

Intelligent assessment of the impact of AI implementation on industrial economic resilience*

Svitlana Turlakova^{1,2,3,4†} and Liudmyla Vasylieva^{5,*†}

¹ Institute of Industrial Economics of National Academy of Sciences of Ukraine, Maria Kapnist Str. 2, 03057, Kyiv, Ukraine

² Center of Excellence "Universities for Science, Informatics and Technologies in e-Society" of Sofia University "St. Kliment Ohridski", James Boucher Blvd. 5G, 1164, Sofia, Bulgaria

³ Technical university "Metinvest Polytechnics" LLC, Pivdenne Hwy. 80, 69008, Kyiv, Ukraine

⁴ National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Beresteyskyi Ave. 37, 03056, Kyiv, Ukraine

⁵ Kyiv National Economic University named after Vadym Hetman, 54/1 Beresteysky ave., Kyiv, 03057, Ukraine

Abstract

The study addresses the problem of assessing the impact of AI technologies on the economic resilience of industrial systems operating under conditions of uncertainty. An intelligent assessment framework is proposed to evaluate the impact of AI implementation on industrial economic resilience. To implement the system (or framework), a conceptual six-level, data-driven architecture is proposed that integrates AI adoption factors, adaptive mechanisms, and resilience outcomes within a unified assessment process. The framework combines data acquisition, semantic integration, data-driven analytics, intelligent industrial economic resilience assessment, decision support services, and human-centered explanation mechanisms. The proposed assessment framework establishes links between technological, organizational, and environmental factors and resilience-oriented assessment processes. Unlike traditional approaches to industrial assessment, it explicitly considers economic resilience as the primary object of assessment and decision support while integrating semantic technologies and data-driven analytics into a unified intelligent environment. The proposed conceptual architecture serves as the implementation basis of the assessment framework and can provide a methodological foundation for future intelligent systems designed for resilience monitoring, strategic planning, and evaluation of digital transformation initiatives in industrial environments. Future research directions are outlined.

Keywords

artificial intelligence (AI), economic resilience, industrial systems, industrial economic resilience, intelligent architecture, impact of AI, industry

1. Introduction

The development of artificial intelligence (AI) technologies has emerged as one of the key drivers of industrial digital transformation. [1-4]. Machine learning, predictive analytics, computer vision, intelligent control systems, and AI-based decision support tools are increasingly being integrated into industrial processes to improve operational efficiency, optimize resource utilization, and support strategic decision-making [5]. Thus, AI is now recognized not merely as a technological innovation but as a strategic factor shaping the long-term development and competitiveness of industrial systems. Recent studies have demonstrated that artificial intelligence contributes to productivity growth, process optimization, predictive maintenance, quality control, and improved decision-making in industrial environments. Parallel research areas have focused on Industry 4.0 and Industry 5.0 technologies, digital transformation, industrial resilience, and intelligent decision support

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^{1†} Corresponding author.

[†] These authors contributed equally.



svetlana.turlakova@unite-coe.bg (S. Turlakova); vasileva.dgma@gmail.com (L. Vasylieva)



0000-0002-3954-8503 (S. Turlakova); 0000-0002-9277-1560 (L. Vasylieva)



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systems. Moreover, recent advances in intelligent industrial architectures increasingly incorporate digital twins, semantic technologies, ontologies, knowledge graphs, and distributed analytics services to support planning and management processes. These architectures typically integrate data acquisition, analytical processing, knowledge representation, and decision support mechanisms within multi-layered frameworks and can serve as a foundation for the intelligent assessment of the impact of AI implementation on industrial economic resilience.

However, despite the significant progress achieved in AI-driven industrial transformation and intelligent industrial architectures, an important research gap remains. Existing approaches primarily focus on operational optimization, production planning, maintenance management, or interoperability issues, while industrial economic resilience is rarely treated as an explicit assessment objective.

Furthermore, the impact of AI technologies on industrial economic resilience is seldom examined within a unified architecture capable of integrating AI implementation factors, adaptive mechanisms, and resilience-related outcomes.

At the same time, industrial enterprises operate in an environment characterized by increasing uncertainty and vulnerability to external disturbances. Geopolitical instability, supply chain disruptions, energy challenges, technological change, and rapidly evolving market conditions create significant obstacles to maintaining stable industrial operations.

Under these circumstances, industrial economic resilience has become a critical characteristic of industrial systems. It is generally understood as the ability to withstand disruptions, adapt to changing conditions, recover from adverse events, and sustain long-term development trajectories.

Against this backdrop, the assessment of industrial economic resilience is of particular importance, especially for Ukrainian industry, which is currently operating under conditions of heightened uncertainty and requires advanced analytical tools for resilience assessment and strategic planning.

The approach proposed in this paper to the intelligent assessment of the impact of artificial intelligence adoption on industrial economic resilience considers AI not only as a productivity-enhancing technology but also as a resilience-enabling factor that strengthens adaptive capabilities through forecasting, risk identification, process optimization, and decision support.

The study contributes to the fields of intelligent systems and knowledge engineering by proposing an intelligent assessment framework, implemented through an integrated six-layer architecture that combines data-driven analytics, semantic knowledge representation, intelligent assessment mechanisms, and human-centered decision support within a unified framework. The proposed architecture is intended to serve as a methodological foundation for the development of future intelligent assessment and decision support systems aimed at strengthening industrial economic resilience under conditions of uncertainty.

2. Literature review

In the study [6], economic resilience is conceptualized as a key indicator of sustainable economic growth. The authors emphasize that the development of the AI industry constitutes a strategic foundation for industrial competitiveness among countries in the context of globalization.

The study by [7] systematically examines the mechanisms, nonlinear characteristics, and spatial heterogeneity of the impact of AI on the resilience of manufacturing industrial chains. The findings

demonstrate that AI has a significant and robust direct positive effect on industrial chain resilience. Furthermore, AI indirectly enhances resilience by promoting macro-economic development.

However, recent research in this field demonstrates a shift from isolated analytical and optimization models toward integrated architectures for assessing the impact of AI implementation on industrial economic resilience. These architectures combine data acquisition, semantic knowledge representation, analytical processing, and decision support services within a unified framework.

Modern industrial assessment systems are expected to ensure interoperability, explainability, scalability, and knowledge reusability while operating in heterogeneous and distributed environments.

One of the rapidly developing directions in this field is the design of digital twin-based architectures. In [8], the authors proposed an ontology-driven digital twin paradigm built upon multiple interacting layers and perspectives, including the physical, logical, and information-processing levels. The architecture separates data exchange, model logic, and user interaction mechanisms, thereby providing a modular foundation for intelligent industrial applications. The authors argue that such separation improves scalability and interoperability, which are essential characteristics of modern assessment industrial economic systems.

Another important research direction focuses on industrial information architectures. In [9], the authors present a reference architecture for the information layer of RAMI 4.0, which formalizes the integration of enterprise requirements, business models, industrial processes, and operational data. This approach demonstrates the importance of structured information models as a prerequisite for intelligent decision support and advanced analytics.

Studies [10] and [11] emphasize semantic technologies as a foundation of industrial intelligence. In [10], the authors propose an ontology ecosystem architecture that enables knowledge integration across manufacturing value networks. Their work highlights the role of semantic interoperability in integrating information from multiple organizational and technological domains. Similarly, [11] presents a knowledge graph-based framework that supports querying, reasoning, updating, and exploration of industrial knowledge through a unified semantic layer. These approaches demonstrate that knowledge representation is becoming a central component of assessing the impact of AI on industrial economic resilience within intelligent industrial architectures, rather than merely a supporting mechanism for data management.

In study [12], the authors proposed a knowledge graph-based framework that explicitly incorporates human factors, operator activities, and human-machine collaboration into industrial decision-making processes. Their findings indicate that intelligent systems for assessing industrial economic resilience should consider not only technological assets and production processes but also workforce-related factors that significantly influence industrial performance.

Research has also begun to focus on architectures specifically designed to assess industrial economic resilience. In [13], the authors present a digital twin-based resilience assessment system that supports the dynamic evaluation of industrial system performance during disruptions and facilitates recovery planning. In [14], a system-of-systems resilience assessment architecture is proposed, in which resilience is conceptualized as an emergent structural property arising from interactions among interconnected subsystems. These studies shift industrial economic resilience from a descriptive concept to an explicit objective of modeling and assessment.

In [15], the authors proposed a distributed analytics system for industrial digital twins that supports descriptive, predictive, and prescriptive analytics within interconnected industrial ecosystems. In [16], a model-catalog architecture is presented that formalizes model management,

data preparation, interoperability, and model orchestration in industrial decision support environments. These studies demonstrate that modern architectures for assessing industrial economic resilience increasingly rely on modular decision support services rather than monolithic analytical solutions. The reviewed studies reveal a common trend (Table 1). Modern intelligent industrial systems are typically organized as multi-layered architectures that integrate data acquisition, semantic knowledge management, analytical processing, and decision support capabilities. Ontologies, knowledge graphs, and digital twins have become key mechanisms for achieving interoperability and enabling cross-domain reasoning in complex industrial environments. At the same time, the functionality of such systems focused on assessing industrial economic resilience remains significantly less developed compared to data integration and operational analytics. Most existing architectures concentrate on production optimization, maintenance, interoperability, or planning support, while industrial economic resilience is rarely considered as an explicit assessment objective.

Table 1
Architectures for Intelligent Assessment and Decision Support in Industrial Economic Resilience Research

Architecture type	Key contribution	Intelligent Industrial Architecture	Study
Ontology-driven Digital Twin	Multi-layer Architecture Integrating Physical and Digital Environments	Architectural Layering and Interoperability	[8]
RAMI 4.0 Information Architecture	Enterprise-to-Shop-Floor Information Integration	Semantic Information Backbone	[9]
Ontology Ecosystem Architecture	Cross-domain Semantic Interoperability	Knowledge Integration Layer	[10]
Knowledge Graph Structure	Unified Semantic Industrial Knowledge Access	Knowledge Representation and Reasoning	[11]
Human-centered Knowledge Graph	Human-centered Industrial System Integration	Human-centered Assessment Layer	[12]
Digital Twin for Resilience Assessment	Dynamic Resilience Assessment and Recovery Planning	Resilience Assessment Mechanisms	[13]
System-of-Systems Resilience Architecture	Structural Resilience Assessment	Resilience Modeling Logic	[14]
Distributed Analytics Architecture	Distributed Analytics and Decision Support Services	Decision Service Layer	[15]
Model-Catalog-Based Decision Support Architecture	Model Orchestration and Management	Multi-model Assessment Environment	[16]

Despite significant progress in the development of intelligent industrial architectures, there remains a lack of integrated tools for the intelligent assessment of the impact of AI implementation on industrial economic resilience that can jointly capture technological factors, adaptive mechanisms, and economic resilience indicators within a unified knowledge- and data-driven environment. Therefore, investigating the processes of intelligently assessing the impact of AI adoption on industrial economic resilience and developing a corresponding architecture based on economic and mathematical models represent an important and highly relevant research direction. The aim of this study is to develop a conceptual intelligent architecture for assessing the impact of AI technology implementation by industrial enterprises on the economic resilience of Ukrainian industry under conditions of uncertainty and digital transformation.

3. Conceptual Foundations of the Intelligent Assessment of the Impact of AI Implementation on Industrial Economic Resilience

The analysis of existing intelligent industrial architectures demonstrates that modern systems for assessing AI implementation in industry increasingly rely on semantic integration, distributed analytics, knowledge representation, and decision support services. Existing approaches primarily focus on operational optimization, maintenance management, interoperability, or industrial system performance assessment. Industrial economic resilience is rarely considered as a distinct assessment objective and is typically addressed only indirectly through technical or operational performance indicators. In the context of industrial systems operating under conditions of uncertainty, industrial economic resilience should be regarded as a multidimensional characteristic that reflects a system's ability to maintain functionality, adapt to changing conditions, recover from disruptions, and sustain long-term development. Such a characteristic cannot be adequately represented by a single indicator and requires the integration of technological, organizational, operational, and managerial factors.

AI plays a distinctive role in this context. Unlike traditional production technologies, AI does not directly generate economic value. Instead, it enhances the adaptive capabilities of industrial systems by improving forecasting accuracy, supporting risk identification, accelerating operational and decision-making processes, and optimizing resource allocation. Consequently, the impact of AI on industrial economic resilience is realized through a set of intermediate adaptive mechanisms.

Based on this assumption, the impact of AI on industrial economic resilience can be represented as a conceptual chain:

AI Adoption Factors → Adaptive Mechanisms → Economic Resilience Outcomes.

The first component characterizes the level of AI implementation in industrial systems. It reflects the availability and utilization of intelligent technologies, including machine learning, predictive analytics, intelligent control systems, computer vision, and AI-based decision support tools.

The second component represents the adaptive mechanisms activated or enhanced by artificial intelligence technologies. These mechanisms include forecasting and early warning capabilities, operational flexibility, process optimization, risk management, resource coordination, and support for management decision-making.

The third component represents the outcomes of industrial economic resilience assessment. These outcomes characterize the ability of industrial systems to maintain operational continuity, recover from disruptions, adapt to changing conditions, preserve competitiveness, and sustain long-term development under conditions of uncertainty. The proposed conceptual chain provides the theoretical foundation for the intelligent architecture for assessing the impact of AI adoption on industrial economic resilience developed in this study. It establishes causal relationships between technological factors and resilience outcomes while introducing adaptive mechanisms as an

intermediate analytical layer in the assessment of industrial economic resilience. This representation makes it possible to view industrial economic resilience not merely as a descriptive characteristic but as an assessable and explainable outcome of the interaction among technological, organizational, and managerial factors (Figure 1).



Figure 1: Conceptual mechanism of AI influence on industrial economic resilience.

4. Data-Driven Intelligent Assessment of Industrial Economic Resilience

Based on the conceptual foundations presented in the previous section, this section introduces the proposed intelligent assessment framework. It represents the principal methodological contribution of the study and provides the architectural basis for assessing the impact of AI implementation on industrial economic resilience. The literature review has shown that modern intelligent industrial architectures increasingly combine semantic knowledge representation, distributed analytics services, digital twins, and decision support mechanisms. At the same time, existing intelligent industrial architectures primarily focus on operational optimization, maintenance management, production planning, and interoperability. Industrial economic resilience is rarely considered as an explicit assessment objective. Moreover, the role of artificial intelligence in the assessment of industrial economic resilience remains insufficiently distinguished and formalized.

To address this limitation, a data-driven intelligent architecture is proposed for assessing the impact of AI technologies on the economic resilience of Ukrainian industry. The architecture integrates data acquisition, semantic knowledge representation, analytical processing, industrial economic resilience assessment, and decision support services within a unified framework. The proposed architecture consists of six interconnected layers (Figure 2). Each layer performs a specific function and contributes to transforming heterogeneous industrial data into explainable knowledge and actionable recommendations for assessing industrial economic resilience. The first layer is responsible for data acquisition, aggregation, and preprocessing from multiple sources. It provides a consistent data environment for subsequent analytical procedures and enables the continuous updating of the assessment process. The semantic integration layer transforms raw data into structured knowledge using semantic models, ontologies, metadata structures, and knowledge graphs. This layer establishes relationships among technological factors, organizational

characteristics, adaptive mechanisms, and resilience indicators. As a result, the architecture creates a unified knowledge space that supports interoperability and enables intelligent reasoning across multiple information domains involved in the assessment of industrial economic resilience.

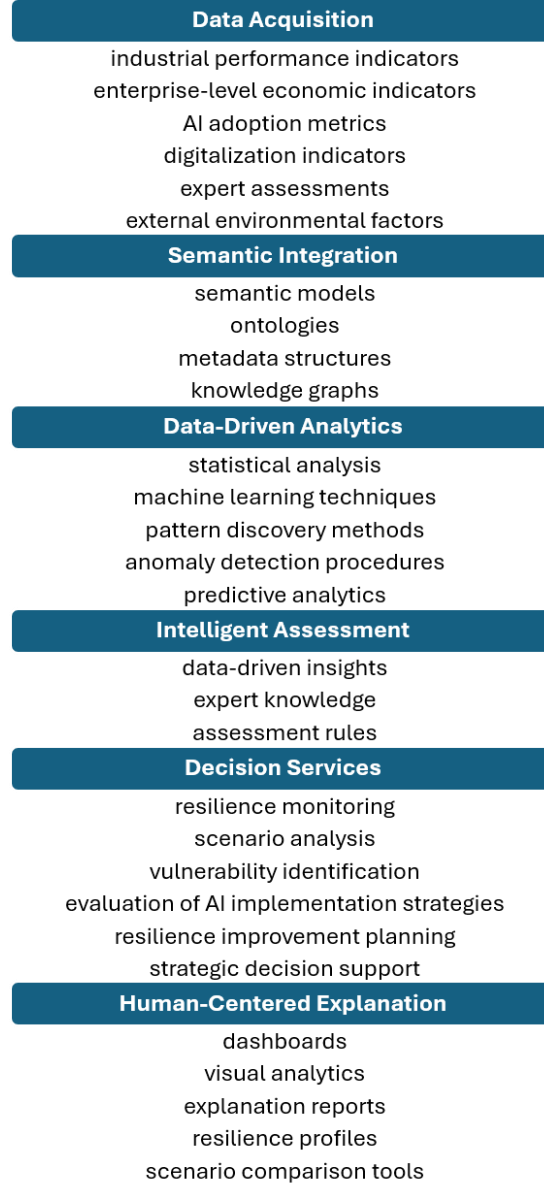


Figure 2: Six-Layer Intelligent Architecture for Assessing the Impact of AI implementation on Industrial Economic Resilience.

The data-driven analytics layer performs analytical processing of the integrated information. Its primary objective is to identify hidden relationships between AI adoption factors and industrial system characteristics associated with economic resilience. Unlike traditional reporting systems, this layer supports the continuous extraction of knowledge from dynamically evolving industrial data for assessing the impact of AI implementation on industrial economic resilience. The intelligent assessment layer for evaluating the impact of AI implementation on industrial economic resilience constitutes the analytical core of the proposed architecture. This layer combines analytical data with expert knowledge and assessment rules to evaluate the impact of AI technologies on industrial economic resilience. Conceptually, the assessment process can be represented as follows:

$$ER = F(AI, AM, E), \quad (1)$$

where:

ER is the integrated economic resilience index;

AI denotes the level of AI adoption in the industrial system;

AM represents the adaptive mechanisms, expressed through the resulting indicators of the economic effects generated by AI implementation at the industrial system;

E represents environmental factors, i.e., external factors that may influence industrial economic resilience.

The AI adoption vector can be represented as follows:

$$AI=\{a_1, a_2, \dots, a_n\}, \quad (2)$$

where the vector elements correspond to indicators describing the level of AI implementation in the industrial system and its impact on industrial economic resilience.

The adaptive mechanisms vector is defined as follows:

$$AM=\{m_1, m_2, \dots, m_k\}, \quad (3)$$

The adaptive mechanisms are expressed through the resulting indicators of the economic effects generated by AI implementation in the industrial system under study, including forecasting capabilities, risk response mechanisms, process optimization, resource coordination, and decision support functions.

The resulting resilience profile can be expressed as follows:

$$ER=\{r_1, r_2, \dots, r_p\} \quad (4)$$

where the indicators characterize operational continuity, recovery capability, adaptability, competitiveness, and sustainable development.

The purpose of this layer is not only to calculate resilience indicators but also to explain the contribution of specific technological and organizational factors to the formation of industrial economic resilience.

To represent the multidimensional nature of industrial economic resilience, the resilience profile can be described by a set of individual components:

$$ER=\{RC, AD, OC, CP, SD\}, \quad (5)$$

where:

RC denotes the recovery capability of the industrial system under study;

AD denotes the adaptability of the industrial system;

OC denotes the operational continuity of the industrial system;

CP denotes the competitiveness of the industrial system;

SD denotes the sustainable development of the industrial system.

Based on these components, the integrated Economic Resilience Index (*ERI*) can be calculated as a weighted aggregation of individual dimensions of industrial system resilience:

$$ERI = \sum (w_i \cdot r_i), i=1, \dots, p, \quad (6)$$

where:

ERI is the integrated economic resilience index of the industrial system;

r_i denotes the value of the i -th resilience component;

w_i is the weighting coefficient corresponding to the i -th component of the industrial system;

p is the number of resilience components of the industrial system.

In practical implementations, the weighting coefficients may be determined using expert-based approaches, entropy-based weighting, or data-driven optimization methods, depending on data availability and the assessment objectives. The proposed formulation is generic because the selection of weighting and validation procedures depends on the characteristics of a particular industrial application and constitutes a direction for future research.

The weighting coefficients satisfy the normalization condition:

$$\sum w_i = 1, i=1, \dots, p. \quad (7)$$

This representation provides a foundation for developing quantitative assessment procedures and enables the integration of various dimensions of economic resilience into a unified system for assessing the impact of AI adoption on industrial economic resilience.

The decision support service layer transforms the results of this assessment into practical recommendations. This layer provides managers, experts, and policymakers with the information required to make informed decisions under conditions of uncertainty.

The final layer (the human-centered explanation layer) ensures the explainability and usability of assessment results. The inclusion of such a mechanism reflects current trends in human-centered intelligent systems. It enables decision-makers to understand how industrial economic resilience assessments are generated and which factors have the greatest influence on the assessment outcomes.

The functional roles of the proposed architecture layers are presented in Table 2.

Table 2
Functional Roles of the Proposed Architecture Layers for Assessing the Impact of AI implementation on Industrial Economic Resilience

Layer	Main Function	Main Outcome
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Data Acquisition	Collection and preprocessing of heterogeneous data	Structured datasets
Semantic Integration	Knowledge representation and interoperability	Integrated knowledge base
Data-Driven Analytics	Pattern identification and predictive analysis	Analytical insights
Intelligent Assessment	Evaluation of resilience-related indicators	Resilience profile
Decision Support Service	Decision support and scenario analysis	Recommendations
Human-Centered Explanation	Interpretation and visualization	Explanation of results

Information generated at each layer is transferred to the next one through standardized semantic representations. The interaction among the six layers of the intelligent architecture for assessing the impact of AI implementation on industrial economic resilience forms a comprehensive data-driven intelligent assessment process. The proposed architecture transforms heterogeneous industrial information into structured knowledge, analytical insights, industrial economic resilience assessments, and explainable recommendations.

This architecture provides a conceptual foundation for intelligent decision support systems aimed at assessing and strengthening the economic resilience of industrial systems operating under conditions of uncertainty.

5. Discussion

The proposed intelligent architecture for assessing the impact of AI implementation on industrial economic resilience extends existing research on digital twins, semantic integration frameworks, knowledge graphs, and decision support systems by introducing economic resilience as an explicit assessment objective. Although modern intelligent industrial architectures provide advanced mechanisms for interoperability, operational monitoring, and analytical processing of data related to industrial system performance, resilience assessment is typically addressed only indirectly and rarely serves as the primary assessment objective.

A distinctive feature of the proposed approach is the integration of three conceptual domains that are typically studied separately: AI implementation, adaptive mechanisms, and industrial economic resilience outcomes. This integration makes it possible to consider resilience as a measurable and explainable characteristic rather than merely as a consequence of the digital transformation of industrial systems.

Unlike traditional architectures focused on performance optimization, the proposed approach is centered on assessment and decision support aimed at enhancing industrial economic resilience.

Another important characteristic of the proposed intelligent architecture for assessing the impact of AI implementation on industrial economic resilience is the integration of data-driven analytics and knowledge-based reasoning. Semantic integration mechanisms, ontologies, and knowledge graphs provide a unified knowledge space that supports the transformation of heterogeneous industrial data into explainable assessment outcomes and recommendations focused on industrial economic resilience.

Furthermore, the human-centered explanation layer enhances transparency and interpretability, which are increasingly recognized as essential requirements for intelligent systems operating under conditions of uncertainty.

The relevance of the proposed intelligent assessment of the impact of AI implementation on industrial economic resilience is particularly evident in the context of Ukrainian industry. Geopolitical shocks, energy security challenges, supply chain instability, and the need for accelerated digital transformation have significantly increased the importance of industrial economic resilience-oriented management.

Under these conditions, intelligent assessment architectures capable of integrating technological, organizational, and environmental factors can provide valuable support for strategic planning and industrial economic development.

Despite its advantages, the proposed study has several limitations. First, the architecture for assessing the impact of AI implementation on industrial economic resilience remains conceptual and has not yet been implemented in a real industrial system. Second, the relationships and indicators incorporated into the architecture require empirical validation using real industrial data. Third, this study focuses on the architectural and methodological aspects of resilience assessment and does not consider specific machine learning algorithms or analytical procedures.

Overall, the proposed architecture for assessing the impact of AI implementation on industrial economic resilience provides a conceptual foundation for future intelligent assessment and decision support systems aimed at evaluating the contribution of AI to industrial economic resilience. By combining data-driven analytics, semantic knowledge representation, industrial economic resilience assessment mechanisms, and explainable decision support, the architecture contributes to the development of intelligent industrial systems capable of operating under conditions of uncertainty (Table 3).

Table 3
Comparison of Existing Architectures and the Proposed Approach

Feature	Existing Architectures	Proposed Architecture
Ontologies	yes	yes
Knowledge Graphs	yes	yes
Semantic Integration	yes	yes
Data-Driven Analytics	yes	yes
Decision Support	yes	yes
Human-Centered Explanation	partially	yes
Economic Resilience Assessment	partially	yes
AI Impact Assessment	rarely	yes

6. Conclusions

This study addresses the problem of assessing the impact of AI technologies on the economic resilience of industrial systems operating under conditions of uncertainty. The analysis of recent studies has shown that modern intelligent industrial architectures increasingly employ digital twins, semantic technologies, knowledge graphs, and decision support services. However, industrial economic resilience is rarely considered as an explicit assessment objective within existing intelligent assessment systems.

To address this research gap, a data-driven intelligent assessment architecture is proposed for evaluating the impact of AI implementation on industrial economic resilience. The developed approach integrates AI adoption factors, adaptive mechanisms, and resilience outcomes within a unified assessment framework. The architecture combines data acquisition, semantic integration, data-driven analytics, intelligent industrial economic resilience assessment, decision support services, and human-centered explanation mechanisms. The main contribution of this study is the development of an intelligent assessment framework, implemented as a conceptual six-layer architecture for assessing the impact of AI implementation on industrial economic resilience, which links technological, organizational, and environmental factors with resilience-oriented assessment processes. Unlike traditional approaches to industrial assessment, which primarily focus on operational efficiency and performance optimization, the proposed intelligent architecture explicitly considers economic resilience as a target object of assessment and decision support. The proposed six-layer intelligent architecture for assessing the impact of AI implementation on industrial economic resilience can serve as a methodological foundation for future intelligent systems designed for resilience monitoring, strategic planning, and evaluation of digital transformation initiatives in industrial environments. The proposed intelligent architecture is particularly relevant for industrial systems operating under conditions of increased uncertainty, where adaptive capabilities and resilience become essential factors for sustainable development. Future research should focus on the formalization of industrial economic resilience indicators, the development of quantitative assessment procedures, and the empirical validation of the proposed architecture using industrial data. Further research directions include the application of machine learning models, digital twins, and simulation mechanisms for assessing adaptive resilience.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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