Kaizen; digital transformation

1. INTRODUCTION

Digital transformation has fundamentally changed the conditions under which business processes are managed and improved. Modern enterprise information systems, automated technologies, and digital platforms continuously generate large amounts of process data in the form of event logs. These data contain detailed information about process execution, activity sequences, timestamps, and process variability.

Although organizations operate in a data-rich environment, they often struggle to transform available process data into actionable insights supporting systematic process improvement. This phenomenon is frequently described in the literature as the “data-rich but insight-poor” problem, where increasing data volume does not automatically improve decision-making.[1]

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Traditional process improvement methodologies such as Kaizen and Lean Six Sigma were originally developed in environments with limited data availability. [1] Process mapping, root cause analysis, and performance evaluation were therefore primarily based on manual observations, workshops, and expert assumptions. In digitally transformed enterprises, however, these approaches often fail to reflect the actual dynamic behavior of processes recorded in information systems.

In recent years, process mining has emerged as an analytical discipline capable of reconstructing and analyzing real process behavior directly from enterprise data. Process mining enables organizations to identify bottlenecks, process deviations, unnecessary repetitions, and hidden process variability. Nevertheless, the isolated implementation of process mining tools without integration into established process improvement methodologies often leads only to analytical outputs without significant operational impact. [2]

The objective of this paper is therefore to propose a conceptual framework for digitally driven process improvement integrating process mining with Lean Six Sigma and Kaizen principles. The paper addresses the current need for systematic integration of data-driven analytical tools with established continuous improvement methodologies.

2. CONTINUOUS IMPROVEMENT IN A DIGITAL ENVIRONMENT

Continuous Improvement (CI) represents one of the fundamental principles of industrial engineering and operational excellence. Its purpose is the long-term and systematic enhancement of process performance through repeated cycles of analysis, optimization, and stabilization.

Traditionally, continuous improvement relied on simplified process models, manual data collection, and periodic evaluation. Such approaches were sufficient in relatively stable production environments with limited process variability. However, digital transformation has significantly increased process complexity and introduced highly dynamic process behavior.

Modern enterprises generate extensive process data from ERP systems, MES systems, workflow systems, and digital platforms. These systems capture the real execution of business processes in real time, including process exceptions, parallel activities, and repeated operations.

Despite this increased data availability, organizations frequently fail to utilize process data systematically. Traditional improvement methodologies were not originally designed for large-scale process data analysis. Consequently, companies often continue to base decisions on simplified assumptions rather than actual process behavior.

This creates a methodological challenge: continuous improvement in a digital environment requires analytical approaches capable of objectively reflecting real process execution. As a result, integrating data-oriented analytical tools into established improvement methodologies becomes necessary. [7]

3. PROCESS MINING AS A SOURCE OF REAL PROCESS KNOWLEDGE ACKNOWLEDGEMENT

Process mining is an analytical approach enabling the reconstruction, analysis, and monitoring of business processes based on event logs extracted from information systems. [2]

Unlike traditional process mapping methods, process mining works directly with real process data and objectively identifies actual process behavior. The primary output of process mining is the as-is process model representing the real execution flow of the process. Process mining provides several important analytical capabilities: identification of process variants, detection of bottlenecks, analysis of waiting times, identification of repeated activities, monitoring of process deviations, evaluation of process performance and variability.

One of the main benefits of process mining in the context of continuous improvement is its ability to identify hidden waste and process inefficiencies. Lean-oriented process mining studies demonstrate that combining process mining with Lean principles enables more systematic identification of non-value-added activities compared with traditional visual management approaches. [5]

Process mining also strengthens analytical decision-making by enabling organizations to work with complete event logs instead of limited data samples. This improves the accuracy of process analysis and reduces subjectivity during problem identification.

However, process mining itself does not represent a complete improvement methodology. Without integration into structured improvement frameworks, analytical findings may remain disconnected from implementation activities and operational decision-making.

3.1 Integration of Process Mining into DMAIC and Kaizen

Lean Six Sigma is one of the most widely used methodologies for systematic process improvement. Its core structure is the DMAIC cycle consisting of the phases Define, Measure, Analyze, Improve, and Control. In traditional Lean Six Sigma projects, data collection and analysis are often partially manual and based on statistical sampling. In digitally transformed enterprises, however, increasing process complexity requires more advanced analytical support. [3, 5]

3.2 Define and Measure Phases

Within the Define phase, process mining enables objective identification of actual process scope and process variants based on real operational data. During the Measure phase, process mining provides quantitative process performance indicators such as: throughput times, waiting times, process frequency, repetition rates,
deviation occurrence. The use of complete event logs improves measurement precision and provides a reliable basis for subsequent analytical activities.

3.3 Analyze Phase

The Analyze phase focuses on identifying root causes of process problems and variability. Process mining extends traditional statistical analysis by enabling structural analysis of real process flows. This allows organizations to identify: repeated loops, non-standard activity sequences, parallel process branches, hidden bottlenecks. The integration of process mining into the Analyze phase reduces subjectivity and improves the accuracy of improvement decisions. [6]

3.4 Improve and Control Phase

In the Improve phase, analytical outputs generated by process mining serve as a basis for designing targeted improvement actions. The integration with Kaizen principles supports incremental implementation and continuous verification of implemented changes. Within the Control phase, process mining enables continuous process monitoring and rapid detection of deviations from newly established standards. This supports long-term stabilization of process performance and facilitates the transition from periodic improvement toward digitally driven continuous improvement.

4. CONCEPTUAL FRAMEWORK FOR DIGITALLY DRIVEN PROCESS IMPROVEMENT

The proposed conceptual framework integrates three mutually connected layers:
Data Layer, Methodological Layer, Implementation Layer

The data layer consists of process data generated by enterprise information systems. Through process mining techniques, these data are transformed into analytical outputs such as: as-is process models, process variants, bottleneck analysis, throughput analysis, process deviation identification. The primary role of this layer is to provide objective and data-driven inputs for improvement activities.

The methodological layer integrates process mining into Lean Six Sigma and Kaizen principles. Process mining primarily supports the Define, Measure, and Analyze phases of DMAIC by providing objective process knowledge and performance data. Kaizen principles support the Improve and Control phases through gradual implementation, standardization, and continuous verification of improvements.

The implementation layer ensures practical application of analytical outputs and improvement methodologies. It includes: responsibility management, standardization of improvement procedures, monitoring of implemented changes, performance evaluation. Without this layer, analytical insights generated by process mining would have limited operational impact.

The proposed framework enables organizations to move from isolated analytical activities toward integrated digitally driven continuous improvement.

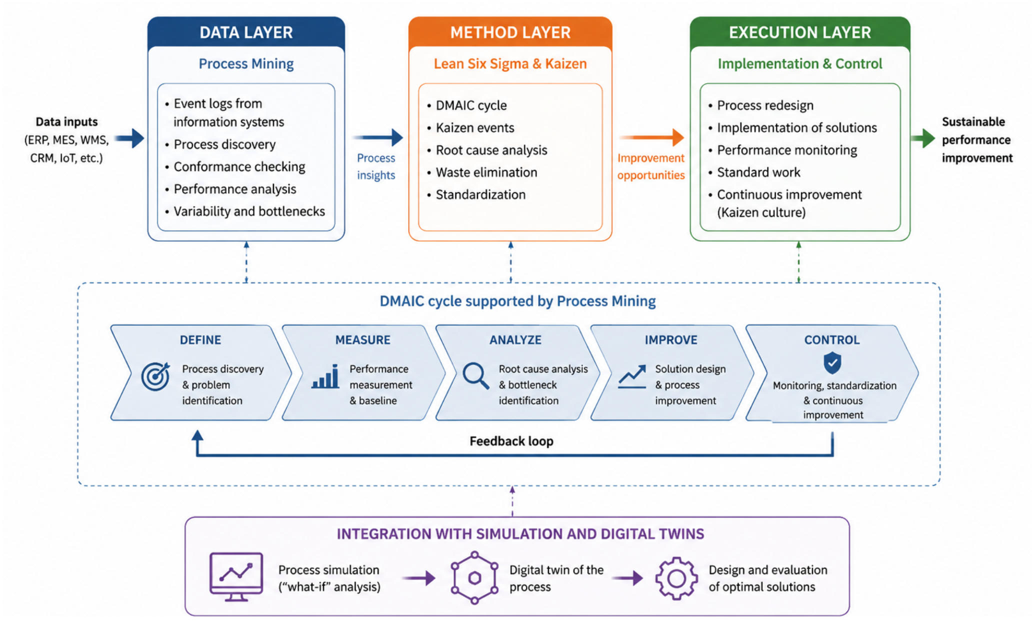

Fig. 1: Conceptual Framework for Digitally Driven Business Process Improvement

5. IMPLICATION PROPOSITIONS AND RESEARCH POTENTIAL

Based on the proposed conceptual framework, the following implication propositions can be formulated:

P1: Integration of process mining into DMAIC analytical phases reduces subjectivity in process problem identification.
P2: Digitally driven continuous improvement enables the transition from periodic process evaluation to continuous process monitoring.
P3: Combining process mining with Kaizen principles increases the sustainability of improvement activities.
P4: Without an implementation layer focused on responsibilities, standardization, and control, process mining has limited influence on operational performance.

The framework also creates methodological foundations for integrating process mining with simulation models and digital twins. In logistics and manufacturing systems, process mining can provide objective as-is process models, while simulation tools can support the testing of future to-be process configurations.

6. CONCLUSION

Digital transformation has significantly increased the availability of process data in modern enterprises. Nevertheless, many organizations still lack systematic mechanisms for transforming process data into structured improvement activities. This paper proposed a conceptual framework for digitally driven business process improvement integrating process mining with Lean Six Sigma and Kaizen principles. The framework combines data, methodological, and implementation layers and creates a mechanism for transforming analytical outputs into sustainable process improvements.

The paper has a conceptual character and therefore represents a foundation for future empirical research. Future studies should focus on practical verification of the proposed framework in manufacturing and logistics systems characterized by high process variability and extensive process data availability.

The framework also establishes a methodological basis for connecting process mining with simulation models and digital twins in the design of lean logistics systems. [8, 9]

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References

[1] VIAL, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*

[2] VAN DER AALST, W. (2016). *Process Mining: Data Science in Action*. Springer.

[3] TERRA, V. S. (2018). *Lean Six Sigma: International Standards and Global Guidelines*. CRC Press.

[4] BERNARD, G., FRIEDLI, T., HÄNGGI, R. (2025). Driving Continuous Improvement with Industry 4.0 Technologies. *Applied Sciences*,

[5] REINKEMEYER, L. (2020). *Lean Process Mining: Linking Process Mining and Lean Management*. Springer

[6] REINKEMEYER, L., VAN DER AALST, W. (2021). Process mining in the large: A tutorial. *Business & Information Systems Engineering*

[7] GEBAUER, J., SCHOBER, F. (2021). Lean Six Sigma and digital transformation: A conceptual framework. *Total Quality Management & Business Excellence*

[8] GRZNÁR, P., GREGOR, M., KRAJČOVIČ, M., MOZOL, Š. (2020). Simulation and digital tools in industrial engineering and logistics systems. University of Žilina.

[9] STRAKA, M., MALINDŽÁK, D., TREBUŇA, P. (2019). Lean logistics and process optimization in industrial enterprises. University of Žilina.

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UTILIZATION OF MODEL CONTEXT PROTOCOL AS A KEY ELEMENT OF INTEROPERABILITY IN HETEROGENEOUS INDUSTRIAL SYSTEMS OF INDUSTRY 4.0 AND 5.0

Abstract

The transition to Industry 5.0 demands semantic interoperability between heterogeneous manufacturing systems. This paper analyses the Model Context Protocol as a unified layer for Artificial Intelligence agents to access industrial resources, compares it with two other established industrial protocols, and examines legacy integration and human-in-the-loop security.

Key words: MCP, interoperability, Industry 5.0, agentic AI

1. INTRODUCTION

Traditional industrial engineering has long relied on the strictly defined layers of the automation pyramid, where data flows upward through sensors, PLCs, SCADA systems, MES, and finally ERP systems [1]. However, this model creates information silos. Each transition between layers results in context loss and time delays, making real-time responses required by modern autonomous systems impossible. The “N × M” integration problem – where N represents different AI agents and M industrial devices – has led to disproportionate growth in development and maintenance costs for custom connectors. [2]

Industry 5.0 brings a new perspective where technology is not merely a productivity tool but a partner to humans. This shift from digital automation toward personalization and social sustainability requires systems that understand the nuances of the manufacturing environment [3]. Research suggests that integration of AI and autonomous robots can reduce error rates by 35% and increase production rates by 20%. [4] However, to

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achieve these results, AI agents must be capable of dynamically discovering tools and data across the entire factory, regardless of whether the target is a modern robotic arm with cloud connectivity or a thirty-year-old injection moulding machine communicating via Modbus. [5] The Model Context Protocol (MCP), introduced by Anthropic in November 2024, functions as a universal adapter enabling agents to bypass the traditional pyramid and obtain precisely the context they need. [6]

Tab. 1. Comparison of Industry 4.0 and Industry 5.0 [7]

Parameter	Industry 4.0	Industry 5.0
Focus	Efficiency and digitalization	Human-centricity and resilience
Human role	Human competing with machine	Human-machine collaboration (Cobots)
Data flow	Hierarchical (automation pyramid)	Decentralized and agentic (MCP)
Technologies	Big Data, Cloud, IoT	Cognitive systems, AI, edge SLM

2. MCP ARCHITECTURE AND MECHANISMS

The Model Context Protocol is an open standard designed to eliminate the need for building ad-hoc integrations for each tool or data source. Inspired by the Language Server Protocol (LSP), MCP defines clear role separation between the host application, client, and server. [2] The host is the environment where the user interacts with the AI agent (e.g. Claude Desktop or the n8n automation platform). The client maintains connections to servers. The server is an externally running service that exposes semantically described tools, resources, and prompts. [8] In industrial settings, an MCP server can run directly on an industrial gateway or as a containerized service on an edge server. [9]

2.1. Transport Layers and JSON-RPC 2.0

Communication within MCP uses JSON-RPC 2.0 messages, ensuring lightweight implementation and message readability [2]. The protocol supports three main transport mechanisms: standard I/O (stdio) for local deployment with the lowest latency; Server-Sent Events (SSE) for cloud-based server streaming; and streamable HTTP for fully bidirectional modern communication [10]. Benchmarks from 2026 show that Rust implementations achieve throughput of up to 4,845 requests per second with average latency of 4.04 ms (Tab. 2), indicating suitability for rapid diagnostic response scenarios. [11]

Tab. 2. Programming language comparison for industrial MCP deployment [11]

Language	Throughput (RPS)	P95 Latency (ms)	Memory (MB)
Rust (Tokio)	4,845	8.20	10.9
Java (Quarkus)	3,610	8.13	194.5
Go (Std Lib)	3,616	12.40	23.9
Python (FastMCP)	259	185.00	258.6

2.2. Protocol Primitives

MCP unifies different types of context into three fundamental primitives: resources (readable data identified by URI – live sensor data, historical records, machine documentation), tools (actions with clearly defined JSON Schema parameters, e.g. get_machine_status), and prompts (templates guiding AI models in solving specific tasks, e.g. automatically fetching the last 100 error messages with the relevant technical manual). [8]

3. COMPARISON WITH INDUSTRIAL PROTOCOLS

The industrial environment is dominated by OPC UA and MQTT. It is important to understand that MCP is not a direct competitor to these protocols but rather their complementary extension, bridging the gap between operational technologies and artificial intelligence [12]. OPC UA is a robust, semantically complex protocol for modelling industrial objects, but its complexity makes direct data consumption by modern LLMs difficult without extensive preprocessing [13]. MQTT excels in scalability and low-bandwidth data transfer with its publish-subscribe model, but does not carry semantic context on its own [14]. MCP acts as an intelligent abstraction layer: the agent does not need to navigate the complex address space of an OPC UA server; the MCP server translates the request and returns processed context directly usable for model reasoning. [1]

Tab. 3. Comparative analysis of OPC UA, MQTT and MCP [13]

Function	OPC UA	MQTT	MCP
Modelling	Object-oriented, complex	Topic-based, flexible	Tool & Context-centric
Interaction	Req-Resp & Pub-Sub	Pub-Sub (Broker)	JSON-RPC (Client-Server)
Security	X.509 certificates	TLS, User/Password	OAuth 2.1, Sandboxing
AI suitability	Low (needs middleware)	Medium (needs semantics)	Native (designed for LLM)

4. INDUSTRIAL IMPLEMENTATION AND CASE STUDY

4.1. Legacy System Integration

Integration of legacy devices into modern AI workflows is one of the greatest challenges. Many older PLCs communicate via archaic protocols such as Modbus RTU or Siemens S7. MCP serves as a semantic bridge. [1] An MCP server functioning as a gateway for Modbus TCP continuously monitors PLC registers and exposes them as Resources with human-readable names – instead of address 40001, the agent sees main_hydraulic_pressure. This approach enables LLM agents to perform diagnostics without deep knowledge of specific hardware [5]. When a new sensor type is added to a production line, it suffices to add a new MCP server or update an existing configuration. Through capability negotiation, the agent automatically discovers new tools upon the next connection, reducing integration complexity from O(N×M) to O(N+M). [2]

4.2. Case Study: Agentic Automation with n8n and MCP

In a realistic manufacturing scenario, n8n can serve as an orchestrator connecting AI agents with physical machines from multiple manufacturers (e.g. Siemens, Fanuc, Beckhoff). Consider an autonomous fault diagnosis workflow [15]: (1) SCADA detects an anomaly and sends a signal to n8n via webhook; (2) the AI Agent node receives investigation instructions; (3) the agent calls list_tools on MCP servers assigned to individual machines; (4) the agent determines that a Beckhoff conveyor reports overload while a Fanuc robot awaits a “ready” signal, and requests logs from both machines via MCP; (5) the agent identifies a mechanical fault on the conveyor preventing part transfer, generates a maintenance ticket, attaches a fault location image (if a camera is connected via MCP), and notifies the foreman via Slack. This workflow is highly flexible, allowing technicians to visually configure flows without writing complex code. [15]

5. SECURITY AND HUMAN-IN-THE-LOOP CONTROL

Deploying AI agents capable of influencing physical reality carries significant risks. MCP is designed from the ground up with security in mind, enforcing “Local-First” and “ReadOnly by Design” principles [8]. Servers run locally within the enterprise network; data does not leave the infrastructure unless explicitly required by the agent. For sensitive operations, Human-in-the-loop (HITL) mechanisms are used – for example, the tool restart_machine can require manual operator confirmation. Article 14 of the EU AI Act explicitly requires that high-risk systems be designed for effective oversight by natural persons [16].

Tab. 4. MCP security architecture and implementation mechanisms

Security layer	Mechanism	Implementation
Transport	TLS 1.3 + mTLS	Encrypted agent-server communication
Authorization	OAuth 2.1 / Bearer	Control over which agent calls which tools
Isolation	Docker / WASM	MCP servers in isolated containers
Output validation	Confidence thresholds	Action blocked below 80% model confidence

Furthermore, MCP supports auditing – every interaction from context queries to tool execution is logged, creating an indelible trail for incident analysis and regulatory compliance. [8]

6. DISCUSSION

Despite its significant potential, MCP adoption in industry faces several challenges. The most notable is latency: although JSON-RPC messages are efficient, transport through the network stack and LLM-level processing introduces delays unacceptable for critical real-time control loops in the millisecond range [9]. Standardization remains an open question – although major players such as Anthropic, OpenAI, and Block have joined the Agentic AI Foundation, the risk of fragmentation through competing protocols (e.g. A2A, ACP) persists [2]. The problem of AI model hallucinations is equally critical: an industrial system cannot afford an agent misinterpreting temperature units or issuing an erroneous command. Precise JSON schema definitions in MCP servers and techniques such as RAG (Retrieval-Augmented Generation) help anchor model responses in real data. [6, 17]

The future of industrial manufacturing trends toward autonomous industrial agents. It is predicted that by end of 2026, 40% of enterprise applications will contain embedded agents utilizing MCP as a standard for tool integration. [10] With the growing performance of Small Language Models (SLMs) running locally on AI-accelerated hardware, MCP is poised to become the nervous system of the intelligent factory. [17]

7. CONCLUSION

The Model Context Protocol is not merely another communication protocol; it is a transformative technology that brings semantic interoperability to the fragmented world of industrial automation. By enabling AI agents to access context rather than raw data, MCP dramatically lowers the barrier for deploying advanced intelligence in manufacturing. For industrial enterprises striving for the transition to Industry 5.0, MCP represents a foundational building block for resilient, flexible, and secure autonomous systems. The successful integration of platforms such as n8n with the MCP protocol enables the democratization of AI in industry, where even smaller enterprises can leverage the power of LLMs to optimize their processes, reduce error rates, and enhance worker safety.

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References

[1] EINNOSYS, 2026. Complete Guide to Modbus TCP [online]. [cit. 2026-05-04]. Available at: https://www.einnosys.com/opc-ua-protocol/.

[2] AYYAGARI, V., 2025. Model Context Protocol for Agentic AI: Enabling Contextual Interoperability Across Systems. International Journal of Computational and Experimental Science and Engineering. 2025, vol. 11, no. 3. ISSN 2149-9144. doi:10.22399/ijcesen.3678.

[3] POLTRONIERI, C. F. et al., 2025. Toward Industry 5.0: Mapping technologies, competencies, and research opportunities. Journal of Entrepreneurship, Management and Innovation. 2025, vol. 21, no. 4, pp. 103-129. ISSN 2299-7075.

[4] VERSTINA, N. et al., 2024. AI and Autonomous Systems: An Experiment in Industry 5.0 Transformation. BIO Web of Conferences. 2024, vol. 86, p. 01094. ISSN 2117-4458.

[5] MARCHUK, S., 2026. modbusua: a cross-platform gateway bridging Modbus and OPC UA [online]. GitHub. 2026 [cit. 2026-05-04]. Available at: https://github.com/serhmarch/modbusua.

[6] GOOGLE CLOUD, 2026. What is Model Context Protocol (MCP)? A guide [online]. [cit. 2026-05-04]. Available at: https://cloud.google.com/discover/what-is-model-context-protocol.

[7] ESPINA-ROMERO, L. et al., 2023. Industry 5.0: Tracking Scientific Activity on the Most Influential Industries. Sustainability. 2023, vol. 15, no. 6, p. 5554. ISSN 2071-1050.

[8] MODEL CONTEXT PROTOCOL, 2025. Specification [online]. 25 November 2025 [cit. 2026-05-04]. Available at: https://modelcontextprotocol.io/specification/2025-11-25.
[9] PGEDGE, 2026. MCP Transport: Architecture, Boundaries, and Failure Modes [online]. 2026 [cit. 2026-05-04]. Available at: https://www.pgedge.com/blog/mcp-transport-architecture-boundaries-and-failure-modes.
[10] DIGITAL APPLIED, 2026. MCP Adoption Statistics 2026: Model Context Protocol [online]. 2026 [cit. 2026-05-04]. Available at: https://www.digitalapplied.com/blog/mcp-adoption-statistics-2026-model-context-protocol.
[11] TMDEVLAB, 2026. MCP Server Performance Benchmark v2: 15 Implementations [online]. 2026 [cit. 2026-05-04]. Available at: https://www.tmdevlab.com/mcp-server-performance-benchmark-v2.html.
[12] WWT, 2026. Manufacturing at the EDGE: SCADA Instrumentation, Model Context Protocol and Agentic Design Patterns [online]. 2026 [cit. 2026-05-04]. Available at: https://www.wwt.com/blog/manufacturing-at-the-edge-scada-instrumentation-model-context-protocol-and-agentic-design-patterns.
[13] PROXUS, 2026. MQTT vs. OPC UA in Modern IIoT: Which Protocol Should You Choose? [online]. 2026 [cit. 2026-05-04]. Available at: https://proxus.io/blog/mqtt-vs-opc-ua-in-modern-iiot/.
[14] SL INDUSTRIES LTD., 2026. OPC UA, MQTT & Data Interoperability: Building a Connected Factory [online]. 2026 [cit. 2026-05-04]. Available at: https://sl-industries.com/opcua-mqtt-interoperability/.
[15] CODINGSCAPE, 2026. How to build n8n workflows with Anthropic MCP integration [online]. 2026 [cit. 2026-05-04]. Available at: https://codingscape.com/blog/how-to-build-n8n-workflows-with-anthropic-mcp.
[16] IBM, 2026. What Is Human In The Loop (HITL)? [online]. 2026 [cit. 2026-05-04]. Available at: https://www.ibm.com/think/topics/human-in-the-loop.
[17] HU, N.-Z. et al., 2026. Applying Model Context Protocol for Offline Small Language Models in Industrial Data Management. In: Eurasia Conference on IoT, Communication and Engineering 2025. MDPI, 2026, p. 31. doi:10.3390/engproc2026134031.

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CLASSIFICATION OF PROCESS IMPROVEMENT METHODOLOGIES IN INDUSTRIAL ENGINEERING: A HIERARCHICAL SELECTION MODEL FOR KAIZEN, LEAN SIX SIGMA AND PROCESS INNOVATION

Abstract

This paper presents a comparative analysis of three pillars of process improvement in industrial engineering – Kaizen, Lean Six Sigma and Process Innovation – and proposes a Hierarchical Selection Model guiding organizations to systematically classify problems and assign the most effective methodology. The model is extended with Industry 4.0 and 5.0 enablers including AI-enhanced DMAIC, process mining and digital twins.

Key words: Lean Six Sigma, Kaizen, process innovation, DMAIC

1. INTRODUCTION

In an era of democratized technology access and globalized supply chains, the ability to achieve operational excellence while simultaneously innovating processes represents one of the few sustainable competitive advantages [1]. Industrial engineering (IE) provides a set of proven methodologies for process improvement, with improvements generally falling into two fundamental categories: incremental improvement (operational excellence) focused on optimizing existing processes through Kaizen and Lean Six Sigma (LSS), and radical transformation (strategic innovation) requiring a fundamental change in how value is delivered to the customer. [2]

A critical practical issue is the so-called “methodology paradox”: organizations, motivated by desire for rapid results, frequently select the wrong tool. Deploying costly LSS statistical projects to solve obvious waste that could be addressed by a simple Kaizen workshop leads to team demotivation and resource waste. [1] Conversely,

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applying incremental tools to a fundamentally obsolete process yields only a local optimum within a suboptimal system. [3] The objective of this study is therefore to develop a Hierarchical Selection Model that enables organizations to systematically diagnose the nature of their problem and assign the most effective methodology, thereby increasing success rates and return on improvement investments.

2. TAXONOMY OF IMPROVEMENT METHODOLOGIES

2.1 Kaizen: Incremental Culture of Flow

Kaizen, the Japanese term for "change for better," represents above all a company culture of continuous improvement realized through small, incremental steps. [4] Its primary goal is identification and elimination of all forms of waste (Muda) that do not add customer value. Key tools include Gemba walks (improvements proposed directly at the workplace), Value Stream Mapping (VSM) for visualizing material and information flow, and SMED (Single Minute Exchange of Dies) for drastically reducing changeover times. Imai (2020) advocates a shift from tactical to Strategic Kaizen (FSL), focusing on Flow, Synchronization and Leveling to ensure Kaizen activities target the largest chokepoints of the entire system rather than the easiest problems. [5] Strategic Kaizen requires basic measurement (flow times, downtimes) but rarely the statistical complexity of LSS.

2.2 Lean Six Sigma: Statistical Control and Project Management

Lean Six Sigma is a project-driven methodology that merges Lean principles (speed, flow, waste elimination) with Six Sigma's statistical rigor (quality, variability reduction) using the structured DMAIC cycle. [6] In the Define and Measure phases, the problem is precisely specified through Critical-to-Quality (CTQ) characteristics and current performance is quantified using DPMO and Sigma Level, supported by Measurement System Analysis (MSA). The Analyze phase – the heart of LSS – employs sophisticated statistical tools (regression, correlation, ANOVA, hypothesis testing) to scientifically determine the relationship Y=f(X) between input variables and output. Solutions are then implemented and permanently anchored through Statistical Process Control (SPC) charts. [7] LSS requires higher upfront investment in training (Green Belts, Black Belts), specialized software (e.g. Minitab), and a rigorous project management culture. [8]

2.3 Process Innovation: Radical Reconceptualization

Process Innovation is a distinct category concerned with radical reconceptualization of a process. [3] When a process is designed for outdated market conditions or technologies, Kaizen and LSS can only achieve a local optimum. Tidd, Bessant and Pavitt (2007) define key phases of innovation management: Scanning (monitoring external environment for new technologies and market shifts), Focusing (strategic selection of projects based on customer value impact), and Implementation supported by prototyping and pilot projects to minimize risk. [3] Innovation is required when the goal shifts from incremental improvement of an existing product to radical change – e.g. transitioning to on-demand manufacturing or complete supply chain restructuring.

Tab. 1. Comparative characteristics of the three methodologies

Dimension	Kaizen (Type A)	LSS (Type B)	Innovation (Type C)	Integration note
Focus	Flow, waste, 5S	Variability, defects, SPC	New customer value, disruption	A→B→C sequential
Tools	VSM, SMED, Gemba, FSL	DMAIC, DoE, MSA, SPC	Scanning, prototyping, BPR	Process mining aids A/B
Expertise	Low–Medium (operators)	High (Green/Black Belt)	Strategic (change mgmt.)	AI upskilling needed
Change type	Incremental, cultural	Project-driven, statistical	Radical, transformational	Digital twins for C
I4.0 enabler	IoT real-time Gemba	AI-enhanced DMAIC	Digital twin simulation	Data foundation shared

3. HIERARCHICAL SELECTION MODEL

The foundation for correct methodology selection is a system that first excludes the need for radical change and then classifies operational problems by their nature. The proposed Hierarchical Selection Model is a three-phase gate process. Each phase acts as a decision filter, progressively narrowing the solution space.

3.1 Phase I: Strategic Gate – Excluding Innovation

The first phase determines whether the process is worth improving incrementally or requires radical change. The team precisely defines the problem and its impact on customer value [2], creates a business case, and answers two key questions: (1) Is the current process strategically viable even after optimization? If the process is obsolete from a technology or market perspective, the team proceeds directly to Type C: Process Innovation. [3] (2) Is the required improvement magnitude radical (e.g. 90% lead-time reduction or introduction of an entirely new technology)? If goals are radical, Type C applies. If the strategic gate is passed, the problem is classified as operational and the team proceeds to Phase II.

3.2 Phase II: Operational Gate – Stability and Flow

Phase II determines whether the problem is simple, visible waste or flow disruption addressable by Kaizen tools. The IE team goes to Gemba, performs VSM to visualize flow, and records non-standard work, waiting times, excessive inventory and inefficient changeovers. Key questions: (1) Is the problem primarily about flow inefficiency (Muda) – e.g. downtime due to tool searching, long machine changeovers, or disorganized workplaces (5S)? (2) Are inputs and outputs so chaotic that reliable data collection is impossible? If answers indicate visible waste, the classification is Type A: Kaizen. If the process appears visually sound but still generates defects and is unpredictable, the team proceeds to Phase III.

3.3 Phase III: Analytical Gate – Variability Confirmation

This phase focuses on problems where the root cause is not visible and requires statistical evidence. The team computes basic statistical metrics (mean, standard deviation) and performs MSA (Measurement System Analysis) to verify data reliability. Key questions: (1) Is the primary metric inconsistency (variability) and defect rate, requiring statistical proof of the Y=f(X) relationship? (2) Does the solution require hypothesis testing, regression analysis or Design of Experiments (DoE)? If both answers are affirmative, the classification is Type B: Lean Six Sigma [6].

Tab. 2. Hierarchical Selection Model – decision summary

Phase	Gate question	If YES	If NO
I – Strategic	Process viable after optimization?	Proceed to Phase II	Type C: Process Innovation
II – Operational	Visible waste, flow disruption, 5S issues?	Type A: Kaizen	Proceed to Phase III
III – Analytical	Statistical evidence of variability needed?	Type B: Lean Six Sigma	Re-evaluate (hybrid)

4. METHODOLOGY SYNERGY AND INTEGRATION

The greatest potential for operational excellence is achieved through integration of the three methodologies, where each serves as a prerequisite for the next. Kaizen must first stabilize the process (Type A) – ensuring standardization (5S) and removing the largest waste sources – so that data collected for LSS is not distorted by chaos. LSS (Type B) cannot be meaningfully applied to an unstable process because statistical analysis of non-standardized operations produces unreliable conclusions [8]. Conversely, after radical Process Innovation (Type C), LSS serves as a validation mechanism: DMAIC or its design variant DMADV/DFSS is deployed to verify that the newly designed process is statistically capable and exhibits low variability [9]. This A→B→C hierarchy represents not merely a selection sequence but a maturity model for organizational process excellence.

5. INDUSTRY 4.0 AND 5.0 INTEGRATION

5.1 Data Acceleration through IoT and Process Mining

The deployment of IoT sensors for real-time data collection eliminates one of the key weaknesses of LSS in the Measure phase – imprecise or manual data collection. LSS thus transitions from reactive to proactive variability management [10]. Process mining, whose market was valued at $3.63 billion in 2025 and is projected to reach $97.88 billion by 2034 [11], is particularly transformative for diagnostic phases of the Hierarchical Selection Model. By automatically reconstructing actual process flows from digital traces (e.g. ERP and MES system logs), process mining reveals hidden variations and rule bypassing that are invisible during Gemba walks [12]. It serves as a powerful objective tool in Phases II and III, confirming whether the problem lies in flow (Type A) or variability (Type B).

5.2 AI-enhanced DMAIC and Agentic Process Intelligence

Artificial intelligence is reshaping the traditional DMAIC cycle into what practitioners increasingly term “intelligent improvement systems” [13]. AI-powered analytics can mine unstructured data (customer complaints, sensor logs) to identify latent problem patterns in the Define phase, while machine learning models in the Analyze phase detect relationships invisible to human analysts. Agentic process mining – an emerging trend combining process mining with autonomous AI agents – continuously monitors activities, detects deviations, and triggers improvements in real time, shifting from periodic audits to continuous self-optimization [11].

5.3 Digital Twins for Innovation Validation

Industry 4.0 technologies transform Process Innovation (Type C) from a high-risk venture into a managed project through digital process twins, enabling radical changes to be tested in simulated environments before committing real resources. The Industry 5.0 paradigm further extends this by adding sustainability and human-centricity dimensions, requiring that improvement methodologies consider environmental impact alongside efficiency and quality. [14]

Tab. 3. Industry 4.0/5.0 enablers mapped to methodology phases

Technology	Kaizen (Type A)	LSS (Type B)	Innovation (Type C)
IoT sensors	Real-time Gemba data	Automated Measure phase	Live prototype monitoring
Process mining	Flow visualization from logs	Root cause pattern discovery	As-is process archaeology
AI / ML	Anomaly alerts	Predictive SPC, AI-DMAIC	Trend scanning, concept generation
Digital twin	Layout optimization	Simulation of DoE scenarios	Risk-free process validation

6. CONCLUSION

Industrial engineering offers a powerful arsenal of tools for both operational and strategic excellence. The proposed Hierarchical Selection Model provides a three-gate diagnostic framework: The Strategic Gate excludes the need for radical innovation; the Operational Gate identifies flow-based problems addressable by Kaizen; and the Analytical Gate confirms variability-driven problems requiring Lean Six Sigma. Key recommendations: organizations should always begin with the Strategic Gate; Kaizen must form the cultural foundation and precede all other projects; LSS should be reserved for complex variability requiring statistical evidence; and the adoption of process mining, IoT, and AI-enhanced DMAIC enables objective, faster diagnostic decision-making. By implementing this model, organizations ensure their improvement projects are scientifically grounded and strategically relevant.

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References

[1] SVOZILOVA, A., 2011. Business Process Improvement. Grada Publishing, Prague, 2011. ISBN 978-80-247-3938-0.

[2] VLCEK, R., 2002. Customer Value. Management Press, Prague, 2002. ISBN 80-7261-068-6.

[3] TIDD, J., BESSANT, J. and PAVITT, K., 2007. Managing Innovation. Computer Press, Brno, 2007. ISBN 978-80-251-1466-7.

[4] IMAI, M., 2007. Kaizen: The Key to Japan's Competitive Success. Computer Press, Brno, 2007. ISBN 978-80-251-1621-0.

[5] IMAI, M., 2020. Strategic KAIZEN (TM): Using Flow, Synchronization, and Leveling [FSL] Assessment to Measure and Strengthen Operational Performance. McGraw-Hill, 2020. ISBN 126014383X.

[6] TERRA, V. S., 2018. Lean Six Sigma: International Standards and Global Guidelines. 2nd ed. CRC Press Taylor & Francis Group, 2018. ISBN 978-1-138-07437-5.

[7] ROSA, C., SILVA, F.J.G. and FERREIRA, L.P., 2017. Improving the Quality and Productivity of Steel Wire-Rope Assembly Lines for the Automotive Industry. Procedia Manufacturing. 2017, vol. 11, pp. 1035–1042. ISSN 2351-9789.

[8] NADEEM, M. K. and CHAUDHRY, K. M., 2023. A Comparative Analysis of Kaizen and Lean Six Sigma Implementation in Manufacturing Sector. Journal of Business Research. 2023, vol. 7, no. 1.

[9] LEYBOURNE, S. A. and WRIGHT, A. L., 2019. Beyond DMAIC: Exploring the role of Innovation in Lean Six Sigma Projects. International Journal of Lean Six Sigma. 2019, vol. 10, no. 4. ISSN 2040-4166.

[10] WRIGHT, P. and JOHNSON, M., 2022. Industry 4.0 Technologies and the Transformation of Manufacturing Value Streams. Journal of Advanced Manufacturing Technology. 2022, vol. 120, no. 5–8.

[11] THE INSIGHT PARTNERS, 2025. Process Mining Market Size and Forecast (2025–2034) [online]. 2025 [cit. 2026-05-20]. Available at: https://www.theinsightpartners.com/reports/process-mining-software-market.

[12] SMITH, L. P. and JONES, K. S., 2021. The Role of Process Mining in Enhancing DMAIC. IEEE Transactions on Industrial Informatics. 2021, vol. 17, no. 5. ISSN 1551-3203.

[13] NORONHA, T., 2025. Lean Six Sigma in 2025: Digital Transformation, AI, and Sustainable Operational Excellence [online]. 2025 [cit. 2026-05-20]. Available at: https://medium.com/@TaniaNoronha/lean-six-sigma-in-2025.

[14] POLTRONIERI, C. F. et al., 2025. Toward Industry 5.0: Mapping technologies, competencies, and research opportunities. Journal of Entrepreneurship, Management and Innovation. 2025, vol. 21, no. 4, pp. 103–129. ISSN 2299-7075.

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OPERATIONAL VALIDATION OF A NEURAL METAMODEL-BASED DECISION SUPPORT SYSTEM FOR CONWIP MANUFACTURING LINES

Abstract

This paper presents the operational validation of a decision support system in which a neural network ensemble metamodel substitutes a discrete-event simulation of a five-station CONWIP manufacturing line. Four realistic scenarios are analysed: a sudden demand surge of 30%, the loss of an operator at the bottleneck workstation, a product-mix-driven batch-size change, and three strategic priority configurations selected by differential evolution. The metamodel evaluates each scenario in milliseconds while preserving the simulation accuracy (R^2 = 0.9955; MAPE = 1.34%) and identifies a configuration that improves throughput-time by 50.8% over the baseline. The results demonstrate the practical use of surrogate-based optimisation for real-time managerial decision support in pull-controlled production environments.

Key words: CONWIP, surrogate optimisation, scenario validation, decision support

1. INTRODUCTION

Industrial managers operating pull-controlled production lines increasingly face decision situations in which the time available to react is shorter than the time required to run a discrete-event simulation (DES) study. Demand fluctuations, operator absences, product-mix changes and shifting strategic priorities arrive with hourly to daily frequency, while a faithful DES experiment takes minutes per replication and hours per Design o Experiments. [1, 2] The CONWIP control policy [3] limits work in progress (WIP), yet the question of how to set its parameters under each new disturbance remains a multi-objective task with conflicting key performance indicators (KPIs). A practical answer is to replace the DES inside the optimisation loop with a fast surrogate. [4] Recent advances in Neural Architecture Search (NAS) [5] enable accurate ensemble metamodels with prediction error below 2% [6], turning what-if analysis into

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an interactive activity. The present paper does not focus on the construction of the metamodel — that pipeline has been published in [6] — but on its operational validation. We answer the question whether the surrogate, when embedded into a differential-evolution-based decision support system, produces actionable recommendations for four typical operational events on a CONWIP line, and we quantify the gap between the baseline configuration and the data-driven optima.

2. SYSTEM AND METAMODEL FOUNDATION

The investigated system is a five-station production line of an engineering company manufacturing large welded structures. Workpieces traverse cutting, welding, machining, assembly and inspection in a fixed routing. The line is governed by CONWIP, where a fixed pool of authorisation cards limits the total WIP. The simulation model is implemented in SimPy and parameterised by ten input factors covering control parameters, capacity, external demand and stochastic reliability (Tab. 1). Five KPIs are observed: throughput time TPT, work in progress WIP, throughput TH, average utilisation Util and the 95th percentile of TPT (TPT_{95}) as a proxy for delivery reliability.

Tab. 1. Input factors and KPIs of the CONWIP line

Group	Factor / KPI	Range / Unit	Symbol
Control	CONWIP limit	[5, 40] pcs	x_1
Control	Batch size	[1, 5] pcs	x_2
Capacity	Operators WS1–WS5	[1, 3] persons	x_3–x_7
External	Daily demand	[150, 350] pcs/day	x_8
Stochastic	MTBF / MTTR	[50, 200] h / [0.5, 2] h	x_9, x_{10}
KPIs	TPT, WIP, TH, Util, TPT_{95}	min, pcs, pcs/h, –, min	y_1–y_5

Tab. 2. Metamodel accuracy on the held-out test set (n = 2 812)

KPI	R^2	RMSE	MAE	MAPE [%]
TPT (y_1)	0.9972	1.72 min	1.06 min	1.5
WIP (y_2)	0.9979	0.28 pcs	0.11 pcs	1.0
TH (y_3)	0.9973	0.19 pcs/h	0.14 pcs/h	1.2
Util (y_4)	0.9931	0.008	0.006	1.1
TPT_{95} (y_5)	0.9918	3.75 min	2.21 min	1.9
Average	**0.9955**	–	–	**1.34**

The metamodel is an ensemble of ten ANN regressors with the architecture identified by NAS (TPE sampler, 200 trials): four hidden layers of 256 Swish neurons with batch normalisation, dropout 0.8% and L2 = 1.65×10^{-6}, trained by Nadam at learning rate 0.0099. Trained on 14 058 Latin-Hypercube-Sampled DES configurations and evaluated on 2 812 unseen samples, the ensemble reaches an average R^2 of 0.9955 and an average MAPE of 1.34% across all five KPIs (Tab. 2). Construction details are documented in [6].

3. DECISION SUPPORT FORMULATION

Each operational situation is reformulated as the following constrained optimisation problem. The decision vector x = (x_1, …, x_{10}) is sought such that a managerial objective f(x) is minimised (or maximised) subject to bounds x_min ≤ x ≤ x_max and operator integrality. The fitness function is replaced by the ANN ensemble, which produces a deterministic prediction in approximately 0.0008 s on an NVIDIA RTX 3090. Thus formulated:

$$\textit{minimise}\ \ f(x) = MMensemble(x)\ ; \quad x\_min \le x \le x\_max \qquad (1)$$

The optimiser is the differential evolution algorithm (DE) [7] from SciPy, configured with strategy best1bin, population 50, 30 generations, mutation 0.8, recombination 0.7, tolerance 10^{-6} and seed 42. The total number of fitness calls per single-objective run is 1 500. With the metamodel as the fitness function the wall-clock time of one run is 1.2 s; with the underlying DES it would be 6.25 min — a 312-fold speed-up that turns optimisation into an interactive operation. Four canonical single-objective problems are defined to expose the conflicting nature of the KPIs: minimise TPT, minimise WIP, maximise TH and maximise Util. Their numerical solutions and the resulting Pareto trade-offs underpin the four scenarios described in the next section.

4. RESULTS OF SCENARIO VALIDATION

All scenarios are evaluated against a shop-floor baseline configuration (CONWIP = 18, batch = 3, two operators per workstation, demand 250 pcs/day) which represents the typical setting prior to any intervention. Each disturbance is evaluated by the metamodel; the output is interpreted as a managerial recommendation.

4.1 Scenario 1 – Demand Surge of +30%

The market shock raises daily demand from 250 to 325 pcs/day. The metamodel estimates the new steady state in 0.8 ms (Tab. 3). The CONWIP card pool absorbs the demand pulse: WIP remains at 15.07 pcs, TPT increases by only 0.3% and TH drops by 0.9%. The system is therefore robust to a demand pulse of this magnitude without any parameter intervention. A persistent demand shift of comparable size would, however, require either an additional operator or a 5–10% CONWIP-limit increase, as confirmed by re-running optimisation under the new bounds.

Tab. 3. Scenario 1 — impact of a 30% demand increase

KPI	Baseline	High demand	Δ [%]
TPT [min]	52.05	52.19	+0.3
WIP [pcs]	15.07	15.07	0.0
TH [pcs/h]	17.51	17.35	−0.9

Util	0.73	0.72	−1.0

4.2 Scenario 2 – Loss of an Operator at the Bottleneck WS3

WS3 is the longest-cycle station and an empirically identified bottleneck. A long-term absence of one of its two operators reduces local capacity by 50 %. The metamodel reveals an asymmetric collapse: TPT increases by 77% to 92.13 min, TH drops by 43.3% to 9.93 pcs/h and overall utilisation falls by 29.3% because downstream stations starve (Tab. 4). WIP is held constant by CONWIP, which masks the issue from a naive operator dashboard but the TPT signal makes it visible immediately.

Tab. 4. Scenario 2 – impact of an operator absence at WS3

KPI	Baseline	After loss	Δ [%]
TPT [min]	52.05	92.13	+77.0
WIP [pcs]	15.07	15.09	+0.1
TH [pcs/h]	17.51	9.93	−43.3
Util	0.73	0.52	−29.3

Re-optimising under this constraint generates three actionable recommendations: a back-up operator pool ranked highest, a temporary 30 – 40% CONWIP-limit increase as a buffer measure, and longer-term WS3 automation. None of these can be inferred from local KPIs alone.

4.3 Scenario 3 – Change of batch size from 3 to 5

A product-mix change forces the line to switch from batches of three to five. Counter-intuitively, the metamodel predicts an essentially neutral KPI footprint (Tab. 5): TPT decreases by 0.6% owing to fewer set-ups, while WIP and TH change by less than 1%. The decision can therefore be taken on factors outside the KPI scope (storage, ergonomics) without performance trade-off.

Tab. 5. Scenario 3 – impact of a batch-size change

KPI	Batch = 3	Batch = 5	Δ [%]
TPT [min]	52.20	51.87	−0.6
WIP [pcs]	14.98	15.07	+0.6
TH [pcs/h]	17.40	17.41	0.0
Util	0.73	0.73	+0.5

4.4 Scenario 4 – Strategic Priority Configurations

Three strategic priorities are translated into single-objective DE runs (Tab. 6). Priority A (minimise TPT) recommends CONWIP = 12, batch = 1 and three operators per station, yielding TPT = 25.6 min — a 50.8% improvement over the baseline at the cost of a 29% utilisation. Priority B (maximise TH/Util) requires CONWIP = 32, batch = 5 and reaches TH = 21.97 pcs/h with utilisation 0.65 but a TPT inflation of 24%. Priority C balances the two and pushes utilisation up to 0.76 with intermediate TPT and WIP. The visible 167% spread in TPT and 478% spread in WIP across the three optima quantifies the underlying TPT-vs.-utilisation trade-off and matches Little's law (WIP = TH × TPT).

Tab. 6. Scenario 4 – strategic priority configurations identified by DE

Priority	CONWIP	Batch	TPT [min]	WIP [pcs]	TH [pcs/h]	Util	Use case
A: Min TPT	12	1	**25.60**	3.97	9.90	0.29	JIT
B: Max Util	32	5	64.48	25.91	**21.97**	0.65	Mass
C: Balance	18	3	59.86	17.93	18.12	**0.76**	Mix

Empirically, the CONWIP threshold of approximately 18 cards separates two regimes: below it the system is starved and utilisation is sub-optimal, above it any TPT gain is non-proportional. The metamodel makes this threshold visible in the optimisation surface, whereas a manager working with periodic DES studies would discover it only after several iterations.

5. DISCUSSION

The four scenarios cover the practical operational spectrum: an external pulse, an internal capacity loss, a planned product-mix change and a strategic re-prioritisation. In all four cases the prediction error of the surrogate stayed below 2%, in line with the held-out test-set performance, which confirms that the LHS-trained ensemble extrapolates to scenario-style queries and not only to scenarios drawn from the same distribution. The 312-fold acceleration is the enabling factor: without it, the multi-objective decision frontier of Tab. 6 would require 18 750 s of DES wall-clock time per management session, which is incompatible with daily operational planning. The principal limitation of the approach lies in the static nature of the trained ensemble. Long-term wear, demand drift outside the training envelope or topological line changes will degrade prediction accuracy. The dissertation framework from which this study is drawn integrates a residual-monitoring layer that triggers fine-tuning at MAPE > 5% and a full NAS retraining at structural changes [8]; its empirical validation is the next step of this research stream.

6. CONCLUSION

This paper validated, on four operationally realistic scenarios, the use of an ANN ensemble metamodel as a fitness function inside a differential-evolution-based decision support system for a CONWIP production line. The combined surrogate-and-DE pipeline returns actionable, KPI-quantified recommendations in approximately 1.2 s per scenario while preserving DES accuracy ($R^2 = 0.9955$; MAPE = 1.34%). Compared with the shop-floor baseline, the framework identified configurations that improve TPT by 50.8%, exposed an asymmetric collapse caused by the loss of a bottleneck operator, and quantified the TPT-versus-utilisation trade-off (167% spread). Future work concerns the validation of the on-line adaptation loop and an extension to multi-product configurations using graph neural networks.

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References

[1] LAW, A. M.: Simulation Modeling and Analysis. 6th ed. New York: McGraw-Hill Education, 2024.
[2] FU, M. C.: Handbook of Simulation Optimization. New York: Springer, 2015.
[3] SPEARMAN, M. L., WOODRUFF, D. L., HOPP, W. J.: CONWIP: a pull alternative to kanban. International Journal of Production Research, Vol. 28, No. 5, 1990, p. 879–894.
[4] BARTON, R. R., MECKESHEIMER, M.: Metamodel-based simulation optimization. Handbooks in Operations Research and Management Science, Vol. 13, 2006, p. 535–574.
[5] AKIBA, T., SANO, S., YANASE, T., OHTA, T., KOYAMA, M.: Optuna: A Next-generation Hyperparameter Optimization Framework. In: Proceedings of KDD 2019, p. 2623–2631.
[6] MOZOLOVÁ, L., GRZNÁR, P., MOZOL, Š., GREGOR, M.: Automated Neural Architecture Search for simulation metamodelling of CONWIP manufacturing systems. International Journal of Simulation Modelling, in press, 2026.
[7] STORN, R., PRICE, K.: Differential Evolution — A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces. Journal of Global Optimization, Vol. 11, No. 4, 1997, p. 341–359.
[8] MOZOLOVÁ, L.: Modelovanie a simulácia v riadení výroby. PhD dissertation, University of Žilina, Žilina, 2026.

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DATA COLLECTION FOR SIMULATION WITH HELP OF DIGITAL TWIN

Abstract

Current trends in industry demand adaptability and the ability to make prompt decisions based on new conditions in the enterprise's environment. Simulations are a tool for simplifying the achievement of this goal. At present, the creation of simulations requires complex data collection as well as a worker with substantial knowledge in the fields of programming, data analysis, and industrial engineering. The digital twin represents a technology that could streamline the process of creating a simulation model.

Keywords: simulation, industry 4.0, process optimization, assembly line, IoT, digital twin

1 INTRODUCTION

The digital twin still lacks a unified, academically recognized definition and remains, terminologically, more of a buzzword than a settled concept. This absence reflects a deeper fragmentation in understanding what a digital twin represents, what functions it should fulfill, and how it relates to the physical object it mirrors. Within the KPI research direction, the concept is oriented toward higher-level entities such as logistics and production agents, strongly supported by simulations, with their integration aimed at producing symbiotic simulations – so-called S3 (system symbiotic simulation).

The term's expansion has also polarized the business environment. Some companies offer digital twins as concrete technological solutions, typically as specialized IoT modules integrated into existing ERP ecosystems and focused on real-time data collection, transmission, and visualization. Others have simply rebranded existing ERP platforms as "digital twin platforms" without changing their functional essence. This has further blurred the term and made it harder for customers and researchers alike to navigate the available solutions.

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From a simulation perspective, a digital twin can play two roles. The first treats it as an IoT platform that collects operational data and exports it to an external simulation tool – a fragmented approach that introduces latency, consistency risks, and limited dynamic model updating since data and model remain in separate environments.

The second role, representing the vision of future research, positions the digital twin as the foundation for symbiotic simulations - the highest level of simulation models – where the physical and digital worlds continuously interconnect, influence, and synchronize in real time. Based on simulation outcomes, the system can reconfigure itself, redirect workers, and analyze corrective actions. This vision addresses a pressing industrial need. Market instability forces companies to frequently reconfigure and retool production, with cascading logistical effects, while still delivering in the shortest possible time. [9] Many firms have grown from small garage-scale operations into complex systems spanning several square kilometers, complicating management, reducing process transparency, and causing imperceptible financial losses. Having developed gradually within a once-stable environment, companies must now transform their character - and need a reliable tool to support that change.

2 MATERIALS AND METHODS

Simulation tools such as Tecnomatix Plant Simulation and AnyLogic have become a de facto standard in industrial enterprises, with outputs informing decisions across the entire enterprise hierarchy – from operational production management to strategic top-management decisions. [4] They are invaluable for capacity planning, identifying bottlenecks, evaluating investments, and designing layout changes without physical intervention in existing processes. [11]

A simulation model is a simplified, computer-based representation of reality used to understand, predict, and optimize a system's behavior. [3] Its level of abstraction must capture the system's key characteristics while remaining practically usable and computationally manageable. Building an effective model requires collecting data from diverse sources - robotic systems, information systems (ERP, MES, SCADA), or direct work measurement - a phase that is typically the most time-consuming and whose quality directly determines the model's credibility, since inaccurate inputs are the most common cause of low validity, as expressed by the "garbage in, garbage out" principle. [3]

In this context, the Digital Twin represents a key concept with the potential to fundamentally optimize data collection, processing, and evaluation for simulation purposes. Defined as a virtual replica of a physical object, process, or system connected to the real world in real time through data flows [1], a Digital Twin – unlike a static simulation model – is a dynamic, continuously updated reflection of the actual system state. This enables continuous performance monitoring, predictive maintenance, automatic calibration of simulation models, and immediate identification of deviations from the planned state. Integrating the Digital Twin with simulation tools thus creates a synergistic effect that strengthens the reliability and timeliness of simulation outputs, and consequently the quality of decisions based on them.

2.1 IoT – Internet of Things

IoT is one of the latest trends in the field of IT. It is a concept of interconnecting devices and the internet with the aim of facilitating the collection, sharing, and transmission of data over a network. [6] IoT systems have gained significant popularity in recent years. The main driving force has been the reduction of acquisition costs and the creation of standardized protocols such as OPC UA or MQTT. As part of the experimentation, the IoT devices Raspberry Pi and the Arduino Kit sensor set were tested. Using ultrasonic or laser sensors, it is possible to detect the presence of material and the lifting height of the forks. Data from these sensors can be transmitted via a Wi-Fi network or the UWB network described in chapter 1.2.

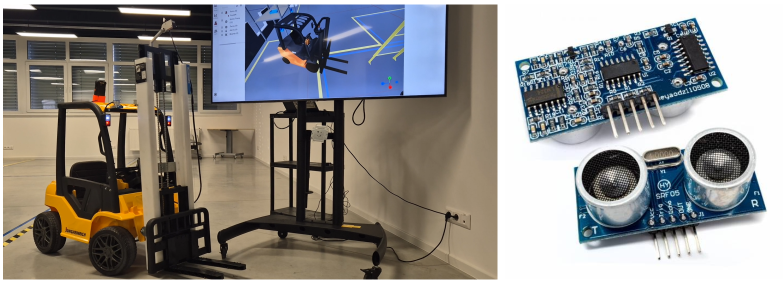

Fig. 1. IoT connected forklift

Using sensors, it is possible to obtain data such as the loaded-to-empty ratio. With this information, it is possible to derive probability distributions and the empty-to-loaded ratio, as well as the handling times during the transport of goods.

2.2 Real Time Location System (RTLS) – Indoor

Building on the IoT foundations from the previous chapter, RTLS can be understood as a subset of IoT devices focused on tracking objects in 3D space. Unlike conventional IoT sensors that measure point quantities (temperature, presence, stroke), RTLS provides continuous spatial information about tracked objects – fundamentally more valuable for simulation purposes - and, as noted in chapter 1.1, also enables data transmission over the network it forms, albeit in smaller volumes than standard Wi-Fi. [7]

While RTLS is most associated with GPS, indoor environments require alternative technologies such as UWB, Bluetooth, Wi-Fi, or ultrasound due to signal interference and reflections [5], with UWB (Ultra-Wideband) increasingly adopted in industrial settings for its 10–30 cm accuracy - sufficient for mapping logistics flows and identifying bottlenecks in production halls [8]. At the database layer, positional data is straightforward: represented in a Cartesian 2D spatial system, each record contains a device identifier, its X and Z coordinates, and a timestamp, enabling trajectory reconstruction and derived metrics such as movement speed or dwell time in defined zones. In a relational database, the data look as follows:

“CREATE TABLE rtls_positions (id INTEGER PRIMARY KEY AUTOINCREMENT, device_id INTEGER NOT NULL, pos_x REAL NOT NULL, pos_z REAL NOT NULL, timestamp INTEGER NOT NULL)”

The following figure shows the data representation of positional data. Based on this data, the simulation engineer can map the processes occurring in the operation, implement corrective measures, and subsequently carry out verification. Visualization of positional data in the form of so-called spaghetti diagrams enables intuitive identification of inefficient routes, unnecessary crossings of material flows, and uneven utilization of individual workplace zones.

RTLS data is highly intensive - under certain settings, with approximately 100 tracked logistics assets, we can collect 2.5 million positions per year, occupying 10 GB in the database. This volume of data requires a well-thought-out storage and archiving strategy. If the monitored process requires it, the orientation of the device can also be configured for the RTLS using an additional sensor. Data from auxiliary sensors can also be attached, such as the lift height of a forklift or information about the presence of material.

2.3 Data Processing Pipeline

After collection, raw data must be cleaned, standardized, and enriched with contextual information such as workstations, equipment, or operation types to make it suitable for the simulation platform. Modern data analytics combined with Large Language Models can accomplish this in minutes, automating pattern recognition in positional data, event classification, and statistical summaries without manual programming. From these systems, engineers can extract information on material handling, distance traveled, storage processes, downtime, and logistics flows. Industrial engineers can work with sensor data using built-in tools in platforms such as RTLS or export it to systems like PowerBI or Python. PowerBI enables quick visualization and interactive dashboards without deep programming knowledge, while Python offers greater flexibility for statistical processing, outlier filtering, and automation of repetitive tasks through libraries such as pandas, NumPy, or scikit-learn.

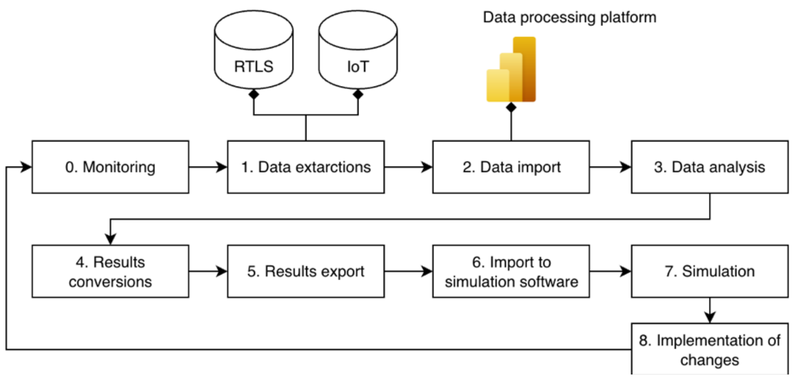

Fig. 2. Simulation data processing pipeline

Fig. 3 shows the current common process of creating simulation models in enterprises using IoT devices. This process is typically sequential - the data is first collected, then manually exported, transformed, and only afterwards imported into the simulation tool, which introduces latency and the risk of errors at each intermediate step. Once science, research, and practice reach the stage of symbiotic simulations, the entire process will be significantly simplified, as the data flow between the physical environment and the simulation model will be automated and continuous, thereby eliminating most manual interventions:

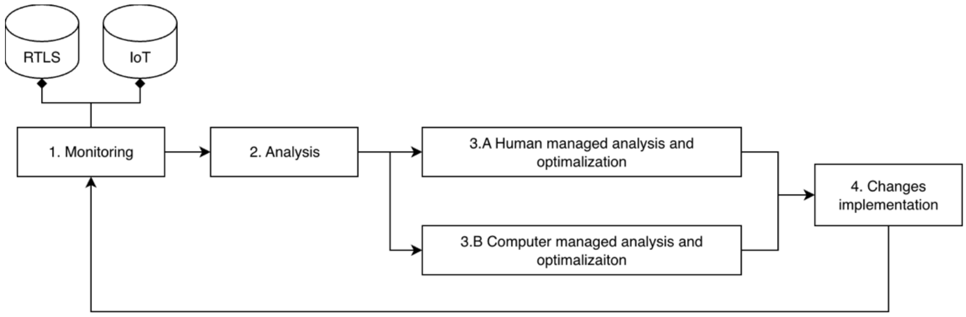

Fig. 3. Next generation of simulation data processing

The data collected through a digital twin has the potential to assist not only in the simulation process but also in the manufacturing and planning processes [10]. The established data pipeline can relate to other enterprise systems and even with the entire network of subcontractors.

3 RESULTS AND DISCUSSION

The developed digital twin is a comprehensive solution combining a three-dimensional virtual world that faithfully reflects the enterprise's physical environment with historical data suitable for simulation models and analytical processes. Its creation began with defining the model's level of abstraction, determining which real-world elements to represent and in what detail, alongside specifying the metrics the system would collect and evaluate. Based on this framework, the enterprise was equipped with a network of IoT sensors and devices for real-time localization of machines, materials, and workers. Sensor data are collected automatically, ensuring continuity and consistency, while worker observations and certain process events are recorded manually as a necessary compromise where automation is not yet feasible or economically justified. The collected data are then either exported as an SQL database directly into the simulation tool for further modelling, or analyzed in Python for statistical processing, visualization, and pattern identification.

4 CONCLUSIONS

In today's volatile market, a company's survival depends on its ability to adapt quickly and respond to challenges before they cause losses. Fast, reliable analytics are key –

they shorten the decision-making cycle and enable informed management decisions. The digital twin accelerates access to data while creating a unified source of truth that eliminates inconsistencies from fragmented systems, and it introduces a standardized way to measure performance over time and across workplaces. Beyond gathering data for simulations, it also enables continuous monitoring after corrective measures are implemented, allowing objective evaluation of their real impact. This frees the industrial engineer's hands, offering a bird's-eye view of operations spread across several square kilometers from a single location – something practically unattainable before the digital twin era. This article presents a specific application of digital twin technology for industrial simulations and summarizes the findings of the study. Using the Python programming language and the Infinity Twin platform - chosen for their flexibility, accessibility, and native support for LLM-based tools - the implementation enabled partial automation of data collection, a previously time-consuming manual process, thereby reducing staff workload and improving data quality and frequency. Future research should aim at a complete symbiosis of digital twin and simulation tools, creating an integrated system capable of simultaneously monitoring current operational states and predicting future ones without manual data transfer, potentially transforming how companies approach decision-making, capacity planning, and fault prevention. [1]

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References

[1] Gregor, M.; Gregor, M.; Pobočíková, I.; Krajčovič, M. Pravdepodobnosť a štatistika v simulácii, 1. vyd.; AT Park: Žilina, Slovakia, 2025; ISBN 978-80-974830-1-2.

[2] Denz N. Process-oriented analysis and validation of multi-agent-based simulations. Logos Verlag Berlin GmbH; 2014 Dec 31.445 s. ISBN 978-3-8325-3874-3.

[3] Bučková. M & Grznár P. 2020, Modelovanie a simulácia, Prvé vydanie. NAKLADATELSTVO: Žilinská univerzita v Žiline v EDIS. 144s. ISBN 978-90-554-1716-5. 144s.

[4] Law, Averill M. Simulation Modeling and Analysis. 5th ed. New York: McGraw-Hill Education, 2015. 775 pages. ISBN 978-1-259-01071-2.

[5] E. Palencik, Š. Mozol, and P. Grznár, "Utilization of Indoor RTLS and IoT in Manufacturing and Logistics Companies," in Technologie, procesy i systemy produkcyjne, 2025, doi: 10.53052/9788367652506.07.

[6] K. Saini and P. Raj, Eds., Advancing Smarter and More Secure Industrial Applications Using AI, IoT, and Blockchain Technology (Advances in Systems Analysis, Software Engineering, and High Performance Computing). Hershey, PA, USA: Engineering Science Reference, 2021, 336 p. ISBN 978-1-7998-8367-8.

[7] E. Palencik, Š. Mozol, and P. Grznár, "Utilization of Indoor RTLS and IoT in Manufacturing and Logistics Companies," in Technologie, procesy i systemy produkcyjne, Dec. 2025, doi: 10.53052/9788367652506.07.

[8] Kaplan, E.; Hegarty, C. Understanding GPS/GNSS: Principles and Applications. Artech House Publishers: Boston, MA, USA, 2017; 1064 p.

[9] P. Grznár, M. Gregor, M. Krajčovič, T. Bielik, et al., "Modeling and Simulation of Processes in a Factory of the Future," Applied Sciences, vol. 10, no. 13, p. 4503, Jun. 2020, doi: 10.3390/app10134503.

[10] B. Micieta, V. Binasova, M. Gašo, and A. Kabat, "The Methodology for Data Collection from a Holonic Manufacturing System," Electronics, vol. 14, no. 24, p. 4865, Dec. 2025, doi: 10.3390/electronics14244865.

[11] L. Mozolová, P. Grznár, Š. Mozol, and M. Krajčovič, "Streamlining utilisation of the assembly line using computer simulation," Acta Logistica, vol. 10, no. 2, Jun. 2023, doi: 10.22306/al.v10i2.365.

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EMPLOYEES' LEISURE ACTIVITIES AND THEIR IMPACT ON WORK PERFORMANCE

Abstract

Leisure time activities play a crucial role in the life of employees and can considerably affect work efficiency, mental state, and general satisfaction with one's job. This article is dedicated to the features of employees' leisure activities and their influence on the working process. Types of leisure activities, such as sport, cultural, educational, relaxing, and social ones, are discussed in this paper. In addition, this article draws attention to the benefits of leisure activities, such as stress reduction, improvement in people's mental health condition, increased levels of motivation, productivity, creativity, and better relationships. Potential drawbacks of these activities due to overstrain both physically and mentally, as well as lack of sufficient rest, are considered. Moreover, the significance of work-life balance, the term used in this article, is mentioned.

Key words: industrial engineering, ergonomics, leisure activities, work performance, work-life balance

INTRODUCTION

Nowadays, more and more attention is paid not only to the work performance of employees, but also to the factors that influence it. One of the significant factors is the extra-work activities of employees, which represent an important part of a person's life. Free time and the way it is spent have a significant impact on the psychological well-being, physical health, motivation and overall work performance of employees. [1]

Extra-work activities can have a different nature. Some employees prefer sports activities, others are engaged in cultural events, education or relaxation. These activities help a person regenerate physical and mental strength, reduce stress and create a balance between work and personal life. [2]

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The aim of the article is to characterize the extra-work activities of employees and point out their positive and negative impact on work performance and overall employee satisfaction. [3]

CHARACTERISTICS OF LEISURE ACTIVITIES

Leisure activities mean actions which people do when they are not at work. Leisure actions are conducted in spare time and mainly are aimed at relaxation, recuperation, self-improvement or just for fun. Spare time plays a vital role in the human life as it makes possible to restore physical and psychological resources after being worn by work. [4, 5]

The necessity of leisure activities becomes more obvious day by day due to the increased tempo of work, stress and even nervous exhaustion. Without a proper rest, one may face such problems as weariness, inability to concentrate, lowered efficiency of work or even burn-out syndrome. [6, 7]

Well-chosen leisure activities make the quality of life of employees much better and also make a contribution to leading a healthy way of life. [8, 9, 10]

TYPES OF LEISURE ACTIVITIES

Leisure activities can be divided into several groups according to their nature. [12]

3.1 Sport Activities

Sporting events should be considered among the most popular ways of using free time. Workers take part in activities like jogging, biking, training, trekking, or playing various sports. Physical activity is beneficial to one's physical health, decreases stress levels, and positively influences mental state. Sports also contribute to better focus, self-discipline, and stress resilience. Those workers that practice sports are usually less sensitive to stress factors and exhibit better performance at work. [12]

3.2 Cultural and Social Activities

These refer to visiting cinemas, theater halls, musical concerts, attending social gatherings, or hanging out with family members or friends. Such activities enhance social relations and also relieve people from work pressures. Interpersonal relations have a major influence on the psychological state of workers. Workers who have enough social backing can easily cope up with job pressures. [12]

3.3 Educational Activities

Certain workers engage in educational pursuits during their leisure time. It involves learning foreign languages, enrolling in professional courses, reading literary works, or undergoing training sessions. Education enhances personal and professional growth.

The obtained information will be beneficial for work efficiency, innovation, and problem-solving skills. [12]

3.4 Relaxation and Rest Activities

Relaxation plays an important role in human rejuvenation. Some of the relaxation techniques include meditation, wellness, listening to music, viewing movies, or simply engaging in nature. Such acts serve to decrease psychological strain, stress, and tiredness. Rest is necessary for preserving one's productivity and good health. [12]

3.5 Volunteering and Rest Activities

Some employees spend their free time participating in volunteering or community activities. Helping others may bring feelings of satisfaction, meaningfulness, and personal fulfillment. Such activities also support the development of communication skills, teamwork, and empathy, which may positively affect the work environment. [12]

THE POSITIVE IMPACT OF LEISURE ACTIVITIES ON WORK

In most cases, leisure activities have a positive impact on work performance and employee satisfaction. [13]

4.1 Stress Reduction

Among the most important advantages that leisure activities provide is the decrease in stress. Stressful conditions such as those in the workplace are characterized by time pressure, responsibilities, and psychological stress. Through leisure activities, employees get the chance to relax. Activities involving sports and relaxation have proved to be effective in reducing stress. Workers who are capable of regenerating can deal easily with their work responsibilities. [13]

4.2 Improvement of Psychological Well-Being

Leisure activities contribute to psychological health and general life satisfaction. Staff that have ample leisure time are unlikely to be irritable, fatigued, and mentally drained. Moreover, psychological health helps prevent burnout syndrome and chronic job dissatisfaction. [13]

4.3 Higher Motivation and Productivity

A well-rested employee is generally more productive and motivated. Leisure activities help restore energy and increase willingness to work. Employees with a balanced work and personal life often demonstrate higher productivity, better concentration, and fewer errors at work. [13]

4.4 Support for Creativity

Leisure time can be productive in enhancing creative skills and problem solving capabilities as well. During leisure, people are able to get organized and view things from various angles. This is especially true in professions that require creativity and innovation. [13]

4.5 Better Interpersonal Relationships

Social interaction and spending time with one's family and friends enhances communication and social relations. Employees who enjoy their private lives tend to establish good working relationships in their professional environment. [13] The right work environment is a contributing factor in enhancing team spirit, communication, and efficiency in work. [13]

THE NEGATIVE IMPACTS OF LEISURE ACTIVITIES ON WORK

Although leisure activities are generally positive, in some cases they may negatively affect work performance. [14]

5.1 Lack of Rest

When an employee spends more time engaging in extracurricular activities than work, he or she will not be able to rest. Participating in sporting activities, attending many social gatherings, and even excessive learning can result in exhaustion. [Concentration, attention, and job performance will be negatively impacted. [14]

5.2 Physical and Mental Fatigue

Some recreational activities could be both physically and psychologically taxing. Overworking oneself could lead to an exacerbation of one's health problems or exhaustion. As a result, workers could end up being less productive and error-prone in their jobs. [14]

5.3 Disruption of Work-Life Balance

It is critical to maintain a proper work-life balance. Without the ability to manage their rest and work-related commitments, employees might experience work overload in the long run. That is why proper planning of both leisure and work activities is essential for achieving a positive impact on one's health and job performance. [14]

THE IMPORTANCE OF WORK-LIFE BALANCE

Work-life balance is one of the key factors that influence employee satisfaction. This means that workers find it possible to perform their job tasks while simultaneously having enough time to relax, be with their families, and pursue their hobbies. [15]

The absence of work-life balance can negatively affect the performance and mental state of employees, as well as cause stress and exhaustion. On the contrary, work-life balance helps achieve higher levels of employee satisfaction, productivity, and psychological well-being. Modern companies attempt to ensure work-life balance through different types of incentives. The most common ones are flexible working hours, telecommuting, sports programs, company events, or healthy lifestyle initiatives. [15]

CONCLUSION

Leisure time activities constitute an integral element in the lives of workers and have considerable influence on their productivity levels and overall state of well-being. Various sports, rest, socialization, and education activities promote regeneration of mental and physical health and maintenance of healthy lifestyle.

In general, leisure activities positively affect the performance of workers by motivating them to perform tasks effectively and productively. Nevertheless, it is crucial to ensure a harmonious balance between leisure time activities and work activities to prevent extreme exhaustion.

It is in the best interest of companies to provide workers with the opportunity for a balanced lifestyle because motivated workers are a vital element ensuring organizational success.

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References

[1] SLAMKOVA, E., DULINA, L., TABAKOVA, M. 2010. Ergonómia v priemysle. GEORG kníhárstvo. 2010. 262 s. ISBN 978-80-89401-09-3.

[2] MICIETA, B., BINASOVA, V., MARCAN, P., GASO, M. 2023. Interfacing the Control Systems of Enterprise-Level Process Equipment with a Robot Operating System. Electronics, Vol. 12(18), Article 18. https://doi.org/10.3390/electronics12183871.

[3] KRAJCOVIC, M., GABAJOVA, G., MATYS, M., FURMANNOVA, B., DULINA, L. 2022. Virtual Reality as an Immersive Teaching Aid to Enhance the Connection between Education and Practice. Sustainability, Vol. 14(15), Article 15. https://doi.org/10.3390/su14159580.

[4] Kopřiva, T. Význam ergonómie pre vývoj moderných a zdravých priemyselných pracovísk. Asseco CEIT. 2024. Available on the internet: https://www.asseco-ceit.com/sk/vyznam-ergonomie-pre-vyvoj-modernych-a-zdravych-priemyselnych-pracovisk/

[5] TRSTENJAK, M., OPETUK, T., ĐUKIĆ, G., CAJNER, H. 2025. Use of Artificial Intelligence (AI) in the Workplace Ergonomics of Industry 5.0. Tehnički Glasnik, 19(2), 335–340. https://doi.org/10.31803/tg-20250105140152

[6] BOLIS, I., MORIOKA, S. N., BRUNURO, C. M., ZAMBRONI-DE-SOUZA, P. C., SZNELWARS, L. I. (2020). The centrality of workers to sustainability based on values: Exploring ergonomics to introduce new rationalities into decision-making processes. Applied Ergonomics, Vol. 88, 103148

[7] DULINA, L. 2023. Uplatnenie ergonómie vo výrobných a logistických systémoch. Žilinská univerzita v Žiline: EDIS. 2023. 106 s. 978-80-554-1960-2.

[8] ANTONACI, F. G., OLIVETTI, E. C., MARCOLIN, F., CASTIBLANCO JIMENEZ, I. A., EYNARD, B., VEZZETTI, E., MOOS, S. 2024. Workplace Well-Being in Industry 5.0: A Worker-Centered Systematic Review. Sensors, 24(17), Article 17. https://doi.org/10.3390/s24175473
[9] SVOZILOVA, A. 2011. Zlepšovaní podnikových procesů. Grada Publishing. 2011. 232 s. ISBN 978-80-247-3938-0.
[10] Springer Professional: Cognitive Ergonomics in Industry 5.0 | springerprofessional.de. 2025. Available on the internet: https://link.springer.com/chapter/10.1007/978-3-031-38165-2_88
[11] AMSTRONG, M., TAYLOR, S. 2015. Řízení lidských zdrojů. Praha: Grada Publishing. 2015. 928 s. 978-80-24752-587.
[12] BEDRNOVÁ, E., a kol. 2009. Management osobního rozvoje. Praha: Management Press. 2009. 359 s. 978-80-72611-980.
[13] KŘIVOHLAVÝ, J. 2003. Psychologie zdraví. Praha: Portál. 2003. 278 s. 8071787744.
[14] VEBER, J., a kol. 2014. Management. Praha: Management Press. 2014. 736 s. 9788072612741.
[15] SINGH, D.: The Economics of Drone Delivery. What Is Industry 5.0 And Its Human-Centric Approach? eLearning Industry. 2024. Available on the internet: https://elearningindustry.com/what-is-industry-5-0-and-its-human-centric-approach

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THE USE OF ARTIFICIAL INTELLIGENCE IN THE JUDICIARY: RISKS AND THE DESIGN OF CONTROLLED PROCESSING OF SUBMISSIONS

Abstract

The use of artificial intelligence fundamentally changes the way legal submissions are prepared and makes them more accessible. This trend has led to an increase in the number of litigation submissions, some of which are generated using AI tools. However, such submissions often contain inaccurate or fictitious information, including non-existent legal norms or incorrect references to case law, which is a consequence of the so-called hallucinations of AI models (Ji et al., 2023).
The aim of the paper is to highlight this phenomenon and propose a systematic approach to addressing it. The paper presents a proposal for a tool supporting the identification of incorrect submissions and the efficient processing of relevant inputs. The proposed solution is based on a combination of automated methods and control mechanisms that make it possible to increase the credibility of the use of artificial intelligence in the judiciary.

Keywords: artificial intelligence, judiciary, legal submissions, hallucinations, retrieval-augmented generation, human-in-the-loop

1. INTRODUCTION

The use of AI in the judiciary has been increasing significantly in recent years (Surden, 2019), especially in the context of efforts to streamline information processing and automate routine activities. At the same time, generative models are changing the way legal submissions are prepared, which can now be created faster and with lower demands on expertise.

This development leads to an increase in the availability of legal instruments, but also to an increase in the number of submissions entering the judicial process. However, AI-generated submissions may contain inaccurate or factually incorrect information, such as non-existent legal standards, incorrect citations of case law or failure to comply with

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legal deadlines. These shortcomings are the result of the so-called hallucinations of artificial intelligence models (Ji et al., 2023).

The result is not only a higher volume of processed submissions, but also an increased need for their control. This situation creates pressure to find approaches that enable the benefits of AI to be realized while minimizing the associated risks.

2. AIM OF THE PAPER

The aim of the paper is to analyze the impacts of the use of artificial intelligence in the preparation of legal submissions in the judiciary, especially in terms of the quality and reliability of input information. The paper focuses on identifying the risks associated with generating inaccurate or unverifiable data. Based on these findings, the paper proposes an approach to their systematic solution through a tool supporting controlled processing of submissions.

3. RISKS AND LIMITS OF THE USE OF AI IN THE JUDICIARY

To identify risks, an expert workshop was carried out in cooperation with the Constitutional Court of the Slovak Republic, focused on the analysis of the shortcomings of submissions prepared using artificial intelligence. The findings point to insufficient consideration of legal requirements, in particular breach of deadlines, absence of mandatory requirements (signatures, attachments, powers of attorney), incomplete identification data or lack of references to file numbers. Errors resulting from the functioning of AI models, in particular hallucinations, i.e. the generation of non-existent legal norms or the misapplication of case law, are a special category. These errors are difficult to identify, as the text is formally correct. These shortcomings lead to an increased burden on the courts, which have to identify and remedy these errors, thus shifting part of the responsibility for the quality of the submissions to the judicial authorities.

4. SOLUTION PROPOSAL

Based on the identified risks, a prototype of a tool for controlled processing of legal submissions was designed. Its purpose is to reduce the impact of incorrect submissions and at the same time support the efficient processing of relevant inputs. The solution combines artificial intelligence language models with a knowledge base of legislation, following a retrieval-augmented approach (Lewis et al., 2020). A key element is the submission processing pipeline, in which submissions are converted into text and image form and analyzed using specialized agents. These agents identify specific types of deficiencies, including formal errors, content inconsistencies, and the absence of mandatory requirements. The solution also includes visual inspections, such as verifying the existence of signatures. The result is an aggregated report providing an overview of the quality of the submission.

The proposed approach combines automated processing with control mechanisms and contributes to increasing the credibility of the use of AI in the judiciary.

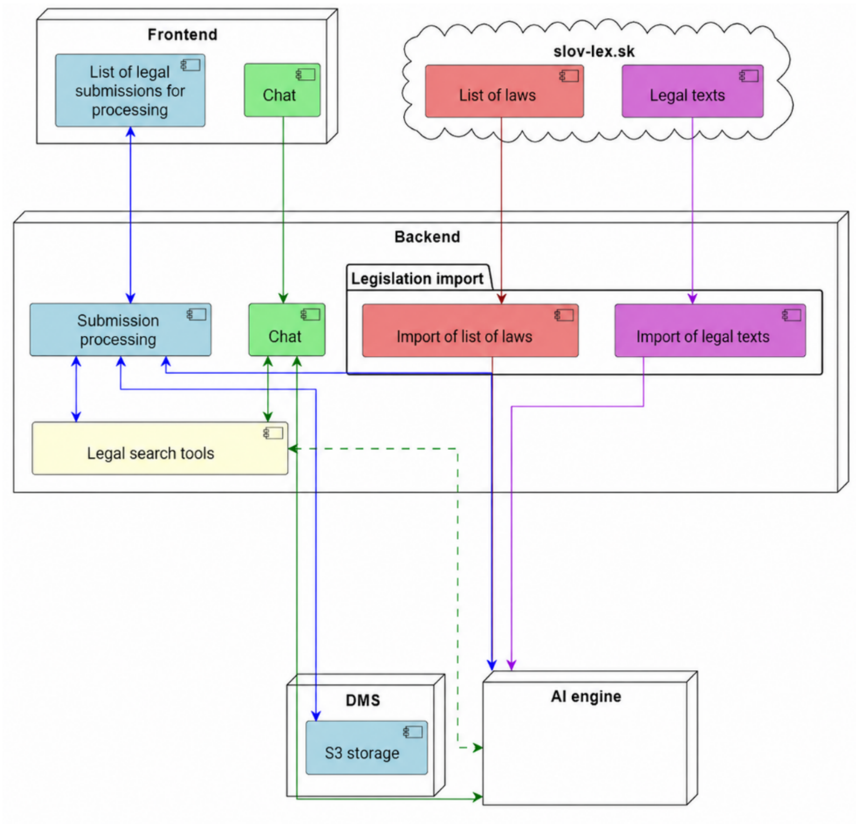

Fig. 1 The proposed approach combines automated processing with control mechanisms

5. CONCLUSION

The use of AI in the judiciary brings significant potential for efficiency gains, but at the same time creates new risks in terms of the quality of input information.
This paper identified the key shortcomings of submissions prepared using artificial intelligence and proposed an approach based on controlled processing that combines automation with verification mechanisms while maintaining human oversight (Amershi et al., 2019).

This approach makes it possible to effectively use the benefits of artificial intelligence while minimizing its negative impacts, thus contributing to reducing the burden on courts and increasing the credibility of its use in legal practice.

Acknowledgement
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References

1. SURDEN, H. (2019). *Artificial Intelligence and Law: An Overview.* University of Colorado Law School
2. JI, Z., LEE, N., FRIESKE, R., YU, T., SU, D., XU, Y., ISHII, E., BANG, Y., MADOTTO, A., & FUNG, P. (2023) *Survey of Hallucination in Natural Language Generation.* ACM Computing Surveys
3. LEWIS, P., PEREZ, E., PIKTUS, A., PETRONI, F., KARPUKHIN, V., GOYAL, N., KÜTTLER, H., LEWIS, M., YIH, W.-T., ROCKTÄSCHEL, T., RIEDEL, S., & KIELA, D. (2020). *Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks* Advances in Neural Information Processing Systems (NeurIPS)
4. AMERSHI, S., WELD, D. S., VORVOREANU, M., FOURNEY, A., NUSHI, B., COLLISSON, P., SUH, J., IQBAL, S. T., BENNETT, P. N., INKPEN, K., TEEVAN, J., KIKIN-GIL, R., & HORVITZ, E. (2019). *Guidelines for Human-AI Interaction.* Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems

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APPLICATION OF LEAN MANAGEMENT PRINCIPLES TO INCREASE THE PERFORMANCE OF MANUFACTURING AND LOGISTICS PROCESSES

Abstract

The proper functioning of modern manufacturing and logistics systems depends on eliminating waste that reduces process efficiency. The aim of this study is to use lean management tools to analyse and propose solutions for streamlining processes. The analysis employed methods such as the Gemba walk, Spaghetti diagram, and Yamazumi diagram to identify time losses and inefficient activities. Results highlighted areas for improvement in material flow and workplace provisioning.

Key words: logistics, material flow, waste, lean manufacturing

1. INTRODUCTION AND THEORETICAL BACKGROUND

Efficiency and effectiveness are two keys but distinct components of process performance. Efficiency is defined as "doing the right things" with a focus on achieving set goals, while effectiveness means "doing things right," with an emphasis on the optimal use of resources and managing their scarcity. [1] Closely related to these concepts is productivity, which represents the ratio between output and input, that is, the ability to achieve outputs without loss or waste. [2] In the context of logistics, productivity focuses on the efficient management of the flow of materials and information from the point of

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entry to the point of delivery with the aim of minimizing total costs. [3] In this regard, the implementation of adaptive logistics systems is becoming crucial for ensuring efficient supply in changing environments. [4] One approach that systematically links these principles is the lean concept, defined as an integrated system of principles and tools aimed at eliminating non-value-added activities and optimizing resources, such as people, materials, and time, in accordance with customer requirements. [5] This approach is based on the Toyota Production System (TPS), which was developed after World War II by Taiichi Ohno, Eiji Toyoda, and Shigeo Shingo in response to a severe shortage of resources in Japan [6]. The lean philosophy is based on five principles: defining value, mapping the value stream, creating a streamlined flow, implementing a pull system, and continuous improvement aimed at perfection. [5]

A key concept of the lean approach is "muda," or waste, which encompasses all activities that consume resources without creating value from the customer's perspective. [7] Traditionally, seven types of waste are identified, known by the acronym TIMWOOD: transportation, inventory, motion, waiting, overproduction, overprocessing, and defects. [5] Later, this list was expanded to include an eighth type of waste, the untapped potential and knowledge of employees. [1]

This human-centric view is closely linked to ergonomics, which plays a vital role in the Industry 5.0 era by ensuring that processes are designed with respect to worker well-being and efficiency. [8] Material flow management is another key aspect of effective system operation. It is defined as the systematic assessment of status and changes in material flows and inventories within a system, encompassing their transportation, transformation, and storage. Proper flow management connects sources, transport routes, and final destinations, thereby significantly influencing project cost control and overall process performance. [9]

The Lean approach also emphasizes specific principles of process management. The pull system ensures that production or transportation occurs only in response to actual customer demand or the next process. [7] Flow continuity means that value is added continuously from the beginning to the end of the process, thereby eliminating downtime and bottlenecks. [10] This is also linked to minimizing inventory, as excess inventory ties up capital, takes up space, and often masks the real problems in processes. [6] A variety of analytical and visualization tools are used to support the implementation of these principles. These include, for example, the Gemba walk, which involves directly observing work at the point of execution and identifying waste. [11] The Spaghetti diagram is used to visualize the movement of people, materials, or information in a space and helps identify inefficient routes. [12] The Yamazumi diagram is a tool for analyzing workload and balancing production lines through a graphical representation of operation times. [2] Modern approaches further extend these analyses through software support and simulation to optimize production and logistics systems. [13] In addition to the tools mentioned above, lean practices also utilize other techniques, such as Kaizen for continuous improvement [14], 5S for workplace organization, Kanban for flow management through visual cues, Jidoka for error prevention, SMED for reducing machine setup times, and Poka-yoke for eliminating unintentional errors. [1] Together, these tools contribute to increasing the efficiency and overall performance of processes.

2. MATERIALS AND METHODS

The following section of this paper describes its main objective as well as the methods used, which served as the basis for analysing the current state of selected production and logistics processes. The main objective of this paper is to present the results of the streamlining of production and logistics processes in an industrial enterprise using selected lean management tools. Lean management tools and methods used to identify bottlenecks: Gemba walk, Spaghetti diagram, Yamazumi diagram, Employee interviews, Material consumption analysis, and Layout analysis. The next section contains a description of the organization, which can be seen in Fig. 1.

Fig. 1: Production hall of an industrial enterprise (own elaboration, 2026)

The process of streamlining logistics and selected manufacturing processes was implemented at a company producing ultra-light aircraft on a custom basis (Fig. 1). The company has a workforce of 90 employees, and its operating schedule is set for a single eight-hour shift.

3. RESULTS AND DISCUSSION

The following section addresses the logistics of the warehousing process (storage of materials and semi-finished products). The Gemba walk method focused on directly observing the material flow, warehouse management, and employee movements in the context of supplying workstations, which enabled the precise identification of forms of waste. The main finding of the analysis is the absence of controlled distribution of materials from the warehouse directly to workstations, which causes a disorganized material flow. This situation forces employees to make frequent transfers to the warehouse, resulting in unproductive time and undesirable interruptions in the continuity of the work process. The current setup of logistics operations thus reveals a low degree of process synchronization with high potential for streamlining. In addition, a method was used that focused on the steps and time employees had to spend as part of their work. Measurements taken as part of the creation of a spaghetti diagram revealed that the average unproductive time spent by employees traveling to the warehouse amounts to 1 hour and 41 minutes per workday. When converted to a weekly basis, this loss increases to 8 hours and 25 minutes, and on a monthly basis, it reaches up to 35 hours and 21 minutes. In terms of the annual time budget, the total amount of time wasted due to inefficient movement is 424 hours and 12 minutes. A graphical representation of this can be seen in Fig. 2.

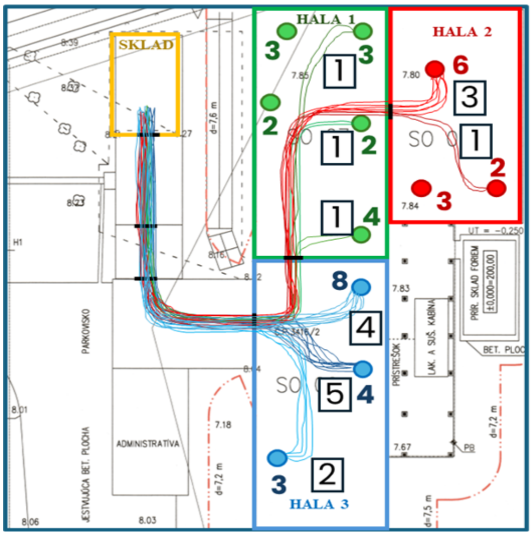

Fig. 2: Application of the Spaghetti Diagram (own elaboration, 2026)

Based on the data presented above, an annual loss was identified that corresponds to approximately 53 person-days (assuming an 8-hour workday) spent on non-value-added activities, confirming the urgent need to restructure the logistics processes identified during the Gemba walk. For a clearer understanding of the calculations derived from the data, see Table 1.

Tab. 1: Time Measurement for Waste Identification (own elaboration, 2026)

Hall	Transfer time	Number of visits	Lost time
Hall 1	6 min	3	18 min
Hall 2	7 min	4	28 min
Hall 3	5 min	11	55 min
Total	--	**18**	**101 min**

Since it was necessary to cross-check our findings, we employed a qualitative method involving interviews with the organization’s employees. To validate and supplement the findings from the Gemba walk, a qualitative survey was conducted in the form of six structured interviews involving representatives from all levels of management, including the CEO, production, logistics, and quality managers, the final assembly supervisor, and a production employee. Interviews with key stakeholders confirmed a critical shortage of consumables directly at workstations, which is a result of the absence of a regular supply system. Respondents unanimously stated that this situation forces employees to frequently leave their workstations to go to the warehouse for materials, which correlates with the measured time losses and undesirable fragmentation of the work process. The interviews thus provided important context for the measured data and confirmed the systemic nature of the identified inefficiencies in the company's logistics chain. The final analysis we conducted was an analysis of warehouse employee workload, the results of which can be seen in Fig. 3.

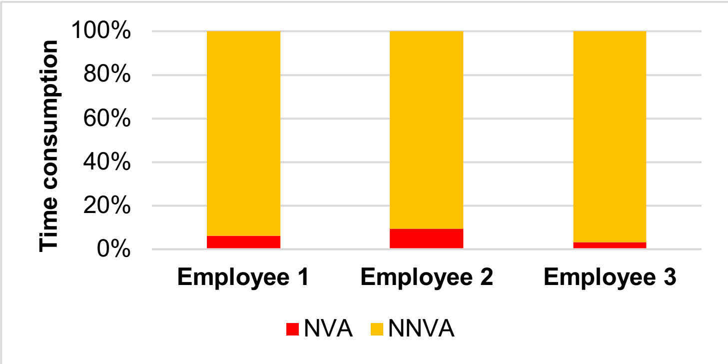

Fig. 3: Warehouse Employee Utilization (own elaboration, 2026)

A Yamazumi diagram (Fig. 3) was used to evaluate warehouse employee utilization with the aim of identifying staffing reserves for the production supply function. An analysis of non-value-added (NVA) activities revealed time reserves for employees Z1 (30 min) and Z3 (15 min), while employee Z2 had the highest NVA share at 45 minutes. Based on these results, employee Z2 was identified as the most suitable candidate for performing supply processes, which allows for the optimization of flows without increasing personnel costs. These findings serve as a basis for the proposals presented in the final section of this paper.

4. CONCLUSIONS

The results of the analysis led to the proposal of two key streamlining solutions in the area of materials storage and logistics, aimed at eliminating the identified waste. The first measure is the implementation of a supply operator who will be responsible for replenishing materials directly at workstations based on a PULL system (requests via telephone). This step will allow production employees to fully focus on their main activities without having to leave their workstations based on the Yamazumi diagram, warehouse employee Z2 was selected for this position. The second strategic recommendation is the implementation of kitting, which involves picking packages and preparing material kits for specific operations according to the production protocol. The main goal of this solution is to significantly reduce unproductive time spent searching for components. The combination of these measures represents a systematic solution for stabilizing supply and increasing the overall throughput of production processes.

Acknowledgement

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References

[1] BERTAGNOLLI, Frank. Lean Management: Introduction and In-Depth Study of Japanese Management Philosophy [online]. Wiesbaden: Springer Fachmedien Wiesbaden, 2022 [cit. 2026-05-06]. ISBN 9783658360863. Available on doi:10.1007/978-3-658-36087-0.

[2] HOSSAIN, Md. Shadman, Tanvirul ISLAM a Md. Irtisham LATIF. Improvement of Overall Efficiency Using Yamazumi Chart and Heuristic Techniques of a Leather Product Industry. In: Proceedings of the International Conference on Industrial Engineering and Operations Management [online]. Michigan, USA: IEOM Society International, 2025, 2025-12-20 [cit. 2026-05-06]. Available on doi:10.46254/ba08.20250207.

[3] MAHAGAONKAR, Sayali Sudhir, KELKAR, Amey A. Application of ABC analysis for material management of a residential building. International Research Journal of Engineering and Technology, 2017, 4.8: 614-620.

[4] POLKA, A. - GREGOR, M. - BUBENÍK, P. Adaptive Logistics Systems for Efficient Supply. In: Industrial Engineering – Invention for Enterprise, InvEnt 2025. Proceedings of the Scientific International Conference InvEnt 2025, Štrbské pleso, 16. - 18. june 2025. Bielskko-Biała, Poland: Fundacja Centrum Nowych Technologii, pp. 62-67. ISBN 978-83-947909-9-8.

[5] GEBEYEHU, Sisay G., Muluken ABEBE a Amdework GOCHEL. Production lead time improvement through lean manufacturing. Cogent Engineering [online]. Informa UK Limited, 2022, 2022-2-22, 9(1) [cit. 2026-05-06]. ISSN 2331-1916. Available on doi:10.1080/23311916.2022.2034255.

[6] NAEEMAH, Ali Jaber a Kuan Yew WONG. Selection methods of lean management tools: a review. International Journal of Productivity and Performance Management [online]. Emerald, 2021, 2021-10-29, 72(4), 1077-1110 [cit. 2026-05-06]. ISSN 1741-0401. Available on doi:10.1108/ijppm-04-2021-0198.

[7] HELMOLD, Marc, Ayşe KÜÇÜK YILMAZ, Triant FLOURIS, Thomas WINNER, Violeta CVETKOSKA a Tracy DATHE. Lean Management, Kaizen, Kata and Keiretsu: Best-Practice Examples and Industry Insights from Japanese Concepts. Management for Professionals [online]. Cham: Springer International Publishing, 2022 [cit. 2026-05-06]. ISBN 9783031101038. ISSN 2192-8096. Available on doi:10.1007/978-3-031-10104-5.

[8] ZUZIK, J. - DULINA, Ľ. - FURMANNOVÁ, B. The Role of Ergonomics in the Industry 5.0 Era. In: Industrial Engineering – Invention for Enterprise, InvEnt 2025. Proceedings of the Scientific International Conference InvEnt 2025, Štrbské pleso, 16. - 18. june 2025. Bielskko-Biała, Poland: Fundacja Centrum Nowych Technologii, pp. 98-103. ISBN 978-83-947909-9-8.

[9] BRUNNER, Paul H. a Helmut RECHBERGER. Handbook of material flow analysis: for environmental, resource, and waste engineers. Second edition. Boca Raton: CRC Press, Taylor & Francis Group, [2017]. ISBN 9781498721349.

[10] PYZDEK, Thomas. The Lean Healthcare Handbook: A Complete Guide to Creating Healthcare Workplaces. Management for Professionals [online]. Cham: Springer International Publishing, 2021 [cit. 2026-05-06]. ISBN 9783030699000. ISSN 2192-8096. Available on doi:10.1007/978-3-030-69901-7.

[11] MIČIETA, B., HOWANIEC, H., BIŇASOVÁ, V., KASAJOVÁ, M., & FUSKO, M. (2021). Increasing work efficiency in a manufacturing setting using Gemba Walk. European Research Studies Journal, 24(s4), 601-620.

[12] SENDERSKÁ, Katarína, MAREŠ, Albert, VÁCLAV, Štefan. Spaghetti diagram application for workers' movement analysis. UPB Scientific Bulletin, Series D: Mechanical Engineering, 2017, 79.1: 139-150.

[13] KOMAČKA, D. - KRAJČOVIČ, M. - KASAJOVÁ, M. Software Support for Design, Simulation and Optimization of Production and Logistics Systems. In: Industrial Engineering – Invention for Enterprise, InvEnt 2025. Proceedings of the Scientific International Conference InvEnt 2025, Štrbské pleso, 16. - 18. june 2025. Bielskko-Biała, Poland: Fundacja Centrum Nowych Technologii, pp. 38-43. ISBN 978-83-947909-9-8.

[14] BALALA, T. - MIČIETA, B. - GAŠO, M. Using Virtual Reality as an Innovative Tool in Kaizen Workshops. In: Industrial Engineering – Invention for Enterprise, InvEnt 2025. Proceedings of the Scientific International Conference InvEnt 2025, Štrbské pleso, 16. - 18. june 2025. Bielskko-Biała, Poland: Fundacja Centrum Nowych Technologii, pp. 8-13. ISBN 978-83-947909-9-8.

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ANALYSIS OF COMPETENCIES REQUIREMENTS FOR LINE MANAGERS IN THE ERA OF HUMAN-TECHNOLOGY INTERACTION

Abstract

Industry 5.0 changes human-technology interaction, requiring new managerial competencies. The main aim of the paper is to compare global competency requirements according to the WEF with the real development of line managers in Slovakia. Statistical testing confirmed significant differences between international trends and local practice. Slovak enterprises prioritize operational standards, revealing a gap in readiness for intelligent human-machine collaboration.

Key words: competencies, human-technology interaction, line managers

1. INTRODUCTION AND THEORETICAL BACKGROUND

The following part of the paper is divided into two thematic sections. The first deals with the definition of the concept of human-technology interaction and the second with the transformation of the competency structure.

Human-technology interaction is a research field that deals with the ways in which humans communicate, control, and collaborate with machines and technologies. These interactions are characterized by a dynamic between humans and technology, where technology ceases to be perceived as a mere tool and becomes an active element influencing human daily activities. [1, 2] Modern approaches emphasize symbiosis, where people and technology create closely interconnected systems in which both sides adapt and jointly develop their capabilities. [3] With the gradual development of technologies, the nature of their use is also changing, with a transition from human operation of technology to their mutual cooperation. Through this interaction, human

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capabilities are complemented and expanded with machine precision, speed, and capabilities [4]. Research highlights that this shift is leading to the creation of synergistic teams, where humans and machines learn to adapt, communicate, and complement each other, while human oversight and ethical considerations are still key. [5, 6] The result of this collaboration is higher productivity, safety, flexibility and creativity. [7]

In the era of Industry 4.0, the role of the human was most often understood as a role where an operator or other person supervised automated and digitalized systems. The goal was to maximize efficiency and productivity through technologies such as IoT, cyber-physical systems or AI. The human entered the processes as an entity who had to manage technological changes, adapt to new processes and ensure the smooth running of complex automated operations. [8, 9, 10]

Industry 5.0 shifts this model towards a human-centric production system, where the integration of human creativity, health, safety and well-being is key. Technologies such as collaborative robots, augmented reality, digital twins and AI are designed in the Industry 5.0 environment to strengthen human-machine collaboration, enable personalization, co-creation and sustainability. In this process, humans are active innovators and co-decision makers. [11, 12] A representation of the connection between the development of competencies in relation to industrial revolutions can be seen in Fig. 1.

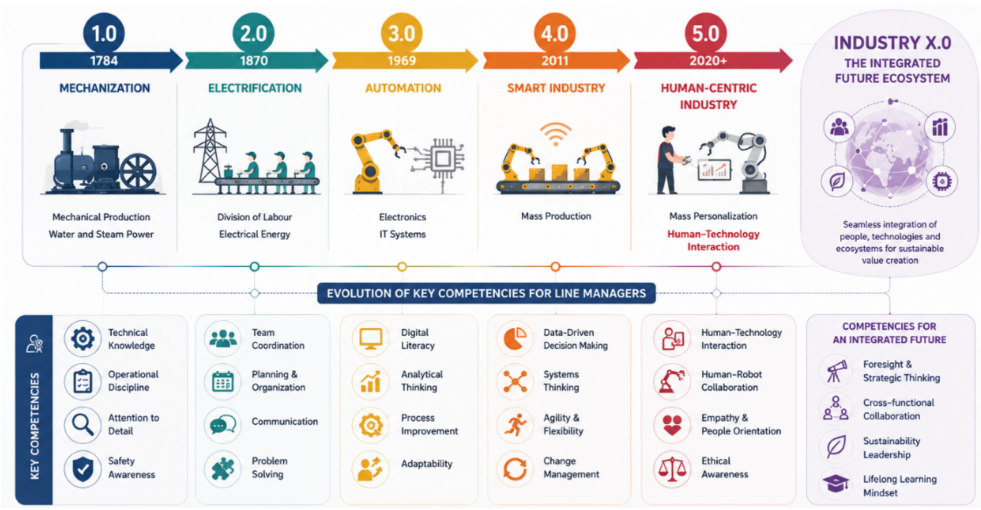

Fig. 1. Evolution of competencies for line managers (own elaboration, 2026)

Managerial competencies in the context of Industry X.0 are a complex set of technical, strategic, social and personal competencies that vary by management level and management context (Fig. 1). In Industry 4.0 and 5.0, management competencies are fundamentally changing due to digital transformation and the growing emphasis on a human-centered approach. Management competency profiles are oriented towards connecting technological, human and innovation competencies. [13] For effective digital transformation in manufacturing, key competencies are strategic change management, digital leadership, human resource planning and development, technological readiness, as well as the ability to connect Lean principles with digital tools. Industry 5.0 adds emphasis on human, social and ethical aspects, participatory leadership, innovation development, and support for inclusion and team well-being. Competency models for line managers in manufacturing emphasize the ability to lead a team in a fast-changing environment, support the adoption of digital tools, manage stress, and ensure effective information transfer. [14] Technological changes and digitalization have fundamentally restructured work, necessitating specific training initiatives and workplace practices that allow employees to best adapt to these emerging challenges. [15] The aforementioned transformation thus places demand not only on technical literacy, but above all on the ability of management to create an inclusive and safe environment for symbiotic cooperation between man and machine.

2. MATERIALS AND METHODS

The main aim of the paper is a comparative analysis of the required competencies of employees in a global context and the actually developed competencies of line managers in industrial enterprises in Slovakia.

The research design is based on a comparison of our own empirical data with the global benchmark The Future of Jobs Report 2025 published by the World Economic Forum. The empirical research was carried out in the form of a survey of HR department representatives and managers in medium and large industrial enterprises operating in the Slovak Republic, who assessed the current competency profiles at the operational management level. Overall, the structure of competencies in 16 selected enterprises representing a representative sample for industrial practice was analyzed. Based on theoretical foundations and global forecasts, we formulated a research hypothesis (RH).

RH1: There is a statistically significant difference between the observed frequencies of technological competencies in enterprises and the expected global trends.

The data were processed into a frequency table, and the Chi-square goodness-of-fit test was used to verify the hypothesis, which allowed for a comparison of observed values with expected trends for the period 2025 – 2030, with statistical significance tested at the alpha = 0.05 level.

3. RESULTS AND DISCUSSION

Current trends in the global labor market, analyzed in detail in The Future of Jobs Report 2025 [16], indicate a rapid and urgent transformation of employee requirements (competency structure). While in the past technical skills closely related to direct production performance dominated, the current prediction for the period 2025 – 2030 (Fig. 2) puts competencies such as AI and Big Data, Technological literacy and Creative thinking at the forefront. The aforementioned global shift creates significant pressure on the adaptability of local enterprises. It is in this context that it seems increasingly crucial to examine the extent to which Slovak enterprises reflect these current dynamic changes effectively.

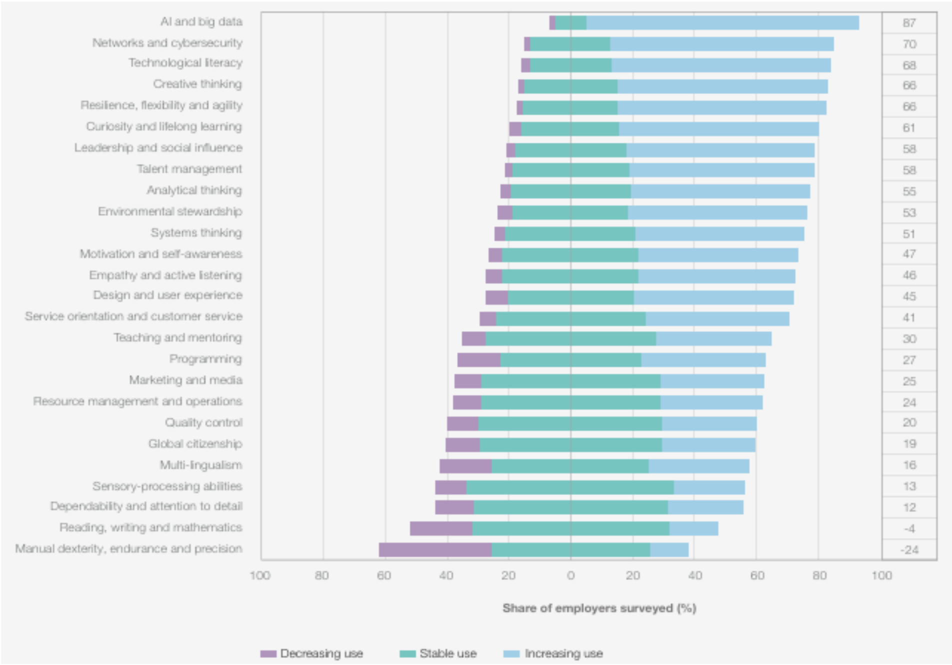

Fig. 2. Global competencies Demand Forecast ([16])

Figure 2 shows that the structure of competencies (skills) is influenced by developments and trends, which organizations should reflect on in order to keep up with trends and at the same time with competition. The authors of the paper conducted research on competency profiles to identify which competencies (skills) are currently preferred and developed in industrial enterprises in Slovakia. The results can be seen in Figure 3.

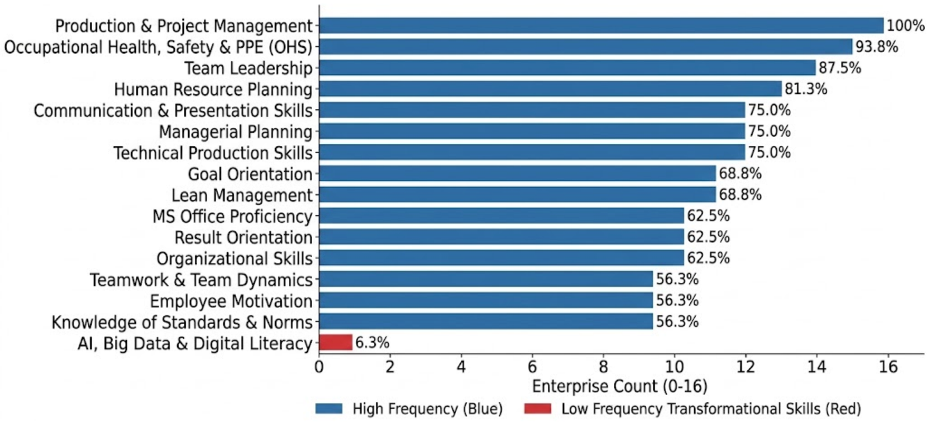

Fig. 3. Frequency of competencies in the surveyed enterprises (own elaboration, 2026)

The graphical analysis (Fig. 3) visualizes the level of representation of key competencies in the monitored set of industrial enterprises. The results confirm the dominance of traditional operational and managerial skills, where “Production and Project Management” reached 100% frequency, followed by the areas of OHS (93.8%) and team leadership (87.5%). A critical finding is the significant disparity between these established requirements and progressive competencies. While soft skills and operational planning show a high frequency of occurrence (over 60%), technological competencies of the future, represented by the category “AI, Big Data & Digital Literacy”, achieved only a minimal, 6.3% representation in current line manager profiles. This visual contrast (highlighted in red) clearly identifies the competency gap in relation to the emerging trends of Industry 5.0.

As part of the research, we verified the validity of the established hypothesis RH1, which assumed the existence of a significant difference between the local demand for competencies and the global trends predicted by the World Economic Forum.
RH0: There is no statistically significant difference between the observed frequencies of technological competencies in enterprises and the expected global trends.
RH1: There is a statistically significant difference between the observed frequencies of technological competencies in enterprises and the expected global trends.

The first step was to compare the observed (measured frequency) and expected frequency of occurrence of competencies, the result can be seen in Table 1.

Tab. 1. Comparison of competency frequencies (own elaboration, 2026)

Competency	Observed frequency (N)	Expected frequency*	Frequency deviation
AI and Big Data / ITC	1	14	-13
Analytical thinking	4	9	-5
Creative thinking	5	11	-6
Technological literacy	3	11	-8
Sum	13	45	-

* The expected frequency is derived from the percentage net increase in Figure 3 converted to the sample size.

The results of the test statistics for the Chi-Square test can be seen in Table 2 below.

Tab. 2. Chi-Square test statistics (own elaboration, 2026)

Statistical indicator	Value
Chi-Square (χ2)	18,421
df (Degrees of freedom)	3
Asymp. Sig. (p-value)	0

Based on the goodness-of-fit test, we found that the achieved significance level was $p < 0.001$, which is less than the set alpha level = 0.05. We reject the null hypothesis and accept hypothesis RH1. The results of statistical processing (Table 2) show that the structure of competencies in the analyzed enterprises in Slovakia shows a high degree of rigidity and does not correspond to dynamic changes in the global labor market. While global forecasts (Figure 3) place the highest emphasis on the areas of AI and Big Data and Technological literacy, in the monitored set of 16 enterprises these competencies achieved a critically low representation (only 6.25% to 18.75% of enterprises). This discrepancy (confirmed by the value of chi^2 = 18.421, $p < 0.001$) indicates that Slovak enterprises are currently focusing primarily on maintaining operational standards (OHS and production management), while underestimating the transformational potential of technologies that will be key in the period 2025–2030.

4. CONCLUSIONS

The research has shown a statistically significant difference between the global trends of Industry 5.0 and Slovak business practice. While the global demand is directed towards AI and digital literacy, domestic line managers are primarily focused on operational stability and OSH. The implication of the findings is the acute need to modernize educational strategies to avoid losing competitiveness. The limitations of the study lie in the smaller research sample, which limits the generalizability of the results. Future research should examine specific barriers that prevent the integration of technological competencies into management practice in a wider set of enterprises.

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References

[1] MAGLIOCCA, Pierpaolo, Rossella CANESTRINO, Elias G. CARAYANNIS a Anna Roberta GAGLIARDI, 2024. Understanding human–technology interaction: evolving boundaries. European Journal of Innovation Management [online]. 2024 [cit. 16.5.2026]. ISSN 1460-1060. Available on: doi:10.1108/EJIM-04-2024-0341

[2] BRANGIER, É., S. HAMMES-ADELÉ a J.-M.C. BASTIEN, 2010. Analyse critique des approches de l’acceptation des technologies : de l’utilisabilité à la symbiose humain-technologie-organisation. European Review of Applied Psychology [online]. 2010, Vol. 60, No. 2, pp. 129–146. ISSN 11629088. Available on: doi:10.1016/j.erap.2009.11.002

[3] INGA, Jairo, Miriam RUESS, Jan Heinrich ROBENS, Thomas NELIUS, Simon ROTHFUSS, Sean KILLE, Philipp DAHLINGER, Andreas LINDENMANN, Roland THOMASCHKE, Gerhard NEUMANN, Sven MATTHIESEN, Sören HOHMANN a Andrea KIESEL, 2023. Human-machine symbiosis: A multivariate perspective for physically coupled human-machine systems. International Journal of Human-Computer Studies [online]. 2023, Vol. 170, pp. 102926. ISSN 10715819. Available on: doi:10.1016/j.ijhcs.2022.102926

[4] WU, Duidi, Pai ZHENG, Qianyou ZHAO, Shuo ZHANG, Jin QI, Jie HU, Guo-Niu ZHU a Lihui WANG, 2026. Empowering natural human–robot collaboration through multimodal language models and spatial intelligence: Pathways and perspectives. Robotics and Computer-Integrated Manufacturing [online]. 2026, Vol. 97, pp. 103064. ISSN 07365845. Available on: doi:10.1016/j.rcim.2025.103064

[5] KYTAINYK, Vladislav. V., Alexander G. YUSHCHENKO a Daniil. Y. LYALIN, 2025. AI - human cooperation in “Second Brain” Technology, as a modern implementation of general evolution in human-machine interaction. V: 2025 7th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (ICHORA): 2025 7th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (ICHORA) [online]. Ankara, Turkiye: IEEE, pp. 1–9 [cit. 16.5.2026]. ISBN 9798331510886. Available on: doi:10.1109/ICHORA65333.2025.11017255

[6] CALLARI, Tiziana C., Ylenia CURZI a Niels LOHSE, 2025. Realising human-robot collaboration in manufacturing? A journey towards industry 5.0 amid organisational paradoxical tensions. Technological Forecasting and Social Change [online]. 2025, Vol. 219, pp. 124249. ISSN 00401625. Available on: doi:10.1016/j.techfore.2025.124249

[7] MIAO, Bin, Jiage ZHANG, Jiaxing ZHANG, Lu LI a Yitong HOU, 2025. Research on the Impact and Path of Human-Machine Collaborative Decision-Making on Dualistic Innovations. IEEE Access [online]. 2025, Vol. 13, pp. 88065–88077. ISSN 2169-3536. Available on: doi:10.1109/ACCESS.2025.3567343
[8] HINES, Peter, Florian MAGNANI, Josefa MULA a Raquel SANCHIS, 2026. Toward lean industry 5.0: a human-centered model for integrating lean and industry 4.0 in an automotive supplier. International Journal of Production Research [online]. 2026, Vol. 64, No. 1, pp. 250–273. ISSN 0020-7543, 1366-588X. Available on: doi:10.1080/00207543.2025.2551238
[9] BONGOMIN, Ocident, Mwewa Chikonkolo MWAPE, Nonsikelelo Sheron MPOFU, Brendah Kembabazi BAHUNDE, Richard KIDEGA, Ibrahim Luqman MPUNGU, Godias TUMUSIIME, Cynthia Awuor OWINO, Yannick Marnaigue GOUSSONGTOGUE, Aregawi YEMANE, Proscovia KYOKUNZIRE, Clement MALANDA, Jimmy KOMAKECH, Dan TIGALANA, Onesmas GUMISIRIZA a George NGULUBE, 2025. Digital twin technology advancing industry 4.0 and industry 5.0 across sectors. Results in Engineering [online]. 2025, Vol. 26, pp. 105583. ISSN 25901230. Available on: doi:10.1016/j.rineng.2025.105583
[10] KOMAČKA, Dávid, Martin KRAJČOVIČ, Marián MATYS a Milan MARČAN, 2026. Optimization of in-plant logistics processes in assembly systems using digital simulation tools: A case study using AGV and Twiserion Design Manager. Transportation Research Procedia [online]. 2026, Vol. 93, pp. 328–333. ISSN 23521465. Available on: doi:10.1016/j.trpro.2025.11.050
[11] NASIR, Vahid, Abbas HOSSEINI, Lucy BINFIELD, Nastaran HASANI, Salar GHOTB, Victoria DIEDERICHS, Galen O FOX, Ashley J MCCANN, Mariapaola RIGGIO, Kelly D CHANDLER a Eric HANSEN, 2025. Human-centric Industry 5.0 manufacturing: a multi-level framework from design to consumption within Society 5.0. International Journal of Sustainable Engineering [online]. 2025, Vol. 18, No. 1, pp. 2551000. ISSN 1939-7038, 1939-7046. Available on: doi:10.1080/19397038.2025.2551000
[12] TRSTENJAK, Maja, Andrea BENEŠOVA, Tihomir OPETUK a Hrvoje CAJNER, 2025. Human Factors and Ergonomics in Industry 5.0—A Systematic Literature Review. Applied Sciences [online]. 2025, Vol. 15, No. 4, pp. 2123. ISSN 2076-3417. Available on: doi:10.3390/app15042123
[13] MAGNANI, Florian, Peter HINES a Juliana Pereira SALVADORINHO, 2026. IPSEN's Shingo Prize journey: driving Industry 4.0 and 5.0 transformation. International Journal of Lean Six Sigma [online]. 2026, Vol. 17, No. 3, pp. 1040–1066. ISSN 2040-4166, 2040-4174. Available on: doi:10.1108/IJLSS-06-2025-0149
[14] FARMANESH, Panteha, Asim VEHBI a Niloofar SOLATI DEHKORDI, 2025. Uprooting Technostress: Digital Leadership Empowering Employee Well-Being in the Era of Industry 4.0. Sustainability [online]. 2025, Vol. 17, No. 19, pp. 8868. ISSN 2071-1050. Available on: doi:10.3390/su17198868
[15] MARCUS, Justin, et al., 2024. LeverAge: A European network to leverage the multi-age workforce. Work, Aging and Retirement [online]. 2024, Vol. 10, No. 4, pp. 309–316. ISSN 2054-4650. Available on: doi:10.1093/workar/waae009
[16] World Economic Forum. (2025). The Future of Jobs Report 2025. Available on the internet: https://www.weforum.org/reports/the-future-of-jobs-report-2025/

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AMO THEORY: THE BASIS OF A PERFORMANCE MANAGEMENT SYSTEM FOR GENERATION Z EMPLOYEES

Abstract

The aim of the article is to address the gaps in traditional performance management for Generation Z by proposing a conceptual model based on the AMO theory with development-oriented practices. It can be assumed that if performance management systems consider the need for continuous growth and technological inclusion of young employees, this can lead to an increase in their work initiative. For management practice, this theoretical assumption represents a strategic starting point that, through the AMO theory, enables effective management of human capital in a dynamic environment.

Key words: AMO theory, generation Z, performance management

1. INTRODUCTION

The advent of the digital economy and the transformation of the work environment in recent years have fundamentally changed the paradigm of human resource management. Traditional performance management models, which were oriented towards administrative control and retrospective evaluation of results, appear ineffective in the context of the needs of the emerging Generation Z. [6] Generation Z is shaped by technology and the blending of work and private life, which brings a new value setting to organizations that requires a more agile, development-oriented approach. [8]

One of the possible approaches to strategic human resource management is the AMO theory. It is based on the assumption that the resulting performance of an individual is determined by three interconnected components: professional competence (Ability), internal and external motivation (Motivation), and the degree of opportunities created for involvement in processes (Opportunity). [3] Although this model is well established in academia, its application to the specific needs of Generation Z within performance management systems remains unresolved. Current research suggests that while

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previous generations reflected mainly on financial and material motivators, for Generation Z, factors such as digital autonomy, continuous development of competencies and meaningfulness of work are key determinants of performance. [7,10] This article focuses on a conceptual reconstruction of the AMO model, which interprets the strategic framework of new generation employee performance management systems.

2. LITERATURE REVIEW

The AMO theory represents one of the most fundamental conceptual frameworks in the field of strategic human resource management. Its basic premise is that to achieve optimal individual performance, it is not enough to have only one component, but rather their synergy with each other [4].

2.1 Components of the AMO Theory

The first component represents Ability. It includes practices focused on recruitment, continuous education and skills training. Current research [5] emphasizes a shift from traditional training to development-oriented performance management practices that focus on long-term employee growth instead of short-term correction of deficiencies. Motivation represents the second component. It includes external forms of motivation such as salary, benefits, but also internal forms such as recognition or meaningfulness. The authors [11] state that motivational tools increase employees' internal identification with the company, which allows them to maintain stable performance even in conditions of low predictability of work tasks. The third component, Opportunity, refers to participative management, autonomy and information sharing. The study [2] states that providing opportunities for participation in problem solving is a key mediator of proactive employee behavior.

2.2 Generation Z and Digital Transformation

Generation Z, born between 1996 and 2010, enters the workforce with a unique set of values. Unlike Generation Y or Generation X, whose motivation in an industrial environment is often linked to stability and financial compensation, Generation Z places a higher emphasis on interesting work content and career growth opportunities [7]. The digital economy is transforming the way Generation Z perceives work. The authors [6] identify digital agility as a key competency for this generation. For this group, work is not just a source of income, but a path to self-fulfillment.

2.3 Performance management as a process

Connecting AMO theory and performance management for Generation Z requires transforming control mechanisms into supportive ones. According to the study [8] is essential to pay attention to the boundaries between work and private life in performance management systems. Their violation leads to increased employee turnover and a decrease in their engagement in work processes. Leadership style also plays a critical role in managing the performance of Generation Z employees.

The authors [9] confirm that younger employees are dominated by a preference for a transformational leadership style that encourages a culture of entrepreneurship and creativity. [1]

3. METHODS AND METHODOLOGY

Given the nature of the study, which is aimed at theoretical synthesis, the chosen procedure is based on a systematic literature search and subsequent analysis of the acquired knowledge. The basis for the processing of the article was 11 professional publications and scientific studies identified in the Scopus and Web of Science databases, supplemented by the Google Scholar search engine. The articles were published between 2019 and 2025. The selection of publications was targeted, focusing on three key areas: conceptual foundations of the AMO theory, value setting with motivational factors of Generation Z, and the transformation of performance management in the digital era. The following methods were used in document analysis:

- **Literature search and synthesis:** collecting and sorting knowledge into key areas.
- **Comparative analysis:** comparing traditional approaches to performance management with the modern needs of Generation Z identified in the analyzed studies.
- **Deductive method:** application of general principles of AMO theory to the specific environment of the digital economy and management of young employees.
- **Modeling:** creating a conceptual design for a performance management system based on the synthesis of findings that integrates components of AMO theory with development practices.

4. RESULTS AND DISCUSSION

Based on the synthesis of the analyzed knowledge, the article presents a conceptual AMO model with development-oriented practices that transforms the traditional perception of performance management into an adaptable system that takes into account the specifics of Generation Z.

4.1 Design of an integrated AMO model for Generation Z

The analysis shows that for effective performance management of Generation Z, it is necessary to update the individual components of AMO to reflect their digital identity and value preferences. The integrated model Fig. 1. shows the individual components of AMO theory developed based on the needs of Generation Z employees:

- **Ability:** Traditional training must be replaced with development-oriented practices. Digital agility and the ability to learn in real time are key for Generation Z. [6] Performance in this regard is not the product of mechanical routine, but the result of continuous self-improvement, which the organization supports through mentoring and digital learning platforms.
- **Motivation:** The study [7] confirms that financial compensation is important, but it loses its power for Generation Z if interesting work content and the possibility of working remotely are missing. Our model proposes motivation based on a psychological contract, where performance is rewarded with autonomy and

flexibility, which directly reduces the tendency to quiet quitting, as confirmed by the study [8].

- **Opportunity:** This is the most critical component for proactivity. For Generation Z, opportunity does not just mean attending meetings but having a real impact on processes through the culture of entrepreneurship. As the authors state [1], performance management systems must create an entrepreneurial culture where employees have the space to experiment without fear of failure.

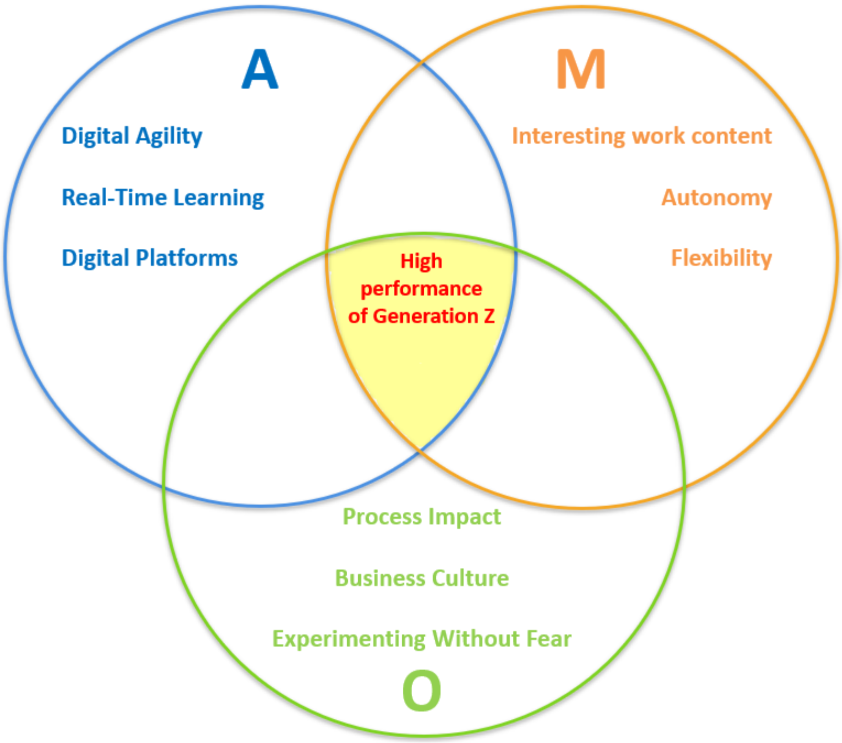

Fig. 1. Integrated AMO model for Generation Z [own elaboration, 2026]

The performance of Generation Z employees is not only influenced by direct HR practices, but also by the quality of workplace interactions. The author [2] emphasizes the importance of the relationship between the leader and the team member, which is confirmed by the study [9], that Generation Z requires leaders who act as coaches, not as controllers. For managers, this means changing their leadership style to a transformational one, which can significantly support the AMO model with development-oriented practices. Theoretical analysis suggests that the performance management of Generation Z must be transformed into a dynamic and continuous process that reflects current needs and immediate feedback. The proposed model emphasizes that high performance in the digital economy is the result of synergy between individual digital competence (**A**), intrinsic motivation based on meaning (**M**) and an entrepreneurial culture in which young employees also have an impact on processes (**O**).

5. CONCLUSION

The presented theoretical article dealt with the update of the theoretical concept of AMO as a strategic basis for managing the performance of Generation Z employees. Based on the analysis of 11 scientific studies published in recent years, we can conclude that traditional performance management mechanisms are insufficiently effective for the current digital generation.

The main theoretical contribution of the article is the finding that for Generation Z, the AMO conceptual model should be integrated with development-oriented practices. The capabilities component shows that the key is not only formal education, but also the support of digital agility and continuous learning. The motivation component confirms that intrinsic factors, such as work meaning and autonomy, outweigh purely transactional incentives. The opportunities component states that organizations must create space for an entrepreneurial culture and proactivity, which are factors directly related to higher organizational commitment.

In conclusion, the AMO theory remains a relevant tool even in the digital era, but its success depends on the ability of organizations to adapt HR practices to the values and needs of the new generation of workers.

References

[1] ALSHAAR, Q. et al. High-Performance Work Systems and Intrapreneurial Behavior: The Mediating Role of Knowledge Centered Culture. In Organizacija . 2023. Vol. 56, no. 3, s. 206–220. https://doi.org/10.2478/orga-2023-0014

[2] AL-TIT, A.A. The impact of AMO-HR systems on proactive employee behavior: The mediating contribution of leader-member and team-member exchange. In International Journal of Engineering Business Management . 2020. Vol. 12, s. 184797902094723. https://doi.org/10.1177/1847979020947236

[3] BOON, C. et al. A Systematic Review of Human Resource Management Systems and Their Measurement. In Journal of Management . 2019. Vol. 45, no. 6, s. 2498–2537. https://doi.org/10.1177/0149206318818718

[4] BOS-NEHLES, A. et al. Examining the Ability, Motivation and Opportunity (AMO) framework in HRM research: Conceptualization, measurement and interactions. In International Journal of Management Reviews . 2023. Vol. 25, no. 4, s. 725–739. https://doi.org/10.1111/ijmr.12332

[5] GIAMOS, D. et al. What is Known About Development-Oriented Performance Management Practices? A Scoping Review. In Human Resource Development Review . 2025. Vol. 24, no. 1, s. 37–69. https://doi.org/10.1177/15344843241278405

[6] KRAIDENKOV, Y. - SVIRIDOVA, L. Management of generation Z staff in the digital economy. In AKATOV, N. - ANTIPYEV, K.Ed. SHS Web of Conferences . 2021. Vol. 116, s. 00015. https://doi.org/10.1051/shsconf/202111600015

[7] MAŘÍKOVÁ, M. et al. Factors of Work Motivation in Production Engineering for Baby Boomers, Generations X, Y and Z. In Management Systems in Production Engineering . 2025. Vol. 33, no. 3, s. 321–331. https://doi.org/10.2478/mspe-2025-0031

[8] MATHUR, G. et al. Work-life balance and withdrawal behaviors among knowledge workforce: High performance work system comes into play for managing boundaries. In Global Business and Organizational Excellence . 2024. Vol. 43, no. 6, s. 24–40. https://doi.org/10.1002/joe.22257

[9] MOLEK, N. et al. Leadership Styles and Generational Differences in Manufacturing and Service Organizations. In Organizacija . 2023. Vol. 56, no. 3, s. 221–232. https://doi.org/10.2478/orga-2023-0015
[10] PHAM, T.-H. et al. A bibliometrics analysis of studies on Generation Z's self-perceived careers. In Cogent Business & Management . 2024. Vol. 11, no. 1, s. 2327120. https://doi.org/10.1080/23311975.2024.2327120
[11] UJMA, M. - INGRAM, T. Perception of ability-motivation-opportunity oriented HRM practices and organizational commitment: The role of task uncertainty. In Journal of Entrepreneurship, Management and Innovation . 2019. Vol. 15, no. 4, s. 139–162. https://doi.org/10.7341/20191545

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CORPORATE SOCIAL RESPONSIBILITY OF INDUSTRIAL COMPANIES AS A FACTOR IN CUSTOMER PURCHASING BEHAVIOR

Abstract

This paper examines corporate social responsibility (CSR) as a factor influencing consumer purchasing behaviour, with emphasis on generational differences. It synthesizes literature from Scopus, Web of Science and Google Scholar and complements it with bibliometric mapping in VOSviewer. The findings indicate that CSR can shape consumer preferences mainly through trust, reputation and value alignment. The paper recommends adapting CSR communication to the expectations of different customer generations.

Keywords: social responsibility, customer, purchasing behavior, generations

1. INTRODUCTION

Corporate Social Responsibility (CSR) refers to the voluntary consideration of social and environmental aspects alongside a company's economic objectives. It includes activities ranging from environmental protection and fair working conditions to supporting the communities in which the company operates. Growing pressure for sustainability, transparency, and ethics is transforming CSR into a strategic tool for building trust, loyalty, and relationships with stakeholders, which can also boost competitiveness. Consumer behavior is changing in addition to price and quality, brand values and stances are increasingly taken into account when making purchases. Perceived CSR can translate into loyalty, recommendations, and a willingness to accept a higher price. The generational context is also important: surveys indicate that Generation Z and millennials are more sensitive to CSR compared to older generations, while Generation X and baby boomers are often dominated by traditional attributes, particularly quality, reliability, and price.

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2. LITERATURE REVIEW

In the literature, CSR is defined as the voluntary integration of social and environmental considerations into corporate strategy and decision-making, alongside a focus on economic performance. [10] In practice, CSR is implemented in the environmental sphere (e.g., emissions reduction, eco-innovation), the social sphere (e.g., working conditions, diversity, and inclusion), and the community sphere (e.g., philanthropy, local partnerships). [11] In corporate management, CSR is shifting from a supplementary activity to a strategic tool for strengthening reputation, competitive position, and the quality of relationships with stakeholders. [16] Trust is built primarily when a company's behaviour is consistent and there is consistency between its declared values and actual actions. [16] Empirical studies report more favourable results in the areas of image and reputation and, in some cases, positive correlations with financial performance. [9, 12] These findings support the argument that CSR can be an investment in immaterial assets, brand equity, and trust. From a marketing perspective, CSR is significant when it translates into brand perception and consumer decisions. Consumers are increasingly taking into account the values and attitudes of brands, which can strengthen brand preference, reduce price sensitivity, and support longer-term relationships. [13] Perceived CSR is associated with loyalty, word-of-mouth recommendations, and a willingness to pay a higher price. [14] However, the effect depends on transparent and consistent communication and on linking CSR to the core of the business; otherwise, it may provoke scepticism. [16] The issue of generational differences is receiving particular attention. Surveys indicate that CSR carries greater weight among Generation Z and Millennials, including a willingness to switch brands in the event of a values mismatch. [1, 2, 8] For older generations, CSR tends to play a supplementary role, and quality, reliability, and price more often dominate purchasing decisions. [7] These differences suggest that CSR may not affect all consumers equally and that its impact should be analysed in the context of market segmentation, particularly when developing brand strategy and communication.

3. METHODS AND METHODOLOGY

This paper is a literature review focusing on the relationship between corporate social responsibility (CSR) and consumer decision-making. The aim of the paper is to conduct a literature review on CSR and its relationship to consumer preferences. The chosen approach is based on a qualitative synthesis and thematic analysis of findings from published empirical studies and relevant professional reports. The review was conducted using a combination of academic databases and search engines (Scopus, Web of Science, and Google Scholar) and supplementary practical sources, including the EIOPA Consumer Trends Report 2024, Deloitte Gen Z and Millennial Survey 2024, KPMG Survey of Sustainability Reporting 2020, and selected Slovak surveys. The search terms used included combinations of keywords: CSR/corporate social responsibility, sustainability reporting, consumer behavior, purchase intention, customer loyalty, willingness to pay, brand trust, corporate reputation, Generation. Sources published between 2019 and 2024 were primarily preferred; older works were included only if they provided basic definitions or conceptual foundations.

The following were included in the synthesis:

- peer-reviewed scientific articles and conference papers that explicitly addressed CSR or its dimensions and examined the link to consumer outcomes,
- studies using age segmentation,
- methodologically transparent expert reports from reputable institutions.

The selection process consisted of two steps: screening of titles and abstracts, and evaluation of the full text. The following data were primarily extracted from the included sources: context and industry, country and sample characteristics, method of CSR measurement, generations/age groups included, and outcome variables (loyalty, purchase intention). The results may be influenced by publication bias, differing definitions of CSR indicators and items across studies, and sample heterogeneity. Another limitation is language availability and source selection. For these reasons, the findings are interpreted as a synthesis of trends. To complement the structured literature review, bibliometric mapping was conducted in VOSviewer to identify thematic clusters in the literature based on keyword co-occurrence [15]. Bibliographic records were exported from Web of Science (metadata: authors, title, keywords) and merged into a single file. To reduce noise, synonyms of keywords (e.g., CSR vs. corporate social responsibility) were standardized using the VOSviewer file. VOSviewer was used primarily to create co-occurrence maps of keywords and to identify topic clusters. Full counting was used when creating the maps, and the minimum occurrence threshold for terms was set to 2 occurrences to ensure the maps remained interpretable.

4. RESULTS AND DISCUSSION

A synthesis of available surveys indicates that CSR is becoming an increasingly important part of business practice and sustainability initiatives. According to the KPMG Survey of Sustainability Reporting 2020, 76% of the largest Slovak companies report sustainability activities, although Slovakia's ranking of 40th out of 52 countries suggests further room for improvement. [3] UniCredit Bank's survey shows that sustainability principles are already embedded in many companies, particularly through environmentally friendly waste management, emission reduction and the use of renewable energy sources. [5] Public expectations are also relevant: the Business Leaders Forum (2023) found that people most often associate responsible business with environmental responsibility, care for employees and safe working conditions. [4] Generational differences further shape the perception of CSR. Deloitte's 2024 Gen Z and Millennial Survey shows that younger generations attach strong importance to a company's social impact and community engagement when choosing employers and brands. [2] Similarly, the EIOPA Consumer Trends Report (2024) highlights the increasing role of sustainability, ethics, transparency and digital communication among younger EU consumers. [1] However, CSR priorities differ across groups: older generations may place greater emphasis on quality and price, while Moisescu and Gică (2020) suggest that Generation X may value the social dimension of CSR more than the environmental one. [6] These findings point to the need for targeted, evidence-based and consistent CSR communication adapted to generational expectations. As part of this study, a bibliometric analysis was conducted using publications exported from Web of Science. The analysed dataset consisted of N = 40 records published between 2019 and 2024. Author keywords and index keywords were analysed in VOSviewer, and a thesaurus file was used to standardize synonymous terms such as “CSR” and “corporate social responsibility”. The analysis identified 29 terms grouped into 5 clusters. The dominant nodes were “corporate social responsibility” and “purchase intention”, while “consumer behaviour” also played an important bridging role, indicating that the analysed literature frames CSR mainly through its influence on purchase intentions and consumer behaviour.

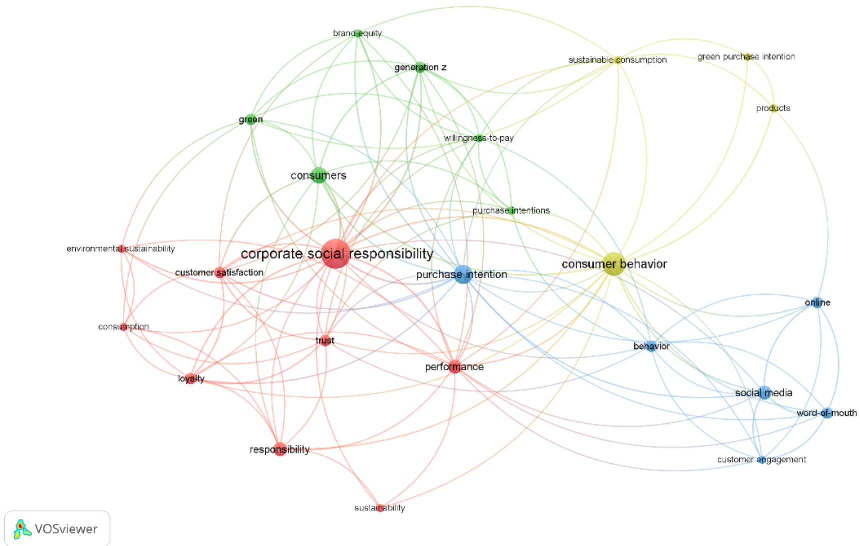

Fig. 1. Bibliometric analysis of publications (own processing)

Fig. 1 shows that corporate social responsibility is the most central concept and is most strongly linked to the themes of purchase intention and consumer behaviour, which act as “bridges” between the clusters. The red cluster brings together economic and marketing outcomes and evaluative variables (e.g., loyalty, trust) along with links to sustainability. The green cluster is linked to segmentation and is dominated by consumers, Generation Z, and brand equity. The yellow cluster focuses solely on “green” behaviour (sustainable consumption, green purchase intention) and is firmly linked to consumer behaviour. The blue cluster clearly distinguishes the digital environment (social media, online, word-of-mouth) and suggests that CSR effects often spread and intensify through online interactions.

5. CONCLUSION

This paper synthesizes findings on how corporate social responsibility (CSR) influences consumer decision-making and what role generational differences play in this relationship. The research suggests that CSR most often does not have a direct effect, but rather an indirect one through brand trust, perceived reputation, value alignment, and consumer identification with the brand. If a company communicates CSR authentically and demonstrates consistency between its statements and practices, these mechanisms typically translate into higher brand preference, purchase intent, recommendations, and loyalty. Regarding willingness to pay a higher price, the results are more mixed and sensitive to product category, price level, and the credibility of information sources. The impact of CSR also depends on the industry and the degree of consumer engagement. From a generational perspective, it has repeatedly been shown that younger generations (especially Gen Y and Gen Z) report greater sensitivity to environmental and social issues and more frequently expect transparency and evidence-based CSR claims (measurable results, independent verification, clear goals). However, their actual behaviour may be significantly limited by price and availability, which highlights the gap between attitudes and actual purchasing behaviour. Generation X is more pragmatic: CSR builds trust and reputation among this group, but without clearly communicated added value and personal relevance, it may not lead to brand switching. This highlights the need to segment CSR communication by generation, channel, and motivation.

Supplementary bibliometric mapping of keywords in VOSviewer confirms that research naturally centres on the link between CSR and consumer behaviour, often followed by a line of purchasing behaviour. Variables that capture mediating mechanisms (e.g., trust, perceived value, satisfaction, and loyalty) also repeatedly appear in the network, supporting the conclusion that CSR effects are often transmitted through relational and value-based factors. At the same time, a distinct branch of the digital environment (online, social media, word-of-mouth) is clearly emerging, highlighting the importance of marketing communication channels in translating CSR into customer behaviour and engagement. The generational dimension is also captured directly (particularly through Generation Z), which underscores the need to differentiate CSR approaches by generation and specific communication channels. Despite positive trends in the area of CSR in Slovakia, there are several reasons why it is necessary to continue researching this topic.

- First, while the proportion of companies reporting CSR activities is growing, Slovakia still ranks below other countries in the region, such as Hungary and Poland; understanding the factors that hinder the development of CSR can help in formulating strategies to improve this situation.
- Second, growing public awareness is increasing pressure on companies to transparently communicate their CSR activities; examining public perceptions and expectations can help companies better tailor their strategies and communications.
- Third, legislative changes and the implementation of the European Corporate Sustainability Reporting Directive (CSRD) require more detailed and standardized sustainability reporting; therefore, understanding the implications of these changes is key to both compliance and effective reporting.
- Fourth, companies that effectively integrate CSR into their strategy can gain a competitive advantage, attract talented employees, and strengthen customer loyalty; identifying best practices can serve as inspiration for other businesses.

Future research should focus on experimentally verifying the effects of CSR communication by industrial companies and on comparing the purchasing behaviour of different generations of customers.

References

[1] EUROPEAN INSURANCE AND OCCUPATIONAL PENSIONS AUTHORITY: *Consumer Trends Report 2024* (EIOPA-BoS-24/584). 2024. Available on the internet:https://www.eiopa.europa.eu/publications/consumer-trends-report-2024_en

[2] DELOITTE: *2024 Gen Z and Millennial Survey: Living and working with purpose in a transforming world*. 2024. Deloitte Touche Tohmatsu Limited. Available on the internet:https://www2.deloitte.com/global/en/pages/about-deloitte/articles/genz-and-millennialsurvey.html

[3] KPMG: *The time has come: The KPMG Survey of Sustainability Reporting 2020*. 2020. KPMG International. Available on the internet:: https://home.kpmg/sustainabilityreporting

[4] BUSINESS LEADERS FORUM: *Od zodpovedných firiem ľudia očakávajú najmä zdravé a bezpečné podmienky pri práci, ukázal prieskum*. Business Leaders Forum, 27. september 2023 Available on the internet: https://www.blf.sk/aktuality-partnerov/od-zodpovednych-firiem-ludia-ocakavaju-najma-zdrave-a-bezpecne-podmienky-pri-praci-ukazal-prieskum/

[5] KANCELÁRIE.SK: *Prieskum UniCredit: Investície do ESG rastú*. 7. december 2023. Available on the internet: https://www.kancelarie.sk/poradna/prieskum-unicredit-investicie-do-esg-rastu

[6] MOISESCU, O.-I., GICĂ, O.-A.: The impact of environmental and social responsibility on customer loyalty: A multigroup analysis among generations X and Y. *International Journal of Environmental Research and Public Health*, vol. 17, no. 18, 2020, article no. 6466. Available on the internet: https://doi.org/10.3390/ijerph17186466

[7] RAZA, M., ZAMAN, S. U., QABOOL, S., ALAM, S. H., SHAFIQ-UR-REHMAN: Role of marketing strategies to Generation Z in emerging markets. *Journal of Organisational Studies and Innovation*, vol. 9, no. 3, 2022, pp. 16–43. Available on the internet: https://doi.org/10.51659/josi.21.166

[8] SERVERA-FRANCÉS, D., PIQUERAS-TOMÁS, L.: The effects of corporate social responsibility on consumer loyalty through consumer perceived value. *Economic Research – Ekonomska Istraživanja*, vol. 32, no. 1, 2019, pp. 66–84. Available on the internet: https://doi.org/10.1080/1331677X.2018.1547202

[9] NADANYIOVA, M., GAJANOVA, L., MAJEROVA, J.: Green marketing as a part of the socially responsible brand's communication from the aspect of generational stratification. *Sustainability*, vol. 12, no. 17, 2020, article no. 7118. Available on the internet: https://doi.org/10.3390/su12177118

[10] THOMAS, G.: Corporate social responsibility as a sustainable business practice: A study among Generation Z customers of Indian luxury hotels. *Sustainability*, vol. 14, no. 24, 2022, article no. 16813. Available on the internet: https://doi.org/10.3390/su142416813

[11] JELINKOVA, M., TETREVOVA, L., VAVRA, J., MUNZAROVA, S.: The sharing economy in the context of sustainable development and social responsibility: The example of the Czech Republic. *Sustainability*, vol. 13, no. 17, 2021, article no. 9886. Available on the internet: https://doi.org/10.3390/su13179886

[12] HOANG, V. H., NGO, Q. D., MAI, A. K., LE, H. M.: The impact of corporate social responsibility on customer loyalty in multi-channel distribution: A generational perspective. *Journal of Distribution Science*, vol. 22, no. 12, 2024, pp. 23–34. Available on the internet: https://doi.org/10.15722/jds.22.12.202412.23

[13] NARAYANAN, S.: Does Generation Z value and reward corporate social responsibility practices? *Journal of Marketing Management*. Advance online publication, 2022. Available on the internet: https://doi.org/10.1080/0267257X.2022.2070654

[14] POPOVICS, A.: Characteristics of consumer segments based on consumer habits and preferences from an environmental and social responsibility perspective. *Acta Polytechnica Hungarica*, vol. 21, no. 12, 2024, pp. 133–146

[15] VAN ECK, N. J., WALTMAN, L.: Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics, vol. 84, no. 2, 2010, pp. 523–538. Available on the internet: https://doi.org/10.1007/s11192-009-0146-3

[16] HĄBEK, P., WOLNIAK, R.: Assessing the quality of corporate social responsibility reports: The case of reporting practices in selected European Union member states. Quality & Quantity, vol. 50, no. 1, 2016, pp. 399–420. Available on the internet: https://doi.org/10.1007/s11135-014-0155-z

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COMPARATIVE ANALYSIS OF MATURITY MODELS FOR THE ASSESSMENT OF GREEN AND SUSTAINABLE MANUFACTURING IN INDUSTRIAL ENTERPRISES

Abstract

This paper focuses on comparing selected maturity models that can be used to assess green and sustainable manufacturing in industrial enterprises. The aim of the paper is to identify the main characteristics, assessed areas, maturity levels, methodological approaches, and application possibilities of five models from the professional literature. Attention is given to models focused on sustainable production, green production orientation, the sustainability of small and medium-sized enterprises, remanufacturing, and the integration of Lean and Green approaches. The result is a comparative overview that highlights the differences between the models from both a content-application and a structural-methodological perspective. The paper also lays the groundwork for further research on assessing the level of green manufacturing implementation in industrial enterprises.

Key words: green manufacturing, sustainable manufacturing, maturity model, sustainability assessment

1. INTRODUCTION

Green and sustainable manufacturing is a key area of development for industrial companies, as the manufacturing sector is directly linked to the consumption of materials, energy, and water, as well as waste generation and other environmental impacts. Companies are therefore seeking ways to reduce the negative environmental impacts of manufacturing processes while maintaining their competitiveness. In the manufacturing sector, there is a growing need for more efficient use of resources and for evaluating progress in implementing sustainable manufacturing approaches. [1]

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One of the tools that enable the systematic assessment of companies' progress in the area of green and sustainable manufacturing are maturity models. These models make it possible to determine a company's current level, identify areas for improvement, and set the direction for further development based on criteria for higher levels of maturity. They typically operate with multiple development levels, with each level representing a certain stage of development in processes, practices, or management systems. In the context of sustainable manufacturing, they may focus, for example, on material and energy efficiency, water use, environmental management systems, green manufacturing strategies, remanufacturing, or the integration of lean and green manufacturing. [1, 3, 5]

The importance of maturity models is growing, particularly because companies do not apply green production approaches to the same extent, and their activities may be inconsistent, incomplete, or dependent on specific operations. At the same time, a challenge in the field of green manufacturing is that many maturity models do not have sufficiently clearly defined maturity levels or are not sufficiently empirically validated [2]. For this reason, attention must be paid to comparing models that allow for the assessment of the level of development of green and sustainable manufacturing from various perspectives. Small and medium-sized enterprises require special attention, as they often lack the capacity, financial resources, or technical infrastructure to implement comprehensive assessment systems. For these enterprises, models that enable a simpler assessment of sustainability maturity through environmental knowledge management, environmental strategies, practices, and management systems are therefore particularly suitable. [3]

Similarly, in the field of remanufacturing, there is a need for simpler assessment procedures, as companies operating in this sector may not have sufficient capacity to utilize complex theoretical models. [4] The relevance of this issue is further supported by recent review studies, which indicate that research on sustainable production is linked to technological, environmental, and socio-economic aspects. [6] At the same time, these studies emphasize the need for clear frameworks that would enable companies to identify relevant areas for improvement and to implement sustainable production practices in practice. [7] In this context, the importance of maturity models expanded to include environmental attributes of production is also evident, as they allow for linking the evaluation of production processes with the transition to environmentally responsible production. [8]

The aim of this article is to compare selected maturity models applicable to the evaluation of green and sustainable production in industrial enterprises. The focus is on identifying their core focus, assessed areas, maturity levels, methodological approach, and practical application possibilities. The compared models include approaches oriented toward sustainable production, green production orientation, sustainability of small and medium-sized enterprises, remanufacturing, and the integration of Lean and Green approaches.

2. METHODS AND METHODOLOGY

The methodological section of the article was based on a review and comparative analysis of five selected scientific papers focusing on maturity models in the field of green and sustainable production. The selection of articles was deliberate, as the aim was not to conduct a systematic literature review, but to compare relevant models applicable to the assessment of green or sustainable production in industrial enterprises. [1-5]

Four criteria were considered in the selection of articles: the presence of a maturity model or evaluation framework, a link to a manufacturing enterprise or manufacturing process, a focus on environmental sustainability, and the possibility of comparing models according to uniform criteria.

The analysis therefore included models focused on sustainable production, green production orientation, small and medium-sized enterprises, remanufacturing, and the integration of lean and green approaches. The analysis was conducted in two steps. In the first step, individual articles were evaluated separately in terms of the model's name, main focus, areas of assessment, and application context. In the second step, the models were compared on two levels. The first level was content- and application-based and focused on the model's main strength, its primary focus, and suitable practical applications.

The second level was structural and methodological and took into account the number of maturity levels, the nature of these levels, and the model's methodological approach. The result of this methodological procedure is a comparative synthesis presented in two tables, which allow for the identification of common and distinct features of the selected maturity models and their applicability in the assessment of green and sustainable production.

3. RESULTS AND DISCUSSION

Based on the chosen methodological approach, the selected maturity models were compared on two levels: content and application, and structure and methodology. The content and application comparison focused on the main focus of the models, their strengths, and their potential for use in industrial enterprises. The structural-methodological comparison examined the number of maturity levels, the nature of these levels, and the methodological approach of each model.

The comparison showed that all analyzed models are based on the common idea of the gradual development of a company from a lower to a higher level of maturity. Their common feature is the effort to determine the current state of the enterprise, identify areas for improvement, and support the systematic implementation of green or sustainable production approaches. [1-5] Differences between the models are evident primarily in their thematic focus, the areas assessed, and their practical applicability.

Tab. 1. Comparative synthesis of selected maturity models (Own research, 2026)

Article	Model name	Main strength	Main focus	Suitable application
Jain & Rachuri (2014) [1]	**SM3 – Sustainable Manufacturing Maturity Model**	emphasis on measurable indicators of resource efficiency	materials, energy, water	assessment of manufacturing plant sustainability
Shukla & Adil (2021) [2]	**MSM-GMO – Maturity Stage Model of Green Manufacturing Orientation**	the most direct link to green manufacturing	green manufacturing orientation	assessment of an enterprise's strategic orientation toward green manufacturing
Vasquez et al. (2021) [3]	**SMMM – Sustainability Maturity Model for MSMEs**	practical applicability for SMEs and data-based assessment	environmental knowledge, practices and systems	assessment of SMEs' sustainability maturity
Golinska & Kuebler (2014) [4]	**Method for Assessment of Sustainability Maturity in Remanufacturing Companies**	specific focus on product recovery and reuse	remanufacturing	assessment of enterprises' maturity in circular manufacturing
Verrier, Rose & Caillaud (2016) [5]	**Lean and Green Maturity Deployment Model**	integration of lean tools and environmental improvement	Lean and Green	elimination of production and environmental waste

From a content and application perspective, it can be noted that Model [1] focuses primarily on assessing sustainable production at the plant level, with an emphasis on materials, energy, and water.

Model [2] has the most direct link to green manufacturing, as it assesses the development of a green manufacturing orientation from a legislatively driven approach to a strategic and proactive level. Model [3] is particularly suitable for small and medium-sized enterprises, as it links environmental knowledge, practices, and management systems with data-driven assessment.

Model [4] is specifically focused on remanufacturing and the assessment of economic, environmental, and social performance. Model [5] links environmental improvement with lean management and focuses on eliminating production and environmental losses. It follows from the above that the analyzed models are not entirely interchangeable. Their use depends on the assessment objective, the type of enterprise, data availability, and the level of environmental management implementation. If the objective is to assess the resource efficiency of production, model [1] is appropriate. When assessing a company's strategic orientation toward green production, model [2] is the most suitable. Model [3] is practically applicable for small and medium-sized enterprises, model [4] for the remanufacturing sector, and model [5] for companies using lean management.

Tab. 2. Structural and methodological comparison of selected maturity models (Own research, 2026)

Article	Number of maturity levels	Character of levels	Methodological approach
Jain & Rachuri (2014) [1]	5	from the initial level to the Best-in-Class level, i.e. the highest level compared with benchmark enterprises	conceptual model design based on a review of initiatives, standards and indicators of sustainable manufacturing
Shukla & Adil (2021) [2]	4	from a legislation-driven approach to the position of a leader and promoter of green manufacturing	synthesis of the literature and design of a maturity model for an enterprise's green manufacturing orientation
Vasquez et al. (2021) [3]	4	from an insufficient to a consolidated level of sustainability maturity	Design Science Research, i.e. an approach focused on the design and validation of a practically applicable model, complemented by data analytics and classification algorithms
Golinska & Kuebler (2014) [4]	4	from a basic existing process to advanced optimization management	questionnaire-based self-assessment according to the economic, environmental and social dimensions of sustainability
Verrier, Rose & Caillaud (2016) [5]	5	from limited implementation to advanced integration of lean and green manufacturing	use of the Capability Maturity Model Integration logic, i.e. an approach based on gradual improvement of process maturity, applied to the Lean and Green approach

A structural and methodological comparison showed that the analyzed models most often use four or five maturity levels. These levels reflect a gradual transition from a basic, reactive, or partially developed approach to a systematic, optimized, or strategically managed application of the principles of green and sustainable production.

The differences between the models relate primarily to whether the maturity levels are formulated generally for sustainable production or are adapted to a specific context, such as green production orientation, SMEs, remanufacturing, or the Lean and Green approach. Another significant difference is the degree of practical validation of the models.

Models [2], [3], and [4] have been applied to specific companies or samples of companies, thereby increasing their practical applicability. Model [1] is more conceptual in nature but provides a clear foundation for assessing sustainable manufacturing at the plant level. Model [5] is particularly valuable in that it links environmental improvement with existing lean tools, which may be more practical for companies than implementing a separate assessment system.

Based on this comparison, it can be concluded that maturity models are a suitable tool for initial diagnosis and for guiding the further development of green and sustainable production. However, their practical applicability depends not only on the number of maturity levels, but primarily on the clarity of the evaluation criteria, the availability of necessary data, and the possibility of reusing the model within the specific conditions of a given enterprise. For small and medium-sized enterprises, it is therefore important to prioritize models that are simple, clear, and require minimal input data.

4. CONCLUSION

The aim of this paper was to compare selected maturity models that can be used to assess green and sustainable production in industrial enterprises. Based on an analysis of five models, it can be concluded that maturity models are a suitable tool for systematically assessing a company's current level, identifying areas of weakness, and planning further improvements. A common feature of these models is the division of a company's development into multiple levels, which allows for tracking the shift from a basic or reactive approach to systematically managed and strategically integrated green or sustainable production. The compared models differ primarily in their focus, methodological approach, and practical application possibilities. Model [1] is oriented toward assessing the resource efficiency of production; model [2] provides the most direct link to a green production orientation; model [3] is suitable for small and medium-sized enterprises; model [4] is specifically focused on remanufacturing; and model [5] links environmental improvement with lean management. The comparison suggests that the selection of an appropriate model should be based primarily on the assessment objective, the type of enterprise, data availability, and the level of development of environmental management. The results also confirm the need for simple, understandable, and reusable evaluation frameworks that can take into account the varying conditions of industrial enterprises. This need is particularly significant for small and medium-sized enterprises, where the implementation of complex assessment systems may be limited by the availability of data, capacity, and expert resources. Current research also highlights the growing interconnection between sustainable production and technological, environmental, and socio-economic aspects, which increases the importance of practically applicable maturity models [6], [7], [8]. This paper provides a foundational overview for further research in the field of assessing the level of green manufacturing implementation. The findings can be used in the development or adaptation of assessment tools that will take into account the needs of industrial enterprises, data availability, and the requirement for the gradual improvement of the environmental performance of manufacturing processes.

References

[1] JAIN, S., & RACHURI, S. (2014). *Maturity Model Concepts for Sustainable Manufacturing*. NISTIR 7989. National Institute of Standards and Technology. DOI: http://dx.doi.org/10.6028/NIST.IR.7989.

[2] SHUKLA, G. P., & ADIL, G. K. (2021). *A four-stage maturity model of green manufacturing orientation with an illustrative case study*. Sustainable Production and Consumption, 26, 971–987. DOI: https://doi.org/10.1016/j.spc.2021.01.009.

[3] VASQUEZ, J., AGUIRRE, S., PUERTAS, E., BRUNO, G., PRIARONE, P. C., & SETTINERI, L. (2021). *A sustainability maturity model for micro, small and medium-sized enterprises (MSMEs) based on a data analytics evaluation approach*. Journal of Cleaner Production, 311, 127692. DOI: https://doi.org/10.1016/j.jclepro.2021.127692.

[4] GOLINSKA, P., & KUEBLER, F. (2014). *The method for assessment of the sustainability maturity in remanufacturing companies*. Procedia CIRP, 15, 201–206. DOI: https://doi.org/10.1016/j.procir.2014.06.018.

[5] VERRIER, B., ROSE, B., & CAILLAUD, E. (2016). *Lean and Green strategy: the Lean and Green House and maturity deployment model*. Journal of Cleaner Production, 116, 150–156. DOI: https://doi.org/10.1016/j.jclepro.2015.12.022.

[6] SETYADI, A., SOEKOTJO, S., LESTARI, S. D., PAWIROSUMARTO, S., & DAMARIS, A. (2025). Trends and Opportunities in Sustainable Manufacturing: A Systematic Review of Key Dimensions from 2019 to 2024. Sustainability, 17(2), 789. https://doi.org/10.3390/su17020789

[7] SCHARMER, V. M., VERNIM, S., HORSTHOFER-RAUCH, J., JORDAN, P., MAIER, M., PAUL, M., SCHNEIDER, D., WOERLE, M., SCHULZ, J., & ZAEH, M. F. (2024). *Sustainable Manufacturing: A Review and Framework Derivation*. Sustainability, 16(1), 119. https://doi.org/10.3390/su16010119

[8] ZOUBEK, M., POOR, P., BROUM, T., BASL, J., & SIMON, M. (2021). *Industry 4.0 Maturity Model Assessing Environmental Attributes of Manufacturing Company*. Applied Sciences, 11(11), 5151. https://doi.org/10.3390/app11115151

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DATA INTERACTIONS BETWEEN VIRTUAL AND PHYSICAL ENVIRONMENTS IN BIMANUAL ROBOTIC CONTROL USING CYBERGLOVE II

Abstract

This paper focuses on data interactions between virtual and physical environments in industrial automation using wearable motion sensing technologies. The proposed system integrates CyberGlove II data gloves, a virtual control environment, and robotic manipulators into a unified real-time control architecture. The original single-hand configuration was extended to support synchronized bimanual robotic control through independent communication channels, modular software architecture, and parallel sensor processing. The implemented system enables accurate motion transfer between the human operator and physical robotic hands while maintaining stable real-time operation. Experimental verification confirmed reliable synchronization, independent calibration, and simultaneous control of both robotic manipulators. The proposed approach demonstrates the potential of virtual-physical interaction systems for teleoperation, intelligent manufacturing, and advanced human–robot collaboration in Industry 4.0 applications.

Key words: virtual reality, cyber-physical systems, robotic control, data glove

1. INTRODUCTION

The integration of virtual and physical environments represents an important trend in modern industrial automation and intelligent manufacturing systems. The rapid development of virtual reality technologies, cyber-physical systems, motion sensing

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devices, and real-time communication architectures enables new approaches to human-machine interaction and robotic control. These technologies allow operators to control robotic systems using natural human movements, improving intuitiveness, flexibility, and operational efficiency in industrial applications. [1]

One of the key technologies used in virtual-physical interaction systems is wearable motion sensing equipment. Data gloves enable real-time acquisition of hand and finger movements and provide direct mapping of human motion into virtual or physical robotic environments. Such systems are increasingly used in teleoperation, robotic manipulation, virtual training environments, rehabilitation systems, and collaborative robotics applications. [2-4]

In industrial automation, many manipulation tasks require coordinated bimanual operation. However, a significant number of existing glove-based robotic control systems are limited to single-hand operation or rely on proprietary hardware and software solutions with limited extensibility. These limitations reduce the applicability of such systems in advanced industrial scenarios requiring synchronized interaction between virtual and physical systems

.

The work presented in this paper focuses on data interactions between virtual and physical environments using CyberGlove II wearable sensing technology and robotic manipulators. The original system configuration enabled control of a single robotic hand within a virtual control environment. The proposed research extends this architecture toward synchronized bimanual robotic control through modular software implementation, parallel sensor processing, independent communication channels, and real-time motion synchronization.

The main objective of this research is to design and experimentally verify a virtual-physical interaction architecture capable of simultaneous control of two robotic manipulators using dual CyberGlove II data gloves. The proposed solution introduces a modular control framework enabling stable real-time operation, synchronized motion transfer, and independent calibration of both robotic hands.

The presented approach demonstrates the potential of wearable motion sensing technologies and virtual-physical interaction systems for applications in Industry 4.0, intelligent manufacturing, teleoperation, and advanced human-robot collaboration.

2. VIRTUAL-PHYSICAL INTERACTION ARCHITECTURE

The proposed system architecture is based on real-time data interactions between a virtual control environment and physical robotic manipulators. The system integrates wearable sensing technology, communication interfaces, virtual control modules, and robotic actuators into a unified cyber-physical control framework.

The primary input devices of the system are two CyberGlove II data gloves assigned independently to the left and right hand of the operator. Each glove captures finger and hand movements using multiple embedded motion sensors, enabling accurate mapping of human hand kinematics into robotic manipulation tasks [5]. The acquired sensor data are transmitted to the control software, where individual sensor values are processed, calibrated, and mapped to corresponding robotic hand movements. The implemented architecture enables parallel processing of sensor data streams from both gloves. Independent communication channels were established for the left and right robotic manipulators to ensure stable real-time operation and synchronized bimanual control. The software structure was redesigned into modular control units separating sensor acquisition, calibration routines, communication handling, and servo actuation for each robotic hand independently.

The virtual control environment provides real-time visualization of sensor activity, actuator response, and communication status. This interface enables monitoring of system operation, calibration procedures, and synchronization between the virtual and physical components of the system. Real-time visual feedback significantly improves system controllability and operational reliability during robotic manipulation tasks.

The proposed architecture also includes automatic device detection and communication port assignment. This functionality eliminates manual configuration of communication interfaces and enables reliable identification of connected robotic devices during system initialization. Independent device management additionally improves system scalability and simplifies future integration of additional robotic modules or manipulators. The complete virtual-physical interaction process can be described as a continu
ous data flow consisting of motion acquisition, sensor processing, real-time data transmission, virtual representation, and physical robotic actuation. This architecture enables stable and intuitive human-robot interaction suitable for teleoperation, intelligent manufacturing systems, and advanced Industry 4.0 applications.

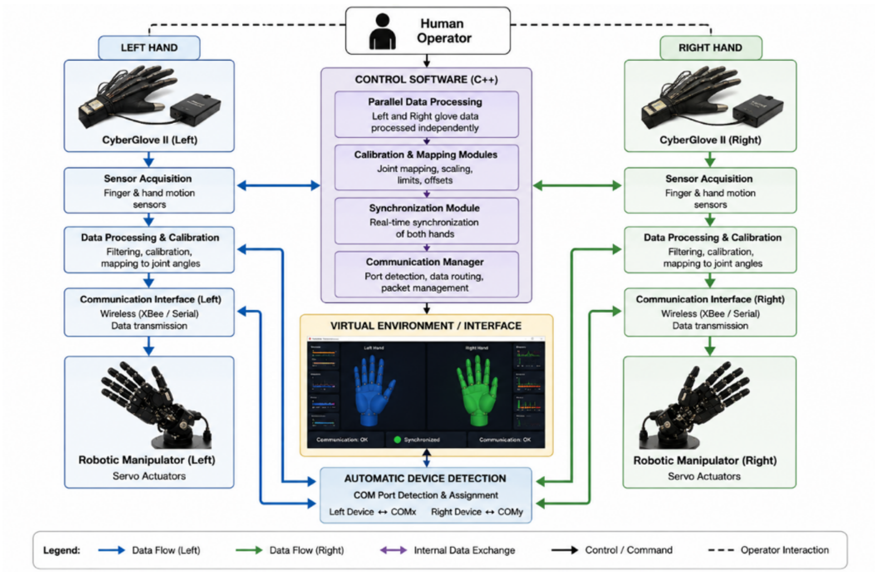

Fig. 1. Architecture of virtual-physical interaction between CyberGlove II devices and robotic manipulator

3. EXPERIMENTAL SYSTEM AND METHODS

The experimental system was designed to enable real-time interaction between a human operator, a virtual control environment, and two physical robotic manipulators. The implemented configuration consists of CyberGlove II wearable sensing devices, robotic hands equipped with servo actuators, wireless communication interfaces, and custom-developed control software implemented in the C++ programming language.

Fig. 2. Experimental setup and future extension of the virtual-physical robotic interaction system

The original system architecture supported control of only one robotic hand. During the experimental implementation, the control framework was extended to support synchronized bimanual operation using two independent CyberGlove II data gloves. Each glove was assigned to a dedicated robotic manipulator and processed through an independent communication and control channel. The CyberGlove II devices acquire finger and hand movements using embedded motion sensors positioned along the individual joints of the fingers. The sensor values are continuously transmitted to the control software, where the incoming data are filtered, calibrated, and mapped to corresponding servo positions of the robotic hands.

To ensure accurate motion transfer, independent calibration procedures were implemented for both robotic manipulators. Each servo motor was configured using individual parameters including minimum and maximum movement limits, sensitivity coefficients, and offset correction values. This calibration process enabled stable synchronization between the operator's hand movements and robotic actuator response.

The software architecture was redesigned into modular control units enabling independent processing of the left and right robotic hands. Separate modules were implemented for:

- sensor acquisition,
- communication handling,
- servo control,
- device initialization,
- and calibration procedures.

This modular architecture improved system scalability and simplified implementation of synchronized bimanual operation.

A dedicated automatic device detection mechanism was also implemented within the communication layer of the system. During initialization, the software automatically identifies connected communication ports and assigns the corresponding robotic manipulators to the left and right control modules.

```
private: void findPorts(void)
                 {
                //find available COM ports
                array <Object^>^objectArray = SerialPort::GetPortNames();
                //add string array to combobox
                this->comboBox_RH_ComPort->Items->AddRange(objectArray);
                this->comboBox_LH_ComPort->Items->AddRange(objectArray);
```

```
private: void findPorts(void)
                 {
                ////find available COM ports
                //array <Object^>^objectArray = SerialPort::GetPortNames();
                ////add string array to combobox
                //this->comboBox_RH_ComPort->Items->AddRange(objectArray);
                //this->comboBox_LH_ComPort->Items->AddRange(objectArray);
                        try{
                                List<DeviceListItem^>^ connectedDevices = Usc::getConnectedDevices();
                            for each (DeviceListItem^ dli in connectedDevices)
                                {
                          this->comboBox_LH_ComPort->Items->Add(dli->ToString());
                                this->comboBox_RH_ComPort->Items->Add(dli->ToString());
                                }
                            }
                        catch (System::Exception ^e)
                        {

                        }
 }
```

Fig. 3. Automatic communication port detection and initialization of robotic control modules

This functionality eliminates unstable manual port assignment and improves overall system reliability during repeated system startup and reconnection procedures.
The virtual control interface enables real-time monitoring of sensor activity, actuator response, calibration status, and communication stability. Visual feedback provided by the interface significantly improves operator control and allows immediate verification of synchronization between the virtual and physical system components.
Experimental verification was focused on evaluating:

- stability of real-time communication,
- synchronization of bimanual robotic control,
- accuracy of motion transfer,

- independent operation of both manipulators,
- and reliability of automatic device initialization.

The implemented experimental configuration demonstrates a functional cyber-physical interaction system capable of stable dual-hand robotic manipulation in real time.

4. RESULTS AND DISCUSSION

Experimental verification confirmed stable real-time operation of the proposed virtual-physical interaction system and successful implementation of synchronized bimanual robotic control. Both CyberGlove II devices were correctly initialized and independently assigned to their corresponding robotic manipulators through automatic communication port detection.

The implemented modular control architecture enabled simultaneous acquisition and processing of sensor data from both data gloves without communication instability or synchronization loss. Real-time transmission of motion data allowed continuous and accurate mapping of operator hand movements to the physical robotic hands.

During experimental testing, both robotic manipulators responded independently and synchronously to the movements of the operator.

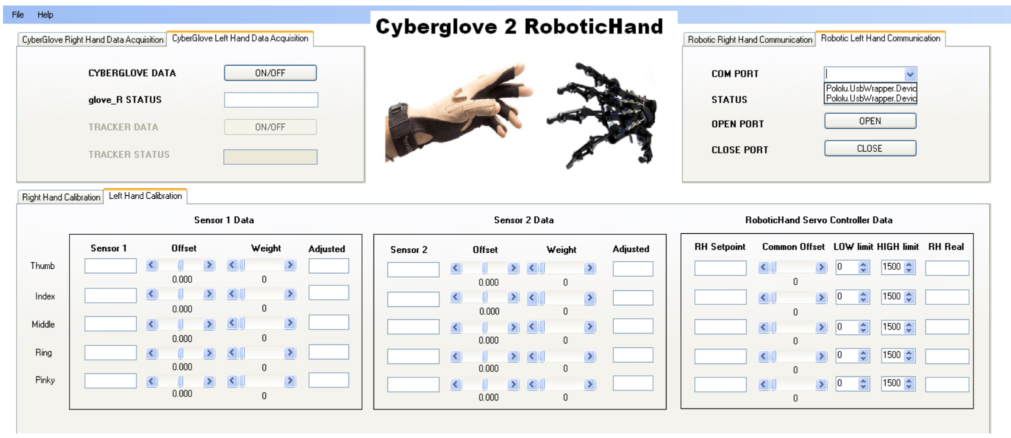

Fig. 4. Experimental verification of synchronized dual-hand robotic control

The implemented calibration procedures enabled accurate adjustment of servo sensitivity, movement limits, and motion scaling for each robotic hand individually. This significantly improved movement precision and reduced unstable actuator behavior during grasping and manipulation tasks.

The virtual control interface provided continuous visualization of sensor activity, actuator response, and communication status. Real-time visual feedback simplified system monitoring and enabled rapid verification of synchronization between the virtual environment and the physical robotic system.

Compared with the original single-hand configuration, the proposed solution significantly extends the functional capabilities of the system. The redesigned software architecture enables:

- synchronized dual-hand robotic control,
- parallel communication processing,
- independent calibration of both manipulators,
- automatic device initialization,
- and improved scalability for future system extensions.

The proposed approach demonstrates the advantages of modular virtual–physical interaction architectures for advanced robotic control applications and confirms the applicability of wearable sensing technologies in human-robot interaction systems [2, 3]. The implemented system can be applied in teleoperation, intelligent manufacturing systems, operator training, collaborative robotics, and Industry 4.0 environments requiring intuitive human-robot interaction.

The presented research also confirms that wearable sensing technologies combined with real-time robotic control architectures represent a promising direction for future cyber-physical manufacturing systems and Industry 4.0 environments [1]. The modular structure of the implemented solution additionally enables future extension toward robotic arms, multi-joint manipulators, and more advanced virtual reality interaction systems.

5. CONCLUSION

This paper presented a virtual-physical interaction system enabling synchronized bimanual robotic control using dual CyberGlove II data gloves. The proposed solution extends the original single-hand robotic control configuration toward a modular cyber-physical architecture capable of real-time interaction between a human operator, a virtual control environment, and physical robotic manipulators.

The implemented system integrates wearable motion sensing technology, real-time communication, parallel sensor processing, and robotic actuation into a unified control framework. Experimental verification confirmed stable operation of both robotic manipulators, reliable communication, synchronized motion transfer, and independent calibration of the left and right robotic hands.

The redesigned modular architecture significantly improves system scalability and enables future integration of additional robotic modules and advanced interaction components. Automatic communication port detection and independent device initialization additionally increased system robustness and operational reliability.

The presented research demonstrates the potential of virtual-physical interaction systems for applications in teleoperation, intelligent manufacturing, collaborative robotics, and Industry 4.0 environments [1-3]. Future work will focus on extending the system toward full robotic arm control, advanced motion tracking, and integration of additional sensory feedback mechanisms for more complex industrial manipulation tasks.

Acknowledgements

This article was created by the implementation of the grant project APVV-19-0418 “Intelligent solutions to enhance business innovation capability in the process of transforming them into smart businesses”, APVV-17-0258 “Digital engineering elements application in innovation and optimization of production flows”, VEGA 1/0383/25 “Optimizing the activities of manufacturing enterprises and their digitization using advanced virtual means and tools”, KEGA 003TUKE-4/2024 „Innovation of the profile of industrial engineering graduates in the context of required knowledge and specific capabilities for research and implementation of intelligent systems of the future“, VEGA 1/0160/26 „Integration of Digital Technologies into Business Processes in the Context of Industry 4.0/5.0“, KEGA 037TUKE-4/2026 “EduSmart 5.0: Innovative Education for Competence Development in the Era of Industry 4.0 and 5.0.”

References

[1] LEE, J.; BAGHERI, B.; KAO, H.A. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, 2015, 3, 18–23.

[2] Dipietro, L.; Sabatini, A.M.; Dario, P. A survey of glove-based systems and their applications. *IEEE Transactions on Systems, Man, and Cybernetics Part C*, 2008, 38(4), 461–482.

[3] Kim, H.; Lee, J.; Bae, J. A wearable hand motion capture device using flexible sensors for human- robot interaction. *Sensors*, 2019, 19(10), 2205.

[4] Glauser, O.; Wu, Y.; Hilliges, O. A data glove with low-cost sensors for real-time hand tracking. *IEEE Access*, 2020, 8, 200896–200907.

[5] LIN, J.; WU, Y.; HUANG, T.S. *Modeling the constraints of human hand motion in robotic manipulation.* IEEE Robotics and Automation Letters, 2017, 2(2), 110–117.

[6] KOVÁČ, J.; RUDY, V.; MALEGA, P. *Prepojenie robotizovaných systémov s dátovou rukavicou CyberGlove II.* In: Proceedings of the Conference, Západočeská univerzita v Plzni, Czech Republic, 2021. Available online: http://hdl.handle.net/11025/46405

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MULTIMODAL BIOPHYSICAL APPROACHES IN STEM CELL RESEARCH

Abstract

Stem cell behavior is regulated by biochemical, mechanical, electrical and structural signals. This review examines advances in mechanotransduction, hydrogels, engineered matrices and biophysical stimulation. By comparing strategies for differentiation and regeneration, the paper evaluates extracellular vesicles and their role in therapeutic outcomes. The literature suggests that combining multiple physical cues is more effective for tissue engineering than a single-factor approach.

Key words: stem cells, biophysics, mechanotransduction, regeneration

1. INTRODUCTION

Stem cells represent a cornerstone of regenerative medicine due to their capacity for self-renewal and lineage-specific differentiation. However, conventional protocols relying solely on soluble biochemical factors often fail to recapitulate the complexity of the native *in vivo* microenvironment. Recent advances in regenerative engineering emphasize that stem cell fate is governed by a complex interplay of biophysical cues, including substrate stiffness (Young's modulus), surface topography, and exogenous physical stimuli [1, 6, 10].

Cells interact with their environment through transmembrane integrins that connect the extracellular matrix (ECM) to the actin cytoskeleton via focal adhesion complexes. Mechanical stimuli activate focal adhesion kinase (FAK) and RhoA/ROCK signaling, increasing actomyosin contractility and intracellular tension [1]. These forces regulate mechanotransduction partly through the Hippo signaling pathway, where inhibition of LATS1/2 kinases promotes dephosphorylation and nuclear translocation of YAP and

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TAZ. Increased cytoskeletal tension may additionally influence nuclear pore stretching and chromatin organization, thereby modulating mechanosensitive gene expression. [1, 10]

Emerging fabrication techniques, including 3D bioprinting and conductive supramolecular hydrogels, have shifted scaffolds from passive structural supports to active, instructive interfaces. [4, 5, 7] These systems enable the simultaneous presentation of multiple cues; however, their integration remains a major bioengineering challenge. [5, 7, 10] For example, hydrogel stiffness influences cell spreading and focal adhesion formation, which in turn modulates responses to secondary stimuli such as direct electrical coupling. [4]

This review examines current multimodal biophysical strategies in stem cell research, focusing on engineered ECM mechanics, dynamic mechanical loading, and electrical and vibrational stimulation [3,4]. It further explores how these environments influence the therapeutic potential of stem cell-derived extracellular vesicles (EVs), aiming to identify more robust and reproducible strategies for tissue-specific regenerative applications. [2, 9]

2. LITERATURE REVIEW

This section reviews how biophysical cues, engineered matrices, and active stimulation integrate to regulate stem cell fate and secretome quality.

2.1 Mechanotransduction and Cytoskeletal Remodelling

Stem cell lineage commitment is driven by the integration of biomechanical and biochemical cues through mechanoadaptation. Putra et al. [1] demonstrate that cells function as active sensors, where environmental structural signals dictate cytoskeletal organization. This mechanical "memory" explains why identical biochemical media yield different differentiation outcomes on substrates of varying stiffness [1,10]. Central to this process is actomyosin contractility and the nuclear translocation of mechanosensitive transcription factors, specifically YAP and TAZ, which act as the primary molecular bridges between physical tension and gene expression. [1]

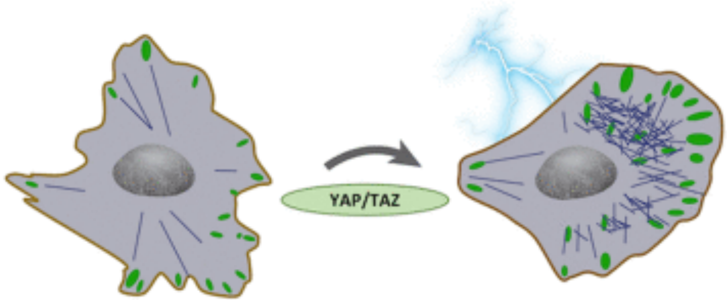

Fig. 1. Schematic representation of YAP/TAZ-mediated mechanotransduction and cytoskeletal remodelling in response to mechanical and electrical cues under varying substrate stiffness [1].

2.2 Engineered Niches and Hydrogel Viscoelasticity

Scaffold engineering has shifted from static supports to dynamic, biomimetic interfaces. While 3D bioprinting allows for precise control of ligand density and porosity [5], recent focus has turned to the viscoelasticity of supramolecular hydrogels. Unlike purely elastic materials, the stress-relaxation properties of these matrices provide a physiologically relevant environment. This time-dependent mechanical behavior is highly advantageous for mesenchymal stem cell (MSC) chondrogenesis, as it better mimics the natural relaxation of cartilaginous tissues and facilitates active cellular remodeling of the microenvironment. [7]

2.3 Active Biophysical Stimulation Strategies

Biophysical stimulation is now recognized as a primary regulator of osteogenic commitment. Strategies include extrinsic mechanical loading (strain, compression) and intrinsic microenvironmental cues. These external forces activate mechanosensitive ion channels and MAPK/ERK signaling pathways, significantly enhancing mineralized matrix deposition. [6, 8]

Beyond mechanics, the mode of electrical delivery determines the scaffold design. Direct electrical stimulation (ES) utilizes conductive interfaces (e.g., carbon nanotubes, PEDOT:PSS) to influence MSC migration and proliferation through direct current (DC) or biphasic pulses. [4] In contrast, Pulsed Electromagnetic Fields (PEMF) operate via non-contact electromagnetic induction, typically employing external electromagnetic coils to induce secondary currents within the tissue or culture medium. While conductive scaffolds can modulate the local distribution of induced fields, PEMF does not fundamentally require a conductive substrate to function, representing a distinct biophysical modality. [4, 6]

2.4 Biophysical Impact on Extracellular Vesicles (EVs)

A transformative shift in the field is the link between niche design and the quality of stem cell-derived secretomes. The biophysical properties of the culture microenvironment directly influence the proteomic and miRNA cargo of extracellular vesicles (EVs). In accordance with current MISEV guidelines, EV populations should be characterized by their physical properties (e.g., size distribution, particle concentration) and biochemical markers (e.g., presence of CD63, CD81 and absence of non-EV markers), rather than attempting to prove a specific endosomal origin, which remains a significant technical challenge. Optimizing these physical interfaces is vital for ensuring the anti-inflammatory and regenerative potency of EVs, particularly for musculoskeletal applications where multimodal cues can prime the secretome for enhanced tissue repair. [2]

3. METHODS AND METHODOLOGY

This article was prepared as a formal narrative review focusing on the recent developments in the multimodal biophysical regulation of stem cell behavior. To ensure a comprehensive evaluation of the field, a systematic search of the literature published between 2022 and 2025 was conducted using the PubMed, Web of Science, and Scopus databases. The search strategy employed specific keyword combinations, including "stem cell mechanotransduction," "multimodal biophysical stimulation," "viscoelastic hydrogels AND MSC," "electrical stimulation AND conductive scaffolds," and "MISEV extracellular vesicles." The selection process was governed by predefined inclusion criteria, prioritizing peer-reviewed primary research and high-impact review articles that specifically addressed the synergy of at least two simultaneous biophysical cues or the direct impact of engineered physical niches on the therapeutic potential of extracellular vesicles (EVs). From the identified literature, data from 10 key representative studies were selected for qualitative synthesis. This synthesis aimed to identify emerging technological trends in material characterization, evaluate the efficacy of integrated stimulation protocols, and highlight current challenges in the standardization of biophysical niches for regenerative medicine.

4. RESULTS AND DISCUSSION

The reviewed studies indicate that stem cell fate is more effectively regulated when biophysical cues are combined through multimodal platforms. [6, 10] Substrate stiffness remains a key regulator of YAP/TAZ mechanotransduction, with its effects strongly modulated by ligand density and scaffold composition. Recent advances in supramolecular hydrogels with tunable viscoelastic properties demonstrate improved biomimicry and support active cellular remodeling. [5, 7]

Tab. 1. Integrated summary of biophysical modalities in regenerative research [2–8,10].

Biophysical Cue	Typical Platform	Dominant Molecular Response	Regenerative applications	Ref.
Matrix Stiffness	Hydrogels, PEG/Alginate	Integrin signaling, YAP/TAZ activity	Bone/Cartilage modeling	[5,7,10]
Mechanical Strain	Bioreactors, Flexcell	Ion channel activation (Piezo1), MAPK	Load-bearing tissues	[6,8]
Electrical Input	Conductive polymers (PEDOT:PSS)	Voltage-gated Ca^{2+} flux, Galvanotaxis	Neural/Cardiac repair	[4]
Acoustic/Vibration	Ultrasonic platforms	EV secretion and cytoskeletal remodeling	Cell-free therapeutics	[2,3]

Active biophysical stimulation strategies, including mechanical loading and electrical systems, further enhance differentiation. However, a clear distinction must be made between contact-based stimulation via conductive materials (like PEDOT:PSS) and non-contact PEMF induction [4,6]. Likewise, biophysical niche design influences the therapeutic quality of EVs. Following MISEV recommendations, emphasis is placed on standardized characterization of these vesicles to ensure reproducibility [2,9]. Despite these advances, clinical translation remains limited by insufficient standardization of material characterization, highlighting the need for reproducible multimodal systems. [2]

These findings are synthesized in Table 1, summarizing the main biophysical modalities, associated molecular responses, and regenerative applications reported in the literature [2-8, 10].

5. CONCLUSION

Multimodal biophysical approaches integrating matrix mechanics, electrical stimulation, and dynamic loading offer a physiologically relevant alternative to traditional biochemical induction. This synergy more accurately recapitulates native regulatory signals, directing stem cell lineage commitment with higher precision while critically influencing the therapeutic quality of their secretome.

However, clinical translation is contingent upon developing standardized protocols for material characterization and precise stimuli delivery. Achieving this standardization is essential for the reproducibility required in therapeutic applications. Ultimately, the convergence of advanced biomimetic materials and active physical stimulation represents a transformative direction for both cell-based and cell-free regenerative therapies.

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References

[1] PUTRA, Vina DL; KILIAN, Kristopher A.; KNOTHE TATE, Melissa L. Biomechanical, biophysical and biochemical modulators of cytoskeletal remodelling and emergent stem cell lineage commitment. *Communications Biology*, 2023, 6.1: 75.

[2] XU, Yang, et al. Optimizing biophysical properties of cellular niches to enhance stem cell-derived extracellular vesicle function in musculoskeletal regeneration. *BMEMat*, 2026, 4.1: e70012.

[3] AMBATTU, Lizebona August; YEO, Leslie Y. Sonomechanobiology: Vibrational stimulation of cells and its therapeutic implications. *Biophysics Reviews*, 2023, 4.2.

[4] ZHANG, Kaiwen, et al. The bionic interface: considering the material mediated electrical stimulation of stem cells. *Advanced Materials*, 2026, 38.2: e12399.

[5] LEWNS, Francesca K., et al. Hydrogels and bioprinting in bone tissue engineering: creating artificial stem-cell niches for in vitro models. *Advanced Materials*, 2023, 35.52: 2301670.

[6] ZHA, Kangkang, et al. Recent advances in enhancement strategies for osteogenic differentiation of mesenchymal stem cells in bone tissue engineering. *Frontiers in Cell and Developmental Biology*, 2022, 10: 824812.

[7] YANG, Rong, et al. Engineering the dynamics of biophysical cues in supramolecular hydrogels to facile control stem cell chondrogenesis for cartilage regeneration. *Composites Part B: Engineering*, 2023, 250: 110429.

[8] SUN, Yuyang, et al. Mechanical stimulation on mesenchymal stem cells and surrounding microenvironments in bone regeneration: regulations and applications. *Frontiers in cell and developmental biology*, 2022, 10: 808303.
[9] CHEN, Renxin, et al. Mesenchymal stem cell–immune cell interaction and related modulations for bone tissue engineering. *Stem Cells International*, 2022, 2022.1: 7153584.
[10] BAKHSHANDEH, Behnaz, et al. Recent progress in the manipulation of biochemical and biophysical cues for engineering functional tissues. *Bioengineering & translational medicine*, 2023, 8.2: e10383.

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CORRECTION OF SURFACE NORMAL ORIENTATION FOR CAD MODELS IN UNITY3D

Abstract

The integration of CAD models into real-time environments such as Unity is commonly associated with graphical and geometric compatibility issues. One of the most frequent problems is the occurrence of backface culling, where polygon surfaces become invisible when viewed from a specific direction due to incorrect surface normal orientation. This issue significantly affects the visual quality and usability of imported models, particularly in virtual reality applications and industrial training simulations. This article focuses on the analysis of backface culling problems occurring after importing 3D models into Unity. The theoretical background of polygon rendering and surface normals is described, together with the principle of backface culling used in modern rendering pipelines for performance optimization. Several methods for correcting incorrectly oriented normals in Blender are analyzed, including manual face normal correction and automatic normal recalculation.

Key words: Unity3D, Blender, backface culling, surface normals

1. INTRODUCTION

The increasing use of virtual reality technologies in industrial environments has created a growing demand for accurate and visually reliable 3D models. Real-time development platforms such as Unity are widely used for the creation of training simulations, visualization systems, and interactive maintenance applications due to their flexibility, hardware compatibility, and support for VR devices. In many industrial projects, 3D

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assets are not created directly for game engines, but are instead imported from CAD software used in engineering and manufacturing processes.

Despite the high geometric precision of CAD models, their integration into real-time rendering environments is often associated with several compatibility problems. One of the most common issues is incorrect surface visibility caused by backface culling. This phenomenon occurs when polygon faces become invisible from certain viewing angles because their surface normals are oriented in the opposite direction expected by the rendering engine. As a result, imported objects may appear partially transparent, visually incomplete, or entirely invisible from one side after being imported into Unity.

Backface culling is commonly implemented in modern rendering pipelines as an optimization technique intended to improve rendering performance by excluding surfaces facing away from the camera. While this approach is efficient for real-time graphics applications, it becomes problematic when imported models contain incorrectly oriented normals or inconsistent polygon orientation. Such issues are particularly noticeable in models converted from CAD environments, where geometry generation principles differ from those used in polygon-based rendering systems.

Several methods can be used to correct surface normal orientation problems. Basic approaches include manual flipping of polygon normals or automatic recalculation of normals in 3D modeling software such as Blender. However, these methods become inefficient when working with highly detailed industrial assemblies containing thousands of individual surfaces. Manual correction is time-consuming, while automatic recalculation may also modify surfaces that were originally oriented correctly.

This article focuses on the analysis and correction of backface culling issues occurring during the import of CAD-based models into Unity. Particular attention is given to the use of the Solidify modifier in Blender as a practical and efficient solution for ensuring proper model visibility in real-time applications. The presented approach is evaluated in the context of complex industrial models intended for virtual reality training environments. [1]

2. BACKFACE CULLING

Backface culling is a rendering optimization technique commonly used in modern real-time graphics systems and game engines such as Unity. Its primary purpose is to reduce the computational load of the graphics pipeline by preventing the rendering of polygon surfaces that are not visible to the camera. In most 3D scenes, the rear side of a polygon cannot normally be seen by the user, and therefore rendering these surfaces would unnecessarily consume GPU resources.

The visibility of a polygon surface is determined by the orientation of its surface normal. A surface normal is a vector perpendicular to the polygon face that defines its outward direction. During rendering, the graphics engine compares the direction of the polygon normal with the viewing direction of the camera. If the polygon is determined to face away from the camera, the renderer excludes it from the final image. [2]

The principle of surface normal orientation can be expressed as:

$$\vec{n} = (n_x, n_y, n_z) \tag{1}$$

In correctly prepared polygon models, all normals are consistently oriented outward from the object surface. However, during the conversion or export of CAD models, incorrect polygon orientation may occur. As a result, some surfaces may have normals pointing inward instead of outward. When such models are imported into Unity, the rendering engine interprets these polygons as back-facing surfaces and removes them from the rendered image. This causes parts of the model to become invisible from specific viewing angles (Fig. 1).

The problem becomes especially visible in virtual reality applications, where the user can freely move around the object and observe it from multiple perspectives. Incorrectly oriented surfaces negatively affect the visual quality, realism, and usability of the simulation. In industrial training environments, invisible geometry may also reduce the clarity of maintenance procedures and assembly instructions. [3]

Fig. 1. Comparison of Correct and Incorrect Surface Rendering in Unity3D

Although backface culling is essential for maintaining high rendering performance in real-time systems, improperly oriented normals significantly reduce the reliability of imported CAD geometry. For this reason, correcting surface orientation represents an important step in the preparation of 3D assets for interactive applications and VR simulations.

3. SOLVING BACKFACE CULLING ISSUES IN BLENDER

Incorrect surface visibility caused by backface culling can be corrected using several tools available in Blender (Fig. 2). Since the problem is directly related to the orientation of polygon normals, the correction process focuses primarily on adjusting the direction of these normals before exporting the model into Unity.

The complexity of the correction process depends mainly on the geometric structure and detail level of the imported model. [4]

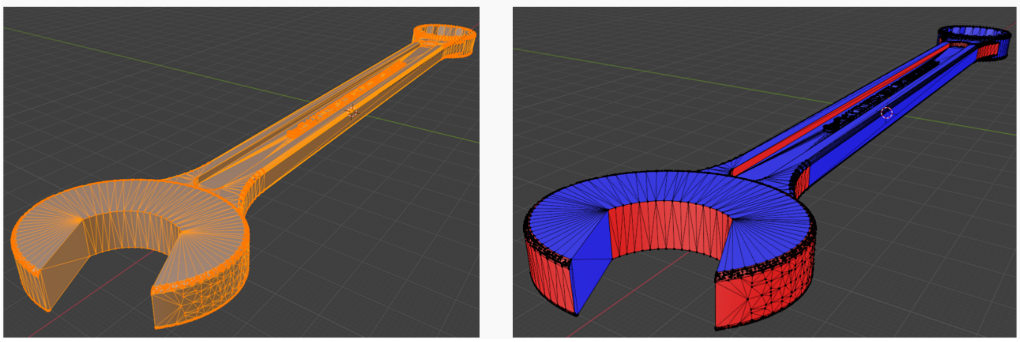

Fig. 2. Surface Normal Visualization in Blender Edit Mode

3.1 Manual Surface Normal Correction

One of the most straightforward methods for solving backface culling problems is manual correction of polygon normals in Edit Mode. Blender provides visualization tools that allow users to identify incorrectly oriented surfaces. Using the Face Orientation overlay, correctly oriented faces are typically displayed in blue, while incorrectly oriented faces are highlighted in red.

After identifying problematic surfaces, individual polygon faces can be selected manually and their normals can be inverted using the Flip operation. This approach allows precise control over surface orientation and can be effective for simple models containing a limited number of polygons [4].

However, manual correction becomes highly inefficient when working with complex industrial CAD assemblies. Detailed engineering models often contain thousands of polygon surfaces, making individual face correction extremely time-consuming (Fig. 3).

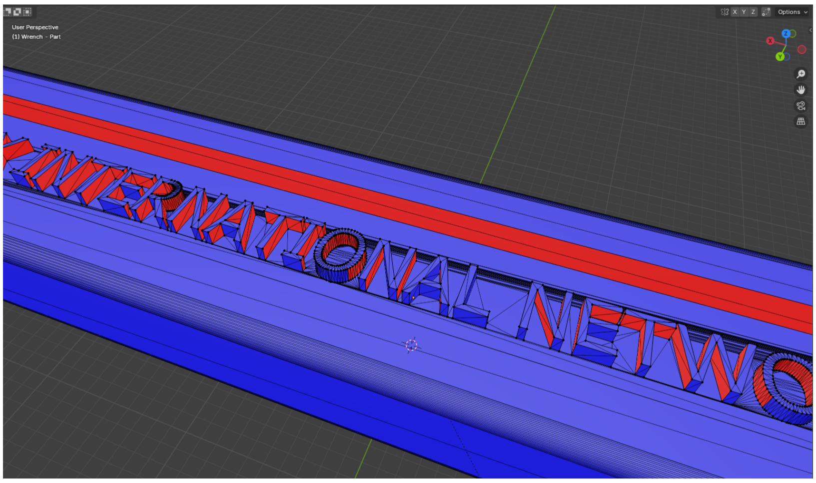

Fig. 3. Complex CAD Model with Inconsistent Surface Normal Orientation

Additionally, manually identifying incorrectly oriented surfaces may become difficult in geometrically dense models with overlapping components and internal structures. For these reasons, manual correction is generally unsuitable for large-scale industrial models intended for real-time VR applications. [4]

3.2 Automatic Recalculation of Normals

To simplify the correction process, Blender also provides automatic normal recalculation tools. By selecting the entire model and applying the Recalculate Outside operation, the software attempts to orient all polygon normals consistently toward the exterior of the object.

This method significantly reduces the time required for model preparation and is often sufficient for simple or moderately complex geometry. Automatic recalculation can efficiently correct large groups of incorrectly oriented polygons without requiring manual selection of individual faces.

Despite its advantages, this approach also has several limitations. In highly detailed CAD models, the algorithm may incorrectly interpret complex geometry, thin surfaces, internal cavities, or overlapping structures. As a result, some polygons that were originally correct may become inverted after recalculation, while other problematic surfaces may remain unresolved (Fig. 4).

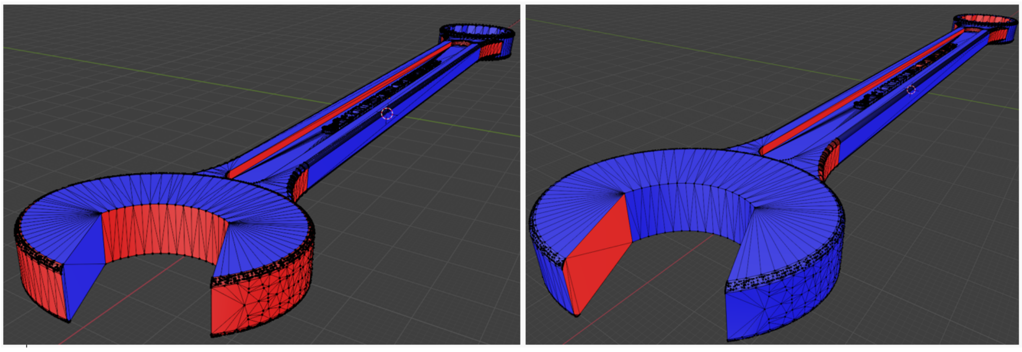

Fig. 4. Result of Automatic Normal Recalculation on a Complex Model

The reliability of automatic recalculation decreases further in models imported from CAD environments, where polygon topology is often non-uniform and not optimized for real-time rendering systems. Consequently, additional correction methods are required to achieve fully consistent surface visibility in Unity [4].

4. SOLIDIFY MODIFIER

A more reliable solution for correcting backface culling issues in complex CAD models is the use of the Solidify modifier in Blender. Unlike manual normal correction or automatic recalculation, this approach does not rely solely on reorienting existing polygon normals. Instead, the modifier generates additional geometry by creating a thin outer shell around the model surface [5].

The principle of the Solidify modifier is based on adding thickness to polygon surfaces. During this process, the software duplicates the existing geometry and offsets it along the direction of the surface normals, effectively creating an additional outer layer. As a result, the model obtains properly defined exterior and interior surfaces with consistently oriented normals.

One of the main advantages of this method is its effectiveness when working with highly detailed industrial models. Since the modifier automatically generates new surface geometry, it eliminates the need for manually identifying incorrectly oriented faces. At the same time, it avoids the risks associated with automatic normal recalculation, where already correct surfaces may become inverted (Fig. 5). [6]

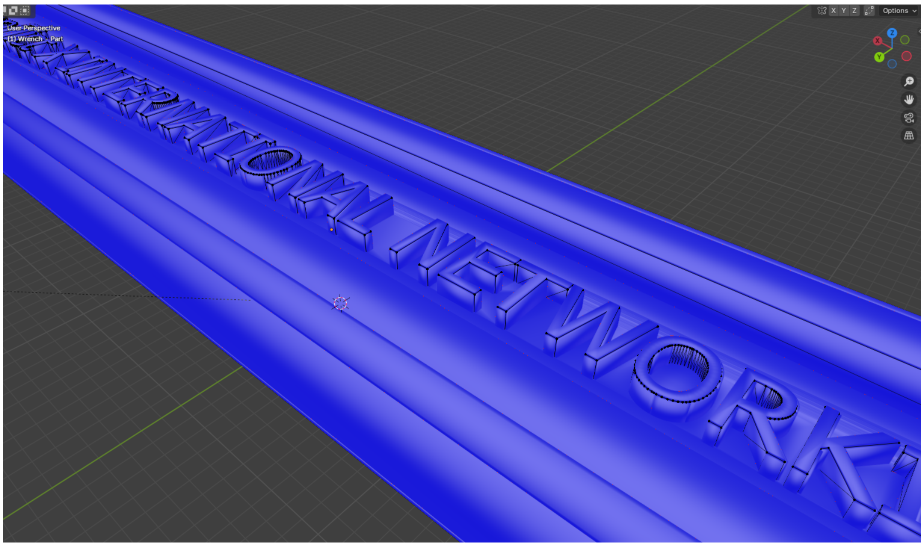

Fig. 5. Model After Applying the Solidify Modifier with Correct Surface Orientation

After applying the Solidify modifier, the corrected model becomes fully visible in Unity from all viewing angles. The method also improves visual consistency in virtual reality environments, where users can closely inspect objects and interact with them from multiple perspectives.

Another important advantage is the speed of the correction process. Even complex CAD assemblies containing thousands of surfaces can be repaired within a short time using a single modifier operation. This significantly improves workflow efficiency during the preparation of industrial assets for real-time rendering applications. [7]

Although the Solidify modifier slightly increases polygon count due to the creation of additional geometry, the resulting performance impact is generally acceptable for modern hardware systems, especially when compared to the visual issues caused by unresolved backface culling. For this reason, the Solidify approach represents a practical and efficient solution for preparing CAD-based models for VR simulations and interactive training applications. [8]

5. CONCLUSION

This article analyzed the causes of backface culling and presented several methods for correcting surface normal orientation using Blender. Manual normal correction provides precise control over polygon orientation but becomes impractical for highly detailed industrial assemblies due to the large number of surfaces requiring adjustment. Automatic recalculation of normals significantly accelerates the correction process; however, its reliability decreases when working with geometrically complex CAD models containing thin structures, internal cavities, or inconsistent topology.

The presented results demonstrate that the Solidify modifier represents a more effective solution for resolving backface culling issues in complex models. By generating additional surface thickness and creating consistently oriented geometry, the modifier ensures correct model visibility from all viewing angles after import into Unity. The method also substantially reduces the time required for model preparation compared to manual correction techniques.

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References

[1] UNITY TECHNOLOGIES: ShaderLab: Culling and Depth Testing. Unity Manual. Available on the internet: https://docs.unity3d.com/Manual/SL-CullAndDepth.html

[2] WIKIPEDIA CONTRIBUTORS: Back-face culling. In: Wikipedia, The Free Encyclopedia. Available on the internet: https://en.wikipedia.org/wiki/Back-face_culling

[3] KLEVERUD, F.: Interactive visualization of CAD data in real time rendering. Master's thesis. Chalmers University of Technology, 2018. Available on the internet:: https://odr.chalmers.se/bitstreams/42549b26-7cf7-4054-a9e9-85df47a002d1/download.

[4] BLENDER DOCUMENTATION: Normals. Blender Manual. Available on the internet:: https://docs.blender.org/manual/en/latest/modeling/meshes/editing/mesh/normals.html

[5] MARANGOS, C.: A Better Method to Recalculate Normals in Unity. Scheming Developer, 2014/2017. Available on the internet:: https://schemingdeveloper.com/2014/10/17/better-method-recalculate-normals-unity/

[6] OHTAKE, Y. et al.: Multi-level Partition of Unity Implicits. ACM Transactions on Graphics, Vol. 22, No. 3, 2003, pp. 463–470.

[7] SAMBHAV, K. et al.: CAD Based Geometric and Force Modeling of Single Point Cutting Tool. Computer-Aided Design and Applications, Vol. 10, No. 1, 2013, pp. 45–57.

[8] ALL3DP: Blender: Recalculate Normals – Simply Explained. All3DP, 2022. Available on the internet: https://all3dp.com/2/blender-recalculate-normals-simply-explained/

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DECISION SUPPORT IN PRODUCTION ENGINEERING BASED ON SIMULATION ANALYSIS AND PARETO OPTIMISATION

Abstract

This paper presents a decision-support method in production engineering that employs modelling and simulation in the process of multi-criteria selection of the optimal production workflow variant. The aim of the study was to develop a decision-making procedure based on Pareto optimisation, enabling an objective assessment of individual technological scenarios by integrating the results of simulation studies with a graphical analysis of the solution set. The proposed approach provides support for informed design and managerial decision-making.

Key words: Production management, Multi-criteria analysis, Modelling and simulation.

1. INTRODUCTION AND JUSTIFICATION OF THE RESEARCH PROBLEM

The dynamic development of industry and increasing market demands contribute to the growing complexity of manufacturing systems. Under such conditions, a key engineering challenge is not only the design of manufacturing technologies, but above all the appropriate configuration of production resources and the selection of suitable variants for organising the production process. The justification for addressing this issue is the growing need to reduce uncertainty in the processes of manufacturing enterprises. This problem becomes particularly significant in situations requiring substantial changes in the structure of the manufacturing system, such as the implementation of new products, the reconfiguration of production lines, or the modernisation of machinery and equipment. The aim of this paper is to develop a decision-support procedure in production engineering that integrates the results of simulation studies with a graphical analysis of the set of feasible solutions and the Pareto optimisation method.

2. DECISION SUPPORT IN PRODUCTION ENGINEERING

Modern manufacturing systems operate under conditions of high variability, which necessitates the use of reliable analytical methods in process management. Such

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an approach enables the acquisition of data that are essential for the empirical verification of adopted technological scenarios. [1] However, it should be noted that the high level of complexity of these processes, as well as the variability of the environment in which they are carried out, constitute a significant barrier to their proper understanding. [2]

2.1 The use of Simulation Modelling in Manufacturing Systems Engineering

The ability to maintain a stable market position under conditions of high competition requires enterprises to implement strategies for the preventive elimination of losses and continuous performance monitoring. [3] The presence of uncertainty often leads to the adoption of less effective solutions and the preparation of imprecise forecasts regarding production outcomes. [4] The use of digital environments makes it possible to test alternative system configurations within a short time frame. [5] The implementation of a simulation project is a multi-stage process that begins with a detailed analysis of the real system's operation. The effectiveness of the developed computer model depends on the quality of the collected data, therefore, it is necessary to obtain and process a broad range of information. On this basis, a logical model structure is developed. After the implementation of the model logic, a verification phase follows, aimed at confirming the correctness of the model's operation. The next key step involves conducting simulation experiments. These consist of deliberate modification of input parameters or introducing changes to the model, which enables observation of the system's response to different scenarios. [6]

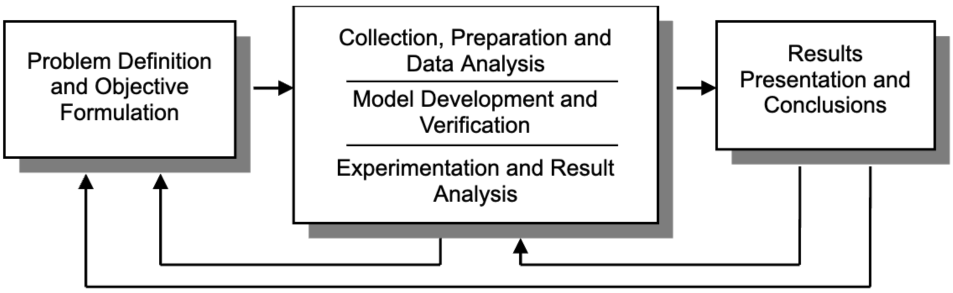

Fig. 1. Simulation Model Development Framework [7]

The output data obtained through experiments are subjected to analysis and evaluation, which enables a measurable verification of the impact of modifications on production, while simultaneously allowing for an increase in production volume and process efficiency [8]. A priority challenge for future digital environments is the ability to model systems with a high degree of complexity. [9]

2.2 Multi-criteria Optimisation as a Basis for Selecting Technological Variants

Multi-criteria decision-support methods enable the simultaneous consideration of multiple criteria in the process of selecting an optimal solution. [10] The use of these approaches allows decision-makers to structure and prioritise their objectives. [11] A solution is defined as non-dominated if, within the feasible set, there is no alternative variant that would improve the value of at least one criterion without simultaneously worsening the results in the remaining aspects. All mutually non-dominated variants form the Pareto-optimal set. Their graphical representation in the objective space is defined as the Pareto front. [12] This establishes the boundary of the best possible compromises available to the decision-maker, excluding non-promising configurations. [13] The accumulation of interdependent parameters means that the process of selecting the final variant requires advanced analysis in order to identify the optimal compromise. [14]

3. METHODOLOGY FOR THE VALIDATION OF SCENARIOS USING SIMULATION MODEL AND PARETO ANALYSIS OF THE SET OF SOLUTIONS

The applied research procedure is based on an iterative process of modelling and optimisation, divided into four key stages (as shown in Fig. 2).

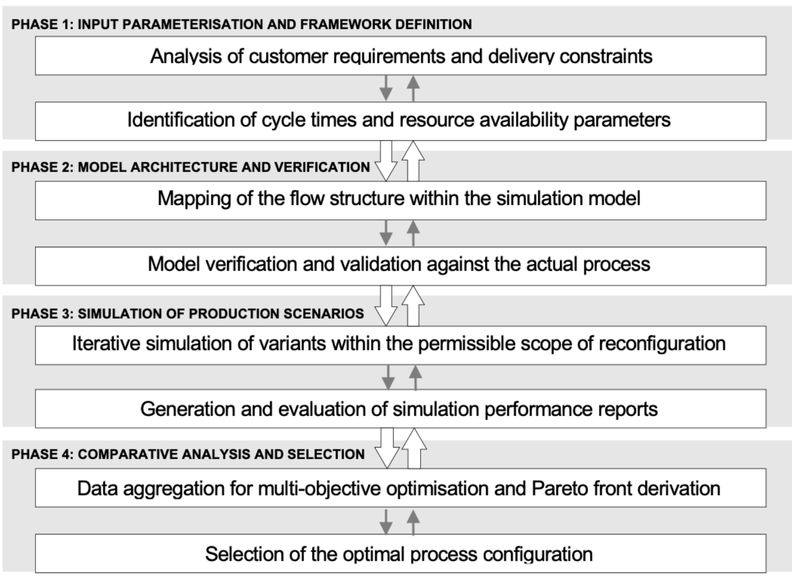

Fig. 2. Conceptual model of the simulation-based decision support system for production reconfiguration *[own elaboration]*

The research process began with the definition of the analysis framework, which included an examination of customer requirements and the identification of actual cycle times as well as resource availability parameters. The collected data formed the foundation for developing the model architecture, in which the process flow structure was represented using a set of symbol libraries. The proper processing of these data was critical to the reliability of the entire analysis. After confirming the correctness of the model, the phase of experimental simulation was undertaken, involving iterative testing of production organisation variants. These scenarios were based on the existing machine park and available workforce, examining different options for work organisation and the utilisation of additional workstations available to the enterprise. Simultaneously, production costs were determined within the Arena simulation environment based on adopted assumptions, including, among others, costs related to resource utilisation time and their idle time. A key stage involved the compilation of results generated in the form of reports.These data were directly incorporated into the optimisation procedure, which enabled the identification of non-dominated solutions forming the Pareto front. This approach made it possible to determine the influence of resource management and production organisation on final outcomes. As a result, variants were identified to ensure the most favourable balance between production costs and order completion time. The primary objective of this research was to design and evaluate a production organisation strategy based on the representative order of one hundred pieces of the ski lift components, treated as an exemplary case study of an urgent production requiring the shortest possible completion time. The representative segment of the simulation logic, illustrating the flow through the production system, is presented in Fig. 3.

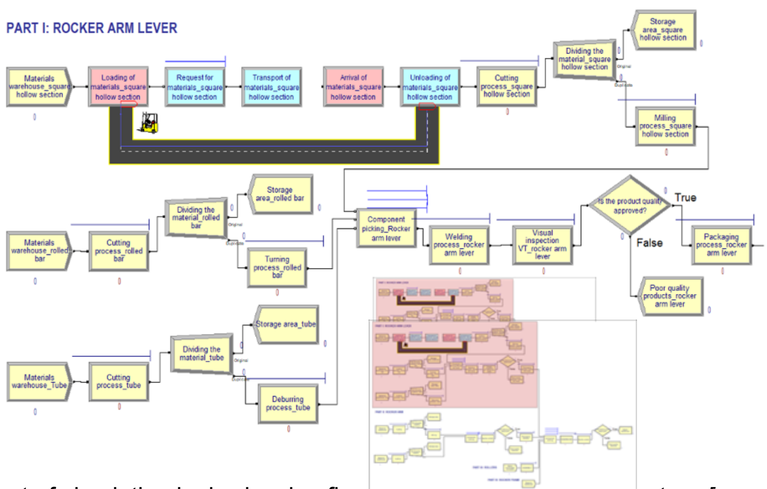

Fig. 3. Excerpt of simulation logic showing flow through the production system *[own elaboration]*

The model captured key characteristics of the production environment, including the parallel processing of parts across workstations within a single working shift and the utilisation of available stock from warehouse inventories, as certain subassemblies had been manufactured in advance and stored. Production costs were explicitly integrated into the model to enable a more comprehensive evaluation of alternative production scenarios and their associated economic implications.

4. ANALYSIS OF EXPERIMENTAL RESULTS AND MULTI-CRITERIA EVALUATION OF PRODUCTION VARIANTS BASED ON SELECTED TECHNOLOGICAL SCENARIOS

The pilot analysis demonstrated that the fulfilment of an order for one hundred components under the current resource configuration – assuming the availability of one workstation per operation and two stations each for cutting, milling, and turning – requires over 139 hours of production time. The resulting reconfiguration scenarios were denoted S1 to S10. Increasing the number of available workstations, where feasible within the adopted assumptions, led to reduction in production time and this was accompanied in total production costs. Further adjustments were therefore introduced, including changes to the warehouse release schedule and frequency, as well as the reassignment of suitably qualified employees to alternative tasks, all aimed at accelerating completion of the priority order. The simulation results were compiled in spreadsheet form and subsequently subjected to Pareto optimisation analysis, in which the Pareto front was determined (Figure 4). Within the simulation-based comparative framework, production variants were evaluated according to two objective criteria – total production cost and batch lead time. Given the priority assigned to the minimisation of lead time, variant S10 was identified as the optimal solution. It achieved the greatest reduction in the production cycle within the constraints of the available machine park and workforce, while maintaining production costs at an acceptable level for the enterprise.

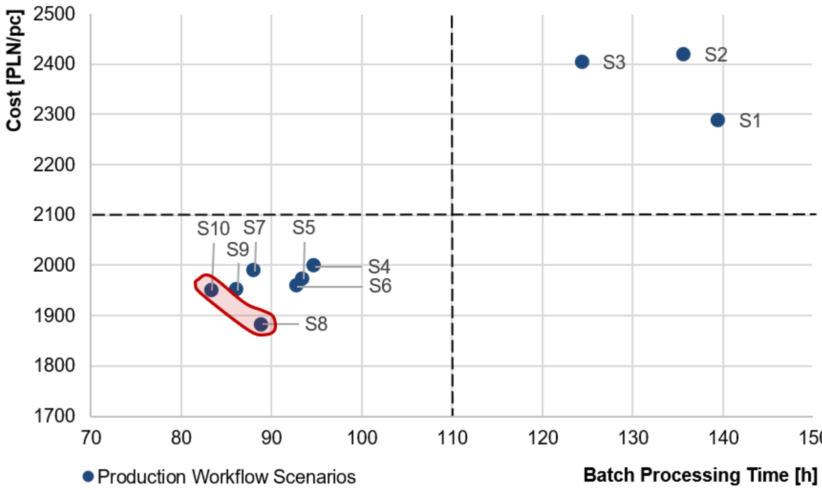

Fig. 4. Determination of the set of non-dominated solutions based on simulation reports for the analysed scenarios (S1–S10) *[own elaboration]*

5. SUMMARY AND CONCLUSIONS

The analysis of possibilities for shortening order completion times while maintaining production capacity requires consideration of the variability and interdependencies present within the production flow structure. In this study, an approach based on mapping this flow in a digital environment was proposed, which enabled the verification of numerous work reorganisation variants without the need to interfere with the ongoing operations of the enterprise. The proposed approach allows for an objective assessment of production flow variants and the identification of configurations that ensure a balance between production system performance and the adopted technological and organisational constraints. The use of multi-criteria analysis makes it possible to determine compromise solutions that simultaneously take into account various parameters of the manufacturing system's performance.

References

[1] BARTOŠ, M., BULEJ, V., KURIC, I.: Conceptual Design and Simulation of Cable-driven Parallel Robot for Inspection and Monitoring Tasks. 25th Polish-Slovak Scientific Conference on Machine Modelling and Simulations (MMS 2020). MATEC Web of Conferences 357(3):02024, 2022.https://doi.org/10.1051/matecconf/202235702024

[2] KRAJČOVIČ, M., BASTIUCHENKO, V., FURMANNOVÁ, B., BOTKA, M., KOMAČKA, D.: New Approach to the Analysis of Manufacturing Processes with the Support of Data Science. Processes 2024, 12(3):449. https://doi.org/10.3390/pr12030449

[3] DULINA, L., ZUZIK, J., FURMANNOVA, B., KUKLA, S.: Improving Material Flows in an Industrial Enterprise: A Comprehensive Case Study Analysis. Machines 2024, 12(5):308.https://doi.org/10.3390/machines12050308

[4] DE TEMMERMAN, A., VERBEKE, M: Improved multi-objective decision-making in manufacturing processes through uncertainty quantification and robust pareto front modeling. Scientific Reports, 15(1):14411, 2025. https://doi.org/10.1038/s41598-025-97508-z

[5] BULKOVÁ, Z., KAMPF, R., GAŠPARÍK, J., CODRUT NEMTANU F.: Simulation-Based Approach to the Optimization of Material Flows and Workstation Layout in a Manufacturing Company. Results in Engineering 30:110392, 2026. https://doi.org/10.1016/j.rineng.2026.110392

[6] MOZOLOVA, L., GRZNÁR, P., MOZOL, S., KRAJČOVIČ, M.: Streamlining utilisation of the assembly line using computer simulation. Acta logistica – International Scientific Journal about Logistics, 10(2), 2023, pp. 165-173. https://doi.org/10.22306/al.v10i2.365

[7] PLINTA, D.; RADWAN, K.: Improving material flow in a modified production system. Applied Computer Science, 19(1), 2023, pp. 95-106. https://doi.org/10.35784/acs-2023-07

[8] DIAS, A.S.M.E., ANTUNES, R.M.G., ABREU, A., ANES, V., NAVAS, H.V.G., MORGADO, T., CALADO, J.M.F.: Utilisation of the Arena simulation software and Lean improvements in the management of metal surface treatment processes. Procedia Computer Science 204(1):140-147, 2022.https://doi.org/10.1016/j.procs.2022.08.017

[9] GRZNÁR, P., GREGOR, M., KRAJČOVIČ, M., MOZOL, Š., SCHICKERLE, M., VAVRÍK, V., ĎURICA, L., MARSCHALL, M., BIELIK, T.: Modeling and Simulation of Processes in a Factory of the Future. Applied Sciences 10(13):4503, 2020. https://doi.org/10.3390/app10134503

[10] TAHERDOOST, H.; MADANCHIAN, M.: Multi-Criteria Decision Making (MCDM) Methods and Concepts. Encyclopedia 2023; 3(1):77-87. https://doi.org/10.3390/encyclopedia3010006

[11] ANYSZ, H.; NICAŁ, A.; STEVIĆ, Ž.; GRZEGORZEWSKI, M.; SIKORA, K. Pareto Optimal Decisions in Multi-Criteria Decision Making Explained with Construction Cost Cases. Symmetry 2021, 13(1):46. https://doi.org/10.3390/sym13010046

[12] OSIKA, Z., ZATARAIN SALAZAR, J., ROIJERS D.M., OLIEHOEK, F.A., MURUKANNAIAH, P.K.: What Lies beyond the Pareto Front? A Survey on Decision-Support Methods for Multi-Objective Optimization. Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence (IJCAI-23), 2023, pp. 6741-6749. https://doi.org/10.48550/arXiv.2311.11288

[13] MATUSZEK, J., KURCZYK, D.: Projektowanie procesów i systemów produkcyjnych z wykorzystaniem technologii komputerowej wirtualizacji. Innowacje w zarządzaniu i inżynierii produkcji, 2(12), 2017, pp. 741-752.

[14] WHITE, S.E., WITING, F., WITTEKIND, C.I.H., STRAUCH, M., STRAUCH, M.: Distilling the Pareto Optimal Front into Actionable Insights. Environmental Modelling & Software 191:106508, 2025.https://doi.org/10.1016/j.envsoft.2025.106508

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MODULAR CONSTRUCTION OF PRODUCTS AS A TOOL FOR SMES

Abstract

This article presents the concept of modular product design and its benefits for small and medium-sized enterprises. It highlights how modularity supports flexibility, cost reduction and faster adaptation to market needs. As part of the analysis, modular product structures were examined, leading to the identification of key design solutions.

Keywords: modular product construction, customisation, make-to-order

1. INTRODUCTION

Contemporary market environments are characterised by intensified competition and pronounced volatility, accompanied by a continuous increase in customer requirements. Technological progress, globalisation processes, and the widespread availability of information contribute to the gradual erosion of traditional sources of competitive advantage. Concurrently, customers increasingly demand products tailored to individual specifications while still expecting cost levels comparable to those associated with mass production.

This issue is particularly relevant for small and medium-sized enterprises (SMEs) engaged in the design and manufacture of made-to-order products. In response to the pressures associated with the paradigm of mass customisation, such enterprises are compelled to identify methods for reducing production costs while preserving a high degree of product individuality and production flexibility.

In this context, the modular construction of products constitutes a significant design approach, enabling the configuration of diverse product variants based on standardised modules. This solution facilitates the optimisation of production processes while maintaining the capacity to satisfy customer requirements.

The objective of this article is to examine the modular construction of products as a tool supporting SMEs involved in unit and small-batch production in achieving cost efficiency while sustaining a high level of customisation and operational flexibility.

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2. LITERATURE REVIEW

The growing market demand for customised products, shorter delivery times, and cost-efficient manufacturing has encouraged companies to search for more flexible approaches to product development and production management. In this context, modular product architecture has become an important concept that enables enterprises, especially SMEs, to improve operational efficiency while maintaining the ability to adapt products to changing expectations. [1]

The essence of modularity lies in dividing a product into independent yet compatible modules that can be combined in different configurations. Such an approach allows companies to standardise selected components while simultaneously offering diversified product variants. As a result, enterprises may reduce the complexity of product development processes, simplify assembly operations, and decrease inventory-related cost. [2] For SMEs, which often function under financial and technological constraints, these advantages can significantly improve resource utilisation and production planning.

Another important benefit of modular product structures is the improvement of manufacturing and assembly processes. Integrating modularity with Design for Assembly (DFA) principles enables organisations to optimise production already at the conceptual design stage. Simplified assembly sequences, reduced numbers of unique parts, and improved compatibility between components may contribute to shorter production cycles and lower manufacturing costs. [3] Nevertheless, the implementation of modular systems may require organisational changes, interdepartmental coordination, and investment in design capabilities, which can be challenging for smaller firms.

The level of product modularity also plays a strategic role in enterprise management. A properly balanced modular structure can increase production flexibility and facilitate faster adaptation to evolving market requirements. At the same time, an excessively fragmented product structure may generate coordination difficulties and increase management complexity. Therefore, enterprises should seek an optimal degree of modularity that supports both operational efficiency and product variety. [1] For SMEs, modular product architecture is particularly valuable in the context of mass customisation strategies. Through the use of common modules, companies are able to create multiple product configurations without the need to redesign entire products from scratch. This approach allows manufacturers to respond more effectively to individual customer requirements while maintaining relatively stable production costs. Consequently, modularity supports both market responsiveness and competitiveness. [4] In addition, modular product architecture aligns with the principles of Industry 4.0 and digital manufacturing systems. Modular production environments are more adaptable to automation, digital integration, and rapid process reconfiguration. This flexibility increases the ability of enterprises to adjust production systems to changing market conditions and technological developments. [5]

An additional benefit of modular solutions is the possibility of gradually expanding the product portfolio without the need to develop entirely new product structures.

The same modules can be reused in different product configurations, which increases the efficiency of development activities and reduces the workload of design departments. For small and medium-sized enterprises, this translates into greater organisational flexibility and long-term cost optimisation potential. [2]

3. AN EXAMPLE OF MODULAR CONSTRUCTION OF PRODUCTS

In the present analysis, the design solutions implemented in the mixer were identified, with particular emphasis placed on the bearing housing region and, more specifically, on the coupling interface. An exemplary configuration of the coupling connection is presented in Fig. 1.

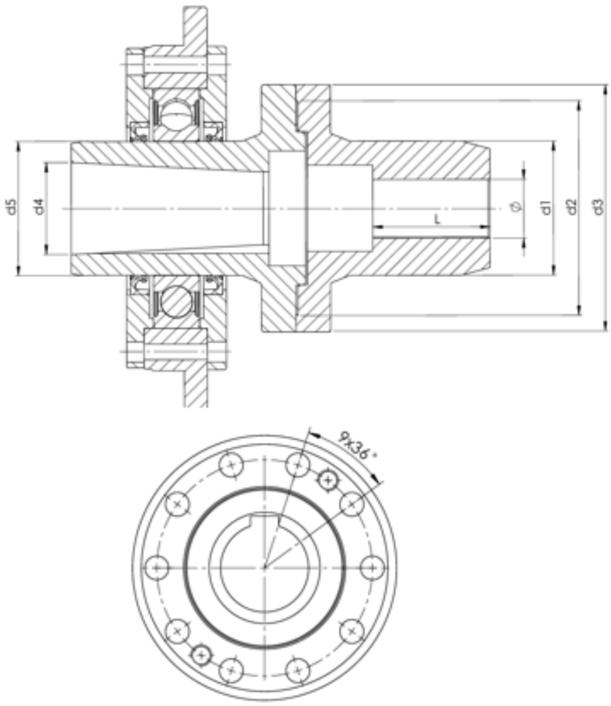

Fig. 1. Coupling halves

At the initial stage, an evaluation of the applied geared motoreducers was performed, followed, by their classification into two groups based on dimensional differences. This approach enabled the standardisation of the component selection procedure and a reduction in the number of possible design configurations. The results of the analysis are presented in Tab. 1.

For each group, appropriate coupling halves were selected, with the required safety level adopted as the primary selection criterion, determined mainly by the geometric parameters of the first coupling half. Subsequently, the remaining elements of the drive system, grooves, and bearings were matched, which allowed the development of standardised and repeatable design variants.

Tab. 1. Structural analysis of the bearing system

		FF87	FF77	FF67	FF57	FF47
MOTOREDUCER		**60m6**	**50k6**	**40k6**	**35k6**	**30k6**
	L	120	100	80	70	60
	M (Nm)	630			230	
	Center hole	M20	M16	M16	M12	M10
	Safety factor	3.2	3.1	3.2	3.6	3.6
COUPLING HALF 1	**(d1)**	90			60	
	(d2)	140			102	
	(d3)	150			112	
	Number of bolts	10			8	
	Bolt size	M12			M10	
	Bolt material	8.8				
GROOVE	**b**	18	14	12	10	8
	h	4.4	3.8	3.3	3.3	3.3
	l	45	56	70	34	43
	lo	27	42	58	24	35
COUPLING HALF 2	**Outer shaft diameter (d5)**	90			60	
	Inner shaft diameter (d4)	60			40	
BEARING	**Designation**	6318			6312	

The scope of the presented considerations is limited to selected aspects related to design optimisation. The developed overview is open-ended and may be extended in the future to include additional drive system configurations, including solutions with different bearing arrangements.

4. CONCLUSION

Modular product architecture can be treated as a practical and effective approach supporting both engineering and managerial activities in small and medium-sized enterprises. Its application allows companies to combine product variety with production efficiency while simultaneously reducing structural complexity and increasing the flexibility of manufacturing systems. As a result, SMEs gain better conditions for responding to market changes, improving work organization, and strengthening their competitive position. The presented example illustrated an attempt to rationalise the design of a coupling in a mixer using a modular construction approach.

In conclusion, the implementation of modular solutions within product structures should be viewed as part of a broader enterprise development strategy, which also includes component standardisation, functional product analysis, and the gradual optimisation of design and production processes. A key aspect is the conscious shaping of product architecture in a way that balances design flexibility with implementation costs and the organisational capabilities of the company.

References

[1] SOLTYSOVA, Z., MODRAK, V.: Product Modularity in Management Studies: A Measurement Perspective. Polish Journal of Management Studies, vol. 31, no. 1, 2025, pp. 280–299

[2] MLECZKO, J., BYRDY, Ł., CIEŚLA, B., KŁAPTOCZ, K.: Modular Product Architecture as an Opportunity for Achieving Savings in Engineer-to-Order and Make-to-Order Enterprises. Polish Production Management Society, 2020

[3] MONETTI, F., M., LUNDRSTOM, A., MAFFEI, A.: Integrating Design for Assembly in Modular Product Architecture: Barriers, Insights, and a Framework for Early-Stage Guidance. Production & Manufacturing Research, vol. 13, no. 1, 2025

[4] MONETTI F., M., MAFFEI, A.: Towards the Definition of Assembly-Oriented Modular Product Architectures: A Systematic Review. Research in Engineering Design, 2024

[5] MODRAK, V., SOLTYSOVA, Z.: Exploration of the Optimal Modularity in Assembly Line Design. Scientific Reports, vol. 12, 2022

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