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ASSESSING THE LEVEL OF DIGITAL DEVELOPMENT AND DEVELOPING AN ARTIFICIAL INTELLIGENCE-BASED MECHANISM FOR IMPROVING THE EFFICIENCY OF INDUSTRIAL ENTERPRISES

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Abstract. The aim of this study is to assess the level of digital development of industrial enterprises using a system of multifactor indicators and to develop a mechanism for enhancing production and management efficiency through the application of artificial intelligence (AI) technologies. Within the proposed framework, the level of digital development is evaluated using indicators related to technological infrastructure, automation, the application of artificial intelligence, information systems integration, digital competencies, and production efficiency. The artificial intelligence module is employed to analyse the current state of an enterprise, forecast key performance indicators, and generate alternative management scenarios. This approach provides an integrated analytical basis for evaluating digital development and supporting evidence-based managerial decision-making in industrial enterprises.

Keywords. artificial intelligence, industrial enterprises, digital development, digitalisation, digital maturity, machine learning, econometric analysis, forecasting, production efficiency, managerial decision-making.

Аннотация. Целью данного исследования является оценка уровня цифрового развития промышленных предприятий на основе системы многофакторных показателей и разработка механизма повышения эффективности производственной и управленческой деятельности посредством применения технологий искусственного интеллекта (ИИ). В рамках предлагаемого подхода уровень цифрового развития оценивается с использованием показателей, характеризующих технологическую инфраструктуру, автоматизацию, применение искусственного интеллекта, интеграцию информационных систем, цифровые компетенции и эффективность производства. Модуль искусственного интеллекта используется для анализа текущего состояния предприятия, прогнозирования ключевых показателей деятельности и формирования альтернативных сценариев управления. Предлагаемый подход формирует комплексную аналитическую основу для оценки цифрового развития и поддержки принятия обоснованных управленческих решений на промышленных предприятиях.

Ключевые слова. искусственный интеллект, промышленные предприятия, цифровое развитие, цифровизация, цифровая зрелость, машинное обучение, эконометрический анализ, прогнозирование, эффективность производства, принятие управленческих решений.

INTRODUCTION

In the global industrial sector, digital technologies are increasingly evolving from auxiliary production tools into strategic resources that support productivity, competitiveness, and effective management. Artificial intelligence (AI), the Internet of Things (IoT), big data analytics, cloud computing, ERP/MES/SCADA systems, and automated management tools enable real-time production monitoring, equipment-condition forecasting, energy management, and data-driven decision-making. At the same time, the economic benefits of introducing digital technologies depend on the effectiveness of their integration into enterprise operations. The outcomes of digital transformation are closely associated with the quality of technological infrastructure, data utilisation capacity, employee competencies, the level of process automation, and the integration of digital and management

systems. Previous studies indicate that enterprise size, innovation activity, and digital readiness are important factors associated with the level and effectiveness of digital transformation.

Empirical research further indicates that digital transformation can contribute to increased total factor productivity, optimised production costs, improved sales performance, and enhanced innovation activity. Artificial intelligence, in particular, can support higher production and energy efficiency through monitoring, forecasting, real-time control, and optimisation of technological parameters. These developments also create opportunities for further methodological advancement, particularly in developing a unified quantitative indicator of digital development, assessing the relationship between AI adoption and economic outcomes, and translating analytical results into effective managerial decisions.

LITERATURE REVIEW

Recent studies on the digital development of industrial enterprises increasingly conceptualise digital transformation not merely as the adoption of individual technologies but as an integrated process combining production, management, data exchange, and human capital. Wu et al. (2024) assessed digital transformation in manufacturing firms through digital readiness and data utilisation capacity and demonstrated that firm size, product innovation, and production characteristics are associated with different levels of digital development. This approach highlights the importance of evaluating digital maturity not only through technological infrastructure but also through organisational and information capabilities.

The relationship between digital transformation and economic performance has also received considerable attention in the academic literature. Liu found that digital transformation strategies and the application of cloud technologies, artificial intelligence, big data, and other digital components are positively associated with total factor productivity. Wei and Shen further demonstrated that the effects of digital transformation on manufacturing performance are realised through increased sales, optimised production costs, and enhanced innovation activity. These findings indicate that the economic value of digitalisation is closely related to the extent to which digital technologies are effectively integrated into core business and production processes.

Recent research also emphasises the growing application of machine learning, deep learning, and reinforcement learning in industrial energy management. Keramati Feyz Abadi et al. demonstrated that these methods are increasingly employed in energy monitoring, forecasting, real-time control, and the optimisation of technological parameters. Their application provides opportunities to enhance the efficiency of industrial energy management and strengthen the analytical basis for data-driven production and managerial decision-making.

RESEARCH METHODOLOGY

The study employs an integrated quantitative methodology combining digital development assessment, econometric analysis, and artificial intelligence (AI) methods. First, indicators related to technological infrastructure, AI and data utilisation, human capital, and production efficiency are normalised and aggregated into a Digital Development Index (DDI). Econometric models are subsequently applied to estimate the relationships between AI adoption, automation, digital investment, employee competencies, Internet of Things (IoT) technologies, and indicators of production and energy efficiency.

In addition, machine learning methods are employed to identify potential nonlinear relationships and forecast enterprise performance. The resulting analytical outputs are incorporated into a decision-support mechanism based on continuous monitoring and feedback. This mechanism enables managerial decisions to be adjusted in accordance with observed performance outcomes and provides an analytical basis for improving the efficiency of digital transformation processes within industrial enterprises.

Statement on the Use of Artificial Intelligence. In the preparation of this study, artificial intelligence (AI) tools were used to a limited extent, accounting for approximately 10% of the overall research process. Their use was primarily confined to language refinement, technical editing, and structural support. The selection of research methods, collection and analysis of empirical data, interpretation of the findings, formulation of scientific conclusions, and development of practical recommendations were carried out and verified by the author.

ANALYSIS AND RESULTS

To provide a comprehensive and objective assessment of the level of digital development of industrial enterprises, it is appropriate to establish a system of interrelated functional indicators. Digitalisation is most effectively evaluated not only through the availability of technical equipment and information systems but also through a broader set of technological, organisational, human-capital, and performance-related dimensions. Accordingly, a comprehensive assessment should incorporate technological infrastructure, the application

of artificial intelligence and data analytics, employees' digital competencies, and production and economic performance.

Within the framework of this study, the indicators characterising the digital development of an industrial enterprise are classified into four functional groups (Table 1).

Table 1
Classification of indicators characterizing the level of digital development of an industrial enterprise by functional dimensions¹

Dimension	Main indicators	Designation
Technological development	automation level, use of IoT technologies, integration of ERP/ MES/SCADA systems	(X ₁ -X ₃)
AI and data	level of AI adoption, real-time data availability, analytical systems	(X ₄ -X ₆)
Human capital	digital competencies, share of IT/AI specialists, professional training	(X ₇ -X ₉)
Economic and production performance	energy intensity, equipment failures, defect rate, production efficiency	(X _{10} -X _{13})

Since the selected indicators are measured in different units, they must first be transformed onto a comparable scale. For this purpose, the min–max normalisation method is applied.

For indicators that have a positive relationship with digital development:

$$z_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}}$$

For indicators for which lower values represent more favourable outcomes, such as energy intensity, defect rates, or equipment failure rates:

$$z_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}}$$

As a result, all normalised indicators take values within the interval:

$$0 \leq z_{ij} \leq 1$$

This transformation ensures comparability across indicators and provides the methodological basis for constructing an integrated digital development index.

The overall level of digital development of enterprise (i) is determined using the following integral indicator:

$$DDI = \sum_{j=1}^m w_j z_{ij}$$

where:

DDI- Digital Development Index of enterprise (i);

z_{ij} - normalized value of indicator (j);

w_j - weight assigned to indicator (j);

$$\sum_{j=1}^m w_j = 1.$$

¹ Developed by the author based on the systematization and generalization of the research results.

Where there is insufficient empirical evidence to justify differentiated weights, equal weights may be applied at the initial stage:

$$w_j = \frac{1}{m}$$

This approach helps minimise subjectivity in the weighting process and enhances the transparency and comparability of the index across enterprises. The proposed index serves not only as an aggregate measure of digital development but also as a diagnostic instrument for identifying technological, organisational, and production areas with potential for further development.

To assess the relationship between artificial intelligence and other digitalisation factors and enterprise performance, the following econometric model is proposed:

$$PE_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 AUT_{it} + \beta_3 INV_{it} + \beta_4 DC_{it} + \beta_5 IoT_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where:

(PE) – production efficiency;

(AI) – level of artificial intelligence adoption;

(AUT) – level of automation;

(INV) – investment in digital technologies;

(DC) – employees' digital competencies;

(IoT) – use of sensors and IoT infrastructure;

μ_i – enterprise-specific unobserved effects;

λ_t – time effects;

ε_{it} – random error term.

A separate model may be used to evaluate energy efficiency:

$$EI_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 AUT_{it} + \alpha_3 IoT_{it} + \alpha_4 DC_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where (EI) represents energy intensity.

If:

$$\alpha_1 < 0$$

and the coefficient is statistically significant, this indicates that a higher level of AI adoption is associated with lower energy intensity, holding the other variables included in the model constant. Such a relationship would be consistent with empirical evidence reported in the international literature.

Traditional econometric models are commonly used to estimate specified relationships between variables, including linear relationships. However, the associations between digitalisation factors and enterprise performance may also involve nonlinearities and complex interactions. Therefore, machine learning algorithms such as Random Forest and Gradient Boosting can be applied alongside regression analysis.

The general forecasting function can be expressed as:

$$\widehat{PE} = f(AI, AUT, INV, DC, IoT, EI, \dots)$$

The predictive accuracy of the model is evaluated using standard indicators:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

and:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2}$$

The combined application of econometric and machine learning methods makes it possible to identify interpretable statistical relationships while also capturing more complex nonlinear patterns in enterprise data.

Proposed Adaptive Digital Management Mechanism

A central outcome of the study is the development of a mechanism that conceptualises industrial digitalisation not as a collection of isolated technological projects but as a continuous process encompassing diagnosis, forecasting, decision-making, implementation, monitoring, and feedback.

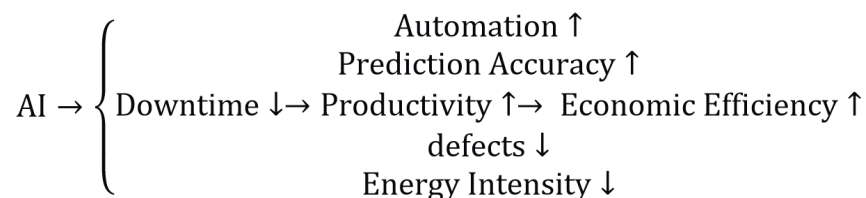
The functional structure of the proposed mechanism comprises the following stages:

1. Production, technological, financial, and energy-related enterprise data are collected and integrated.
2. The indicators are normalised, and the Digital Development Index is calculated.
3. Econometric models are applied to assess the factors associated with production and economic efficiency.
4. AI and machine learning models are employed to identify nonlinear relationships and forecast future performance.
5. Baseline, intensive, and conservative development scenarios are formulated.
6. The decision-support module generates alternative management options.
7. The responsible specialist evaluates the AI-generated recommendations and determines whether to accept, modify, or decline them.
8. The actual KPI outcomes associated with the implemented decision are returned to the analytical system.
9. Model parameters are recalibrated on the basis of newly accumulated data.

Thus, the proposed mechanism establishes a closed management loop: Diagnosis - Prediction - Decision - Implementation - Feedback.

This structure transforms digitalisation assessment from a static measurement procedure into an adaptive management and decision-support system.

Based on the theoretical framework and empirical evidence, the relationship between artificial intelligence adoption and industrial enterprise performance can be represented conceptually through several interconnected channels:



This conceptual relationship suggests that AI can contribute to enterprise performance through several channels simultaneously. Higher levels of automation and improved prediction accuracy can support more stable production processes, while reductions in downtime, defect rates, and energy intensity can contribute to improved operational and economic performance.

The proposed approach extends existing methods for assessing industrial digitalisation in three important directions.

First, the digital development of an enterprise is evaluated not solely by the number of information systems, robots, IoT devices, or AI solutions implemented, but by the extent to which these technologies are integrated into production, energy management, quality control, and economic performance. This provides a more comprehensive assessment of digital maturity.

Second, artificial intelligence is considered not as a substitute for the existing management system but as an analytical instrument that supports data processing, forecasting, scenario development, and managerial decision-making. Within this framework, final managerial decisions remain under human responsibility, while AI strengthens the analytical basis supporting those decisions.

Third, the proposed framework incorporates a continuous feedback mechanism. AI-generated recommendations are treated as analytical inputs rather than final decisions. The actual outcomes of implemented decisions are returned to the system and subsequently used for model recalibration. This transforms the framework from a static analytical model into an adaptive decision-support mechanism capable of learning from newly accumulated enterprise data.

Such an approach is particularly relevant in industrial environments, where the economic effectiveness of AI depends not only on the technology itself but also on data quality, technological infrastructure, human capital, and integration with existing production processes. Accordingly, the proposed mechanism provides a flexible methodological basis for assessing and managing digital transformation across enterprises with different levels of technological and organisational readiness.

CONCLUSION AND RECOMMENDATIONS

The continuing advancement of digital transformation in industrial enterprises requires artificial intelligence (AI) technologies to be considered not as isolated technological tools but as integral components of a broader system encompassing production, economic, and managerial processes. Such an integrated perspective enables AI to be incorporated more systematically into enterprise development and decision-support mechanisms.

This study developed a diagnostic approach based on the Digital Development Index (DDI), which integrates indicators related to technological infrastructure, the level of automation, AI adoption, information systems integration, human capital, and production efficiency. The proposed approach provides a comprehensive methodological framework for assessing the current level of digital development of an enterprise and identifying priority areas for its further advancement.

The practical significance of the proposed mechanism lies in considering AI adoption not as an end in itself but as an analytical and technological instrument for enhancing production efficiency, optimising the use of energy and other resources, improving equipment reliability, and strengthening the analytical basis of managerial decision-making. The integration of continuous monitoring and feedback further enables the mechanism to adapt to changes in enterprise performance and newly accumulated data.

The findings also indicate that the economic effectiveness of artificial intelligence is closely associated with an enterprise's level of digital readiness and its organisational and technological conditions. Accordingly, differentiated AI implementation strategies tailored to the digital development level and operational characteristics of individual enterprises may provide a more flexible and context-sensitive approach than the application of a single universal model of AI adoption.

Future research could extend the proposed framework by testing the mechanism using multi-enterprise panel data, conducting external validation over time, comparing the predictive performance of AI and machine learning models with classical econometric approaches, and assessing model explainability using methods such as SHAP (SHapley Additive exPlanations). These research directions can contribute to further strengthening the reliability, interpretability, empirical validity, and practical applicability of the proposed framework for managing digital transformation in industrial enterprises.

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