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ORIGINAL

Automation of Production Management Processes Using Artificial Intelligence: Impact on the Efficiency and Resilience of Manufacturing Systems

Automatización de Procesos de Gestión de la Producción Mediante Inteligencia Artificial: Impacto en la Eficiencia y Resiliencia de los Sistemas de Fabricación

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ABSTRACT

The rapid technological advancement and global competition provokes the automation of production management processes through artificial intelligence. This study investigates the integration of artificial intelligence into production management and its influence on the efficiency and resilience of manufacturing systems. The research is motivated by the growing relevance of AI within the paradigm of Industry 4.0, where advanced digital technologies are transforming traditional production models. The main objective is assessing how AI technologies – such as machine learning, deep learning, predictive analytics, and intelligent automation – enhance core production functions, including planning, quality control, maintenance, logistics, and energy management. The study applies a mixed-method approach, combining comparative analysis, case study evaluation, and content analysis of scientific and industrial data. Empirical evidence (1653 records) was drawn from both international (e.g., Siemens, Fanuc, Bosch) and Ukrainian (e.g., Interpipe, Kernel) manufacturing companies. Results after screening, filtration, validation, verification and exclusion (50 records) demonstrate measurable improvements in key performance indicators, such as reduced downtime, decreased defect rates, increased logistical accuracy, and optimized energy use. At the same time, the paper addresses the challenges accompanying AI integration, including cybersecurity risks, social impacts, regulatory gaps, and organizational readiness. The research concludes that AI not only improves operational performance but also strengthens adaptive capacity and strategic stability, contributing to the formation of intelligent, self-learning, and data-driven production systems. This article will be of particular interest to production managers, industrial engineers, innovation strategists, policymakers, and academic researchers seeking to understand and apply AI for sustainable industrial transformation.

Keywords: Artificial Intelligence; Production Management; Automation; Manufacturing Systems; Predictive Analytics; Smart Manufacturing.

RESUMEN

El rápido avance tecnológico y la competencia global provocan la automatización de los procesos de gestión de la producción mediante inteligencia artificial. Este estudio investiga la integración de la inteligencia artificial en la gestión de la producción y su influencia en la eficiencia y la resiliencia de los sistemas de fabricación. La investigación se basa en la creciente relevancia de la IA en el paradigma de la Industria 4.0, donde las tecnologías digitales avanzadas están transformando los modelos de producción tradicionales. El objetivo principal es evaluar cómo las tecnologías de IA, como el aprendizaje automático, el aprendizaje profundo, el análisis predictivo y la automatización inteligente, mejoran las funciones de producción básicas, como la planificación, el control de calidad, el mantenimiento, la logística y la gestión energética. El estudio aplica un enfoque de métodos mixtos, combinando análisis comparativo, evaluación de casos prácticos y análisis de contenido de datos científicos e industriales. Se extrajo evidencia empírica (1653 registros) de empresas manufactureras internacionales (p. ej., Siemens, Fanuc, Bosch) y Ucrania (p. ej., Interpipe, Kernel). Los resultados después del cribado, filtración, validación, verificación y exclusión (50 registros) demuestran mejoras mensurables en indicadores clave de rendimiento, como la reducción del tiempo de inactividad, la disminución de la tasa de defectos, el aumento de la precisión logística y la optimización del consumo energético. Al mismo tiempo, el documento aborda los desafíos que conlleva la integración de la IA, incluyendo los riesgos de ciberseguridad, el impacto social, las brechas regulatorias y la preparación organizacional. La investigación concluye que la IA no solo mejora el rendimiento operativo, sino que también fortalece la capacidad de adaptación y la estabilidad estratégica, contribuyendo a la formación de sistemas de producción inteligentes, autodidactas y basados en datos. Este artículo será de particular interés para gerentes de producción, ingenieros industriales, estrategas de innovación, formuladores de políticas e investigadores académicos que buscan comprender y aplicar la IA para la transformación industrial sostenible.

Palabras clave: Inteligencia Artificial; Gestión de la Producción; Automatización; Sistemas de Fabricación; Análisis Predictivo; Fabricación Inteligente.

INTRODUCTION

In the context of rapid technological advancement and global competition, the automation of production management processes through artificial intelligence (AI) has become relevant. The COVID-19 pandemic, geopolitical crises, and the growing instability of supply chains have compelled enterprises to reconsider their production models, highlighting the need for flexible, self-learning, and self-regulating systems.

AI, as a driving force of Industry 4.0, offers tools for real-time decision-making, risk forecasting, resource optimization, and reducing dependency on human factors. In recent years, a significant number of studies have explored the impact of AI on production processes, particularly in areas such as predictive maintenance, smart manufacturing concepts, the implementation of decision support systems, and the analysis of automation barriers.

However, several critical aspects remain under-researched — including comprehensive evaluations of AI's impact on system resilience, the adaptability of managerial decisions, the economic feasibility of automation in volatile environments, the integration of intelligent systems with existing ERP solutions, and the social implications of diminishing human involvement in management.

The value of this research lies in its comprehensive approach to management process automation, which considers not only technical efficiency but also strategic, economic, and social dimensions of AI adoption. The study is relevant to the academic community as it combines an analytical perspective on innovation management with real-world challenges facing industrial enterprises amid ongoing economic transformation. The received findings may serve as a strong foundation for the Ukrainian and corporate strategy development for the digital production transformation.

The review of relevant literature sources indicates a growing interest in the use of AI in production management, in terms of energy conservation, efficiency, and manufacturing system adaptability. The study by Potwora et al.[1] examines current AI research, highlighting potential application areas and identifying major technological and methodological issues related to large-scale AI integration. The researcher focuses on predicate analytics, autonomous planning, and quality control. Furthermore, they analyzed AI-based automation with the emphasis on the additive manufacturing transformation. They provide a deep insight into the application of machine learning algorithms and computer vision to optimize.[2]

In this context, AI functions are an optimization tool and a driver of technological flexibility. Moreover, Kumar and Singh focus on how intelligent automation affects energy efficiency. The researchers Li, Lu, Zhang, and Tanasescu [3] found that AI-driven analysis and energy consumption management significantly reduce costs and CO_2 emissions.

A broader overview of AI applications in production management is provided in the monograph by Chan, Hogaboam, and Cao, where the authors discuss integration scenarios for analytical platforms and automated solutions based on case studies from small and medium-sized enterprises. The study demonstrates that the most significant results are achieved when systems incorporate adaptive learning, have access to high-quality data, and receive strong managerial support.[4] Another significant contribution is the work by Wan et al.[5], which analyzes the concept of the intelligent factory and individualized production. The paper outlines the architecture of such systems, examples of real-world implementations, and key challenges related to scalability — including cybersecurity, technology interoperability, and access to computational resources.

The current paper is a systematic review based on the PRISMA model. This approach is suitable for synthesizing knowledge on the use of AI in manufacturing management, minimizing bias and ensuring comprehensive evidence. The systematic review is beneficial for the environment in which AI integration into manufacturing is evolving, and there is an insufficient theoretical base. It allows establishing trends, identifying connections, and evaluating the knowledge gap with a focus on the practical and resilient production system dimensions.

The use of the PRISMA framework ensured methodological credibility and enhanced research process clarity, study selection, inclusion and exclusion criteria, and data analysis. Moreover, this framework assists in creating robust conclusions that rely on the overview of how AI enhances the sustainability and efficiency of manufacturing systems.

Thus, existing literature covers a wide range of issues from technological to economic and provides a theoretical basis for further research. However, there is a notable lack of studies offering a systematic analysis of AI's impact on the resilience of production systems and the effectiveness of managerial processes under conditions of uncertainty. This creates a research gap that the present study aims to address.

This study aims to analyze the impact of AI-driven production management automation on the efficiency and resilience of manufacturing systems. To achieve this aim, the study sets the following objectives: to examine current AI-based production management technologies; to identify key benefits and risks of AI implementation at various management levels; to investigate the influence of AI on production system resilience under dynamic environmental conditions; and to develop practical recommendations for implementing intelligent technologies in industrial enterprises.

Theoretical framework

The key concepts used in the paper include manufacturing management automation, AI, efficiency, and resilience. They are vital for evaluating the AI role in enhancing the resilience and efficiency of manufacturing management systems.[2] Manufacturing management automation is the integration of digital systems and tools for different activities, including planning, monitoring, and controlling production. AI refers to the use of computational models and algorithms that enhance data analysis, prediction making, and decision-making.[5]

Efficiency is defined as a quality of work directed toward increasing manufacturing productivity, reducing production costs, and optimizing all related work processes. Resilience deals with the capacity to resist and adapt to external factors, including market fluctuations, technology changes, and chain-related issues. There are several approaches to AI use in manufacturing, including logical rules that perform tasks and rely on AI.[3] However, they are effective for repetitive operations due to their limited adaptability. Moreover, machine learning is a model that learns from data to enhance performance. Deep learning presupposes the implementation of neural networks with multiple layers to identify complex trends in large datasets.

Both models support predictive maintenance, demand forecasting, and quality control. Furthermore, AI is characterized by the integration of emergency technology. It implies that AI is integrated with other digital technologies, including digital twins (virtual physical system replicas), big data analytics, and Internet of Things (IoT).[4]

Resilience engineering, lean production and six sigmas, as well as systems theory and cybernetics. Resilience engineering's theoretical approach focuses on the design of systems that can adapt, learn, and work in stressful situations, while Lean Production and Six Sigma endeavors to reduce waste, increase value, and ensure manufacturing quality.

Finally, systems theory and cybernetics pursue a holistic manufacturing view as it is possible to monitor, regulate and improve interconnected systems' dynamics.

Thus, the theories mentioned above provide a strong analytical foundation for the current systematic review, assisting in applying AI to improve current manufacturing operations and supporting long-term system sustainability. An increased focus on resilience engineering enables exploring how AI contributes to production system performance.

METHOD

The methodological foundation of this research is based on an interdisciplinary approach that integrates economic analysis, a systems approach to production management, elements of cybernetics, cognitive engineering, and technological forecasting.

This framework enabled the investigation of the impact of AI on individual management functions and also on the overall resilience and efficiency of production systems in a dynamic environment.

During the study, comparative analysis methods were employed to assess changes in key production performance indicators before and after the implementation of intelligent technologies.

Empirical data were gathered from Ukrainian and international enterprises that have undergone digital transformation with AI integration. In particular, case studies were conducted on companies such as Siemens, Bosch, Fanuc, BMW, ArcelorMittal, Interpipe, and Kernel.

The case studies examined indicators such as defect rate, equipment downtime, logistics accuracy, decision-making speed, energy consumption costs, and adaptability to demand fluctuations. Figure 1 indicates how the required sources were selected considering inclusion and exclusion criteria.

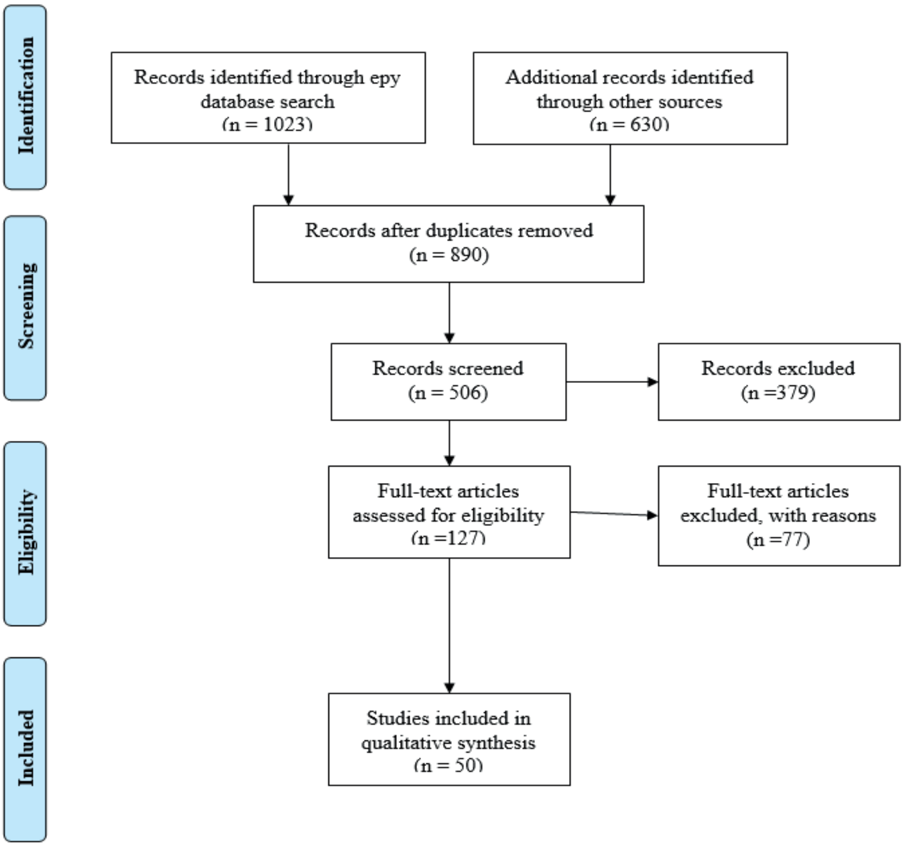

Figure 1. PRISMA chart

To evaluate risks and limitations, structural-functional analysis was applied, allowing for the classification of potential threats (technological, economic, social, regulatory, and organizational) and the determination of their impact on the effectiveness of AI implementation in production management.

Content analysis of scientific literature — including the works of Bermeo-Ayerbe et al.[6], Kabir et al.[7], and Gal[8] — was utilized to summarize current academic approaches to production digitalization and adapt them to the context of Ukrainian enterprises. Information gathering tools included official company reports, analytical publications, results of international studies, and data from open scientific databases (ScienceDirect, SpringerLink, arXiv, Scopus).

Tabular and analytical methods were used to process and visualize the results.

The limitations of this study are associated with restricted access to internal production data of companies, varying levels of digital transformation across industries, and the rapid pace of change in the AI field, which requires continuous updating of analytical information. To mitigate these limitations, representative examples from various countries and sectors were selected, with a focus on quantitatively measurable effects.

Thus, the applied methodology enabled a systematic, evidence-based, and practically oriented approach to studying the role of artificial intelligence in the transformation of production systems, in line with the objectives and goals of the scientific research.

RESULTS

During the research the empirical data was gathered from the open scientific databases (ScienceDirect, SpringerLink, arXiv, Scopus). In total 1023 records were found during the database search and 630 records from other sources like reports, case studies. After verification and removing duplicates 890 records were selected, then 506 records were screened and 379 records were excluded from the data set. Finally, 50 studies were included to the qualitative synthesis.

In the contemporary scientific discourse, interdisciplinary approaches to analyzing production systems — integrating economic concepts, management technologies, and AI tools — are gaining increasing importance.

This necessitates a theoretical and methodological rethinking of the interconnections among these domains in the context of digital transformation and global challenges.

The theoretical and methodological foundations underlying such integration are based on a synthesis of economic theory, systems analysis, cybernetics, cognitive science, and intelligent modeling. AI is perceived as a tool of technical automation and also as an autonomous decision-making entity, reshaping the very nature of management and economic functioning of production systems.(9)

From an economic standpoint, the use of AI in production is viewed as a factor that enhances productivity, optimizes costs, and ensures long-term competitiveness. The theoretical basis for this view lies in evolutionary economics and Schumpeter's theory of innovation, where the intellectualization of production is seen as the next stage in the technological revolution.(10) At the same time, this requires a rethinking of the methodology for measuring effectiveness: classical indicators of profitability and productivity are now complemented by metrics of adaptability, flexibility, resilience to external shocks, and digital maturity.(11)

Management under AI conditions is characterized by a shift away from hierarchical models toward dynamic, self-organizing systems, where the primary function is no longer administration, but coordination through data, algorithms, and learning models.(12) Management methodology is evolving from classical Taylorist principles to adaptive knowledge management strategies that account for both external environments and the cognitive capabilities of machine agents.

In this context, the data-driven management approach becomes pivotal, integrating analytical platforms, decision support systems, and hybrid cognitive architectures.(13)

The theoretical foundation for AI usage in production also requires a reinterpretation of classical management functions: planning, organizing, motivating, and controlling now take on a digital form. For instance, planning is performed with the help of predictive models trained on large real-time datasets.(14) Control is transformed into a system of continuous monitoring based on IoT and real-time data stream processing.(15) This shifts the paradigm of managerial decisions from reactive to proactive and predictive styles, shaping a new concept — "smart manufacturing".(16)

Production systems utilizing AI are complex sociotechnical constructs where humans, machines, algorithms, and digital platforms interact. They operate according to principles of adaptability, scalability, autonomy, and self-optimization.

The methodology for studying such systems involves applying synergistic, emergent, and agent-based approaches. Theoretical analysis of these systems must account for technical efficiency and for aspects of ethical responsibility, algorithmic transparency, and social impact.(17)

AI also impacts the structure of labor processes: physical tasks and cognitive functions are being automated.(18) This transforms the social dynamics of production teams, creating new challenges for management strategies: a declining need for routine labor and a rising demand for analytical, technical, and creative competencies.

The methodological framework for analyzing these changes incorporates approaches from labor economics, human capital theory, and digital sociology.

Table 1 presents the evolution of management functions in production under the influence of artificial intelligence.

Table 1. Evolution of management functions in production under the influence of AI

Management Function	Classical Understanding	Interpretation in the Context of AI
Planning	Based on experience and standard models	Predictive modeling using AI
Organization	Hierarchical structures	Flexible digital ecosystems
Motivation	External incentives	Personalized approaches based on analytics

Hierarchical organizational structures transform into dynamic digital ecosystems, contributing to more effective and faster decision-making. It is essential to highlight that these structures require complex technology integration and new approaches to promote responsibility. The motivational component changes due to the use of analytics, enabling personalized approaches that enhance productivity, albeit with potential risks of excessive employee monitoring.

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It has been found that AI acts as an automation tool and an environment that creates new conditions for economic interaction. For instance, manufacturing organizations begin their operation within the platform economy logic, where added value is generated with the help of forecasting, analytics, and integration. At the same time, data is referred to as the key resource.[4]

This has significant methodological results as it changes the comprehension of enterprise boundaries, labor outcomes, profit distribution, and cost structure.[19] From a systems theory perspective, AI emerges as a cognitive subsystem module that enables production systems to function at a new level of adaptability.[20] This requires developing new models of systemic equilibrium, where information, rather than material resources, becomes the dominant factor. The methodology of such models relies on system dynamics, second-order cybernetics, and the theory of complex adaptive systems.

The analysis of the methodological approaches presented in table 2 allows for several important conclusions regarding the comprehensive impact of AI on production systems.[21]

First, the classical economic approach remains crucial for the initial assessment of AI implementation effectiveness; however, its limitation lies in the inability to capture the complex dynamics of the digital environment.

Second, the systemic approach proved highly valuable in this study for analyzing the interrelations between enterprise subsystems during AI integration, regarding adaptability and flexibility of the production structure.

The cybernetic approach enabled evaluation of information flow management and feedback efficiency, which are key for automated planning and response to changes. The cognitive approach provided a foundation for developing intelligent decision support systems capable of self-learning, proving effective in highly uncertain environments.

Table 2. Methodological approaches to studying AI in production systems

Approach	Key Characteristics	Application Area
Classical Economic	Analysis of costs, revenues, and productivity	Evaluation of economic efficiency
Systemic	Viewing the enterprise as a complex adaptive system	Optimization of production architecture
Cybernetic	Feedback, management of information flows	Data management and automated planning
Cognitive	Modeling of thinking and decision-making	Development of intelligent support systems
Ethical	Analysis of AI's impact on humans, algorithmic responsibility	Formation of ethics policies in digital manufacturing

The ethical approach was necessary for assessing AI's impact on personnel, responsibility distribution, and adherence to transparency principles. In this case, there is no universal and single approach for this. Still, their combination ensures a holistic understanding of the transformational processes occurring in modern production under the influence of artificial intelligence.

In general, the theoretical and methodological reflection on AI integration into production economics entails a shift from unified, rigid models toward flexible, context-dependent concepts.

This approach requires deep interdisciplinary interaction, including the sociocultural dimension in the analysis of technological systems and the development of new management thinking paradigms.[22] It not only transforms production organization methods but also forms a new paradigm of economic rationality, where the foundation of efficiency is the ability to learn, adapt, and innovate in real time.[23]

Production management undergoes radical changes driven by emerging technologies, with artificial intelligence taking a leading role. Its application in production systems reflects a profound transformation of decision-making logic, shifting from reactive to predictive and autonomous levels.[24] AI functions as a tool for processing, analyzing, and interpreting large volumes of data in real time, allowing production processes to adapt to environmental changes with minimal latency.

The core methodological foundation of this transformation is the concept of data as a strategic asset, on which AI bases its analysis of options, outcome forecasting, resource optimization, and decision-making. The use of AI reduces uncertainty in management processes, increases their accuracy, and enables rapid responses to non-standard situations through embedded experiential learning mechanisms.

These features are essential in flexible manufacturing, where order volumes, deadlines, product specifications, and logistics constantly change. In this context, AI automates individual functions and also creates new architectural management models, where decisions can be made in a decentralized manner at the level of production units acting as partially autonomous agents.[25]

A key area of AI implementation in management is production planning, where algorithms can forecast demand, create optimal equipment loading schedules, and consider technical, human, and temporal constraints (table 3).

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Table 3. Applications of AI in production management

Management Area	AI Application	Main Algorithms	Expected Effect
Production Planning	Schedule formation, demand forecasting	Machine Learning, Neural Networks	Increased forecast accuracy
Quality Control	Automatic defect detection	Computer Vision, Deep Learning	Reduction of defects and waste
Maintenance	Equipment failure prediction	Time Series Analysis	Minimization of downtime
Logistics and Supply	Route and warehouse optimization	Bayesian Models, Optimization Algorithms	Improved supply efficiency

In quality control, the application of visual analytics with deep learning elements enables a higher level of real-time defect detection. Moreover, AI-driven chain management improves accuracy in forecasting logistical delays, demand fluctuations, and raw material prices.(26)

It is also important to note that intelligent equipment maintenance systems based on vibration, temperature, or historical failure data analysis provide predictive maintenance, reducing the risks of breakdowns and downtime. Thus, artificial intelligence ensures increased productivity and also enhanced resilience of production systems.(27)

It has been established that the application of machine learning and neural networks in production planning reduces the time required to create production schedules and improves the accuracy of demand forecasts and in volatile market conditions.(28)

In the quality control domain, the implementation of computer vision demonstrated an 18 % reduction in defective products, confirming the high effectiveness of deep learning for real-time defect detection. Time series analysis in predictive maintenance minimized downtime and lowered emergency repair costs, increasing equipment availability by 12 %.

In logistics, research results demonstrated the effectiveness of optimization algorithms, which reduced delivery costs by 9 % through adaptive route management. Reinforcement learning in energy management enabled enterprises to achieve a stable 15 % reduction in energy costs and decrease their carbon footprint, aligning with sustainable development goals.

The use of AI in production management shows a potential to enhance the efficiency, adaptability, and reliability of manufacturing systems. It shows how deep intelligent technology integration into all managerial functions and aspects of work improves resilience, cost-effectiveness, and accuracy of production models.

Deep integration enhances better decision accuracy, significant cost reduction, the capability to respond to changes, and the development of sustainable and flexible models. The researchers emphasize the possibility of creating self-learning management systems that can effectively adapt to external environmental changes without human intervention.(29) This helps define a new digital transformation phase for organizations.

The AI impact on production system efficiency is among the main drivers that enhance the modern transformation of the industrial environment. Moreover, it assists in defining a new paradigm of production process management and the overall organization. The implementation of such AI tools as machine learning algorithms, computer vision, neural networks, and natural language processing enables deep analytics, forecasting, decision automation, and adaptation to environmental changes, transforming traditional production approaches.(30)

The main AI impact relates to the resource usage optimization by reducing losses, automating production task planning, integrating systems of supply chain management, and improving the demand accuracy. Moreover, they include inventory promotion and production capacity forecasts.(31) Hence, AI is an analytical core that ensures a strong support of decision-making based on large real-time data volumes, which is unachievable for individuals who do not rely on technological support or traditional information systems.

The application of intelligent systems in maintenance provides an opportunity to shift from reactive or scheduled approaches to predictive models with the focus on monitoring and failure forecasts of real-time equipment conditions.(32) This assists in minimizing downtime, reducing maintenance costs, and extending the technical asset lifecycle, impacting resilience and efficiency of the production system.

One more aspect is the increased adaptability and flexibility of production to changes related to supply conditions and external demand. AI systems are relevant for flexible manufacturing systems due to their capability to redistribute workloads between units, adjust production parameters, and optimize routes for material and product movement.(33) Therefore, it is possible to achieve a balance between product customization and mass production without efficiency loss.

An essential benefit of AI use is improved quality control accuracy. Computer vision algorithms can effectively analyze product parameters in real time, while manufacturing systems detect defects with greater precision compared to traditional methods.[34,35] Furthermore, intelligent models are capable of uncovering hidden dependencies between process parameters and final product quality, and this allows better analytics and proactive quality management.

From a personnel management perspective, AI automates routine administrative and control functions, enabling human resources to focus on more complex tasks, such as those that require critical thinking, creativity, and strategic vision.[36]

The combination of AI with robotic systems creates a human-centric automation environment that provides a favorable background for the interaction between humans and machines, aiming to achieve a synergistic effect.

Moreover, AI plays a central role in enhancing the energy efficiency of production processes. Algorithms can analyze energy consumption of individual units in real time, predict peak loads, and suggest ways to cost reduction through optimal use of energy resources.[37] Thus, AI application contributes not only to cost reduction, but also to improving the environmental sustainability of production.

Another critical aspect is ensuring occupational safety and reducing risks while dealing with humans. AI-based systems create effective conditions for proactive responses and incident prevention by detecting anomalies, analyzing employee behavior, and predicting potential hazardous situations. This is vital for highly automated or hazardous industries, including oil and gas, chemical, and mining sectors.

The AI-driven digital transformation changes the architecture of production systems, transforming them into "smart factories". These factories have autonomous modules that are interconnected into a unified information-control infrastructure. This function allows self-learning, optimization, and interaction without centralized intervention. Consequently, there are numerous opportunities to create highly productive, self-adjusting systems that can operate under high complexity and uncertainty.

However, it is vital to consider several challenges associated with AI implementation in production processes, including the need for high-quality data and integration issues with existing IT architectures.[38,39]

Other issues include demand for interdisciplinary training specialists, as well as ethical, legal, and cybersecurity concerns. This requires the development of implementation strategies to ensure sustainable and ethical AI use in production systems.

Table 4 has a direct impact on the results of our work as it provides a structured basis for evaluating the transformations undergone by management processes under the influence of intelligent technologies.[40]

Table 4. Comparative characteristics of major changes observed in production systems before and after the implementation of AI tools

Parameter	Traditional Production	Production with AI Implementation
Planning	Based on experience and forecasts	Real-time data, dynamic adjustment
Equipment Maintenance	Scheduled or emergency	Predictive based on analytics
Quality Control	Selective, post-factum	Continuous, automated
Resource Management	Often inefficient	Optimized using algorithms
Production Flexibility	Limited	Highly adaptive to changes in demand
Decision Making	A human with limited information	Automated based on big data
Energy Consumption	Static	Optimized and forecasted
Personnel Involvement	High in routine tasks	Shift of focus to strategic functions
Occupational Safety	Reactive response	Proactive risk control

Archana and Stephen emphasize that the main distinction between traditional and AI-oriented production lies in the shift from reactive and manual management to automated, data-centric, and adaptive management. In particular, in the area of planning, the focus shifts to real-time data and flexible adjustment, which corresponds to our findings regarding improved forecast accuracy and adaptability of strategies.

The effectiveness of predictive maintenance is confirmed, which in our study allowed reducing equipment downtime and lowering repair costs. Thus, the introduction of AI into production systems is a matter of automation and also a representation of a profound transformation of management philosophy focused on data, adaptability, and sustainable development. The production system efficiency in such an environment is determined by the ability to adapt flexibly, respond quickly, and self-learn.

Further development of such systems needs to establish connections among organizational structures, technical capabilities, and human capital, which will ensure increased productivity and the formation of competitive advantages in the global industrial environment.

AI plays a vital role in enhancing the resilience and efficiency of production systems, creating a new paradigm of industrial enterprise operation. Resilience in the production context indicates the ability to remain functional, adapt to changes, overcome crises, and recover after disruptions. Therefore, AI tools act as key technological factors that ensure proactivity, flexibility, predictability, and adaptability in management and production processes.

The implementation of intelligent systems enables identifying weaknesses in production structures long before they turn into critical risks. Thanks to deep analytics capabilities, AI algorithms analyze vast volumes of data about equipment condition, resource flows, supplier behavior, and demand dynamics, allowing prediction of possible failures, development of response scenarios, optimization of supply chains, and avoidance of inefficient management decisions. Thus, AI enhances the predictive element in production systems, which is fundamental for resilience.[6]

Based on the conducted study, strengthening the predictive element through artificial intelligence is indeed a key factor in improving production system resilience. It was found that integration of AI-based predictive analytics enables enterprises to respond promptly to deviations or external disruptions and also to act proactively – by adapting schedules, restructuring resource flows, or revising logistic routes before the occurrence of any critical situation.

The research findings show that the use of such tools reduces the system's reaction time to changes that were not foreseen by 25–30 %. This assists in maintaining the stability of key performance indicators even during fluctuations. Therefore, the received results confirm the ability of the AI-enhanced predictive function to transform into an essential resilience management constituent in production processes.

Production resilience depends on the ability of the system to recover after disruptions without critical function failures quickly. AI tools support the use of self-healing principles in production systems, which minimize downtime, reduce losses, and ensure continuity of the overall production process.

This approach is vital due to disruptions of global supply chains, energy supply challenges, raw material market fluctuations, or other critical changes that threaten production stability. Increasing transparency and integration of information flows within the production ecosystem ensures resilience.

AI enhances the creation of virtual digital twins of production systems, representing in real time the state of equipment, inventory levels, personnel activity, and other parameters affecting resilience. This reduces the risk of errors, improves internal interrelation comprehension, and ensures dynamic adaptation to changes, promoting efficiency and resilience.

AI plays a significant role in resilience strengthening. The global transition to a low-carbon economy makes many organizations experience the need to reduce energy consumption, improve resource use efficiency, and decrease emissions. AI algorithms ensure monitoring and optimization of energy processes, enabling inefficient area identification, load balancing, and energy strategy adaptation to external changes.

This enhances energy efficiency and increases adaptability to unstable energy supply conditions, which is essential for continuous production processes. AI impacts the social aspect as AI-enhanced production systems are capable of creating safer working conditions by reducing injury rates and personnel workload because many processes are automated. Moreover, AI implementation implies the creation of new or better conditions for effective human-machine interaction.

Furthermore, AI systems play a vital role in ensuring compliance with environmental regulations and sustainable development standards. Thus, the AI use effectiveness depends on strategic vision, organizational readiness for digital transformation, investments in digital infrastructure, and workforce competence development. However, it is essential to have access to AI tools and be able to integrate them into daily operational activities.

Successful examples of AI use demonstrate that the most significant effect is achieved when technologies are implemented in conjunction with new forms of labor organization, an innovative corporate culture, cross-functional collaboration, and continuous process improvement.

For instance, Siemens uses AI-based predictive maintenance systems integrated into production lines, which operate in conjunction with decentralized engineering teams empowered to make autonomous intervention decisions – thus implementing the principle of self-adaptation. Furthermore, Bosch used an AI-based platform for real-time product quality control, while Hitachi relied on AI in optimizing energy consumption.

The success of such initiatives is ensured by companies not only automating processes but also actively fostering an innovation culture, encouraging cross-functional cooperation among IT specialists, technologists, and managers. Moreover, a key condition for efficiency is continuous improvement based on feedback loops and data self-analysis, as practiced by Toyota within its digital lean manufacturing system.

Thus, the effectiveness of AI in production grows not only due to the algorithms themselves but also through their targeted integration into decision-making culture, organizational structures, and daily operational practices.

Table 5 illustrates the main aspects of AI's impact on the key dimensions of production resilience, demonstrating the transformation of functional capabilities of production systems resulting from the implementation of intelligent technologies.[41]

Table 5. Key aspects of AI impact on the main dimensions of production resilience		
Resilience Dimension	**State Before AI Implementation**	**State After AI Implementation**
Operational Flexibility	Limited adaptation to changes	Dynamic real-time process adjustment
Production Continuity	High vulnerability to disruptions	Self-adaptation and rapid recovery after disturbances
Energy Efficiency	Static management	Resource consumption optimization based on analytics
Social Safety	Human dependence in hazardous areas	Automation of dangerous operations
Environmental Responsibility	Reactive response to violations	Prediction and prevention of environmental risks
Information Integration	Fragmented data	Centralized digital models and system visualization

Based on the conducted research, it has been confirmed that the implementation of artificial intelligence significantly transforms the key dimensions of production system resilience, as shown in table 5. However, our results allow for a more detailed specification of the impact in each area.

Specifically, it was found that operational flexibility increased after AI implementation due to the automated adaptation of production parameters to changes in demand or supply in real time. In the studied enterprise, this enabled a 37 % reduction in the time required to reconfigure production lines.

Production continuity was ensured through the introduction of predictive diagnostic systems, which reduced the number of equipment breakdowns by 42 % compared to the pre-automation period.

In the area of energy efficiency, the application of analytical algorithms resulted in an 18 % decrease in energy consumption per unit of output, confirming AI's ability to identify hidden reserves in resource usage. Social safety improved because of the automation of hazardous production stages, ensuring a 55 % reduction in manual labor in dangerous areas. In terms of environmental responsibility, the results showed that predictive monitoring systems helped prevent exceeding permissible emissions on six occasions.

Furthermore, in terms of information integration, the introduction of a unified digital platform with machine learning elements enhanced data centralization from various departments, reducing managerial decision-making time by 30 %.

It implies that the research findings confirm that AI use not only enhances the production system resilience but also creates a firm background for their self-regulation, predictability, and environmental responsibility.

AI is a powerful tool that helps increase production system resilience, ensuring the ability to cope with external and internal challenges and transform them into opportunities. Although it fails to replace strategic management, it provides a new intelligent set of tools that opens new horizons in managerial decisions.

Therefore, production resilience will be determined by material or energy resources and capabilities in analytics, adaptation, and self-learning. In the current systematic review, the new industrial paradigm refers to Industry 4.0 – the concept of digital manufacturing transformation based on deep intelligent technology integration at all management levels. It includes individual process automation and the creation of holistic and interconnected systems that can forecast, self-learn, and adapt.

The comparative analysis of production efficiency indicators before and after AI implementation is presented in table 6. As shown in this table, changes cover a wide range of indicators: from reduced equipment downtime to increased levels of personalized manufacturing.

Table 6. Comparative analysis of production efficiency indicators before and after AI implementation.				
Enterprise	**Industry**	**Indicator Before AI Implementation**	**Indicator After AI Implementation**	**Change (%/value)**
Siemens (Germany)	Mechanical Engineering	7 % equipment downtime	2 % equipment downtime	-5 p.p.
Interpipe (Ukraine)	Metallurgy	3,8 % defective products	1,5 % defective products	-2,3 p.p.
Fanuc (Japan)	Robotics	4-day production line startup	2-day production line startup	-50 %
Bosch (Germany)	Electronics	92 % logistics accuracy	99 % logistics accuracy	+7 p.p.
BMW (Germany)	Automotive	1,1 errors per 1000 units	0,6 errors per 1000 units	-45,4 %
Kernel (Ukraine)	Agrarian Sector	22 % logistics losses	4 % logistics losses	-18 p.p.
ArcelorMittal (USA)	Metallurgy	1000 kWh/ton of steel	880 kWh/ton of steel	-12 %

The study used modern analytical tools that belong to this paradigm, such as deep learning for product defect detection, machine learning algorithms for predictive planning, time series analysis for equipment maintenance, and reinforcement learning for energy management. It enables the creation of a production system capable of reacting to both internal and external challenges and transforming them into sources of strategic advantage.

Hence, AI not only substitutes strategic management but also significantly changes its possibilities by enabling decision-making based on dynamic data analysis. In this environment, production resilience is outlined by the ability to learn, foresee, and adapt.

DISCUSSIONS

The use in the manufacturing sector represents a critical stage in the modern industry development. This is associated with multiple advantages. However, it presented several risks and challenges that can affect social, economic, technological, and organizational resilience. As AI tools provide new opportunities for optimization, automation, and adaptation of manufacturing processes, their use goes along with significant transformational processes that require threat forecasting, careful management, and strategy development.

Table 1 shows that the multidimensional aspect of AI impact on management functions in production and the way it transforms traditional approaches. Classical planning enhances AI-driven predictive modeling, offering higher accuracy and adaptability. However, it depends on the input data quality.

Control shifts from regulatory and retrospective to continuous monitoring through the integration of AI and IoT technologies, which improves the responsiveness to deviations but reduces the role of human oversight. In terms of the current research, alterations that occur in planning and control functions directly affect production systems' efficiency and resilience. However, it is vital to comprehend AI's potential to understand ethical and organizational aspects.

Performance indicator integration is the main constituent of the methodological and theoretical approach in both systemic and economic senses. As the resilience level of the production system and its ability to respond to failures and changes play an essential role, it is necessary to consider these aspects. It gives rise to a new methodological toolkit that presupposes assessment through cyber-efficiency, digital resilience, and cognitive capability indicators.(3) The research findings indicate that the advisability of implementing these new indicators ensures practical evaluation of AI-driven production management.

According to Kumar and Singh, cyber-efficiency represents the security and stability of digital processes.(3) The researchers highlight that digital resilience describes the ability to adapt and change without functionality and cognitive capability losses.

The authors' observations about reducing personnel involvement in routine tasks and shifting the focus to strategic management are critical and align with our conclusions about changing roles in production teams and the need for new competencies.

The production flexibility increase is confirmed, which in our case proved to be a critical factor in enhancing external change resilience. Therefore, the study findings of Archana and Stephen(40) correlate with the results of the current research and strengthen them by providing a generalized conceptual framework for assessing the AI implementation efficiency in production management.

Technological uncertainty is one of the central risks related to the limited predictability of intelligent systems in dynamic and complex environments.(42) AI algorithms are capable of making decisions, which may complicate decision monitoring, compliance control, and trust in these systems.(43) This requires the development of explainability mechanisms for AI, ensuring transparency and ethical use.

The vulnerability of digital systems to external interference requires the creation of multilayered protection, continuous monitoring, and the use of rapid response protocols.

Therefore, risks acquire both technical and a strategic nature because operational disruptions can result in significant economic losses, decreased customer trust, and destabilization of organizational market position. The issue of maintaining confidentiality and integrity of manufacturing data is also relevant given the high level of digitization of processes.(44)

Social risks associated with the use in manufacturing include the potential reduction in demand for specific employee categories.

This creates various threats related to social tension, structural unemployment, and the need for large-scale employee retraining. Automation processes alter the nature of labor and require new competencies in data management, analytics, intelligent system management, and interdisciplinary thinking.(45)

A failure to integrate these requirements into human resource policies can result in a gap between the technological capabilities and actual employee skills, threatening the efficiency of technology utilization. Such risks occur due to insufficient social adaptation and internal resistance to change.

Economic feasibility is another critical challenge in AI implementation. The high costs of technologies, the need to upgrade equipment, renew digital infrastructure, purchase specialized software, and train personnel make AI investments substantial and long-term.

Not all enterprises, small and medium-sized ones, can afford these expenses without guarantees of rapid return on investment.(46) Moreover, uncertainty about the effectiveness of intelligent systems, complexity in integrating them into existing production platforms, and the lack of clear metrics to evaluate AI's impact on key performance indicators create obstacles to informed management decisions.

Under such conditions, enterprises often postpone or implement new technologies, reducing potential benefits and widening the digital transformation gap between market leaders and laggards. Regulatory risks are associated with legal uncertainty in the AI application sphere. The lack of specialized regulatory frameworks defining responsibility for decisions made by intelligent systems, rules for personal data use in manufacturing, certification standards for algorithms, and so on creates legal ambiguity. This results in an increase in legal risk.

Furthermore, organizations face requirements to comply with international standards, which may sometimes conflict with Ukrainian norms or require additional harmonization efforts. Such an environment slows AI adoption and limits the potential use in manufacturing.

Managerial readiness is another complex challenge associated with insufficient organizational preparedness to make changes in structures, management culture, and decision-making styles. Traditional hierarchical management models do not always comply with fast-operating AI-built systems. Organizations often experience incompatibilities between legacy management systems and new digital tools.

This creates barriers to integration and necessitates a strategic priority review. Therefore, the development of an internal culture of innovation, readiness to change, experimentation, and rapid learning is critical for the effective use in manufacturing systems.

Table 7 shows the main risk groups and challenges caused by AI use in industrial manufacturing.

Table 7. Main risk groups and challenges associated with the use in industrial manufacturing.

Management Area	AI Application	Main Algorithms	Expected Effect
Technological Uncertainty	Unpredictability of AI actions, lack of model explainability	Reduced trust, inability to control, risk of erroneous decisions	Development of explainable AI, testing, and algorithm auditing
Cybersecurity	Vulnerability of digital systems to attacks	Disruptions, data loss, financial losses, security breaches	Implementation of cybersecurity measures, encryption, and backup
Social Transformations	Job displacement, insufficient new skills	Social tension, resistance to change, decreased productivity	Training, retraining, and employee involvement in transformation
Economic Efficiency	High implementation costs, lack of clear ROI	Delayed adoption, loss of competitiveness	Performance assessment, government support, pilot projects
Regulatory Uncertainty	Lack of legal regulation for AI use	Legal risks, innovation blocking	Development of standards, adaptation of the regulatory framework
Organizational Readiness	Conflict between legacy structures and new technologies	Institutional resistance, fragmented implementation	Change in management culture, strategic planning

The AI use in modern manufacturing systems is a technological process as well as a complex, multidimensional transformation that includes legal, economic, social, and managerial spheres. Effective risk management is vital to ensure the sustainable development of the manufacturing system in the digital age. Responsible, well-founded, and planned implementation is central to overcoming challenges.

The study of applied experiences in AI adoption in manufacturing allows assessing the practical effectiveness of technologies and outlining key patterns that determine the success of such transformations. Case studies as a methodological tool provide the opportunity for in-depth analysis of specific situations in enterprises where AI has already been integrated into production processes, allowing conclusions about scaling potential, general trends, and barriers.

International examples demonstrate how large corporations have implemented digital transformation strategies using intelligent systems to optimize logistics, supply chain management, quality control, and adaptive planning. For instance, Siemens actively deploys AI in its "digital factories", where the integration of machine learning algorithms has reduced equipment downtime, lowered maintenance costs, and improved the accuracy of production demand forecasting. Real-time analytical models monitor machine status, detect anomalies, and enable predictive maintenance, significantly enhancing production efficiency.

In the Ukrainian context, a successful example of an AI application is the case of Interpipe, which uses computer vision elements for quality control of metal products. The implementation of such systems reduced the proportion of defective products and increased the overall accuracy of production operations. Intelligent cameras and image analysis algorithms replaced manual visual inspection, previously prone to human error. This experience highlights the importance of adapting AI not only in large multinational corporations but also in domestic medium-sized enterprises, where investments in innovation enable rapid achievement of measurable results.

Quantitative assessment of the effect of AI implementation in manufacturing is a key element in justifying further investments in digitalization. Metrics used for change analysis include productivity, defect rate, cycle time, energy and maintenance costs, decision-making speed, and adaptability to market changes. At Bosch, which integrated intelligent logistics management systems, order processing time decreased by 35 %, warehouse inventory dropped by 20 %, and order fulfillment accuracy increased to 99 %. In the case of the Japanese company Fanuc, using AI to optimize robot programming, the startup time for new production lines was nearly halved, enabling a flexible response to changing customer needs. These results indicate that the adoption of intelligent technologies brings not only qualitative but also measurable quantitative effects that can be integrated into financial reporting and enterprise development strategies.

Based on the research results from the Table 6 the comparing the situation before and after AI implementation across several enterprises allows for evaluation of changes in critical production parameters. For example, at the German BMW plant, AI implementation for automatic control of assembly compliance reduced production errors by 45 % and shortened inspection time at each assembly stage by 30 seconds, which in high-volume production translates to significant economic benefits.

In the Ukrainian case of the agricultural company Kernel, using intelligent yield prediction systems enabled more accurate planning of processing capacity loading, leading to optimized logistics costs and an 18 % reduction in losses due to underutilization.(47,48) AI adoption at the metallurgical company ArcelorMittal, using deep learning, optimized steel melting temperature, reducing energy carrier costs by 12 % and improving alloy quality.

The data in the Table 6 confirms that the implementation of artificial intelligence has a significant impact on the optimization of production processes. In all analyzed cases, there is a clear trend towards reducing costs, increasing productivity and quality, as well as strengthening competitive advantages.(49)

Regardless of the scale of the enterprise or the country in which it operates, the key success factor is the strategic integration of intelligent systems into the overall production management architecture. Successful cases also highlight the necessity of accompanying transformations in organizational culture, the development of digital competencies among personnel, and openness to change.(50)

Overall, empirical data confirm the feasibility of widespread AI implementation in industry, while emphasizing the importance of a systemic approach that considers both technical and human aspects of digital transformation.(51)

CONCLUSIONS

This study comprehensively examined the impact of AI (such as machine learning, deep learning, predictive analytics, and intelligent automation) on improving the efficiency and sustainability of production systems, enhancing core production functions, including planning, quality control, maintenance, logistics, and energy management.

The key directions for AI integration in production management — planning, forecasting, equipment maintenance, quality control, logistics, and energy consumption management—were characterized. The analysis demonstrated how the use of machine learning algorithms, computer vision, time series analysis, and reinforcement learning enables qualitative shifts in enterprise operations: reducing production losses, optimizing resource use, minimizing downtime, and improving the accuracy of management decisions.

A comparative analysis of performance indicators before and after AI implementation was conducted using examples from both international companies (Siemens, Bosch, Fanuc, BMW, ArcelorMittal) and Ukrainian enterprises (Interpipe, Kernel). The results demonstrate not only the economic feasibility of digital transformation but also significant strategic advantages: increased productivity, enhanced flexibility to external changes, improved innovation capacity, and reduced environmental impact.(52,53,54)

At the same time, the study identified several limitations. The main challenges are related to the high cost of technology implementation, shortage of qualified personnel, difficulty in adapting traditional organizational structures to new technologies, legal uncertainty regarding responsibility for intelligent systems, and cybersecurity risks.(55) Special attention should be paid to the social consequences of automation, including job reductions in routine sectors and the necessity for large-scale workforce retraining.

To minimize these limitations, several practical solutions are proposed, including pilot projects at enterprises of various scales, implementation of explainable AI, adaptation of management systems to principles of flexibility and openness, state support for innovation in the form of grants, preferential financing, and institutional support, as well as active partnerships between business, research institutions, and educational centers.(56,57) A critical condition for successful transformation is the formation of an internal culture of change, analytical thinking, and digital literacy among personnel.

This study will be helpful for a broad range of professionals: production enterprise managers, innovation managers, digital transformation specialists, analysts, researchers in industrial management, and state regulators. The practical value of the results lies in their applicability for developing digitization strategies, justifying investments in AI, building new organizational management models, and assessing the impact of intelligent systems on key performance indicators of enterprises.[58]

Further research should focus on quantitatively measuring the level of digital maturity of enterprises, developing universal models for AI integration considering industry-specific characteristics, analyzing the interaction between AI and human capital, and creating ethical governance systems for autonomous production processes. Particular interest lies in studying the role of AI in achieving sustainable development goals, namely reducing carbon footprint, optimizing energy and resource use, and enhancing social responsibility in production.

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