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ARTIFICIAL INTELLIGENCE FOR CONTROLLING THE OPERATIONAL EFFICIENCY OF METALLURGICAL ENTERPRISES: A REVIEW OF MODERN APPROACHES, TECHNOLOGIES, AND CHALLENGES

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This study is dedicated to examining the transformational potential of artificial intelligence (AI) and, in particular, large language models (LLMs) in controlling the operational efficiency of metallurgical enterprises. It examines contemporary approaches, advanced technologies, and key challenges associated with integrating AI into such critical areas as automated manufacturing process management, quality control, predictive maintenance, supply chain management, and workforce management. Based on a comprehensive literature analysis, this article elucidates how LLMs can enhance efficiency, accuracy, and adaptability within the metallurgical industry, and it also identifies gaps in existing research that warrant further investigation.

The integration of AI and LLMs in the metallurgical industry faces complex challenges such as the specificity of industry data and terminology, the opacity of "black box" algorithms, insufficient adaptation of models to industrial conditions, high computational demands, and real-time issues. Additionally, there is a need for qualified personnel, cultural changes, and the development of service staff.

A comprehensive approach for the successful implementation of AI technologies in the management of the operational activities of a metallurgical enterprise will include targeted research that takes into account practical, economic, and social aspects. The key directions are the development of physics-informed AI with the integration of metallurgical knowledge, the creation of hybrid systems combining LLMs with traditional methods, and the application of unsupervised learning to overcome data scarcity. The priority is to enhance the interpretability of models, integrate with Digital Twins for real-time monitoring, embed safety constraints through predictive control models, and fine-tune universal LLMs for metallurgical applications.

Keywords: *Artificial Intelligence, Large Language Models, Metallurgical Industry, Operational Activity, Digital Twins, Predictive Maintenance, Quality Control, Management.*

Детюк Сергій, Койфман Олексій. Штучний інтелект для управління ефективністю операційної діяльності металургійного підприємства: огляд сучасних підходів, технологій та викликів

Дослідження присвячено вивченню трансформаційного потенціалу штучного інтелекту (ШІ) та, зокрема, великих мовних моделей (ВММ) в управлінні ефективністю операційної діяльності металургійних підприємств. Розглядаються сучасні підходи, передові технології та основні виклики, пов'язані з інтеграцією ШІ в такі критично важливі сфери, як автоматизоване управління виробничими процесами, контроль якості, прогнозне обслуговування, управління ланцюгами постачання та кадровий менеджмент. На основі всебічного аналізу літератури висвітлено, як ВММ можуть підвищити ефективність, точність і адаптивність металургійної промисловості, а також ідентифіковано прогалини в наявних дослідженнях, що потребують подальшого вивчення.

Інтеграція ШІ та ВММ-моделей у металургійній промисловості стикається з такими комплексними викликами, як специфічність галузевих даних і термінології, непрозорість алгоритмів «чорного ящика», недостатня адаптація моделей до промислових умов, високі обчислювальні вимоги та проблеми реального часу. Додатково виникають потреба в кваліфікованих кадрах, культурні зміни та розвиток обслуговуючого персоналу.

Комплексний підхід для успішного впровадження ШІ-технологій в управлінні операційною діяльністю металургійного підприємства буде включати цілеспрямовані дослідження, що враховують практичні, економічні та соціальні аспекти. Ключовими напрямами є розвиток фізично-інформованого ШІ з інтеграцією металургійних знань, створення гібридних систем поєднання ВММ із традиційними методами, застосу-

вання неконтрольованого навчання для подолання дефіциту даних. Пріоритетним є підвищення інтерпретованості моделей, інтеграція із цифровими двійниками для моніторингу реального часу, вбудовування обмежень безпеки через прогнозні контрольні моделі та доналаштування універсальних ВММ для металургійних застосувань.

Ключові слова: *штучний інтелект, великі мовні моделі, металургійна промисловість, операційна діяльність, цифрові двійники, прогнозне обслуговування, контроль якості, управління.*

Introduction. The metallurgical industry is the cornerstone of the modern economy, providing the raw material base for key sectors such as mechanical engineering, construction, aircraft engineering, and electronics [1]. However, this sector faces significant challenges, including high energy consumption, substantial CO_2 emissions, low resource use efficiency, frequent machine breakdowns, and issues related to labor productivity [1; 2]. These problems threaten the sustainability and competitiveness of the industry in the context of rising environmental standards and global competition [1; 2].

Traditionally, operational activities in manufacturing encompass the comprehensive organization of processes from design to the finished product, including the management of workforce, quality, maintenance, and supply [3]. Before the spread of automation, these processes were optimized using human-oriented methods [4]. The development relied on testing and visualizing prototypes, while cost control relied on human experience and judgment, and maintenance was either preventive or reactive. Quality control was carried out by human experts, and it was time-consuming.

In traditional metallurgy, this led to low resource utilization, labor inefficiency, and frequent equipment failures. Moreover, a number of manufacturing enterprises are still operating with outdated systems that lack the necessary flexibility and interoperability for seamless integration with modern technologies [5].

However, efforts to automate operational processes face significant challenges due to the complexity and dynamism of the metallurgical processes themselves. Information for decision-making is fragmented and often requires manual collection and analysis, creating bottlenecks and slowing down the response to changes [6]. In addition, high initial investments in modernization and integration with outdated systems remain significant barriers.

In response to these challenges, digital transformation and the implementation of artificial intelligence (AI) technologies have become key strategies for enhancing the efficiency, flexibility, and resilience of manufacturing processes [1; 2; 3; 7; 8; 9]. In particular, the concepts of Industry 4.0 and 5.0, which involve the integration of the Internet of Things (IoT), robotics, Big Data, analytics, and AI, are revolutionizing traditional manufacturing paradigms [1; 4; 7; 8; 9].

The latest advancements in the field of Large Language Models (LLMs), such as the GPT family from OpenAI, represent a significant breakthrough in the area of Natural Language Processing (NLP) [4]. These models, enhanced by expanded computational resources and advanced algorithms, have demonstrated exceptional skill in understanding context, answering questions, and generating content [4]. In the manufacturing sector, including metallurgy, these opportunities are gradually revealing their enormous potential [4; 6].

This occurs due to the powerful capabilities of logical reasoning, knowledge transfer, and text processing, which allow LLMs to automate the generation of reports and technical documentation, facilitate knowledge exchange, and provide deep analysis of vast amounts of data [4]. Thanks to this, they contribute to increasing operational efficiency, improving quality control, forecasting maintenance needs, and optimizing production schedules, which leads to innovations and resource savings in the metallurgical and other manufacturing industries [4; 6].

LLMs are capable of transforming the manufacturing sector by offering new opportunities for process optimization, increasing efficiency, and stimulating innovation [4]. They can automate and improve various aspects of production, from product design and development to quality control, supply chain optimization, and talent management [4]. Their ability to understand and execute complex instructions, extract valuable information from vast amounts of data, and facilitate knowledge sharing makes them an extremely valuable tool [4].

Thus, the research and development of automated systems for controlling operational efficiency in metallurgical enterprises using specialized AI language models is extremely relevant. This will allow the industry to overcome existing limitations, increase productivity, and ensure sustainable development in the context of constant market changes and technological progress [2].

The purpose of this analytical study is to analyze and summarize existing knowledge regarding the application of Artificial Intelligence and, in particular, LLMs, for optimizing the operational activities of metallurgical enterprises. This review will serve as a theoretical basis for further scientific research in the field of developing automated systems for managing operational efficiency in metallurgical enterprises.

Materials and Methods. Artificial Intelligence (AI) has significantly transformed various industries, bringing revolutionary changes to operational efficiency and competitive dynamics worldwide [2]. In particular, LLMs, such as GPT-4V, have significant potential to transform the manufacturing industry by offering new opportunities for process optimization, increasing efficiency, and fostering innovation [4]. Their capabilities in understanding and generating natural language, contextual comprehension, answering questions, as well as logical reasoning and knowledge transfer make them a powerful tool for automating and enhancing various aspects of production [4].

LLMs can revolutionize product design processes by exploring vast design spaces, generating diverse and innovative solutions, and optimizing designs based on given parameters [3]. They can contribute to the development of products that have increased efficiency, effectiveness, and safety, especially in the post-pandemic era [3]. The integration of LLMs into computer-aided design (CAD) and computer-aided manufacturing (CAM) significantly accelerates the preliminary phases of the CAD process, automates routine tasks, and optimizes the “design-manufacture” sequence [4]. For example, GPT-4V can design electric vehicles, providing key points of enhanced design and visual images [4].

LLMs have the potential to improve quality control processes by effectively detecting and identifying defects and anomalies in various products [3]. They can create virtual models of products, allowing the simulation of the manufacturing process, which helps in the early detection and prevention of potential defects [3]. The application of AI, including LLMs, is proposed for monitoring industrial processes, diagnosing faults, and controlling product quality [3]. In metallurgy, AI quality control systems are already being used, for example, at ArcelorMittal to improve product quality and reduce waste [2].

Predictive maintenance (PM) is a proactive strategy that uses data, analytics, and machine learning to predict the likelihood of equipment or machine failure. AI can be applied at various stages of the PM, from data collection to deployment and monitoring [3]. This helps prevent future failures and minimize downtime [3; 4; 7; 9; 10]. In the metallurgical industry, AI-driven PM is becoming increasingly widespread, helping to extend the lifespan of machines and reduce unplanned downtime [2]. In metallurgical production, systems based on machine learning models are being implemented to manage the rolling rates and extraction of slabs from furnaces, which leads to increased productivity.

Demand forecasting is vital for optimizing production processes, effective inventory management, and meeting customer needs [3; 4]. AI, including LLMs, can analyze market trends, consumer behavior, and sales data, enhancing the accuracy of demand forecasting [3; 4; 10]. LLMs can also optimize delivery routes and schedules, significantly reducing transportation costs [4]. For example, Tata Steel has transformed its logistics operations using AI-driven predictive software [1].

LLMs, such as ChatGPT, can be integrated into work settings as an element of an individual network of applications that goes beyond simple text generation [3]. They can analyze and synchronize various elements, such as workforce planning, shift schedules, job description analysis, and performance management [3]. LLMs can also automate the screening and initial interview processes in HR departments [4].

LLMs have transformational capabilities in planning the work of robots, especially with the use of multimodal input data, such as visual and auditory data [4; 9; 10]. They can generate code fragments and entire programs for robots with high accuracy, significantly reducing the time and effort required for task design [4]. Examples include the use of LLMs for coordinating the actions of robots based on instructions and visual perception [4]. The use of robots for cutting, welding, and processing materials in metallurgy significantly reduces manual labor and mechanical errors [2].

One of the implemented projects is an AI solution at Metinvest based on computer vision for real-time quality control of semi-finished products. The system automatically detects defects during slab production: it tells the operator where and what kind of defect is found, helping to correctly trim the material [11]. The next stage after a thorough analysis of defects during the production of semi-finished products is the integration with physical robotic systems for full process automation [11].

LLMs play a significant role in promoting the bioeconomy by facilitating research, innovation, and the effective translation of scientific discoveries into practical applications [4]. They can process vast amounts of scientific literature and data, providing researchers and manufacturers with information that accelerates the design and optimization of bioengineering processes [4]. LLMs simplify the patent filing process by automating labor-intensive text work and generating draft applications [4].

They also facilitate the extraction and exchange of knowledge from factory documents and expert data [4].

Overall, LLMs contribute to the transformation of manufacturing procedures by optimizing processes, improving product design, enhancing quality control, and promoting overall efficiency and innovation in the industry [3]. LMMs can analyze Big Data to identify patterns and insights that enable more informed decision-making, improved forecasting, and optimized production schedules [2; 4; 5; 7; 8; 10].

Integration of the LLMs with Digital Twins (DT) is a key direction for maximum productivity, especially in the steel industry [6]. DT are virtual copies of physical systems that allow real-time monitoring, optimization, and analysis [6]. LLMs can democratize access to information by providing real-time answers to various operational and planning questions using structured and validated data available in the DT [6]. This significantly enhances operational efficiency, productivity, and decision-making capabilities [6]. The use of simulation software, such as ESI Group ProCast, for modeling casting processes demonstrates how virtual experiments can predict temperature distribution, metal flow vectors, and potential defect formation, which can also be enhanced by LLMs.

The analyzed sources use various methodological approaches to study the application of AI and LLMs in production, including metallurgy. This allows for a comprehensive understanding of the topic, which is useful for developing the methodology of a dissertation study:

1. Many sources are based on qualitative research and a critical review of existing literature to identify the impact of digital transformation and AI on manufacturing processes [3]. This approach allows for the systematic evaluation, analysis, and integration of the existing body of knowledge.

2. Some studies use a mixed approach, combining qualitative and quantitative analysis [2; 5; 9; 12]. For example, a content analysis of the annual reports of leading industrial corporations is conducted using QDA Miner software to identify connections between “smart manufacturing”, strategy, and performance indicators [12].

3. The research includes the collection of empirical data, the study of case studies, the results of experiments, and the theoretical foundations related to each area of research [5; 9]. Examples include the analysis of AI implementation at specific metallurgical enterprises, such as Tata Steel, ArcelorMittal, Baowu Steel, and others [1; 2].

4. Aggregating data through surveys in manufacturing companies to assess the impact of AI on key performance indicators [5]. Interviews are also conducted with industry experts, managers, and engineers to gain working knowledge into the challenges and benefits of AI implementation [2].

5. A comparative analysis is used between production processes that have implemented AI and those that have not, to identify significant improvements in labor efficiency, machine reliability, and sustainability [2].

These methodological approaches provide a comprehensive understanding of both the theoretical concepts and the practical implications of integrating AI and LLMs into industrial processes.

Results. Despite significant advantages and potential, the integration of AI and LLMs in the metallurgical industry faces a number of challenges and research gaps that require further attention.

The authors have identified the following general challenges of AI and LLMs integration:

1. The metallurgical domain encompasses highly specialized and very complex data characterized by specific terminology, regulatory frameworks, and dynamic market conditions [4]. This requires complex comprehension capabilities from the models. Despite the large amount of technological data coming from automated control systems, ensuring their high quality, consistency, and integration capability remains a critical challenge [2; 9].

2. Many AI models, especially deep learning ones, remain “black boxes”, which complicates understanding their decisions [7; 9]. In industrial conditions, where safety and accuracy are critical, the development of transparent and explainable AI models (Explainable AI – XAI) is necessary to enhance trust and broader implementation [4; 9].

3. LLMs designed for general tasks may perform poorly with specific terminologies and complex interconnections in the metallurgical industry [4; 9]. Further research is needed on the adaptation of LLMs to specific domains by training models on specially selected arrays of production data, technical documents, and industry standards [4].

4. The application of LLMs, especially the latest models, is associated with high computational demands, significant energy consumption, and latency issues during real-time processing [4; 7]. This is a significant limitation for their widespread implementation in industrial conditions [1; 2; 5].

5. The implementation of AI requires not only technological updates but also cultural changes within the organization to embrace new approaches to automation and data-driven decision-making [2; 5]. There is a shortage of qualified AI and data specialists in the manufacturing sector [1; 2; 5]. Research often underestimates the scope and

complexity of workforce development, which is necessary [1].

On the other hand, there are specific gaps and future research directions:

1. Despite the successful results, the architecture of AI and the physical characteristics of metallurgical processes were mainly considered independently of each other [7]. Further research is needed on the design of AI structures that possess physically interpretable behavior, which will allow for a better understanding and optimization of the characteristics of relevant AI models by integrating domain knowledge [4; 7].

2. Although LLMs excel at processing unstructured data and generating human-like text, they may have difficulties with tasks that require precise numerical calculations or strict logical reasoning [4]. Researchers are studying hybrid approaches that combine LLMs with traditional rule-based systems or numerical optimization methods [4; 7; 9].

3. The complexity of the stochastic and nonlinear nature of manufacturing systems at the systemic level creates difficulties for decision-making processes. The application of machine learning at the system level remains limited [9]. A deeper understanding of manufacturing processes and the selection of appropriate AI methods and algorithms is needed.

4. Achieving a comprehensive understanding of the relationships between the material, its processing, and characteristics is vital to ensure the desired performance of manufactured parts [9]. AI has the potential to simplify the modeling process and increase forecasting accuracy, thereby enhancing productivity in various manufacturing processes.

5. LLMs, in essence, are language models, whereas production applications, such as planning, require “world models” [7]. Synergistic integration of LLM and world models can open a potential path to solving common planning problems.

6. There is a significant gap between the theoretical potential of digital solutions and their actual implementation in the metallurgical industry [1]. Research often focuses on engineering developments, without considering the larger operational, cultural, and organizational contexts necessary for successful implementation [1]. More comprehensive approaches to integration are needed.

7. The growing demand for the speed and accuracy of sensors, data transmission, and AI implementation processing brings the limitations of hardware to the forefront [7]. The development of specialized hardware for the new generation of AI algorithms can bring enormous benefits to AI in manufacturing.

Conclusions. These gaps in research highlight the need for further, more targeted studies that will not only develop new AI models and algorithms but also consider the practical, economic, and social aspects of their implementation in such a critical industry as metallurgy. This will allow for the creation of more reliable, interpretable, and efficient systems for managing operational activities.

Future research may focus on integrating knowledge of metallurgical production into AI models (physics-informed AI), which will ensure domain consistency and increased prediction accuracy, especially in conditions of limited or incomplete data.

Priority efforts should be directed towards several key areas to improve the application of LLMs.

First, to handle the specialized and complex nature of production data and meet the high engineering expectations for accuracy and reliability, focus should be placed on developing advanced methods for domain adaptation and hybrid AI approaches that combine LLMs with traditional rule-based systems or numerical optimization methods.

Second, to reduce challenges related to data scarcity and the need for large-scale data annotation, emphasis will be placed on unsupervised and semi-supervised learning paradigms, while simultaneously enhancing the interpretability of LLMs for critical decisions by ensuring transparent reasoning processes. Moreover, for decision-making based on AI in critical operational scenarios, embedding safety constraints through integration with Model Predictive Control will be crucial to prevent catastrophic consequences.

Third, a key direction is the further development of hybrid solutions that combine generative AI with DT to enhance real-time monitoring, simulation, and process optimization, allowing DT to invoke LLMs to solve complex tasks.

Finally, the field of research should develop by utilizing and fine-tuning universal LLMs with knowledge of metallurgical production to promote broader application in areas such as system design, planning, and diagnostic thinking, while simultaneously focusing on enhancing their energy efficiency.

BIBLIOGRAPHY:

1. Digitalization in the Steel and Mining Industries: Overcoming Challenges by Comprehensive Technological Innovation to Enhance Sustainability. 2024. Nhat Anh Tran. URL: https://urn.fi/URN:NBN:fi:aalto-202405263585

2. Artificial Intelligence applications in traditional steel manufacturers. 2024. Nuojin Hao. URL: https://www.theseus.fi/handle/10024/873279

3. Doanh D. C., Dufek Z., Ejdys J., Ginevičius R., Korzynski P., Mazurek, G., Ziemba, E. Generative AI in the manufacturing process: theoretical considerations. *Engineering Management in Production and Services*. 2023. Vol. 15, No. 4. P. 76–89. DOI: https://doi.org/10.2478/emj-2023-0029

4. Li Y., Zhao H., Jiang H., Pan Y., Liu Z., Wu Z., Liu T. Large language models for manufacturing. *arXiv preprint arXiv:2410.21418*. 2024. DOI: https://doi.org/10.48550/arXiv.2410.21418

5. Waqar M., Bhatti I., Khan A. H. AI-powered automation: Revolutionizing industrial processes and enhancing operational efficiency. *Revista de Inteligencia Artificial en Medicina*. 2024. Vol. 15, No. 1. P. 1151–1175. URL: https://redcrevistas.com/index.php/Revista/article/view/285

6. de Oliveira Mendonça M., Pereira F. A. C., e Silva G. R. L., Alexandre D., Vieira G. Generative AI and Digital Twins: a win-win integration for maximum productivity in the steel industry. *26º Seminário de Automação e TI*. São Paulo, Brasil, 2024. P. 502–511. DOI: http://doi.org/10.5151/2594-5335-41154

7. Gao R. X., Krüger J., Merklein M., Möhring H. C., Váncza, J. Artificial Intelligence in manufacturing: State of the art, perspectives, and future directions. *CIRP Annals*. 2024. Vol. 73, No. 2. P. 723–279. DOI: https://doi.org/10.1016/j.cirp.2024.04.101

8. Arvindan Badrinarayanan. AI in Manufacturing: Driving Operational Excellence. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2024. Vol. 10, No. 6. P. 585–594. DOI: https://doi.org/10.32628/CSEIT24106199

9. Bin Akhtar Z. Artificial intelligence (AI) within manufacturing: An investigative exploration for opportunities, challenges, future directions. *Metaverse*. 2024. Vol. 5, No. 2. P. 2731. DOI: https://doi.org/10.54517/m.v5i2.2731

10. Lodhi S. K., Gill A. Y., Hussain I. AI-powered innovations in contemporary manufacturing procedures: An extensive analysis. *International Journal of Multidisciplinary Sciences and Arts*. 2024. Vol. 3, No. 4. P. 15–25. DOI: https://doi.org/10.47709/ijmdsa.v3i4.4616

11. Digital breakthrough in metallurgy: How Metinvest Digital is training machines to control metal quality // *Metinvest Holding* : [веб-сайт]. URL: https://www.metinvestholding.com/en/media/news/cifrovij-proriv-u-metalurg-yak-metinvest-digital-navcha-mashini-kontrolyuvati-yakstj-metalu (дата звернення: 02.07.2025).

12. Horobet A., Tudor C. D., Dinca Z., Dumitrescu D. G., Stoica E. A. Artificial intelligence and smart manufacturing: An analysis of strategic and performance narratives. *Amfiteatru Economic*. 2024. Vol. 26, No. 66. P. 440–457. DOI: https://doi.org/10.24818/EA/2024/66/440

REFERENCES:

1. Tran, A. (2024). Digitalization in the steel and mining industries: overcoming challenges by comprehensive technological innovation to enhance sustainability. Retrieved from: https://urn.fi/URN:NBN:fi:aalto-202405263585

2. Hao, N. (2024). Artificial Intelligence applications in traditional steel manufacturers. Retrieved from: https://www.theseus.fi/handle/10024/873279

3. Doanh, D. C., Dufek, Z., Ejdys, J., Ginevičius, R., Korzynski, P., Mazurek, G. & Ziemba, E. (2023). Generative AI in the manufacturing process: theoretical considerations. *Engineering Management in Production and Services*, 15(4). DOI: https://doi.org/10.2478/emj-2023-0029

4. Li, Y., Zhao, H., Jiang, H., Pan, Y., Liu, Z., Wu, Z., & Liu, T. (2024). Large language models for manufacturing. *arXiv preprint arXiv:2410.21418*. DOI: https://doi.org/10.48550/arXiv.2410.21418

5. Waqar, M., Bhatti, I., & Khan, A. H. (2024). AI-powered automation: Revolutionizing industrial processes and enhancing operational efficiency. *Revista de Inteligencia Artificial en Medicina*, 15(1), 1151–1175. Retrieved from: https://redcrevistas.com/index.php/Revista/article/view/285

6. de Oliveira Mendonça, M., Pereira, F. A. C., e Silva, G. R. L., Alexandre, D., & Vieira, G. Generative AI and Digital Twins: a win-win integration for maximum productivity in the steel industry. p. 502–511. In: 26º Seminário de Automação e TI, São Paulo, Brasil, 2024. ISSN: 2594–5335, DOI: http://doi.org/10.5151/2594-5335-41154

7. Gao, R. X., Krüger, J., Merklein, M., Möhring, H. C., & Váncza, J. (2024). Artificial Intelligence in manufacturing: State of the art, perspectives, and future directions. *CIRP Annals*, 73 (2), 723–279. DOI: https://doi.org/10.1016/j.cirp.2024.04.101

8. Arvindan Badrinarayanan (2024). AI in Manufacturing: Driving Operational Excellence. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 10(6), 585–594. DOI: https://doi.org/10.32628/CSEIT24106199

9. Bin Akhtar, Z. (2024). Artificial intelligence (AI) within manufacturing: An investigative exploration for opportunities, challenges, future directions. *Metaverse*, 5(2), 2731. DOI: https://doi.org/10.54517/m.v5i2.2731

10. Lodhi, S. K., Gill, A. Y., & Hussain, I. (2024). AI-powered innovations in contemporary manufacturing procedures: An extensive analysis. *International Journal of Multidisciplinary Sciences and Arts*, 3(4), 15–25. DOI: https://doi.org/10.47709/ijmdsa.v3i4.4616

11. Metinvest Holding. (2024, July 2). Digital breakthrough in metallurgy: How Metinvest Digital is training machines to control metal quality. *Metinvest*. Retrieved from https://www.metinvestholding.com/en/media/news/cifrovij-proriv-u-metalurg-yak-metinvest-digital-navcha-mashini-kontrolyuvati-yakstj-metalu

12. Horobet, A., Tudor, C. D., Dinca, Z., Dumitrescu, D. G., & Stoica, E. A. (2024). Artificial intelligence and smart manufacturing: An analysis of strategic and performance narratives. *Amfiteatru Economic*, 26(66), 440–457. DOI: https://doi.org/10.24818/EA/2024/66/440