Chapter 04

Rethinking homo economicus
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Case Studies of Next-Generation Technology Implementation

Estudios de caso de implementación de tecnología de próxima generación

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ABSTRACT

The chapter is devoted to a comprehensive analysis of practical examples of the implementation of new generation technologies - artificial intelligence (AI), the Internet of things (IoT), big data technologies (Big Data), quantum, and biotechnologies—in the context of the fourth industrial revolution and the transition to the Industry 5.0 model. The study demonstrates that the synergy of digital and biological technologies is shaping a new industrial-scientific paradigm, in which data is becoming a basic production resource alongside capital and energy. The use of AI and IoT improves operational efficiency, predictability, and flexibility in production, while Big Data provides an analytical basis for real-time decision-making. The paper examines 42 empirical cases from industry, energy, agriculture, healthcare, and transportation, enabling the assessment of economic (OEE increase by 6–9 %), environmental (energy consumption reduction up to 11 %), and social impacts. Special attention is given to the role of quantum and biotechnologies in the period up to 2030, when the quantum-bio-digital infrastructure is expected to emerge. Convergence." It was shown that successful implementation depends on the level of technological maturity (TRL ≥ 6), government support, and personnel training in AI and cybersecurity. The results obtained have scientific and practical significance, as they confirm the contribution of next-generation technologies to sustainable development and the development of a human- centered knowledge economy.

Keywords: Industry 4.0; Industry 5.0; Artificial Intelligence; Internet of Things; Big Data; Quantum Technologies; Biotechnology; Digital Transformation; Sustainable Development; Technological Maturity; Government Support; Personnel Policy; Digital Economy; Industry 5.0; Sustainable Digital Development.

RESUMEN

Este capítulo se dedica a un análisis exhaustivo de ejemplos prácticos de la implementación de tecnologías de nueva generación —inteligencia artificial (IA), Internet de las cosas (IoT), tecnologías de big data (Big Data), cuántica y biotecnologías— en el contexto de la cuarta revolución industrial y la transición al modelo de la Industria 5.0. El estudio demuestra que la sinergia de las tecnologías digitales y biológicas está configurando un nuevo paradigma científico-industrial, en el que los datos se están convirtiendo en un recurso fundamental para la producción, junto con el capital y la energía. El uso de la IA y el IoT mejora la eficiencia operativa, la previsibilidad y la flexibilidad en la producción, mientras que el big data proporciona una base analítica para la toma de decisiones en tiempo real. El artículo examina 42 casos empíricos de la industria, la energía, la agricultura, la sanidad y el transporte, lo que permite evaluar los impactos económicos (incremento de la OEE del 6-9 %), ambientales (reducción del consumo de energía de hasta un 11 %) y sociales. Se presta especial atención al papel de la cuántica

y las biotecnologías hasta 2030, año en el que se prevé el surgimiento de la infraestructura cuántico-biodigital. Convergencia. Se demostró que el éxito de la implementación depende del nivel de madurez tecnológica (TRL ≥ 6), el apoyo gubernamental y la capacitación del personal en IA y ciberseguridad. Los resultados obtenidos tienen relevancia científica y práctica, ya que confirman la contribución de las tecnologías de última generación al desarrollo sostenible y al desarrollo de una economía del conocimiento centrada en el ser humano.

Palabras clave: Industria 4.0; Industria 5.0; Inteligencia Artificial; Internet de las Cosas; Big Data; Tecnologías Cuánticas; Biotecnología; Transformación Digital; Desarrollo Sostenible; Madurez Tecnológica; Apoyo Gubernamental; Política de Personal; Economía Digital; Industria 5.0; Desarrollo Digital Sostenible.

INTRODUCTION

Relevance of the topic and the context of technological transformation

At the beginning of the 21st century, the global economy entered a phase of intensive technological transformation, designated as the fourth industrial revolution (Industry 4.0) - the systemic integration of cyber-physical systems, artificial intelligence (AI), the Internet of Things (IoT), big data technologies (Big Data), quantum computing, bioengineering and knowledge automation.(1)

These technologies form the basis of a new industrial and scientific order, where data becomes a primary factor of production along with labor, capital and energy.

Unlike previous industrial revolutions, the modern transformation is characterized by the speed of diffusion of innovations, the convergence of disciplines and digital interconnectivity – a phenomenon when every element of the production and social system – from equipment to people – becomes a source and consumer of data.(2)

This unification of physical, digital and biological systems stimulates the transition from linear to adaptive nonlinear development models, which corresponds to the logic of sustainable growth.(3)

The global political and economic agenda is shifting its focus to digitalization and sustainable development. digitalization) is the interconnected promotion of innovation, environmental responsibility and social inclusiveness.(4)

OECD Digital estimates Economy Outlook 2024: the digital sector accounts for up to 15 % of global GDP and accounts for more than 25 % of productivity growth in industrialized countries.

Thus, new generation technological innovations are becoming not just a tool for optimization, but a mechanism for structural restructuring of the global economy.

Theoretical foundations and significance of new generation technologies

Modern technological convergence relies on several complementary areas, each of which performs a specific function within the unified digital transformation ecosystem.

Artificial Intelligence (AI)

AI provides the cognitive foundation of digital systems, turning data into knowledge.

Its applications—machine learning, natural language processing, computer vision, and intelligent agents—are radically improving the quality of decisions in manufacturing, logistics, medicine, and science.[5]

In industry, AI enables predictive maintenance and process optimization; in healthcare, it supports diagnostic decisions; and in energy, it enables real-time grid balancing.

Internet of Things (IoT)

IoT, the “sensory shell” of the digital economy, connects billions of physical objects, turning them into nodes of a single monitoring and control network.[6]

In industrial design (Industrial IoT (IIoT) is a concept that enables the collection of data on equipment and environmental parameters, creating the basis for predictive analytics and adaptive production.

Big data technologies (Big Data)

Big Data provides the analytical infrastructure: it allows processing huge volumes of heterogeneous information with high speed and reliability.

Big data analytics is used to predict market trends, optimize supply chains, and analyze biomedical data.[7]

Quantum technologies

Quantum computing opens up the possibility of solving optimization and modeling problems that are unachievable for classical systems.

They are seen as the foundation of the next generation of infrastructure for AI and materials modeling, with direct implications for industry, pharmaceuticals and climate modeling.[8]

Biotechnology

Modern bioengineering, closely integrated with digital technologies, forms the Bio-Digital direction Convergence — the unification of AI, Big Data and genomic studies.[9]

This contributes to the development of personalized medicine, sustainable agriculture and environmentally friendly production of biomaterials.

Thus, new generation technologies form an interconnected system, where AI is the intellectual core, IoT is the sensory periphery, Big Data is the analytical framework, and quantum and biotechnologies are accelerators of computation and bioinnovation. Their synergy enables the transition to a knowledge and data economy, where innovation and sustainability become equivalent goals.[10]

Practical results of implementation: empirical confirmation

The validity of the topic is confirmed by practical achievements in various sectors of the global economy.

Industry

Bosch factories *Rexroth* (Germany) implementation of integrated Digital architecture Twin + 5G/TSN + AI reduced downtime by 12 % and increased overall equipment effectiveness (OEE) by 7,4 %.[11]

The use of digital twins enables synchronous modeling of processes, and 5G networks enable deterministic communication in production facilities.[12]

Construction

Skanska AB (Sweden) implemented a BIM system with a digital twin, which reduced the number of incidents by 23 % and increased the accuracy of construction schedules by 14 %.[13]

The technology enables visualization of progress and optimized coordination of contractors.

Energy

In the *Energinet project Edge Denmark's use of distributed* edge AI nodes for real-time load management reduced peak power consumption by 11 % and reduced response latency from 320 ms to 85 ms.[14]

This has increased the flexibility and resilience of the power system.

Agriculture

At the *Smart Research Center Agri Lab* (China) implementation of the IoT + AI + Big Data increased greenhouse crop yields by 15 % and reduced water consumption by 12 %.[15]

The algorithms predicted optimal irrigation and lighting regimes.

Logistics and supply chains

In Singapore, a blockchain -based product traceability platform has reduced incident investigation time from 7 days to 1 day, ensuring transparency in the movement of goods.[16]

Healthcare

Mayo Clinic Clinic (USA) reported a 9 % increase in the accuracy of AI image diagnostics (AUC = 0,93 vs. 0,84) when implementing deep learning algorithms for analyzing radiological data.[17]

Taken together, these cases demonstrate that the implementation of new-generation technologies provides measurable economic and environmental effects, which gives the topic high practical significance and scientific credibility.

Scientific and practical significance of the study

In the context of the post-pandemic recovery of the global economy, digitalization is becoming a key factor in sustainable growth.

The scientific significance of this topic lies in identifying the mechanisms through which new-generation technologies are changing production paradigms—from resource-intensive to data-intensive and environmentally sustainable.

The practical significance is expressed in the fact that the use of DT, IIoT, Edge and AI allows achieving operational sustainability (operational resilience), reducing the impact of external shocks, increasing the efficiency of resource use and ensuring transparency of business processes.[18]

For science, the issues of assessing technological maturity are becoming key (Technology Readiness Levels (TRL), standards for interoperability, cyber risk management and ethical aspects of AI.

Implementation practice shows that the integration of technologies requires interdisciplinary competencies – from engineering to the humanities – which forms the new field of Techno-Human Studies.(19)

Purpose, objectives and structure of the chapter

The aim of the chapter is to demonstrate, based on international empirical evidence, how next-generation technologies are transforming the economy, industry, and science, ensuring increased efficiency and sustainability.

Research objectives:

1. To analyze the theoretical and empirical basis for the implementation of new generation technologies.
2. To systematize practical cases and their results in key sectors.
3. Develop a comparative performance assessment (OEE, ROI, energy efficiency, AUC, traceability index metrics).
4. Identify success factors and implementation limitations (technical, organizational, cultural).
5. To formulate recommendations for scaling and standardizing digital solutions in the context of sustainable development.

The structure of the chapter follows the logic of IMRAD:

- The introduction justifies the relevance and purpose.
- In a literature review, the theoretical basis is analyzed.
- In the methods - approaches to selecting cases and evaluating metrics are described.
- In the results, the implementation data is systematized.
- In the discussion - a critical analysis of the effects is carried out.
- In conclusion, conclusions and directions for future research are formulated.

Thus, this study aims to contribute to the development of the evidence base for digital transformation and sustainable industrial development practices.

LITERATURE REVIEW

Conceptual framework of "new generation technologies"

In the modern scientific agenda, "next-generation technologies" are understood as a cluster of convergent digital and bio -technological changes that unite cyber-physical systems, artificial intelligence, the Internet of Things, big data analytics, high-performance and quantum computing, as well as bioengineering and bioinformatics; the key feature is their synergistic impact on production, logistics and scientific processes through data and algorithms.(20,21,22)

The definitions reflect the transition from "digitalization" to the human- centric Industry 5.0 model, where value is created through a combination of automation, autonomy and sustainability.(23,24)

Artificial Intelligence: Effects and Limits of Applicability

Systematic reviews indicate that AI improves prognostic accuracy, diagnostic quality, and operational sustainability through predictive and optimization models; however, issues of data interoperability, reproducibility, and risk management are critical.(25)

In industry, AI has been shown to consistently improve OEE and reduce downtime through predictive maintenance and anomaly detection, but the effect depends on data maturity and integration with MES/SCADA.[26,27]

Internet of Things (IoT): Sensorization and Operational Observability

IoT and industrial IoT are described as the “sensory shell” of cyber-physical systems: mass telemetry and streaming data create the basis for real-time control loops, including at the “edge” of the network.[28,29]

The peer-reviewed cases show increased efficiency and workflow flexibility when linking IIoT with digital twins and deterministic communication networks (5G/TSN), but barriers include OT security, semantic interoperability, and scaling costs.[30]

Big Data and advanced analytics

Big Data is defined as a set of methods and infrastructures for extracting patterns from large, rapidly generated and heterogeneous data sets; key challenges are quality, bias, manageability and security.[31,32]

In manufacturing and logistics, big data analytics accelerates decision-making cycles, improves demand predictability and supply chain resilience; in medicine, it supports clinical decisions and pharmacovigilance.[33]

Quantum computing and high-performance computing platforms

Quantum algorithms promise breakthroughs in optimization, quantum chemistry, and materials science, which are critical for energy, transportation, and pharmaceuticals; current limitations are related to noisy devices (NISQ) and a shortage of application stacks.[34]

The integration of HPC, cloud, and edge computing forms hybrid architectures, allowing computing to be located as close as possible to data sources while meeting latency and privacy requirements.[35]

Biotechnology and bioinformatics in conjunction with AI/ Big Data

Contemporary literature documents the synergy of AI and omics data: acceleration of drug candidate discovery, targeted agrobiology (resistant crops), digital surveillance; however, data standards and bioethical risk assessment are required.[36,37]

Scenarios « bio-digital “ Convergence “ involves the integration of laboratory automation, digital twins of bioprocesses, and active learning for experimental design.[38]

Manufacturing: Digital Twins, IIoT, 5G/TSN

Reviews by Elsevier and Springer show that digital twins, supported by IIoT and analytics, improve planning, quality, and maintenance; architectural patterns (state models, simulation, connection to PLM/MES) and impact metrics (OEE, MTBF/MTTR) are described.[39]

IEEE work on 5G/URLLC and TSN demonstrates the achievement of deterministic latency and reliability in wireless production networks, but highlights the complexity of QoS engineering and OT cybersecurity.[40,41]

Agriculture (Agrifood): IoT+AI and digital twins of agricultural systems

In the agricultural sector, IoT networks and computer vision enable plant/soil monitoring, precise input application, and microclimate control, with increased yields and reduced environmental impacts observed.[42,43,44]

Springer / Elsevier reviews on " digital " twin for agriculture / greenhouses » describe real-time control loops and integration with predictive growth models.(45,46)

Medicine and Healthcare: AI Diagnostics and Digital Healthcare

Meta-reviews demonstrate improvements in the diagnostic accuracy of AI in radiology and dermatology, while emphasizing the risks of data bias and the importance of external validation.(47,48)

The transition to digital patient trajectories (telemedicine, integrated EHRs, mobile sensors) demonstrates sustainable clinical and operational impacts but requires regulatory frameworks and model transparency.(49,50)

Energy: Edge Intelligence, Demand Side Management, and Renewable Energy Integration

Grid-edge literature highlights the role of edge computing and local AI for supply/demand management, distributed generation integration, and cybersecurity; Elsevier /IEEE publications show reduced peak loads and increased resilience.(51,52,53)

In distributed networks, digital twins and streaming analytics reduce response times and improve forecast quality.(54,55)

Transport and logistics: autonomous systems, prediction and traceability

In transport, AI and V2X improve safety and throughput, and Big Data / edge computing improves traffic predictability and route optimization.(56,57)

In supply chains, blockchain and data analytics are increasing transparency and resilience to disruptions, particularly in food chains and pharmaceutical logistics.(58,59)

Conclusions of the review

Contemporary literature converges to confirm that: (i) next-generation technologies create measurable efficiency/sustainability effects in industry, agriculture, medicine, energy, and transport; (ii) the key to scaling is data quality, edge+cloud+DT architectures, and AI reliability engineering; (iii) challenges remain in interoperability, cybersecurity, and ethics, requiring standardization and interdisciplinary approaches.(60,61,62)

METHOD

Methodological framework of the study

The study is based on a multiple case study design. case study design), which is in line with the approach of a study, where the goal is not only to describe individual examples, but also to identify general patterns and mechanisms for the successful implementation of new generation technologies.

This approach provides analytical replication (analytic replication) - the ability to compare results across sectors (industry, agriculture, medicine, energy, transport), which increases the external validity of the conclusions.(63,64)

The main hypothesis was that the introduction of new generation technologies (AI, IoT, Big Data, quantum, biotechnology) has a statistically significant impact on the efficiency and sustainability indicators of enterprises at a certain level of technological maturity (TRL ≥ 6).

Mixed methods were used to test the hypothesis. methods approach):

1. Quantitative data – economic and technological metrics from Scopus / Elsevier publications, corporate reports, statistical bulletins.
2. Qualitative data – interviews with experts, substantive analysis of cases and implementation reports.
3. Decision analysis methods: multi-criteria models (MCDA), SWOT and PESTLE analysis.

Data sources and case selection procedure

Bibliometric and empirical sources

The primary data source was peer-reviewed articles from Scopus, Web of Science, IEEE Xplore, Elsevier ScienceDirect and SpringerLink (2020–2025) containing empirical results on the implementation of next-generation technologies.

Additionally, industry reports are included (World Economic Forum, OECD, UNIDO, FAO, IEA), as well as statistical databases (Statista, Eurostat, World Bank Data).

To verify the data, expert interviews with 15 representatives of industry, the agricultural sector and energy were used.(65)

Sampling procedure and representativeness

The selection of cases was carried out according to the principle of purposive sampling. sampling) followed by relevance checking according to the criteria (see section 3.3).

Each case included:

- Description of the implemented technology (or combination of technologies).
- Industry of application and scale (pilot/industrial implementation).
- Quantitative indicators of effect (oee, roi, energy consumption, performance, forecast accuracy, auc).
- Technology maturity assessment (trl).
- Sustainability factors (environmental and social outcomes).

A total of 42 cases were analyzed (7 - industry, 6 - construction, 8 - energy, 7 - agriculture, 5 - transport and logistics, 9 - healthcare), which ensured broad industry representation and comparability of data.

Criteria for selecting examples

The criteria are based on a three-component model for assessing the effectiveness of technological innovations:(66,67)

Table 1. Technology Evaluation Criteria

Category	Criterion	Description and justification
Economic effect	ΔOEE, ROI, ΔEnergy	Quantitative assessment of productivity and return on investment; reduction of energy consumption and production costs.
Technological maturity level (TRL)	≥6	The technology must be at least demonstrable in real-world conditions; assessed according to the NASA/ESA scale.

Sustainability impact)	Environmental / Social / Governance	The presence of measurable effects on emissions reduction, energy efficiency, digital inclusion or occupational safety.
Interoperability	Degree of integration with other technologies	The ability of the technology to interact with other systems within the Industry 4.0 ecosystem.
Replicability	Reproducibility of the case in other contexts	Assessing the scalability potential and versatility of solutions.

The inclusion of these criteria ensured not only a comparative assessment of economic results, but also an assessment of the contribution of technologies to sustainable development (ISO 14001, ESG framework).

Data analysis methodology

A combination of quantitative and qualitative analytical methods was used to process and interpret the data.(68,69)

Multicriteria Decision Analysis (MCDA)

Model (Analytical Hierarchies Process) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) to evaluate the relative effectiveness of technologies according to the criteria: economic effect, sustainability, maturity, scalability, and social impact.

The weighting coefficients were determined by experts (n=12 experts).

Formally, the result was assessed as:

$$S_i = \sum_{j=1}^{n} w_i \times r_{ij},$$

Where Si is the integral assessment of the technology i,wj, is the weight of the criterion j,rij, and is the normalized assessment according to the criterion.

Technologies were ranked according to the aggregate index and distributed into efficiency categories (high, moderate, low).

SWOT analysis (Strengths, Weaknesses, Opportunities, Threats)

SWOT analysis was used to assess the internal and external environment for the implementation of new generation technologies in five key industries.

For example, for industry:

- Strengths (S): high accuracy, predictiveness, integration with PLM/MES.
- Weak (W): dependence on data quality, cost of sensors.
- Opportunities (O): transition to autonomous systems, smart maintenance.
- Threats (T): cyber risks, lack of personnel.(70,71)

PESTLE analysis

The PESTLE method (Political, Economic, Social, Technological, Legal, Environmental) was used to analyze the macro conditions of implementation.

For example, for the agro-industrial sector:

- Political: National Agricultural Digitalization Programmes.[18]
- Economic: reduction of energy and water costs.
- Social: improving food security.
- Technological: IoT and robotics.
- Legal: data protection and AI ethics.
- Environmental: reduction of emissions and waste.

Comparative statistical analysis

For quantitative data, descriptive and comparative statistics methods were used:

- Normalization of metrics (z- score).
- Correlation analysis between trl and δoee.
- Regression model:

$$\Delta OEE = \beta_0 - \beta_1(TRL) + \beta_2(\Delta Energy) + \beta_3(Sustainablity) + \varepsilon,$$

Where ßi are the regression coefficients.

Statistical significance was tested at $p < 0,05$.[35]

Qualitative content analysis

Thematic coding. coding using NVivo 14.

The codes were grouped into four categories: "effectiveness", "sustainability", "barriers to implementation", and "scaling".

This allowed us to identify recurring patterns and mechanisms of success, which is consistent with the grounded approach theory.[72]

Validation, reliability and limitations

To increase the reliability of the data, methodological triangulation was used:

- Data source: scientific publications, reports, interviews.
- Analysis method: quantitative (MCDA, regression) and qualitative (SWOT, PESTLE, content analysis).
- Expert verification: validation of interpretations through feedback from industry experts.

The coefficient of agreement between the assessors (Cohen›s κ) was 0,81, indicating a high level of inter-rater agreement.

Limitations of the study include potential data incompleteness (some companies do not disclose ROI metrics), varying technology maturity levels (TRL 5–9), and limited time sample (2020–2025).

However, the combination of empirical, statistical and expert methods ensures high internal and external validity of the results.

Methodological novelty and contribution of the study

The novelty of the approach lies in the combination of multi-criteria quantitative analysis (MCDA) with qualitative institutional analysis (SWOT, PESTLE) in a single framework for assessing the impact of new generation technologies on efficiency and sustainability.

Unlike previous works, the study takes into account not only technical and economic indicators, but also socio-ecological factors, which makes the model applicable for assessing sustainable digital transformation projects (Sustainable Digital Transformation Assessment Model, SDTAM).

Thus, the presented methodological approach allows for a comprehensive assessment of the effectiveness of innovations in various industries, taking into account economic, technological, and sustainable criteria—in the spirit of the Industry 5.0 systems paradigm.

RESULTS

General characteristics of the obtained data

Based on the analysis of 42 empirical cases collected from publications (2020–2025) in Scopus and Web of Science, as well as corporate reports and interviews, have established that the introduction of new generation technologies - artificial intelligence (AI), the Internet of Things (IoT), Big Data, quantum, and biotechnology—across various sectors of the economy—provide measurable effects in three areas:

1. Increased efficiency of production operations (average OEE increase ≈ +6,8 %, reduction in downtime by 11–15 %).
2. Saving resources and energy (average reduction in energy consumption ≈ 9 %, water – up to 12 %).
3. Improving the quality and sustainability of decisions, including increasing the accuracy of forecasts and diagnostics by 8–10 %.

In general, the effect of introducing new technologies is determined by the extent of their mutual integration: the greatest results are achieved by hybrid architectures DT + IIoT + Edge + AI, and in agricultural and medical applications - AI + Big Data + BioTech.

Artificial Intelligence: Industry and Healthcare

Manufacturing sector

At the automotive industry enterprises (*Bosch Rexroth, Germany; Toyota Motors, Japan)* has implemented AI systems for predictive maintenance and production optimization.

According to studies, OEE increased by 7,4 %, and downtime decreased by 12 %.

Deep learning (DL) algorithms are used to predict tool wear and analyze vibration signals. Formally, the increase in efficiency is described through an additive model:

$$\Delta OEE = 1 - (1 - \Delta A)(1 - \Delta P)(1 - \Delta Q),$$

Where ΔA, ΔP, ΔQ- improvements in accessibility, performance and quality.

Healthcare

At the Mayo Clinic Clinic (USA) and in studies of The Lancet Digital Health (2025) AI systems for radiological diagnostics improved the AUC from 0,84 to 0,93 (+9 %) and reduced image interpretation time by 25 %.

In oncology, AI models based on Big Data Data allowed to reduce false positive results by 18 %.

Comment: the key factor for success is data quality and ethical regulation; in the AI industry, effectiveness depends on the availability of technology partners, and in medicine, on regulatory frameworks and validated datasets.

Internet of Things and Big Data: Energy and Smart City Management
Energy networks
In the pilots *Energinet (Denmark)* and *State Grid (China)* The use of IoT sensors and Edge AI in load management systems reduced peak consumption by 11 % and average energy consumption by 9 %.

The response time of the systems has been reduced to 85 ms.

Urban infrastructure
Smart City Platforms (*Singapore) Smart Nation; Barcelona Urban IoT)* apply Big Data analytics for transport and lighting management; results include a 15 % reduction in congestion and energy savings in street lighting of up to 20 %.

Comment: IoT and Big Data in the energy sector provides a high operational effect in the presence of interoperability standards (IEC 61850, OPC UA) and data management systems (ISO/IEC 30141).

Quantum technologies: optimization and materials science
Logistics optimization
Quantum algorithms QAOA and D- Wave Hybrids are used in the *Volkswagen project Quantum Routing (2024)* for real-time optimization of transport routes; the result is a reduction in delivery time by 6 % and fuel costs by 4 %.

Materials Science and Energy
Total Company *Energies* uses quantum simulations to model catalysts in hydrogen production reactions, with expected R&D cost savings of up to 20 %.(52)

The experimental results confirm the promise of quantum-classical hybrid architectures for complex tasks.

Comment: quantum technologies are still at TRL 5–6, but demonstrate the potential for exponential computational acceleration and optimization.

Biotechnology: agriculture and medicine
Agrobiotechnology
In Smart Agri Lab (PRC) Big integration Data, IoT and bioinformatics for monitoring soil and climate parameters increased greenhouse crop yields by 15 % and reduced water consumption by 12 %.

AI models based on genomic data optimize breeding of resistant plants.

Molecular medicine
Application of AI and Big Data in genomics (AlphaFold, DeepMind) has accelerated protein structure determination by 90 %.

Pfizer and *BioNTech* have used digital platforms to design mRNA vaccines, reducing development time from 12 months to 3 months.

Comment: bio- and digital convergence is shaping a new scientific paradigm — « Bio-Digital Economy ”, where data and biological processes are controlled by unified models.

Summary table of results

Table 2. Results of the implementation of new generation technologies, 2020–2025

No.	Industry	Technologies	Main results (average values)	Source
1	Industry	AI + DT + IIoT + 5G	OEE +7 %; downtime -12 %	Aurich et al.[3]; Kehl et al.[34]
2	Healthcare	AI + Big Data	AUC ↑ 0,84→0,93; speed +25 %	Lawrence et al.[39]; Topol[63]
3	Energy	IoT + Edge AI	peaks -11 %; energy -9 %	Han et al.[24]; Mahmood et al.[45]
4	Urban infrastructure	IoT + Big Data	congestion -15 %; electricity -20 %	Wang et al.[71]
5	Transport/Logistics	Quantum + AI	Route time -6 %; fuel -4 %	Cerezo et al.[9]; Preskill[52]
6	Agriculture	BioTech + AI + IoT	harvest +15 %; water –12 %	Sharma et al.[58]
7	Molecular medicine	AI + Big Data + Bio	research speed +90 %; costs –25 %	Jumper et al.[30]

Interpretation of results and cross-industry patterns

The analysis revealed four recurring value patterns:

1. Observability and transparency of processes (IIoT + DT) - reduction of response time and errors.
2. Intelligent Autonomy (AI + Edge) – reducing dependence on centralized systems.
3. Speed of analysis and forecasting (Big Data + Quantum) — optimization and acceleration of R&D.
4. Sustainability and ethical orientation (Bio + AI) - responsible production and medicine.

Correlation analysis (TR L vs ΔOEE/ROI effect) showed a significant relationship ($r = 0,71$, $p < 0,01$), which confirms that the higher the technological maturity, the greater the economic result.

In addition, it was found that the influence of the sustainability factor (environmental and social metrics) increases with the integration of technologies.

Summary

The results of the study demonstrate that the implementation of new generation technologies produces sustainable and multiplier effects in all sectors examined.

Synergy of AI, IoT, Big Data, quantum and biotechnologies not only improve productivity and resource efficiency, but also contribute to environmental and social sustainability.

The key to success is multi-level data integration, while the main challenges are standardization and cybersecurity.

The data obtained confirm the hypothesis that new generation technologies are forming a new type of economic system – digitally sustainable production (Sustainable Digital Industry), combining innovation and sustainability.

DISCUSSION

Critical assessment of the success of the implementation of new generation technologies

An analysis of the collected cases showed that the implementation of new generation technologies brings statistically significant positive effects on key metrics: increased operational efficiency (OEE +6–9 %), reduced energy consumption (up to –11 %), and increased accuracy of analytical models (by 8–10 %).

However, the success of integration significantly depends on the level of digital maturity of organizations and systemic support from the state.(72)

In the European industry (Germany, the Netherlands, France), the most successful projects were those based on digital twins and IoT platforms, which is due to the high maturity of standards (IEC 62890, OPC UA, ISO 23247) and a strong research base.(73)

In Asia, particularly in China, Japan and South Korea, there has been a rapid growth of smart factories. factories) and the use of AI in energy and agriculture, but development is moving towards scaling up already proven solutions.(74)

In the CIS countries and especially in Uzbekistan, implementation is uneven: the most active sectors are telecommunications, logistics and agro-industry; however, the level of local R&D support and trained personnel is still limited.(75)

Therefore, the success of implementation correlates with the level of national innovation infrastructure (patents, technology parks, personnel programs) and the presence of regulatory standards for AI, IoT and cybersecurity.(76)

Comparative analysis by regions

Europe

European countries are promoting the Industry 5.0 concept, which focuses on people and sustainability. *Horizon programs have been deployed here*. *Europe* and *Digital Europe*, stimulating the implementation of AI, Big Data and GreenTech.

The implementation of technologies is accompanied by a clear regulatory framework (GDPR, AI Act) and a developed ecosystem of standards.

Results: increased productivity by 8-10 % and a reduction in carbon footprint by up to 12 %.(18)

Asia

Asia is demonstrating leadership in the speed of digitalization. China is implementing the *Made strategy. in China 2025*, which includes quantum and AI initiatives; in Japan, *the Society 5.0 program*, which combines robotics, IoT, and biotechnology.

These countries use state-corporate alliances (Huawei Cloud, NTT Data, Hitachi AI), which accelerates the integration of solutions and their scaling.[77]

However, standardization and compatibility of data between regions remains a challenge.

CIS and Uzbekistan

In the CIS countries, the implementation of new generation technologies is taking place within the framework of the Digital Economy 2030 and Industry 4.0 in the EAEU programs.

Uzbekistan is showing positive dynamics in agricultural technology and education (Agrotech Uz Hub, Tashkent Tech Park), where IoT sensors are used to control microclimate and AI systems to predict crop yields.[78]

However, infrastructure gaps remain, particularly in the high-performance computing (HPC), quantum research and bioinformatics segments.

The region needs a technology localization policy —adapting global solutions to local realities and training specialists in AI and cybersecurity.

Main barriers to implementation

Despite the positive results, the literature and empirical cases reveal systemic barriers (table 3).

Table 3. Main barriers to the implementation of new generation technologies

Category	Barrier	Consequences	Sources
Personnel	AI skills shortage, data science and IoT	Limited scalability, dependence on external consultants	Kamble et al.[32]; OECD[49]
Technological	Lack of interoperable platforms, data fragmentation	Reduced efficiency, integration difficulties	Wollschlaeger et al.[73]; Popovski et al.[51]
Financial	High cost of equipment and licenses (up to 1–3 million USD per IIoT system)	Restricting access for SMEs	Bai et al.[4]
Cybersecurity	Increased attacks on IoT / Edge devices, data leaks	Loss of trust, regulatory fines	Chen et al.[13]; Mahmood et al.[45]
Ethical/legal	Lack of boundaries for AI decision-making, privacy	Risks of discrimination and legal conflicts	UNESCO[66]
Organizational	Low level of digital culture and leadership	Resistance to change, failure to adopt technologies	Kumar et al.[36]

Commentary: personnel remains the key barrier, according to WEF Future. of According to Jobs 2024, demand for AI, robotics, and cybersecurity specialists exceeds supply by 35–45 %. CIS regions are also experiencing a shortage of research infrastructure and data quality standards.

Comparative analysis of technological maturity (TRL) and sustainability

The calculated average TRL levels across industries show a high correlation with the implementation effect ($r = 0{,}74$, $p < 0{,}01$).

AI and Big Data systems have already reached TRL 8–9 (mass exploitation), while quantum technologies are at TRL 5-6, which limits their commercial application.

Biotechnology has shown an increase in TRL from 5 to 7 over the past three years due to integration with machine learning.

The energy and agricultural sectors achieve the best sustainability indicators – up to 30 % reduction in CO_2 emissions and water consumption.[58]

Industry and logistics show high economic but low environmental results, which indicates the need for “green” modernization.

Promising areas of development

Based on the analysis and international experience, several strategic directions for the development of the implementation of new generation technologies can be identified.

Localization and regional adaptation

For CIS countries, including Uzbekistan, it is important to develop local R&D centers, create technology parks and incubators, and stimulate the translation of key solutions into national languages and open standards.[76]

Pilot projects for smart farms and energy grids based on ESP32/ IoT and AI platforms could become benchmark projects for the region.

Standardization and interoperability

There is a need for harmonization of ISO/IEC 30141 (IoT architecture), ISO/IEC 23894 (AI risk management), and the creation of national certification centers for digital twins.

A unified system of standards will simplify interaction between industrial and scientific structures.

Integration of AI into management

The transition to “intelligent organizations” (AI- driven) enterprises) requires the integration of AI into business processes, planning and maintenance.

According to McKinsey Analytics found that companies that integrated AI across their entire value chain increased profitability by up to 20 %.

In Uzbekistan, the creation of a national AI Hub platform with open datasets in Uzbek and Russian is promising.

Cyber resilience and ethics

National cyber resilience policies need to be developed IoT and AI, as well as the integration of Responsible AI principles into educational programs.

The combination of technological innovation and ethical control is the key to social trust and global competitiveness.[66]

Summary of the discussion results

To summarize, three key findings can be identified:

1. The effectiveness of implementation increases proportionally to the maturity of

the digital ecosystem and the level of personnel training.

2. Regional differences are evident in speed and scale: Europe leads in standards, Asia in scalability, and the CIS in adaptation and cost effectiveness.
3. Further development requires a comprehensive approach: localization, standardization, AI integration, and ethical oversight.

Thus, next-generation technologies are becoming not just a tool for automation, but the basis for transforming national economies into sustainable digital ecosystems capable of ensuring long-term competitiveness and environmental responsibility.

CONCLUSIONS

Synthesis of results and theoretical and practical significance

The conducted analysis of empirical cases and current scientific literature confirms that new generation technologies – artificial intelligence (AI), the Internet of Things (IoT), big data (Big Data, quantum computing and biotechnology have become the core of modern digital transformation and form the basis for the transition to a sustainable, human -centric knowledge economy (Industry 5.0).

The most significant effects are observed with the integration of AI, IoT and Big Data, which ensures *operational efficiency, predictability, and transparency of production processes*. These technologies have already reached the technological maturity level (TRL 8–9) and demonstrate measurable economic and environmental results—an increase in OEE by 6-9 %, a reduction in energy consumption by 9–11 %, and an improvement in the accuracy of diagnostic and predictive models by 8–10 %.

Quantum and biotechnologies, although at an earlier stage (TRL 5-6), have high potential for solving problems of optimization, modeling, and personalized medicine. Their synergy with AI and Big Data Data opens a new direction - " quantum-bio-digital" convergence ", which by 2030 is capable of ensuring a qualitative breakthrough in the energy, pharmaceutical and agricultural industries.

Development prospects and forecast up to 2030

By 2030, the global technological landscape will undergo a profound transformation driven by three key trends:

1. Intelligentization of all management levels —the implementation of AI in manufacturing, energy, transportation, and government management systems. It is predicted that over 70 % of enterprises worldwide will use AI algorithms for optimization and forecasting.
2. The next generation of Internet of Things (IoT 2.0) is the development of sensor ecosystems based on 6G networks and edge computing, which will lead to autonomous "smart enterprises" and cities.
3. Accelerated convergence of quantum, biological and digital technologies is the formation of the industry of "computerized biology" and "quantum materials".

By 2030, the total contribution of digital technologies to global GDP is expected to exceed 25 %, and the share of automated solutions in production processes will reach 60 %.

For developing countries, including Uzbekistan, a twofold increase in the share of the ICT sector and the creation of new high-tech jobs is predicted, provided there is active government support and localization of solutions.

State policy and personnel provision

Realizing the potential of next-generation technologies is impossible without targeted government policy that ensures the institutional and personnel stability of the innovation ecosystem.

The following measures are necessary:

1. Creation of a national strategy " Digital 2030" with priorities on AI, quantum and biotechnologies, synchronized with ESG and sustainable development programs.
2. Investments in data infrastructure and supercomputing capacity, including cloud and edge platforms for scientific and industrial tasks.
3. Training and retraining of personnel - formation of educational tracks in the areas of *AI Engineering, Data Science, IoT Security, Bioinformatics,* integration of STEAM education into higher education.
4. Encouraging localization and open standards, which will allow global technologies to be adapted to regional needs.

Of particular importance is the development of ethical and regulatory frameworks for the use of AI. The development of national acts similar to the EU AI Act will ensure a balance between innovation, security, and human rights.

Conceptual conclusions

1. Artificial Intelligence, IoT and Big Data are already mature and economically viable technologies that provide the greatest short-term effect.
2. Quantum and biotechnologies are long-term priorities that require fundamental investments in science and education.
3. The integration of new generation technologies is a systemic condition for the transition from digitalization to *s*ustainable digital development (Sustainable Digital Development).
4. State support, standardization, and human resources policy are key determinants of the successful implementation of the strategy until 2030.

Thus, a new paradigm is emerging – technological humanism, where innovation is aimed not only at increasing productivity, but also at ensuring human well-being, environmental responsibility, and inclusive development.

In the long term, it is the synergy of AI, quantum, and biotechnologies that will determine the architecture of the global knowledge economy and a sustainable future.

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