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Basic Principles and Approaches in Building an Architectural Model of Digital Twins in the Manufacturing Industry

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ABSTRACT

In the context of the digital transformation of the manufacturing industry, there is an increasing need to create holistic architectural models of digital twins that integrate data from the operational to the managerial level. International standards and practical cases show that digital twins can transform production processes, increasing their efficiency and sustainability. The purpose of the study was to identify the basic principles and approaches to building an architectural model of digital twins in the manufacturing industry considering international standards, practical cases, and simulation results. The study was based on the analysis of the five-level architecture and empirical verification of its effectiveness in the environment of AnyLogic and the Python Software Foundation. The key functions of each level, the mechanisms for integrating data flows into centralised storage, and the role of the digital twin as a dynamic link between operational and management circuits were considered. It was established that the combination of "digital shadow – digital sample" ensures the adaptability of the system and high accuracy of forecasting production development scenarios. The simulation showed that consistent architectural integration reduces operating costs by up to 20%, increases total productivity by 12-15%, and reduces downtime by 25-30%. Verification using the example of the "Digital Mine" concept (Sight Power Inc.) confirmed the applicability of the proposed model in the mining industry and the possibility of its scaling into related industry segments. A comparative analysis of integration approaches (point automation and platform architecture) revealed the advantages of the latter, providing stability, transparency, and scalability. It was concluded that the architectural model of digital twins is not only a technological optimisation tool, but also a strategic element of digital transformation, forming the basis for Kazakhstan's long-term industrial policy. The practical significance of the study lies in the fact that its results can be used by industrial enterprises, developers of digital platforms, and government agencies in the design and implementation of digital twin architectures, ensuring increased efficiency of production systems, reduced operating costs and the development of a unified digital ecosystem of industry in Kazakhstan.

Keywords: Data integration, centralised storage, technological roadmap, artificial intelligence, key performance indicators.

Mathematics Subject Classification: 90B30, 90C90

1. INTRODUCTION

Digital twins in the manufacturing industry are becoming one of the key tools for increasing efficiency, ensuring the transition from fragmented automation to holistic integration of production processes. Their architecture is built around interfaced data contours, from Internet of Things (IoT) sensors and Manufacturing Execution Systems (MES) to distributed big data storage (Data Lake) and Enterprise Resource Planning (ERP). This architectural model allows creating a virtual replica of equipment and processes with the ability to monitor, predict and optimise. However, the choice of solutions is linked to Key Performance Indicators (KPI), including cost reduction, increased energy efficiency, reduced accidents, and improved forecast quality. In the context of Kazakhstan's industry, digital twins are considered not as a separate IT tool, but as part of a transformation strategy for manufacturing enterprises aimed at creating a unified information environment from the level of extraction and processing of raw materials to corporate planning (Biloshchytskyi et al., 2026; Yermekova et al., 2024).

Summarising approaches to additive manufacturing, Jyeniskhan et al. (2023) showed that the effectiveness of digital twins is determined not only by the modelling of the production process, but also by the standardisation of data flows and the possibility of their scalable integration into cloud platforms. In furtherance of this idea, Shehab et al. (2024) proved the need for data management-oriented architectures, where Data Lake acts as the core of the digital twin, and verification and quality control minimise the gap between the physical and virtual models. In the practical outline, Serik et al. (2022) demonstrated that the successful implementation of the digital twin of an automated storage line and a robotic arm is possible only with end-to-end integration of IoT, MES, and ERP, which confirms the relevance of a multi-level architecture.

In parallel, the intellectualisation of digital twins is developing: Kunelbayev et al. (2024) have shown that the use of soft computing methods and artificial intelligence (AI) algorithms allows identifying hidden dependencies in industrial data and enhance the predictive functions of architecture. In optimisation problems, Madaminov et al. (2025) proposed a multi-purpose circuit where the digital twin is integrated with Reinforcement Learning (RL) methods, which allows simultaneous balancing of energy consumption and production schedules. The customer-oriented dimension of the problem was revealed by Tazhibayev et al. (2025), showing that digital twins can be part of a service architecture for customers, including customisation and customisation interfaces.

At the level of generalised research, Judijanto and Vandika (2025) documented the transition from monitoring systems to self-tuning architectures with Machine Learning (ML) blocks, and the trend towards combining cloud and peripheral computing (edge computing). The applicability of the principles of digital twins in related industries was confirmed by the case in Amirkhanov et al. (2024), where the integration of a virtual model of a solar inverter helped to increase the efficiency of the energy system. In the infrastructure sector, Sodikov (2024) showed that the digital twin of roads in Uzbekistan serves as a tool for macro-level planning and management, which demonstrates the adaptability of architectural solutions to various national contexts.

Ultimately, Mo et al. (2025) proposed a self-learning digital twin architecture for industrial robots, where the key element is an autonomous decision-making unit. This defines a new stage of development – the transition from predictive models to self-managed digital systems capable of adapting to changing operating conditions (Sabibolda et al., 2024; Smailov et al., 2025a; Yusifbayli et al., 2021).

Thus, digital twins represent not only visualisation and analysis technology, but also the basis for an architectural rethink of the entire production chain. In this paper, the development of the concept is considered through the prism of Kazakhstan's experience and the integration of solutions from Sight Power Inc. (Mine Advisor), AnyLogic, and Python/ML models within the framework of the “digital shadow – digital sample” architecture.

The purpose of the study was to identify key principles and approaches to the development of an architectural model of digital twins in the manufacturing industry based on international standards, analysis of practical cases, and simulation data. To achieve the goal, the following tasks were set: to conduct a comparative analysis of architectural approaches and levels of integration of digital twins; to explore the methodological and technological foundations of their construction using the example of the case of Sight Power Inc. Digital Mine™; to assess the impact of architectural solutions on the KPIs of the industry in Kazakhstan.

2. MATERIALS AND METHODS

The study was conducted from 2024 to August 2025 and was aimed at defining the basic principles and approaches in building an architectural model of digital twins in the manufacturing industry. The material basis was formed by international standards and regulatory documents, including the International Organisation for Standardisation (ISO) 23247:2021 (2021), ISO 14040:2006 (2006) and ISO 14044:2006 (2006), regulating the procedures of Life Cycle Assessment (LCA), American Petroleum Institute (1991), which establishes industrial safety requirements, and the International Organisation for Standardisation and International Electrotechnical Commission (IEC/ISO) 30182:2017 (2017), which defines the rules for ensuring interoperability. The empirical base was formed based on the case of Sight Power Inc. (2024), which implements the Digital Mine™ concept in Kazakhstan. The study additionally used corporate materials from Joint Stock Company (JSC) “AK AltynAlmas” (2017) related to the implementation of the first stage of the Digital Mine project (2016-2020) and the initiation of the second (2020-2024), including reports on the automation of mining and geological complexes, MES systems and production KPIs (Overall Equipment Efficiency (OEE), Operational Expenditure (OPEX), Mean Time To Repair (MTTR), energy intensity). This helped to verify the model based on real data from the Kazakh mining and metallurgical industry.

Within the framework of this project, organisational and technical solutions were considered: the creation of a single database with an open architecture, the integration of IoT devices and monitoring systems into a centralised storage, the connection of ERP/MES systems, the use of predictive physical models, 3D visualisations, and dashboards.

The methodological basis of the research was based on a combination of simulation modelling, econometric analysis, and strategic planning. Simulation modelling was performed in the AnyLogic environment (2024), which helped to reproduce the system dynamics and evaluate the long-term effects of the introduction of digital twins in the 2019-2024 horizon. Aggregated data on 20 subprojects of the first stage of the Digital Mine was submitted to the input of the model, from automation of gold mining plants to the implementation of Safety Instrumented Control (SIC) in underground work, which ensured the verification of the stability of architectural solutions at different stages of the production cycle. Key organisational and technical steps have been implemented within the framework of the Digital Mine project. At the first stage, a single information space was established, ensuring the integration of data from geology, surveying, engineering services, and production units. The second stage included the integration of monitoring data and IoT devices into a centralised database, which helped to receive information in real time and combine it with the results of planned calculations. The third step was to connect ERP systems and planning tools, which provided a direct link between operational data and management decisions. Ultimately, at the final stage, predictive physical models, three-dimensional visualisations and dashboards were introduced for management, which allowed them to create development scenarios, analyse risks, and make informed strategic decisions.

A separate research area was devoted to evaluating the effectiveness of integration approaches in the digitalisation of production systems. For this purpose, comparative and system analysis were used, which allowed comparing the results of the implementation of point automation and platform architecture based on data from manufacturing enterprises in Kazakhstan. The comparison parameters included hardware performance indicators (Availability, Performance, Quality), the share of automated operations in MES, the amount of data transferred via Data Lake, and the impact on financial and economic metrics (Return on Investment (ROI), Net Present Value (NPV), OPEX).

For time series analysis and predictive analytics, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) algorithms were used, including machine learning methods such as Random Forest, implemented in the Python Software Foundation (2024). The econometric analysis included the use of Ordinary Least Squares (OLS) (2025) and panel analysis (Fixed Effects/Random Effects (FE/RE)) (Wooldridge, 2010) models, and the "Difference-in-Differences" (DiD) approach to evaluate the effects of pilot projects (Angrist and Pischke, 2008). The statistical reliability was verified using the Statistical Package for the Social Sciences (SPSS) Statistics for Windows, Version 28.0 (2021) and OriginLab Corporation (2023), which ensured the development of confidence intervals and the control of the significance level $p<0.5$. To develop a step-by-step scaling strategy for digital twins, the Technology Roadmapping (TRM) methodology (2025) was used, covering the horizons of 2025, 2030, and 2040. The TRM identified key drivers (AI, IoT, 5G/6G communication networks, cybersecurity), barriers (staffing shortages, lack of standards, interoperability issues), and KPIs such as reduced OPEX, energy intensity, and the growing share of enterprises with digital twins. Additionally, the effects of implementing Data Management Strategy (DMS) as part of the second stage of the Digital Mine were evaluated, including the integration of ERP Systems, Applications, and Products (SAP) and the creation of a data analysis competence centre based on Sight Power Inc. and IntelliSense Lab. These data were used to refine econometric estimates and verify predictive models.

Special attention was paid to the integration of AI and predictive analytics tools into the architectural model of digital twins. This integration ensured the transition from static monitoring to predictive management, in which decisions are made based on forecasting likely scenarios and early detection of deviations. For this purpose, the trained models based on historical KPIs (OEE, OPEX, downtime) data were used, helping to adapt the management strategy in real time and create digital “images" of production processes.

The integration of system dynamics, agent-based modelling, TRM, LCA, and econometrics ensured the integrity of the methodology and allowed digital twins to be considered as a tool not only for local optimisation, but also for the development of the national digital industrial ecosystem of Kazakhstan.

3. RESULTS

3.1. Characteristics of the architectural model and key principles of integration

The presented architectural model was originally developed in the mining industry of Kazakhstan and was practically tested on the JSC “AK AltynAlmas” Digital Mine project (2017), implemented jointly with Sight Power Inc. As part of this project, a five-tier IoT → MES → Data Lake → Digital Twin → ERP architecture was created, providing end-to-end integration of production data, scenario modelling, and decision automation. This approach became a model example of the digital transformation of Kazakh enterprises and was subsequently adapted for the manufacturing industry.

At the initial stage (IoT), data was recorded using sensors and monitoring systems, which allowed monitoring the status of equipment and technological processes in real time. The MES layer provided dispatching and primary information processing, enabling a quick response to changes. Data Lake plays the role of a centralised repository where heterogeneous data arrays are integrated. At the Digital Twin level, analytics, modelling and forecasting are carried out, which allows simulating future scenarios. The final level, ERP, combines the results of the analysis with management functions: financial, logistical, and production.

The results of the efficiency analysis are summarised in Table 1, which presents the main indicators reflecting the functionality of each architecture level.

Table 1: Key parameters of the architectural model of digital twins.

Architecture level	Main function	KPI
IoT (sensors, sensors)	Real-time data collection	Completeness of data transmission ≥98%; transmission delay ≤1.5 s; percentage of working sensors ≥97%
MES (dispatching)	Process management and control	Stability of technological cycles ≥95%; downtime <3% of working time; accuracy of operational orders ≥96%
Data Lake (storage)	Data integration and structuring	Data availability ≥99.5%; scalability in volume up to 5 petabytes (PB); query time <0.8 s
Digital Twin	Analytics, modelling, forecasting	OEE=82-88%; uptime ≥97%; forecast accuracy ≥92%
ERP	Management decisions, finance, logistics	OPEX reduction by 10-15%; planning efficiency increase by 20-25%; decision cycle reduction by 30%

Note: uptime – proportion of trouble-free time.

Source: compiled by the author based on ISO 23247:2021 (2021); ISO 14040:2006 (2006); ISO 14044:2006 (2006); American Petroleum Institute (1991); IEC/ISO 30182:2017 (2017); Power Inc. (2024).

As can be seen from Table 1, the digital twin acts as a link between the operational levels (IoT, MES, Data Lake) and the management level (ERP). It is not a static model, but a dynamic system combining digital prototype and digital shadow. This combination ensures the model's ability to adapt, continuously update, and generate reliable forecasts, making it a critical tool for improving productivity, reliability, and cost-effectiveness in the context of the digital transformation of industry.

3.2. Verification of the architectural approach to the integration of digital twins using the example of the project Digital Mine (JSC “AK AltynAlmas”)

To confirm the applicability of the proposed architectural principles of digital twins in the manufacturing industry, a practical case of JSC “AK AltynAlmas” was considered. As an experimental confirmation of the feasibility of the architectural approach, the Digital Mine project implemented in Kazakhstan was investigated, in which Sight Power Inc. Digital Mine™ solutions were used to build a digital twin of the production cycle and equipment lifecycle management. To visualise the gradual transition of an enterprise to the status of a Digital Company and the integration of Supervisory Control And Data Acquisition (SCADA)-MES-ERP-Business Intelligence (BI) levels, the corporate model shown in Figure 1 was applied in the project.

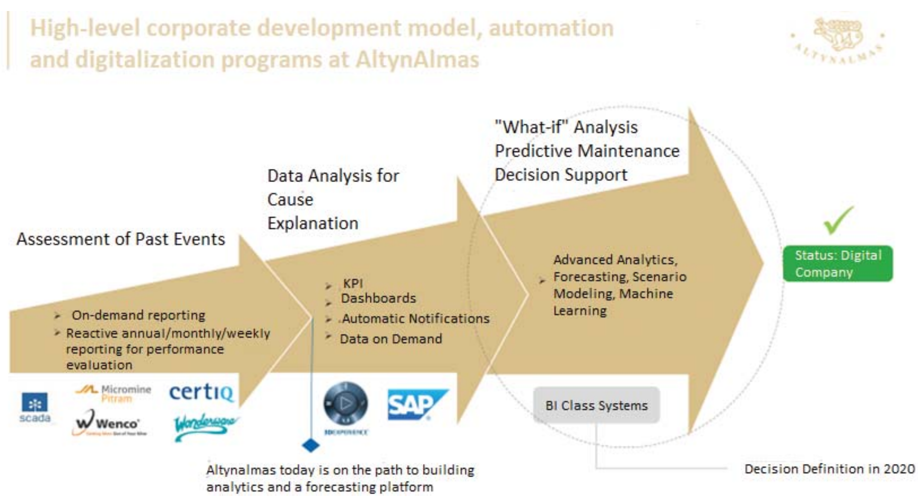

Figure 1. Top-level model of corporate development, automation and digitalisation programmes at JSC “AK AltynAlmas”.

Source: materials of the JSC “AK AltynAlmas” project (used with permission of the copyright holder) (2017).

The model shown in Figure 1 reflects the evolution of corporate analytics from on-demand reporting and event evaluation to forecasting, machine learning, and Digital Company status. This structuring helped to unify production and management circuits, which became the basis for the implementation of a five-level architecture IoT → MES → Data Lake → Digital Twin → ERP. Implementation of the digital twin architecture in JSC "AK AltynAlmas" is reflected in the Digital Mine project, where a single information environment ensures the integration of data from geology, surveying, ERP, SCADA, and laboratories to generate analytical reports and forecast models (Figure 2).

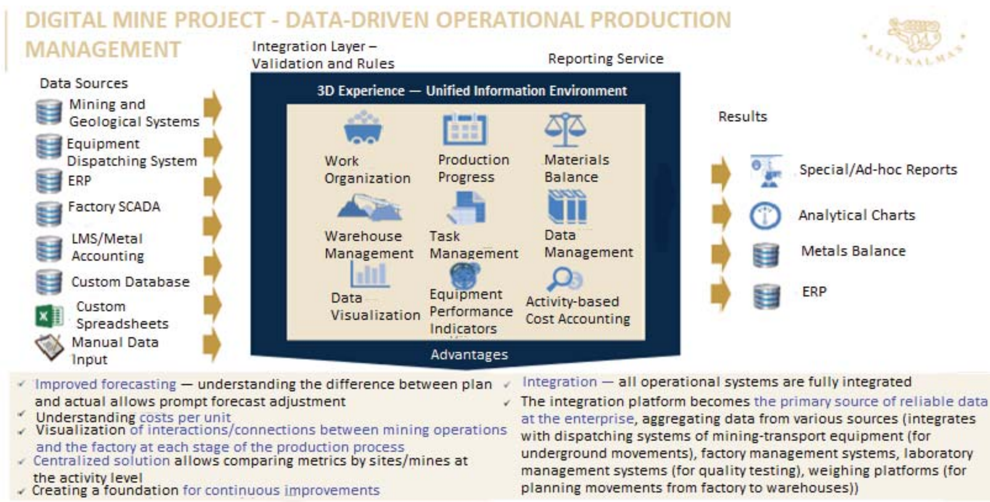

Figure 2. Digital Mine project: data analysis management for operational production management.

Source: materials of the JSC "AK AltynAlmas" project (used with permission of the copyright holder) (2017).

The architecture shown in Figure 2 ensured the integration of all enterprise data sources into a single three-dimensional information space, where geological, technical, production, energy, and management data are combined. This structure made it possible to implement an end–to-end information processing cycle, from the registration of parameters by sensors at the equipment level to the development of management solutions at the ERP system level. The project implemented a predictive maintenance system that uses telemetry data and machine learning algorithms to predict wear on components and plan repairs. Additionally, KPI monitoring mechanisms have been implemented, allowing real-time monitoring of equipment performance, energy consumption, and capacity utilisation. Thus, the digital twin has become not only a process visualisation tool, but also an active management component that ensures the integration of production and analytical circuits (Brescia et al., 2024; 2025; Hadasik et al., 2025).

Figure 3 summarises the results of the operation of this architecture within the framework of the Digital Mine™ project by Sight Power Inc., reflecting the cumulative impact of integrating AI and predictive analytics tools on production efficiency.

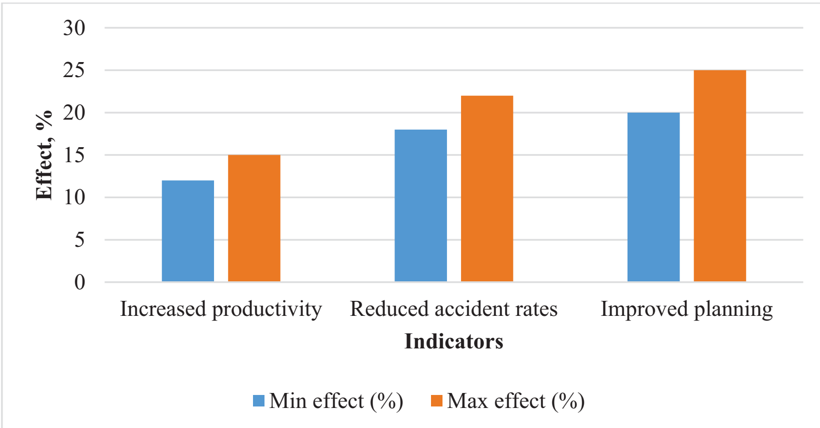

Figure 3. Quantitative effects of the introduction of the Digital Mine concept (Sight Power Inc.).

Source: compiled by the author based on data from Sight Power Inc. (2024).

As can be seen from Figure 3, the introduction of the Digital Mine concept by Sight Power Inc. ensured a consistent increase in key performance indicators. Productivity increased by 12-15% due to optimisation of drilling and blasting and transportation operations, which increased the total production volume without additional capital investments. Accidents and the number of unplanned downtime decreased by 18-22% due to the integration of IoT sensors and monitoring systems, which reduced the risks of technological failures and increased the level of industrial safety. Planning accuracy increased by 20-25%, which helped to more reasonably predict production volumes and resource consumption, ensuring the sustainability of production cycles. The digital twin does not function as an isolated tool, but as a complex architectural model that combines the operational and strategic processes of the enterprise (Khowja et al., 2022; Korotynskyi and Zhuchenko, 2020). This demonstrates the high potential for adapting this approach to the manufacturing industry, where the ability to integrate data and use it in real time is becoming a key factor in competitiveness. Thus, the JSC “AK AltynAlmas” case is an experimental confirmation of the effectiveness of the five-level architecture of digital twins, proving its reproducibility and scalability of enterprises in Kazakhstan.

3.3. Modelling and simulation of architectural scenarios

Modelling of architectural scenarios of digital twins in the manufacturing industry allowed not so much to reproduce individual performance indicators as to identify patterns of system functioning when integrating its key levels. The model parameters were calibrated based on JSC “AK AltynAlmas” production data, which ensured comparability of simulation and actual metrics. The focus was on the “digital shadow – digital sample” bundle, which ensures the transition from fixing current parameters to forecasting and management at the strategic level.

Simulation in the AnyLogic environment (2024) showed that the gaps between operational and management circuits disappear only if all levels are connected sequentially: IoT, MES, Data Lake, Digital Twin, and ERP. The use of predictive analytics methods (LSTM, GRU, Random Forest) in the Python Software Foundation environment (2024) helped to clarify that the digital twin serves as an intermediate link combining real-time data flows with management decisions focused on sustainable development and risk reduction. Table 2 shows the key effects of architectural integration identified during the simulation.

Table 2: System effects of architectural integration of digital twins.

Architecture level	Role in the system	Integration effect (KPI, %)
IoT (sensors, monitoring)	Real-time data collection	Early detection of risks (+25%); reduction of accidents by 20-25%; proportion of correctly transmitted data ≥98%
MES	Operational management	Reconciliation of production plans with real data in 95-97% of cases; reduction of downtime to 3% of working hours
Data Lake/centralised data storage	Centralised storage and processing	Eliminating gaps between departments by 80-85%; reducing search time and data duplication by 40-50%
Digital Twin	Modelling, forecasting	Improved forecast accuracy to 92-95%; reduced technological failures by 18-22%; increased OEE by 8-12%
ERP	Management decisions	OPEX reduction by 15%; increased transparency of budgeting and planning by 25-30%; reduced reaction time to market changes by 20%

Source: compiled by the author based on modelling in AnyLogic (2024); Python Software Foundation (2024); ISO 23247:2021 (2021); IEC/ISO 30182:2017 (2017).

As can be seen from Table 2, the coordinated integration of the architecture levels allows eliminating key gaps between data collection, analytical processing, and management decision-making. The IoT layer provides a continuous flow of real-time data, which is transformed through MES and centralised storage into the basis for building a digital twin (Toibazarov et al., 2021; Trach et al., 2026). The digital twin performs the function of a dynamic predictive tool, providing ERP systems with the opportunity not only to capture the current state of production, but also to form sound management scenarios. This architectural coupling effect confirms that the digital twin should not be considered as a separate application, but as a system element combining the operational and strategic contours of the enterprise (Brescia et al., 2026; Sancio et al., 2022).

The simulation results in the AnyLogic environment have shown that the long-term effects of the introduction of digital twins in the manufacturing industry go far beyond local improvements and become systemic. Figure 4 shows the dynamics of key indicators reflecting the impact of mass adoption of digital twins in the horizon up to 2030.

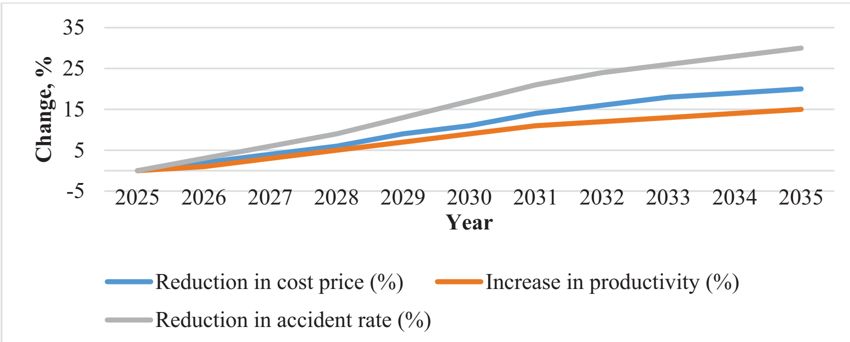

Figure 4. Dynamics of key indicators in the implementation of digital twins (scaling scenario for Kazakhstan until 2030).

Source: compiled by the author based on modelling in AnyLogic (2024).

As can be seen from Figure 4, the simulation results in the AnyLogic environment confirmed that the introduction of digital twins provides systemic improvements in the manufacturing industry. The cost of production showed a decrease of up to 20% by 2030, productivity increased by 12-15%, and the frequency of emergency stops was reduced by 25-30%. These changes point to the development of more stable and predictable production chains, which directly corresponds to the goals of digital transformation. Thus, system dynamics has confirmed that the use of digital twins not only optimises current processes, but also creates prerequisites for structural changes in national industrial policy.

3.4. Effectiveness of integration approaches in the digitalisation of production systems

In the process of digitalisation of production systems, the choice of an architectural approach to integration is of key importance. In the mining industry, the differences are particularly pronounced due to asset distribution and increased requirements for fault tolerance, which enhances the value of a Digital Twin platform architecture. In practice, two mechanisms are most common: point-based ("patchwork") automation and platform architecture. Point-based automation involves the implementation of separate digital solutions without system integration into a single architecture (Sarsembekov et al., 2026; Zhuchenko and Khibeba, 2020; Zinchenko et al., 2020). This approach allows quickly responding to local tasks and is relatively low-cost at the start. However, its weak point is limited scalability and high vulnerability to failures: disparate digital elements often do not have a common data format and require additional coupling costs. The platform architecture, on the contrary, involves building an integrated digital environment where data from all levels – from IoT sensors to ERP systems – is fed into the Data Lake and used in a digital twin model. The advantage of this approach is high scalability, transparency of processes, and resilience to failures (Marxuly et al., 2024). The disadvantage is the relatively high cost of implementation and the need for preliminary preparation of the information technology landscape. The results of the comparative analysis are summarised in Table 3.

Table 3: Comparison of approaches to the integration of digital solutions.

Criterion	Point-based ("patchwork") automation	Platform architecture (with Digital Twin level)
Speed of implementation	Duration of the pilot project is 3-6 months; implementation at the 1st site is up to 9 months.	Pilot implementation time is 9-12 months; full implementation is 18-24 months.
Cost	Start–up costs - USD ≈0.3-0.5 million (for 1 workshop); total costs after 3 years +60-70% due to improvements and incompatibilities	Start-up costs – USD ≈1.0-1.5 million (per enterprise); OPEX reduction by 10-15% in the long term
Scalability	Ability to integrate new modules – ≤40% at no additional cost; increase in integration time of +20% for each new node	Scalability up to 90% with standardised data; increased costs for new modules <5% of the base budget
Fault tolerance	Mean Time to Recovery – up to 12 hours; probability of a critical failure – ≈8-10 per year	MTTR <2 hours; critical failures <2-3 per year; data redundancy > 99.5%
Long-term effectiveness	ROI after 5 years ≤0.8; OEE growth – 3-5%	ROI after 5 years ≥1.4; increase in OEE by 10-12%; decrease in energy intensity by 10-15%

Source: compiled by the author based on the analysis of ISO 23247:2021 (2021); IEC/ISO 30182:2017 (2017); Sight Power Inc (2024).

An analysis of the data in Table 3 shows that point-based ("patchwork") automation and platform architecture differ significantly in their quantitative parameters and long-term potential. By the criterion of speed of implementation, local solutions really demonstrate an advantage: the average duration of a pilot project is 3-6 months, and implementation at one production site takes up to 9 months. For the platform architecture, this indicator is higher – from 9 to 12 months for the pilot and 18-24 months for large-scale implementation. However, after the first year of operation, the platform provides stability and predictability, while patchwork solutions require constant adaptation, which extends the average update cycle by 1.5-2 times. In terms of cost, the differences are particularly pronounced. The initial cost of point automation averages USD 0.3-0.5 million per workshop, but over three years the total cost increases by 60-70% due to incompatibility of modules and the need for improvements. In the platform architecture, the initial investment is higher – USD 1.0-1.5 million per enterprise, but after 2-3 years there is a decrease in OPEX by 10-15% and CAPEX savings of up to 20% due to the elimination of duplication of functions and a single database. In terms of scalability, the difference reaches a threefold gap: point solutions ensure the integration of new modules by no more than 40% at no additional cost and require a 20% increase in implementation time for each new node. The platform architecture allows achieving up to 90% compatibility and connect new functional blocks with an increase in costs of less than 5% of the initial budget. In terms of fault tolerance, there is the greatest difference between the approaches (Polishchuck et al., 2023). With patchwork automation, the MTTR is approximately 12 hours, while 8-10 critical failures per year are recorded. In a platform architecture with redundancy and monitoring, this indicator is reduced to 1-2 hours, and the number of serious incidents does not exceed 2-3 per year with a data availability level of 99.5%. From the standpoint of long-term efficiency, the ROI indicator in five years does not exceed 0.8 for local solutions, whereas for platform systems it reaches 1.4-1.6. In the first case, the OEE increases by only 3-5%, and in the second – by 10-12%, while the energy intensity decreases by 10-15%. Thus, the comparative analysis confirmed that despite the higher start-up costs and moderate speed of implementation, the platform architecture with Digital Twin integration provides strategically sustainable advantages. It helps to reduce total costs in the long term, increase OEE and reliability of production processes, and create a transparent and manageable digital enterprise environment (Savastio et al., 2025). This approach forms the basis for the industry's transition to a model of sustainable development, where efficiency, adaptability, and predictability of production systems become key factors of competitiveness. Notably, the described approach to building the architecture of digital twins is not limited to the manufacturing industry. It was initially developed for mining enterprises and only then adapted for the manufacturing industries, which confirms the universality of its structural principles and methods of data integration.

3.5. Integration of artificial intelligence and predictive analytics tools

One of the key areas for improving the efficiency of the architectural model of digital twins in the manufacturing industry has become the integration of AI and predictive analytics tools. The use of machine learning algorithms has allowed switching from conventional monitoring to proactive management, when decisions are made based on predicting probable events. Figure 5 shows the effects of implementing AI algorithms (LSTM, GRU, Random Forest) into the architecture of a digital twin: reduced operating costs, increased diagnostic accuracy, increased equipment life, and environmental and organisational improvements.

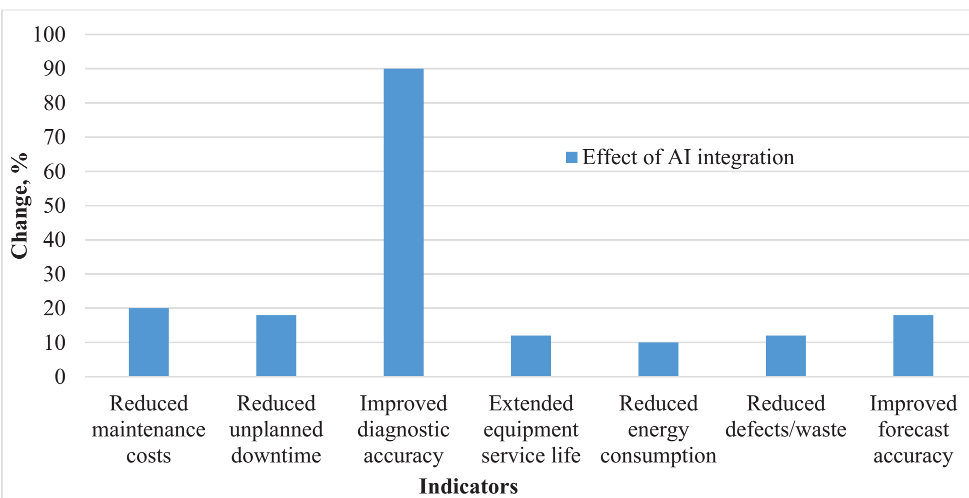

Figure 5. Effects of integrating AI tools into the architecture of a digital twin.

Source: compiled by the author based on the simulation results of AnyLogic (2024); Python Software Foundation (2024).

As can be seen from Figure 5, the integration of AI algorithms (LSTM, GRU, Random Forest) into the architectural model of digital twins provides a comprehensive increase in performance indicators. Figure 4 shows the simulation results reflecting the cumulative effect of the introduction of digital twins in the manufacturing industry of Kazakhstan. Three blocks of effects are highlighted on the graph: economic – reducing maintenance costs by up to 20% and downtime by up to 18%; technological – increasing diagnostic accuracy by up to 90% and increasing equipment service life by 10-15%; environmental and organisational – reducing energy consumption by 10% and waste by 12%. These results confirm the systemic nature of the influence of digital twins, contributing to the sustainable development of the industry. The introduction of artificial intelligence technologies into digital counterparts transforms them from a monitoring tool into the core of intelligent management (Tlebaldinova et al., 2025; Uvaliyeva et al., 2025). The result is the development of a sustainable, self-adjusting production system capable of reducing costs, increasing reliability, and simultaneously providing environmental benefits. Thus, the integration of AI and predictive analytics methods into the architectural model of digital twins creates the basis for the transition to adaptive and self-adjusting production systems. This confirms that digital twins are not limited to the role of monitoring tools, but become the core of intelligent management in the context of the digital transformation of industry.

3.6. Stages and priorities of the digital twins technological roadmap

One of the key areas in developing a sustainable strategy for the introduction of digital twins in the manufacturing industry is the construction of TRM. This tool allows linking technological solutions with market priorities and human resources, determining the sequence of steps, and minimising risks during scaling. The goal of TRM was to develop a step-by-step strategy for scaling digital twins, considering international experience and the specifics of national industrial policy. The planning horizons were set for 2025, 2030, and 2040, which corresponds to the short, medium, and long term.

The drivers of development are the integration of artificial intelligence technologies into predictive analytics, widespread adoption of IoT sensors and monitoring systems, the development of 5G/6G networks, and the growing importance of cybersecurity and trusted data infrastructure. The main barriers remain the shortage of human resources, the lack of unified standards, and the problems of interoperability of existing industrial systems (Efremov, 2026; Smailov et al., 2025b). Within the framework of the TRM, a list of reference pilot projects was identified, and KPIs were recorded: the share of enterprises that have implemented digital twins; the dynamics of OPEX reduction; the level of energy intensity of production processes; the degree of integration of Digital Twin with ERP and MES systems. The results of the analysis are summarised in Table 4, which presents the key roadmap benchmarks by level: "markets – products – technologies – competencies".

Table 4: TRM of the implementation of digital twins in the manufacturing industry.

Horizon	Markets	Products/Solutions	Technologies	Competencies and KPIs
2025	Pilot industries (mining, metallurgy)	Local digital counterparts of individual installations	IoT, Cloud Data Lake, basic AI algorithms (LSTM, RF)	Engineering personnel training; KPIs: 10-15% of enterprises with Digital Twin, OPEX reduction by 5%
2030	Scaling into the manufacturing industry	Integrated Digital Twin with ERP/MES	IoT+5G, advanced analytics, digital shadows and prototypes	Development of integration and cybersecurity competencies; KPIs: 30-40% of enterprises, OPEX − 15%, energy intensity − 10%
2040	National digital industrial ecosystem	Massive digital twins integrated into industry clusters	AI+6G, autonomous systems, quantum computing for simulation	Development of “digital ecosystems”; KPIs: 70-80% of enterprises, OPEX – 25-30%, energy intensity − 20%

Source: compiled by the author based on ISO 23247:2021 (2021); IEC/ISO 30182:2017 (2017); Sight Power Inc. (2024).

As can be seen from Table 4, the construction of TRM demonstrates the progressive nature of the digital transformation of the manufacturing industry. At the first stage (2025), digital twins were implemented mainly in the format of pilot projects at individual installations and production lines. The main objectives of this period were to test the basic architecture, develop competencies, and gain practical experience. The expected effect is expressed in a partial decrease in OPEX and a gradual increase in the share of enterprises that have implemented digital solutions. By 2030, it is planned to switch from local solutions to integrated digital counterparts capable of working in conjunction with ERP and MES systems. On this horizon, the development of the communications infrastructure (5G) is becoming critically important, which will allow working with large amounts of data in real time (Nuralin et al., 2022). Cybersecurity and interoperability issues are becoming increasingly important, as they determine the stability of the entire architecture. The long-term horizon (2040) reflects the transition to the development of a national digital industrial ecosystem. Here, digital twins cease to be a point tool and turn into a systemic element of industrial policy (Sokoliuk et al., 2021). Their integration with quantum computing, autonomous systems, and 6G technologies opens up the possibility of modelling complex scenarios. The key effects of this stage are related to a large-scale reduction in OPEX, an increase in energy efficiency, and a significant increase in the share of enterprises using digital twins. The roadmap confirms that the strategic effect of digital twins is manifested only through the sequential passage of implementation stages – from pilot projects to an integrated digital environment, and then to a large-scale national ecosystem.

3.7. Econometrics and forecasting the impact of Kazakhstan's digital counterparts

Econometric analysis has confirmed that the introduction of digital twins has a statistically significant and sustained effect on production systems. Calculations performed using OLS and panel models (FE/RE) (2025) showed an increase in total equipment efficiency (OEE) by 8-12%, an increase in output by 10-15%, and a decrease in energy intensity by 12-18%. The DiD approach applied to the pilot project data (Wooldridge, 2010) recorded a 15-20% reduction in maintenance costs, which indicates the systemic nature of the effects and their reproducibility in different sectors. An analysis of industry differences has shown that these effects manifest themselves in different ways: in metallurgy, digital twins help to optimise energy consumption and reduce energy intensity by 15-18%, in mechanical engineering – increase production and reduce downtime, and in the chemical industry – reduce waste and stabilise production cycles. This heterogeneous nature of the effects confirms the adaptability of the model and its applicability to different industrial segments. Validation of the results using SPSS Statistics for Windows, Version 28.0 (2021) and OriginLab Corporation (2023) confirmed the statistical significance of the estimates ($p<0.05$). However, confidence intervals for key coefficients indicate the stability of the identified effects even with changes in the initial parameters of the models.

Thus, the econometric analysis not only confirmed the immediate operational benefits (increased OEE, reduced costs and energy intensity), but also revealed a broader strategic effect: digital twins are becoming a factor in increasing the sectoral competitiveness and sustainability of the national economy of Kazakhstan in the context of global digital transformation. To visualise the results obtained and the projected trends, Figure 6 shows scenarios for the introduction of digital twins in the horizon up to 2030.

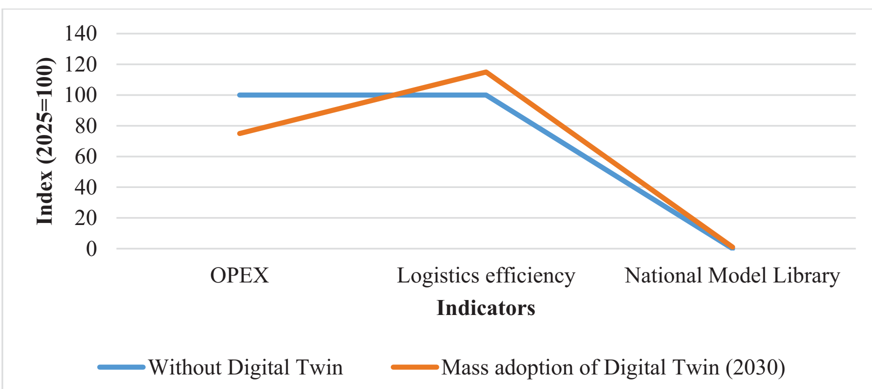

Figure 6. Scenarios for the introduction of digital twins.

Source: compiled by the author based on ISO 23247:2021 (2021); ISO 14040:2006 (2006); ISO 14044:2006 (2006); Chen et al. (2024); Amor et al. (2024).

According to the data in Figure 6, the long-term effects of the introduction of digital twins are manifested in three planes – operational, sectoral, and macroeconomic. At the operational level, enterprises receive tangible benefits in increasing equipment efficiency and optimising resources. The 8-12% increase in

OEE and 15-20% reduction in maintenance costs reflect the shift from routine preventive maintenance to predictive maintenance based on real-world data analysis. This allows extending the service life of the equipment by 10-15% and reducing the frequency of emergency downtime, creating more stable production cycles. At the industry level, digital twins are beginning to transform key production segments. In metallurgy, their use leads to a reduction in energy intensity by 15-18% due to optimisation of temperature conditions and prediction of critical loads. In mechanical engineering, the key result is increased production and reduced downtime, which is especially important in highly competitive conditions. In the chemical industry, digital twins contribute to reducing waste and stabilising processes, ensuring compliance with environmental standards, and increasing predictability of product quality (Babichev et al., 2017; 2019; Petrakov et al., 2019). At the macroeconomic level, the "mass adoption by 2030" scenario shows that the cumulative effects go beyond individual enterprises and begin to form the basis for industrial policy. A 20-25% reduction in OPEX and a 15% increase in logistics efficiency help to rebuild supply chains, making them more resilient to disruptions. It is especially important that the development of a national library of digital models creates an infrastructure for standardisation and unification of solutions: this will allow enterprises to implement digital twins faster without having to start from scratch. Such a step can be considered as a transition from fragmented digitalisation to systemic transformation, where digital twins become the core of the industrial ecosystem.

Thus, digital twins are not just a technological tool, but a mechanism for strategic modernisation of Kazakhstan's economy, combining operational improvements with a long–term industrial policy aimed at sustainability, innovation, and global competitiveness. Their implementation forms the prerequisites for the creation of a unified digital industrial ecosystem in which technological, organisational, and environmental factors are considered as interrelated elements. By reducing operating costs, increasing productivity and predictability of processes, digital twins strengthen the resilience of the national economy to external shocks and global competition. They contribute to the development of human capital, as they require new competencies in the field of information technology, engineering, and data management. In the long term, digital twins are becoming an integral part of the Industry 5.0 strategy, providing Kazakhstan with the opportunity to integrate into global technology chains and position itself as a regional leader in the field of intelligent manufacturing.

4. DISCUSSION

The results of the study confirmed the systemic nature of the effects of the introduction of digital twins in the manufacturing industry. A comparison with the results of research in related sectors demonstrates the versatility of the architectural approach. Thus, in construction, according to Yang et al. (2024), digital twins allow managing complex systems at all stages of an object's life cycle, which is consistent with the ability of digital models identified in this study to ensure the transition from monitoring to strategic management. Similarly, Aheleroff et al. (2020) in the Digital Twin as a Service (DTAAS) concept emphasised the importance of service-oriented architectures that provide scalability and adaptation to industry specifics, which is confirmed by the results obtained, demonstrating the reproducibility of effects in metallurgy, mechanical engineering, and the chemical industry.

Particular attention should be paid to the ratio of technological maturity and the intensity of the introduction of digital twins (Berdenova et al., 2019; Hashimov et al., 2019). The results of the study confirmed that digital twins act not only as a tool to increase operational efficiency, but also as a marker of the innovative dynamics of the industry. This is consistent with the conclusions of Jiang et al. (2021), who considered digital twins as one of the key indicators of the transition to Industry 4.0. The innovative aspect is the integration of artificial intelligence and predictive analytics tools that ensure the transition from reactive to proactive management of production systems. According to Segovia and Garcia-Alfaro (2022), the use of machine learning methods ensures the transition from reactive to proactive management, which is confirmed by this study: the integration of LSTM, GRU, and Random Forest algorithms has demonstrated the potential to reduce downtime and optimise resource consumption. Moreover, Iranshahi et al. (2025) showed that the prospects for the development of digital twins are associated with the use of quantum computing and 6G technologies, which is fully consistent with the conclusions presented in TRM. Similar results were demonstrated in the study by Fan et al. (2021), where a visualised digital twin architecture for flexible production systems was developed. These conclusions are consistent with the data obtained, where digital twins have contributed to increased production and reduced downtime, which confirms the applicability of the concept in a personalised and flexible production environment. Rafsanjani and Nabizadeh (2021) demonstrated the use of digital twins in the architecture, engineering, and construction (AEC) industry. The researchers have shown that digital twins can act as a tool for integrated digitalisation of design and management of construction facilities. These conclusions are consistent with the data obtained, where digital counterparts in the manufacturing industry have also demonstrated the ability to integrate heterogeneous data and form a single information space, providing a systemic effect for managing production processes. In addition, Leng et al. (2022) presented a flexible architecture for individualised production based on digital twins. This approach confirmed the possibility of adapting the concept to the conditions of variable production lines and personalised requests. The results obtained coincide with this conclusion: digital twins have contributed to increased production and reduced downtime, which indicates their applicability in conditions of high variability and the need for personalisation. Omrany et al. (2023) identified key barriers to interoperability in the implementation of digital doubles. These results are comparable to the data from this study, which also showed that the lack of a single integration standard limits the effectiveness of digital solutions. Bellavista and Di Modica (2024) emphasised the importance of distributed architectures and hybrid approaches in building digital twins. This conclusion correlates with the results confirming the advantage of platform architecture over “patchwork automation” and the need for centralised management to ensure the sustainability of digital ecosystems. The case of Li et al. (2024) is also indicative, which demonstrated optimisation of key parameters and increased forecast accuracy for steel production. This result coincided with the identified effects in the results, where digital twins provided a 15-18% reduction in energy intensity and an increase in planning accuracy, which confirms the universality of the approach in various national and industry contexts.

Additional contributions were presented in the study by Perisic and Perisic (2024), where the concept of verification and validation of digital twins within the framework of "quintuple helix" was proposed. It considered technological, social, environmental, and institutional aspects as interrelated. This approach reinforced the data obtained, which also emphasised the need to consider not only the technical, but also the socio-economic component of digital transformations, including the development of human capital and the institutional environment. The applicability and scalability of the concept has been confirmed by Feng et al. (2024), who used digital twins to manage infrastructure facilities (smart pumping stations). These results complement the conclusions about the use of digital twins in the industry of Kazakhstan, where process stabilisation and waste reduction were similarly recorded. In the system overview by Hu et al. (2024), the transition "from methodology to applications" was emphasised. This conclusion is consistent with the results that showed the need to form a national digital industrial ecosystem, where digital twins become the core of Industry 5.0.

In the study by Wang et al. (2025), the City Digital Twins (CDT) were considered as a tool for sustainable urban development. The researchers have shown that digital twins are applicable for integrated management of infrastructure, transport, and energy. This result correlates with data on the processing of large flows of heterogeneous information in the industry of Kazakhstan, where digital counterparts have also demonstrated the ability to integrate multi-domain data and form a systematic basis for decision-making. The study by Santos et al. (2024) introduced a simulation-oriented digital twin architecture to support strategic and operational management. This approach confirmed the conclusions that the architectural model of digital twins in Kazakhstan's manufacturing industry provides not only operational effects but also strategic value – optimisation of logistics and increased supply chain resilience.

In the study by Zeb et al. (2024), digital twins were implemented in the context of mineral processing using surrogate deep learning models to predict complex multidimensional processes. This result is comparable to the calculations obtained, where digital twins provided a reduction in energy consumption and an increase in forecast accuracy. In both cases, the importance of integrating machine learning methods into digital counterparts to improve the quality of forecasting was confirmed. Yang et al. (2024) focused on the transition to Industry 5.0, where digital twins are combined with human-centred principles. This conclusion coincides with the results of the analysis of Kazakhstan, where digital twins were considered not only as a technological tool, but also as a driver of human capital development and social sustainability. De Melo Santos et al. (2025) considered digital twins integrated with machine learning methods to optimise production processes. This result complements the research data, which similarly shows that the integration of predictive analytics algorithms (LSTM, GRU, Random Forest) into digital counterparts can reduce operating costs and increase productivity. The study by Sun et al. (2025) focused on modelling digital twins for intelligent production equipment. The researchers noted an increase in diagnostic accuracy and a decrease in the number of failures due to digital monitoring. This result corresponds to the data obtained, where the introduction of digital twins has reduced emergency downtime by 25-30% and increased the predictability of production cycles.

A comparison with the results of other studies has shown that the use of digital twins in the manufacturing industry of Kazakhstan fits into the global trends of digitalisation and demonstrates stable patterns. Thus, the results obtained not only confirm the reproducibility of international patterns, but also demonstrate their adaptation to the specifics of the national industry of Kazakhstan. This indicates the practical viability of digital twins as a strategic modernisation tool that provides a combination of operational, sectoral, and macroeconomic effects.

5. CONCLUSIONS

The conducted research has confirmed that the introduction of digital twins in the manufacturing industry of Kazakhstan is systemic and goes beyond local optimisations. The described architectural approach was initially developed and tested in the extractive industry of Kazakhstan (JSC “AK AltynAlmas”) and proved to be portable to the processing industries while meeting the requirements for data normalisation and hybrid computing topology. The architectural analysis showed that the five-level model (IoT → MES → Data Lake → Digital Twin → ERP) provides end-to-end data transformation and creates conditions for the integration of operational and strategic management. Simulation of scenarios in the AnyLogic environment revealed natural trends: reduction of production costs by up to 20% in the horizon until 2035, an increase in total productivity by 12-15%, and a reduction in emergency shutdowns by 25-30%. These results indicate the establishment of more stable and predictable production chains, which directly corresponds to the goals of the national digital transformation. Verification using the example of the Digital Mine project by Sight Power Inc. confirmed that digital twins provide a comprehensive increase in efficiency indicators: productivity increases by 12-15%, accident rate decreases by 18-22%, planning accuracy increases by 20-25%. The integration of artificial intelligence tools (LSTM, GRU, Random Forest) into the architecture of digital twins allowed recording a reduction in operating costs by up to 20%, reducing unexpected downtime by 18%, and increasing the accuracy of fault diagnosis by up to 90%. Additionally, an increase in the service life of equipment by 10-15%, a decrease in energy consumption by 10%, and a reduction in defects by 12% were recorded, which indicates the synergistic effect of combining AI with digital counterparts.

Digital twins should be considered not only as a tool for technological optimisation, but also as a strategic mechanism for modernising the economy of Kazakhstan. Their application allows combining local operational effects with long-term priorities of industrial policy focused on sustainability, innovative development, and global competitiveness. The large-scale introduction of digital twins increases the resilience of the national economy to external challenges, stimulates the development of new human capital and opens the way to “Industry 5.0”, where digital transformation harmoniously combines with environmental responsibility and social values. The prospects for further research are related to an in-depth analysis of the integration of digital twins with quantum computing and autonomous systems technologies, the development of unified standards of interoperability, and the assessment of socio–economic effects, from the impact on employment and the structure of the labour market to the development of new models of corporate governance in the context of digital transformation.

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