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# Artificial Intelligence in Energy Pipelines: Opportunities and Risks

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ABSTRACT

Artificial intelligence (AI) is reshaping the operation and management of energy pipelines that transport oil, natural gas, hydrogen, and carbon dioxide. This review provides a critical synthesis of current developments, highlighting how AI is being applied across pipeline life cycle stages—from route design and construction quality assurance to operation, maintenance, and eventual decommissioning. Recent advances in deep learning, transformer architectures, graph neural networks, and physics-informed models demonstrate the ability to detect anomalies, optimize multiphase flows, and support predictive maintenance with greater adaptability and robustness than conventional methods. Case studies illustrate how industrial operators are deploying AI platforms to improve efficiency, reduce environmental impact, and enhance system resilience. Alongside these opportunities, the review identifies systemic risks, including data bias, algorithmic opacity, cybersecurity vulnerabilities, and overreliance on automation, and discusses emerging mitigation strategies such as synthetic data generation, explainable AI, defense-in-depth frameworks, and mixed-initiative human–machine collaboration. Looking ahead, the field is moving toward multi-source heterogeneous data fusion, few-shot and transfer learning for data-scarce environments, and causal inference for decision support. AI applications in hydrogen and $CO_2$ pipelines, though nascent, offer promising directions for building safer and more sustainable infrastructures. This review underscores the need for continued interdisciplinary efforts to balance innovation with reliability, ensuring that AI becomes a trusted enabler of next-generation pipeline systems in the global energy transition.

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## 1. Introduction

Energy pipelines are regarded as the arteries of economical development, effectively and efficiently transporting oil, natural gas, and petrochemicals across provinces, countries, and continents [1,2]. Today, pipelines have been a critical player in carrying new energy like hydrogen, ammonia, biogas, organic substances, and carbon dioxide ($CO_2$) [3,4]. The North America features the world's largest network in natural gas, oil, hydrogen, and $CO_2$ pipelines, while Europe is implementing an ambitious plan in rapid expansion of its hydrogen pipeline network. Notably, the United States operates over 8500 km of $CO_2$ pipelines and 2500 km of hydrogen pipelines [5]. Public and private data sources tell the reality of pipeline landscape in the world, as shown in Fig. 1 [6–8], where a comprehensive database for global $CO_2$ pipelines is lacking.

With the rapid growth of energy pipelines, the industry is increasingly integrating artificial intelligence (AI) techniques with pipeline operation for enhanced efficiency, safety, and sustainability [9]. In pipeline systems, massive datasets are generated from various sources such as supervisory control and data acquisition (SCADA), inline inspection (ILI) tools, sensors, and surveillance, spanning the entire pipeline life cycle. These data serve as inputs for advanced analytics, machine learning (ML) methods, computer vision, and even natural language processing applications [10]. Presently, research on AI applications in energy pipelines contain several major gaps: ① The majority of studies focuses on specific AI applications or techniques without a unifying framework to evaluate their suitability and effectiveness across different pipeline operational contexts. ② The analysis is insufficient in differentiating the AI application needs for various types of pipeline systems, such as the high-pressure transmission systems (high pressure with vast distances), low-pressure urban distribution pipeline network (low pressure with a complex distribution), offshore subsea installations (extreme deep marine environments), and onshore terrestrial systems (varying terrains and accessibility challenges).

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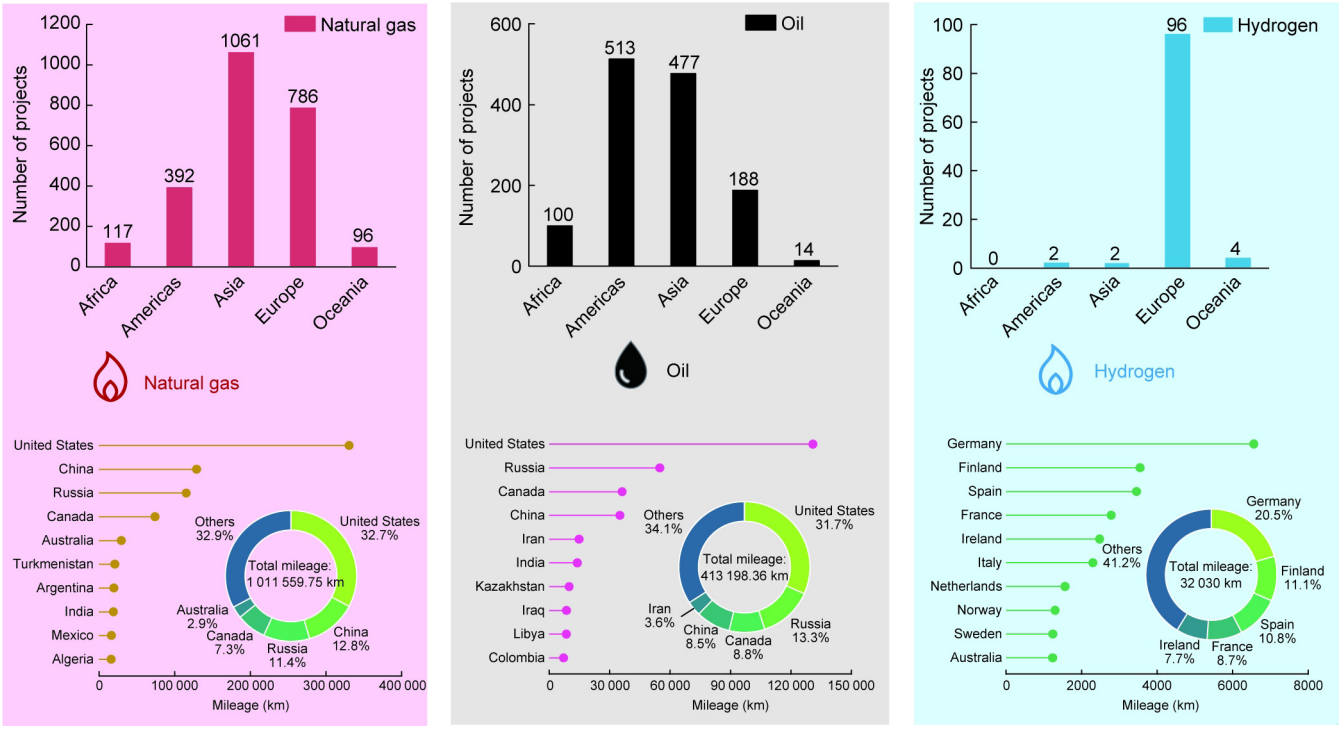


**Fig. 1.** Global distribution and mileages of natural gas, oil, and hydrogen pipelines. For natural gas pipelines, the quantity and mileage data only include transmission pipelines, excluding gathering and distribution pipelines. The data for the quantity and mileage of natural gas [6] and oil [7] pipeline projects include only those in operation, as of December 2023 and May 2024, respectively. The hydrogen pipeline projects include both operational and planning ones, with data as of October 2023 [8]. The figure does not include $CO_2$ pipelines as the global database is currently unavailable.

③ The discussion on AI-related risks, such as data bias, cybersecurity vulnerabilities, and human–machine interaction challenges, is often superficial, lacking quantitative risk assessment and detailed mitigation strategies.

This review attempts to fill these gaps through systematic and critical analysis of AI technology applicable to energy pipelines. Specifically, the analysis includes: ① Synthesizing AI applications across the life cycle stages of pipelines, providing complete perspectives for technology evaluation. ② Analyzing the potential of the latest AI techniques including transformers, graph neural networks (GNNs), and self-supervised learning applicable for safety assessment and operational optimization on pipelines. ③ Conducting in-depth analysis of the risks associated with AI application and the mitigation strategies through case studies. ④ Discussing the perspectives of AI applications in emerging new energy pipelines carrying hydrogen and $CO_2$. It is anticipated that valuable recommendations are provided for policy makers, pipelines operators, and AI technology developers, enabling sustainable development of the energy pipeline industry.

## 2. Analytical approach

This review employs a systematic analytical approach combining comprehensive literature analysis and verified case study for assessing and analyzing the AI applications in energy pipeline systems. The literature analysis is conducted following the established guidelines with the following criteria: ① collect and review peer-reviewed papers from major academic databases such as IEEE Xplore, ScienceDirect, and Web of Science; ② focus on publications in 2021–2025, ensuring the latest development and innovation of the technology, with some selective inclusions of classic literature published earlier; and ③ use the keywords including AI, ML, energy pipelines, natural gas, oil, hydrogen, and $CO_2$ transport.

Case studies were selected based on: ① availability of quantitative performance data; ② coverage of various AI applications in energy pipelines; and ③ verification through peer-reviewed publications or public reports.

## 3. Systematic analysis of AI applications in energy pipelines

To systematically evaluate the AI applications in energy pipelines, this section integrates existing knowledge through a comprehensive analytical framework covering the entire life cycle stages of various types of pipelines. Fig. 2 shows a layered architectural framework that illustrates how AI techniques are integrated into the energy pipeline systems, from foundational data collection through multi-source sensors and inspection tools to AI processing methods and operating applications across safety, analytics, and risk management domains. This architecture represents the interrelated nature of modern pipeline AI systems, where the continuous feedback loops enable iterative improvement and adaptation. The framework imparts how traditional ML approaches coexist with advanced deep learning techniques, while the physics-informed models bridge the data-driven insights and domain expertise. Understanding the architectural perspective is essential to understand the contributions of AI technology to pipeline safety assessment, operating optimization, and risk mitigation throughout the pipeline's life cycle stages.

### *3.1. AI applications across the life cycle stages of pipelines*

The life cycle of energy pipelines typically includes planning and design, construction, operation and maintenance, and decommissioning. Distinct challenges are associated with specific stages in AI application (Fig. 3). In the planning and design stage, there are route selection challenges involving topographic analysis,

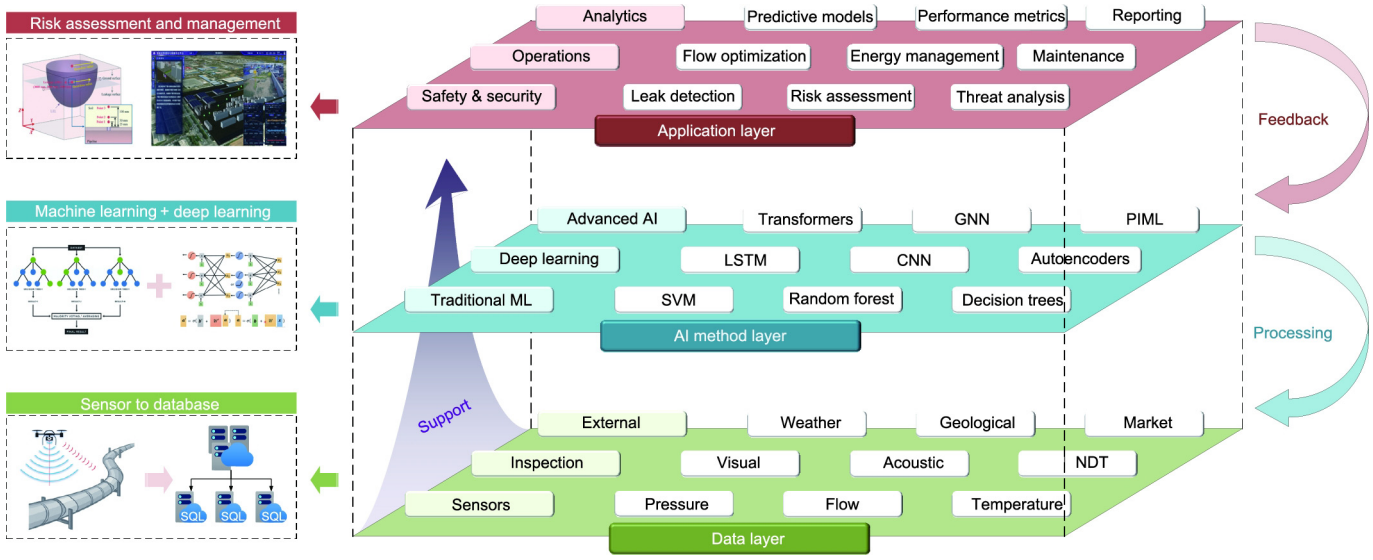


**Fig. 2.** AI architecture for energy pipeline systems. PIML: Physics-informed ML; CNN: convolutional neural network; SVM: support vector machine; LSTM: long short-term memory; SQL: structured query language; NDT: non-destructive testing.

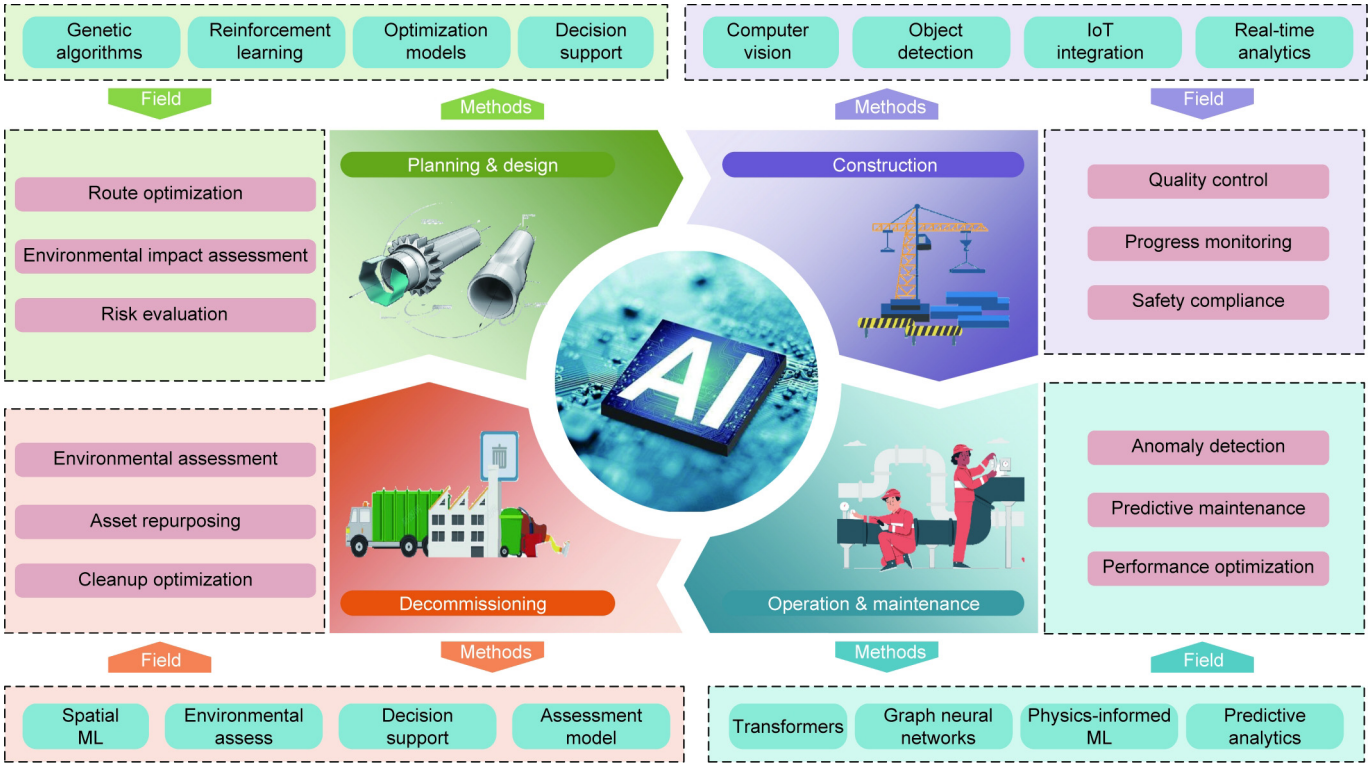


**Fig. 3.** AI applications across the life cycle stages of energy pipelines. IoT: Internet of Things.

environmental impact assessment, and regulatory compliance across diverse terrains. This stage generates abundant geospatial data but limited operating data. The AI applications focus on multi-objective optimization algorithms for route planning, ML models for environmental impact prediction, and risk assessment frameworks incorporating geological, meteorological, and socioeconomic factors. Recent advances include ML-based optimization for subsea pipeline route selection, where hybrid optimization methods demonstrate excellent performance compared with traditional genetic algorithms. This is particularly true for complex offshore environments with multiple constraints including on-bottom stability and obstacle avoidance [11].

The construction stage faces challenges in quality assurance, safety monitoring, and project management across thousands of kilometers of diverse energy infrastructure. This stage generates substantial real-time monitoring data from sensors, cameras, and inspection tools. The AI applications focus primarily on distributed fiber optic sensing systems for detection of real-time pipeline intrusion, the ML algorithms for monitoring of construction progress, and the predictive models for prevention of facility failures and incidents. Recent implementations demonstrate that the AI-powered distributed fiber sensors can collect vibrating signals from pipelines in real-time. The application of AI algorithms analyzes and identifies different types of pipeline intrusion events,

achieving precise detection and localization across the entire pipeline segments [12].

During the operation and maintenance stage, pipelines are challenged with sensitive leak detection, corrosion monitoring, pressure optimization, and effective maintenance across varying environmental conditions. This stage generates the most comprehensive datasets ranging from SCADA measurements to inspection data and environmental monitoring information. The AI applications focus on real-time anomaly detection, predictive maintenance algorithms, operational optimization models, and intelligent inspection-scheduling. Digital twin (DTs) technology emerges as a valuable tool in this stage, demonstrating comprehensive virtual representations that predict risk probability rates and enable proactive maintenance decisions. ML-based prognostic algorithms combined with various data create virtual intelligent integrated automated control systems that provide on-time control actions for entire pipeline network [13].

The decommissioning stage involves complex challenges related to environmental remediation, asset recovery, and regulatory compliance, often dealing with aging infrastructure and limited historical documentation. The AI applications include data-driven decision support systems that leverage historical decommissioning data to predict optimal retirement strategies for oil and gas pipelines. ML algorithms can analyze patterns from previously approved decommissioning projects, considering factors such as facility characteristics, environmental conditions, and regulatory requirements to recommend whether infrastructure should be completely removed, partially removed, or left *in-situ*. By utilizing predictive models trained on comprehensive historical datasets spanning multiple decades of decommissioning activities, these AI systems can significantly streamline the decision-making process that traditionally requires extensive stakeholder consultation and analysis. The implementation of such intelligent systems enables operators to reduce both the time and resources required for decommissioning planning while maintaining compliance with regulatory standards and stakeholder expectations [14].

### 3.2. Differentiation of AI applications across various type of pipeline systems

Energy pipeline systems exhibit different operating characteristics, environmental challenges, and data availability patterns based on pressure levels, locations, and transported fluid. These specific features necessitate AI techniques optimized to meet the system requirements.

Transmission pipelines carry energy (fuels) over long distances, often travelling diverse terrains such as mountain, deserts, rivers/lakes, and remote areas. These pipelines are characterized with limited physical access, sparse sensor coverage, few supplies, and the potential of serious consequences once failed. The harsh operating environment exposes the pipelines to extreme temperature variations, ground movement, and third-party interference risks. The AI applications mainly focus on long-range predictive analytics using distributed sensor network with high computing capabilities. Recent studies demonstrate that thermodynamics-informed neural network coupled with compressor Boolean neural network can provide intelligent dispatching for natural gas pipelines with both safety assessment and energy supply prediction. This is particularly effective for high-pressure natural gas and hydrogen pipelines [15].

Urban gas distribution pipelines usually operate across a high population density, complex neighborhood, and elevated safety risks due to the proximity to residential and commercial areas. These pipelines include dense sensor coverage, frequent access points, and integration with other municipal infrastructure systems such as water and waste pipes. The associated risks include frequent third-party damage from constructions, varied soil conditions, and the need for rapid emergency response. The AI application emphasizes real-time risk assessment and emergency response optimization using advanced monitoring platforms [12].

The offshore pipelines operate in the highly challenging and aggressive environments, installing at depths up to 3000 m with extreme pressures, corrosive environments, and limited accessibility for maintenance and repair. Moreover, the pipelines are usually associated with high installation costs, complex inspection requirements (e.g., autonomous underwater vehicles (AUVs)), and the need for extremely reliable operation due to environmental and economic consequences once failures occur. The safety of offshore pipelines is challenged with dynamic loading from ocean waves, subsea landslides, anchor strikes from vessel traffic, and so forth. The AI applications help autonomous inspection and monitoring using ML algorithms that are optimized for processing AUV-collected data. The ML-based optimization approaches which are specifically designed for subsea pipeline route design have demonstrated superior performance in handling complex offshore constraints, including on-bottom stability criteria and obstacle avoidance, compared to conventional genetic algorithm approaches [11].

## 4. AI technology for safety assessment on pipelines

The safety assessment on pipelines is one of the key areas for AI application. These include anomaly detection, intelligent non-destructive testing (NDT), and visual inspection and data fusion.

### 4.1. Advanced AI technology for anomaly detection

Conventional techniques for pipeline leak and anomaly detection rely on basic ML algorithms like statistical models or support vector machines (SVM) [16]. For example, in early systems, features such as pressure (or flow) sensors combined with SVM or swarm-intelligence-optimized classifiers were used to detect unexpected events [17]. These methods could achieve moderate accuracy with relatively high interpretability and efficiency. However, they have limited ability to solve complex nonlinear questions and to deliver early-warning [18]. In the last decade, data-driven approaches have shifted towards deep learning models such as convolutional neural network (CNN) and long short-term memory (LSTM) recurrent network. These approaches learn temporal and spatial dependence from pipeline sensor data more effectively, improving the detection accuracy up to 99%. Zheng et al. [18] developed a deep learning framework for multi-product pipeline anomaly detection by combining temporal pressure data from multiple stations, accurately detecting small leaks.

Recently, transformer-based architecture and graph-based models have demonstrated further improvement in anomaly detection on pipelines. The latest transformer-based approaches for gas pipeline leak detection show remarkable improvement in temporal pattern recognition although specific implementations require adaptation from general time-series transformer architectures. Advanced transformer models show improved performance in both leak localization and aperture recognition under noisy backgrounds [19]. The GNNs have been applied to model the topology of pipelines and transmit information between sensor nodes. Zhang et al. [20] introduced a model that combined varying Bayesian inferences with graphic attention neural networks for natural gas leak detection. The model captured spatial sensor dependency through attention-based GNN while considering the uncertainty modeling. The probabilistic modeling approach provides a complementary capability for anomaly quantification. Liu et al. [21] used the Bayesian network to estimate leak probability in gas pipelines, allowing quantitative risk assessment of the detected anomalies. The diverse AI techniques (i.e., deep neural

networks, advanced transformers, and probabilistic models), can be chosen or combined based on the characteristics and requirements of pipeline operating data for interpretability.

Generative adversarial networks (GAN) represent another frontier in pipeline anomaly detection by leveraging reconstruction-based approaches for identifying operational anomalies. GANs learn the underlying distribution of normal pipeline operational data and detect anomalies through reconstruction error analysis. Lian et al. [22] developed a digital twin-based anomaly detection method that reconstructs multivariate time series using a GAN model combined with knowledge graph and temporal Hawkes attention mechanisms, achieving a 2.6% performance improvement over conventional ML methods for real-time anomaly detection in oil and gas stations.

### 4.2. Intelligent NDT

The evolution of NDT on pipelines has experienced significant development towards intelligent data analysis. Traditional NDT methods for pipeline inspection employ simple signal processing and classical ML. For example, early studies applied wavelet-based feature extraction with shallow classifiers to detect corrosion defects from the inspection data [23]. While methods like pattern-adapted wavelets and SVM are able to size metal-loss defects, advanced techniques improve the detection accuracy with reduced manual effort.

Current research in intelligent NDT primarily focuses on attention-based deep learning approaches rather than self-supervised learning. Liu et al. [24] developed an attention module magnetic flux leakage (MFL) linked deep residual network for pipeline ILI, achieving 97.7% accuracy in average classification. It used an improved deep residual CNN with a 16-layer deep neural network backbone and attention modules. This approach demonstrated the practical application of attention mechanisms in automated defect detection for pipeline inspection data. Another advance is the integration of attention mechanisms in deep neural networks for defect detection. Xu et al. [25] developed a neural network with attention modules to automatically identify girth weld defects on pipeline from MFL images. The attention-enabled model concentrated on critical defect features than CNN more effectively, resulting in more accurate localization of weld defects.

In data preprocessing, improved noise-handling techniques are critical for reliable NDT interpretation. Traditional filters like empirical mode decomposition (EMD) and principal component analysis (PCA) provide a basic denoising capability. For instance, the variational mode decomposition has been used to separate signal components in inspection signals [26]. Advanced PCA variants, such as adaptive PCA, have been applied to ultrasonic guided wave monitoring to separate defect-related signals from background noise under high-noise or multi-event conditions, thereby improving detection sensitivity [27].

Recent advances demonstrate that deep learning-based denoising can markedly improve the quality of NDT signals. For instance, Wu et al. [28] proposed a 1D CNN denoising autoencoder to enhance weak ultrasonic guided wave signals in pipeline inspection. Their method significantly increased the signal-to-noise ratio by over 30 dB, and enabled reliable detection of defects with only 2% cross-sectional loss, achieving more than 90% recognition accuracy with minimal positioning error. Noise-robust characterization of defects is essential to ensure reliable detection under varying inspection conditions. Deep learning has been applied to quantitative ultrasonic NDT tasks. Pyle et al. [29] demonstrated that a deep CNN achieved significantly higher accuracy in crack sizing from ultrasonic inspection data than traditional amplitude-based methods, improving the reliability of defect assessment. Similarly, advanced AI frameworks can predict the maximum pitting corrosion depth on pipelines. Seghier et al. [30] integrated multiple intelligent algorithms within a hybrid framework, achieving higher accuracy than traditional empirical corrosion growth models. Recent work applies theory-guided ML to corrosion. Miao and Zhao [31] combined ML with mechanistic corrosion models to predict the maximum pitting depth on buried pipelines, demonstrating how physics-informed AI improves prediction accuracy and reliability. These advances also lay the foundation for more autonomous, data-driven NDT processes on pipelines, potentially reducing reliance on human inspection and improving defect detection accuracy.

### 4.3. Visual analysis and multimodal fusion technology

Computer vision applications in pipeline inspection are evolving from single-modal analysis towards integrated sensing and multimodal data fusion. Traditionally, pipeline visual inspection (e.g., analysis of closed circuit television or robotic camera footage) relied on standard object detection or segmentation algorithms. Common approaches included pretrained models like You Only Look Once (YOLO) or Faster Region-based CNN (R-CNN) to detect pipeline defects or leaks in infrared imagery. For example, Xie et al. [32] combined infrared thermography with a Faster R-CNN object detector to automatically recognize leak sites under complex backgrounds, demonstrating improved robustness over traditional image-based methods. Yang et al. [33] developed a vision-based system for automatic classification of weld defects from X-ray images using deep learning. These vision systems primarily relied on a single data modality (visual spectrum images, infrared, or radiography individually) and achieved high accuracy when defect patterns were clear.

Recent research in energy pipeline monitoring highlights significant progress in multimodal data fusion for improving leak detection. Wang and Gao [34] proposed a method that integrates acoustic wave sensing with negative pressure wave monitoring, combining high-frequency acoustic data (1066.67 Hz) and low-frequency pressure measurements (1 Hz) at the data-fusion level. A dual Pearson-threshold strategy together with ensemble EMD was employed for noise reduction, and a 1D CNN was used for classification. Experimental results showed an accuracy of 98.3%, notably higher than typical single-signal approaches achieving about 90%–94%. Another significant development is the integration of multiple sensing modalities for natural gas pipeline monitoring. Miao and Zhao [35] proposed a multi-source heterogeneous information fusion approach for diagnosis of natural gas pipeline leakage, combining laser optical sensing and weak-magnetic signals with deep reinforcement learning (DRL)-based models to improve the detection accuracy and cross-domain generalization under complex operational conditions.

### 4.4. Case study

Several representative case studies from verified industrial implementations demonstrate the AI technology performance in pipeline safety assessment, as described below.

**Case 1: enhanced pipeline monitoring systems.** Enbridge, one of North America's largest pipeline operators, has deployed AI-powered aerial surveillance systems co-developed with Microsoft Azure, which enhance its right-of-way threat detection capability. According to third-party evaluations, the AI-driven Right of Way (ROW) Threat Identification System achieves about a 30% improvement in overall threat detection. In addition, Enbridge leverages Azure-based solutions such as Energy Optimizer, which provides real-time operational insights to optimize energy transport, reduce greenhouse gas emissions, and demonstrate measurable cost savings [36].

**Case 2: AI-powered predictive maintenance for equipment reliability.** Shell has implemented comprehensive AI-driven predictive maintenance systems, achieving a 20% reduction in maintenance costs (about 2 billion USD annually), 35% less unplanned downtime, and 40% fewer equipment failures. The system analyzes real-time sensor data from compressors, pipes, and valves, predicting potential failures weeks in advance with 90% accuracy while processing over 10 billion data points daily. These implementations have led to a 25% improvement in maintenance staff efficiency, 15% growth in operational efficiency, and a significant reduction in gas leaks and emissions [37].

The case studies highlight the substantial improvement of pipeline safety and operation upon integrity of AI techniques with existing pipeline systems. The performance further improves when the AI techniques are used to enhance, rather than replace, the engineering domain knowledge. For example, the AI can be used to interpret complex sensor data patterns, while the engineers and technical experts handle high-level decision-making. Advanced AI techniques have matured to provide remarkable benefits in pipeline safety management.

## 5. AI technology for pipeline operating optimization

In addition to safety management, AI technology has been applied extensively in optimization of pipeline operation. These include forecasting energy demand for pipeline throughput management, modeling multiphase flow for complex fluid transport, and physics-informed controlling for pumping/compression efficiency.

### 5.1. AI-based energy demand forecasting

Accurate energy demand forecasting is fundamental for efficient pipeline operation, guiding compressor station settings, line-pack management, and gas procurement. Traditional approaches mainly relied on time-series models or simple deep neural networks trained on historical consumption data. For example, Petkovic et al. [38] applied a feed-forward deep network to forecast short-term gas demand in a transmission network, showing improved accuracy over conventional methods. Similarly, Laib et al. [39] demonstrated that LSTM-based models can outperform linear techniques in day-ahead consumption forecasting, particularly in capturing complex, nonlinear usage trends. However, these approaches still face challenges in modeling multi-scale temporal dynamics (daily, weekly, and seasonal) and extreme demand spikes.

To address these challenges, more advanced forecasting models have been introduced. The temporal fusion transformer (TFT) architecture demonstrates superior capability for capturing multi-scale temporal dynamics through attention mechanisms, with applications in energy infrastructure now emerging. Lenk et al. [40] applied TFT to predict electricity, heat, and natural gas demand in an industrial automobile production facility, achieving mean absolute percentage error (MAPE) values of 13% for electricity and 39% for natural gas at quarter-hourly resolution. Ding et al. [41] proposed a hybrid time-series framework that decomposes seasonal and trend components before forecasting, improving accuracy in scenarios with overlapping temporal cycles. Zhou et al. [42] used panel semiparametric quantile regression neural networks for electricity demand forecasting based on Chinese provincial data, showing lower MAPE and root mean square error (RMSE) compared with traditional approaches. Although primarily designed for electricity demand, these probabilistic forecasting methods could enhance pipeline throughput forecasting by quantifying prediction uncertainty.

### 5.2. AI applications in multiphase flow modeling

Multiphase flow (e.g., gas–liquid mixtures or dense-phase $CO_2$) poses complex challenges in pipeline transport due to nonlinear hydrodynamics. Traditional modeling relies on solving physical conservation equations via computational fluid dynamics (CFD) or transient flow simulators, which are computationally intensive and unsuitable for real-time applications. AI techniques enable fast surrogate modeling for multiphase flow. Zhang and Shafieezadeh [43] developed a physics-informed neural network (PINN) surrogate that embeds conservation laws into training, achieving accurate predictions of pressure and flow distributions while reducing computational cost compared to CFD.

GNNs provide specific applications in natural gas pipeline analysis. Yang et al. [44] proposed a GNN-based framework for calorific value assignment, achieving a 62% improvement in $R^2$ and a 50% reduction in mean absolute error (MAE). Additionally, Wang et al. [45] applied a multiscale spatio–temporal graph convolutional network (GCN) model to predict energy consumption in gas transmission pipelines, demonstrating GNNs' effectiveness for modeling complex pipeline topologies. DRL has shown verified benefits in pipeline optimization. Liu et al. [46] developed a DRL optimization framework for natural gas transmission networks, incorporating detailed hydrodynamics and compressor characteristics, achieving 4.6% energy savings compared to genetic algorithms and 97.5% faster computation than dynamic programming.

These AI-driven methods complement classical multiphase flow analysis by offering faster and more adaptive solutions. For instance, PINN-based surrogates have also been applied in $CO_2$ transport pipelines to predict transient two-phase flow behavior and identify optimal operating set-points, enabling near real-time system optimization

### 5.3. Physics-informed AI integration paradigms

Physics-informed ML (PIML) represents an important direction in pipeline engineering, aiming to combine the strengths of data-driven models with physical knowledge of pipeline systems. By integrating physical constraints or models into AI algorithms, one can improve model generalization and trustworthiness, especially in regimes where data are sparse or extrapolation is required. Karniadakis et al. [47] provide a comprehensive overview of PIML techniques, highlighting how encoding governing equations or invariants in neural networks can yield models that respect known physics.

In pipeline contexts, PIML approaches demonstrate specific applications in natural gas pipeline systems. Zhang and Shafieezadeh [43] developed nested PINN for analysis of transient flows in natural gas pipelines, directly incorporating conservation equations and boundary conditions into the neural network architecture. Their approach achieved comparable accuracy to traditional CFD while reducing computational time by orders of magnitude, enabling near real-time pipeline monitoring and analysis. These physics-informed methods improve model reliability by ensuring physical consistency in predictions while maintaining computational efficiency for practical implementation [43].

By merging domain physics with AI, these paradigms enhance interpretability and reliability [48,49]. Models that know the laws of fluid mechanics or thermodynamics are less likely to output physically impossible results, increasing operator trust. Furthermore, PIML models often require less data to train, since physics provides a strong prior. A clear trend is emerging in pipeline engineering to embed first-principles knowledge (e.g., pipeline flow equations, material fatigue behavior) into AI for tasks like predictive maintenance scheduling, optimal control, and anomaly diagnosis. This hybrid physics–AI approach is seen as a pathway to

increase AI adoption in safety–critical pipeline operations, as it provides a level of transparency and consistency with engineering expectations that pure black-box models lack.

### 5.4. Case study

Several case studies illustrate the impact of AI on pipeline operational efficiency.

**Case A: operational efficiency optimization for flaring and production.** Saudi Aramco has implemented comprehensive AI and big data initiatives, deploying monitoring systems connected to over 18 000 data sources for flaring prediction and production optimization. Its proprietary AI platforms enable real-time forecasting of potential flaring threshold exceedances, allowing operators to take preemptive actions to minimize losses and environmental impacts. These systems also enhance troubleshooting efficiency by supporting early anomaly detection and automated diagnostics [50].

**Case B: energy consumption optimization for refinery operations.** BP has implemented AI-powered energy optimization strategies achieving 15% reduction in overall refinery energy consumption while lowering operational costs and emissions. The company's AI models assess historical and real-time energy usage data to identify optimization opportunities across cooling, heating, and power distribution systems. Smart automation systems dynamically adjust energy consumption patterns to reduce waste, while AI integration with renewable energy sources ensures efficient utilization of low-carbon alternatives. BP's energy optimization platform enables real-time monitoring and predictive adjustment of energy-intensive refinery processes, delivering substantial cost savings and supporting the company's decarbonization objectives through enhanced operational efficiency and reduced environmental impact [51].

These examples show that AI techniques, particularly when informed by pipeline physics and used in a decision-support role, can unlock significant efficiency gains. Importantly, they also highlight the need for close collaboration between AI specialists and pipeline engineers—building accurate surrogate models and defining appropriate optimization objectives/constraints require deep domain knowledge. As AI tools become more common in pipeline control rooms and network operation centers, developing user trust through transparent performance and incremental adoption will be key. Current deployments generally keep AI recommendations under expert human review before implementation, an approach likely to continue until AI systems have demonstrated reliability over an extended period.

## 6. Systematic risks in AI applications for energy pipelines

As AI technologies become increasingly prevalent in energy pipeline operations, several systematic risk issues emerge. This section provides an analysis of the major categories of risk—data-related risks, algorithmic transparency and bias, cybersecurity threats, and overreliance on automation—along with potential mitigation strategies.

### 6.1. Data-related risks

Data quality, bias, and insufficiency are critical risks in pipeline AI applications. Pipeline integrity and operations datasets are often limited and unevenly distributed. For example, historical failure records are sparse due to the rarity of extreme events, which can lead to AI models that are under-calibrated for rare scenarios. Regional and structural biases also emerge: When an AI leak detector is trained predominantly on data from a single region, pipeline material, or operating environment, it may perform poorly elsewhere due to distributional shift. Ntoutsi et al. [52] highlight that unrepresentative data can amplify model bias and propose mitigation strategies such as re-sampling, re-weighting, and fairness-constrained training to reduce unintended discrimination.

Imbalanced and unlabeled data represent another significant challenge. Pipeline sensors continuously capture large volumes of operational data (e.g., pressure, temperature, and vibration), but only a small fraction corresponds to actual anomalies. Training AI on such highly imbalanced datasets without specialized techniques often results in models that over-predict "normal" and fail to detect rare failures. Table 1 analyzes data quality challenges for different pipeline system types based on existing research. Spandonidis et al. [53] evaluated deep learning methods for oil and gas pipeline leak detection using wireless sensor networks and compared 2D-CNN and LSTM autoencoder approaches. Their experiments showed that 2D-CNN models achieved superior detection accuracy (96.8%) and lower false positive rates (4.2%) compared with LSTM autoencoders (94.3% accuracy, 6.1% false positives), even under conditions with sensor noise, wireless communication interference, and variable environmental disturbances. These findings indicate that deep learning models, when carefully configured, can maintain robustness even in noisy industrial environments where threshold-based detection fails.

To improve data sufficiency, synthetic data generation has become a key solution. Physics-guided flow-network simulation frameworks can generate additional samples of pressure drops and leak signatures, which enhance the diversity of datasets without violating hydraulic constraints and are consistent with negative-pressure-wave theory. Such techniques have been validated in real-network case studies and synthetic-leak tests to strengthen leak-detection robustness and localization precision [54]. Moreover, these synthetic datasets could be used both in offline supervised training and to support real-time anomaly detection via SCADA integration, indicating potential feasibility rather than reporting a deployed operational system.

GANs provide advanced approaches for addressing small-sample limitations and class imbalance. Zhang et al. [55] proposed an improved deep convolutional GAN combining minibatch

**Table 1**
Data quality challenges across pipeline types.

| Pipeline type | Primary data challenges | Potential impact | Mitigation strategies |
|---|---|---|---|
| High-pressure transmission | Rare failure events, remote sensing limitations | Missing subtle leak signatures | Synthetic data generation, physical model augmentation |
| Offshore | Environmental interference, limited sensor access | Increased false alarms, missed defects | Robust preprocessing, multi-sensor fusion |
| Urban distribution | Complex network interactions, limited historical data | Difficulty in anomaly propagation modeling | Graph-based methods, transfer learning from similar networks |
| Hydrogen transportation | Novel failure modes, limited operational history | Knowledge gaps in material–hydrogen interactions | Physics-informed models, accelerated testing data |

discrimination, spectral normalization, and self-attention mechanisms to generate high-fidelity defect images for polyethylene gas pipelines, achieving a 5.5× expansion of the dataset and significantly improving classifier training stability. Similarly, Li et al. [56] integrated a semi-supervised GAN with an isolation forest anomaly detection algorithm for urban gas pipeline monitoring, achieving 95.63% accuracy and a 94.32% harmonic mean of precision and recall (F1) score under highly imbalanced data conditions. In acoustic signal analysis, a recursive generalization self-attention GAN applied to short-time Fourier transform representations of pipeline acoustic emissions achieved 99.84% classification accuracy, demonstrating the potential of GAN-based augmentation in challenging signal-driven leak detection tasks [57].

Finally, robust AI deployment requires deliberate dataset curation and comprehensive bias evaluation. As Ntoutsi et al. [52] recommend, ensuring diversity across operational conditions—such as seasonal variations, geographic environments, and pipeline configurations—combined with fairness-aware training techniques is essential for building trustworthy, reliable, and generalizable AI systems.

### 6.2. Algorithmic transparency issues and solutions

Algorithmic opacity—the "black-box" nature of many AI models—poses significant risks in pipeline operations. Given the safety–critical context and the potentially severe consequences of incorrect decisions, operators and regulators are understandably cautious toward AI systems whose internal reasoning cannot be examined. Lack of transparency can reduce trust and complicate the diagnosis of model outputs (e.g., when a leak alarm is triggered without clear justification). Murdoch et al. [58] emphasize that interpretability methods are essential for safe deployment of AI in high-stakes domains, as they enable human operators to understand, verify, and audit model behavior.

To improve explainability in pipeline applications, interpretable and physics-informed models are gaining traction. Zhou et al. [59] developed a shortcut-Elman neural network (ENN) model specifically for natural gas pipeline network simulation. Unlike black-box deep models, shortcut-ENN incorporates state-space equations directly into the neural architecture, providing mechanism-level interpretability for pipeline operators. Compared with an LSTM baseline, it demonstrates substantial performance gains, achieving approximately an 84.4% reduction in mean squared error (MSE), a 67.7% reduction in MAE, and an $R^2$ improvement from 0.72 to 0.91 while maintaining transparency in how predictions are generated [59]. Attention mechanisms also provide localized explanations for AI-driven leak detection. Zhang et al. [60] proposed an attention-based LSTM model for real-time pipeline leak detection and localization. Their approach achieves an area under the curve (AUC) of 0.99 (meaning the AI system correctly distinguishes between normal and abnormal pipeline conditions 99% of the time, providing highly reliable detection with minimal false alarms), indicating near-perfect separability between normal and abnormal pipeline conditions, and attention-weight visualization highlights the specific pressure and flow sensor signals most responsible for each detection decision. This ensures that the model's reasoning aligns with physically meaningful features rather than spurious noise, providing both high detection accuracy and interpretable insights for operators.

Enhancing interpretability has become a central objective in the development of AI for pipeline monitoring. Whether achieved by embedding domain knowledge into model architectures, leveraging attention-based mechanisms, or integrating complex AI with simpler rule-based surrogates, these approaches enable the construction of more trustworthy, auditable, and regulator-friendly systems. Importantly, they provide transparency without compromising predictive performance, thereby bridging the gap between model complexity and operator confidence.

### 6.3. Cybersecurity threats and defenses

The increasing digitization and AI integration in pipeline systems amplify cybersecurity threats and expand the attack surface of cyber–physical infrastructure [61]. Pipeline control and monitoring infrastructures (SCADA systems, Internet of Things sensors, and AI analytics platforms) could become targets for malicious attacks in line with known industrial control systems (ICS)/SCADA vulnerabilities [62]. AI models themselves introduce new attack surfaces: Adversaries might attempt to feed manipulated data to an AI (a data poisoning or evasion attack) to either mask a real pipeline leak or trigger a false alarm. Research on adversarial attacks against ICS demonstrates vulnerabilities relevant to pipeline monitoring. Anthi et al. [63] studied adversarial attacks on ML cybersecurity defenses in ICS, showing that carefully crafted perturbations can reduce classifier performance by 6–11 percentage points in SCADA-like settings. Survey evidence in critical infrastructure also documents false-data-injection and related integrity attacks (e.g., in smart-grid state estimation), highlighting transferable risks for pipeline ICS [61]. The pipeline sector has already faced cyberattacks (e.g., ransomware or information technology (IT)/operational technology (OT) intrusions affecting SCADA networks), underscoring the need to consider AI-specific threats alongside traditional ICS security concerns [62].

Another threat is model theft or reverse engineering—if an AI model is deployed at edge devices near pipelines, attackers may try to extract the model to find its weaknesses. Adversarial attacks on AI-based surveillance (e.g. fooling a drone's defect detection vision model with adversarial patches) are also conceivable. The pipeline industry has already faced cyberattacks (such as ransomware on SCADA networks); adding AI algorithms into the loop means defenders must also consider AI-specific threats.

A multi-layered cybersecurity approach is required to secure AI-augmented pipeline systems [61]. At the data level, robust training methodologies and anomaly-detection algorithms serve as safeguards against adversarial manipulation. Dang et al. [64] showed that adversarial training achieved 65.41% test accuracy under fast gradient sign method (FGSM) attacks (+18.41%) and 83.0% under DeepFool (+47%), suggesting practical mitigation strategies for pipeline AI systems by analogy [64]. Authenticated, integrity-protected telemetry (e.g., encryption and strong authentication) is essential so that AI models receive trusted data. On the model side, access controls and secure deployment (e.g., hardened edge devices with least-privilege access) help reduce the risk of model exfiltration or tampering. From a system-architecture perspective, defense-in-depth is advised: Use layered controls and continuous monitoring to cross-verify critical decisions, while maintaining conventional rule-based safety interlocks as a back-up. Rather than citing specific regulations, the sources reviewed emphasize aligning with established ICS security frameworks and defense-in-depth practices for critical infrastructure [62]. In summary, recognizing AI as a potential attack vector and proactively hardening it is critical to ensure these smart systems do not become a liability.

### 6.4. Overreliance on automation and human–machine collaboration

A subtler but important risk is the potential overreliance on AI automation and the erosion of human operator skills. As AI systems take on more tasks, there is a danger that human operators become complacent or deskilled, which can degrade overall system resilience. Recent experimental evidence shows that people may over-rely on AI advice even when it conflicts with contextual information or their own assessment, leading to decision errors [65]. In

pipeline control rooms, if operators come to blindly trust an AI leak-detection system, they may respond slower or ineffectively in cases where the AI fails to detect a problem or issues a false alarm—an instance of "out-of-the-loop" risks discussed in human-automation research.

Maintaining an optimal human–machine collaboration is essential. Gombolay et al. [66] showed that mixed-initiative human–robot teaming with context-dependent allocation of control can improve team fluency, while excessive autonomy can reduce human situational awareness, implying that designs should shift authority based on operating conditions and uncertainty levels. For pipeline applications, this translates to systems where AI manages routine adjustments during steady-state operations, but at the first sign of anomaly or when uncertainties increase, the system escalates human involvement or requires human confirmation before major actions.

Enhanced situational-awareness tools are also important. Afzal et al. [67] investigated cognitive load in energy-network control rooms using heart-rate variability and eye-tracking, finding that visualization layout (e.g., seven-screen workspaces) and poor application integration can elevate workload and hinder coordination; they recommend linked views, better integration of procedures, and improved alarm–visual cue coupling to support operators under stress. These insights suggest that AI dashboards for pipeline operations should prioritize layouts and interactions that reduce cognitive load and make system context salient, complementing SCADA views rather than replacing them. Systematic reviews of control-room safety further emphasize training, communication, and human-factors-aware interface design as pillars of reliable operations [68].

## 7. Future prospects

### 7.1. Multi-source heterogeneous data fusion

Multi-source heterogeneous data fusion represents both a core challenge and a major opportunity for future pipeline AI applications. Energy pipeline systems generate vast amounts of diverse data, including operational sensor measurements (pressures, flow rates, and temperatures), integrity inspection data (ILI tool readings and corrosion sensor data), environmental data (surrounding soil conditions and weather), and even economic signals (energy demand and prices). Effectively integrating these disparate data streams can significantly enhance AI model performance and broaden applicability, but it requires models capable of handling high-dimensional, incomplete, and differently timed data.

Attention-based deep learning models are expected to play a prominent role in this area as mechanisms that can adaptively weight features, channels, and time steps. In pipeline leak diagnosis, a self-attention—enhanced 1D CNN has been shown to improve recognition accuracy on acoustic leak signals, illustrating how attention can identify informative patterns under noise; the same principle can be extended to multi-source fusion to weight modalities or sensors as operating conditions change (rather than claiming a demonstrated multi-source fusion case in this reference) [69].

Contrary to describing a heterogeneous graph model over SCADA time series and network topology, Miao and Zhao [35] proposed a multi-source heterogeneous information fusion method that combines laser optical sensing with weak magnetic signals. Their approach converts the two 1D inspection signals into 2D time–frequency images via continuous wavelet transform and performs data-level fusion into red–green–blue (RGB) images, followed by a deep Q-network with an improved capsule network for feature enhancement. Experiments show gains over single-sensor and several state-of-the-art baselines, including improved cross-domain transfer for both formed and potential leak diagnosis.

Another focus will be quantifying and propagating uncertainty in fused data models. Rather than "Bayesian deep learning" *per se*, recent work in pipeline risk assessment has adopted probabilistic frameworks such as hybrid fuzzy Bayesian networks (FBNs), which provide distributions over outcomes and support evidence propagation. A 2024 study integrates fuzzy probabilities derived from expert elicitation with crisp probabilities computed from Pipeline and Hazardous Materials Safety Administration (PHMSA) incident data for a Midwestern US case, and finds that external factors (e.g., third-party interference and outside forces) are influential contributors to pipeline failure risk—without committing to fixed percentage shares. These probabilistic methods give operators calibrated confidence levels and can flag low-confidence scenarios for human review [70].

Overall, the ability to harness the full spectrum of pipeline-related data—operational, inspection, and environmental—via advanced AI will enable a more holistic and predictive pipeline management paradigm. Achieving this vision will require continued research into model architectures that explicitly support data-level, feature-level, and decision-level fusion (e.g., attention mechanisms and RL-augmented feature learners), as well as practical efforts in data infrastructure to break down silos between different pipeline data sources.

### 7.2. Few-shot learning and transfer learning in the pipeline domain

A persistent challenge in the pipeline domain is the difficulty of obtaining large labeled datasets, particularly for failure and anomaly events. Few-shot learning and transfer learning constitute key technologies to address data scarcity and enable rapid deployment of AI solutions for new pipeline scenarios. While general surveys indicate that few/zero-shot methods are promising in low-label regimes (without being pipeline-specific) [71], published pipeline inspection and monitoring applications of few-shot learning remain limited.

Few-shot learning approaches for energy pipeline applications show emerging potential conceptually, and transfer learning already has concrete evidence in pipeline corrosion prediction. Canonaco et al. [72] developed a transfer-learning approach for corrosion prediction in oil and gas pipeline infrastructures under the condition that the target pipeline has no labeled data, leveraging labeled source pipelines with importance weighting (via kernel mean matching) and importance-weighted cross-validation for source selection. Experiments on multiple real-world gas pipelines demonstrate the feasibility of building a predictive model for a new pipeline by transferring knowledge from existing ones [72]. These results support cross-pipeline adaptation for corrosion prediction, whereas broader detection/monitoring systems would require additional validation.

Transfer learning approaches thus offer practical potential for energy pipeline systems: Models trained on one set of pipelines can be adapted to related pipelines when covariate shift is handled explicitly (e.g., importance weighting and source ranking), though deployments across pipelines with markedly different fluid properties and operating conditions will need further study [72].

Cross-domain transfer to emerging media (e.g., hydrogen or $CO_2$ pipelines) should be regarded as a prospective research direction rather than an established result here; the two cited sources do not provide empirical evidence for such transfers. Accordingly, any claim of direct transfer from natural gas to hydrogen/$CO_2$ pipelines is removed pending domain-specific validation [71].

### 7.3. Enhanced causal inference and decision-support capabilities

As AI plays an increasingly important role in pipeline decision-making, enhancing the model's causal inference capabilities is particularly crucial (as general methodology rather than pipeline-specific evidence). Traditional predictive models may capture correlations in data but not understand causal relationships—for example, an AI might notice that a certain valve is often closed during leaks and wrongly infer closing that valve causes leaks. Such misunderstandings can lead to poor decisions if AI is used for automated control. Accordingly, researchers look to integrate causal reasoning so that decisions are grounded in cause–effect logic.

Yao et al. [73] provide a broad survey of causal inference in AI; their insights offer general foundations that could be adapted to pipeline systems. One plausible approach is to build causal graphical models of pipeline operation (e.g., variables for pressure, flow, and equipment status) and use them to inform model structure, feature selection, or counterfactual queries. At present, domain-specific causal frameworks for pipelines remain an active research direction with limited published evidence. Likewise, exploratory tools (e.g., clustering or network analysis) may help generate hypotheses from incident datasets, but comprehensive causal pipelines require further development and validation.

Future AI tools for pipeline management are likely to incorporate causal simulation capabilities. For instance, an AI decision-support system might allow an operator to ask "What if we increase compressor A by 10%?" and, using a causal model, predict the effects on pressures and flows—a capability that is conceptually aligned with counterfactual reasoning under causal models as surveyed by Yao et al. [73]. This concept also aligns, at a high level, with digital-twin practices, although such twins are not examined in Ref. [73].

Additionally, causal understanding helps in alarm management: If multiple alarms trigger, a causal AI can infer which one is the root cause (e.g., a power failure leading to multiple pressure drops) and which are downstream effects, guiding operators to address the true problem first. Incorporating causal inference principles is therefore expected to make models more interpretable and robust and better suited for decision-support roles in safety–critical pipeline operations.

### 7.4. AI prospects in new energy carrier pipelines

As the energy transition accelerates, hydrogen and $CO_2$ pipelines will become increasingly important components of infrastructure and promising domains for AI-driven monitoring, prediction, and decision support. Hydrogen systems face well-documented material challenges such as hydrogen-enhanced fatigue and embrittlement in steels, and $CO_2$ transport/management must account for phase-behavior–driven thermofluid dynamics that complicate anomaly detection and control. These characteristics motivate AI methods that can learn from heterogeneous measurements while remaining consistent with governing physics.

One major application is predictive maintenance and inspection for hydrogen pipelines. Campari et al. [74] present a data-driven framework that compiles fatigue-crack-growth tests in hydrogen and air, trains multiple ML models, and predicts the fatigue acceleration factor and failure probability for hydrogen-exposed low-alloy steels—thereby supporting risk-informed inspection and maintenance planning. This evidence supports AI-enabled integrity management under hydrogen service, without making claims about accelerated-testing inputs or direct remaining-life estimation in the cited work.

Another prospect is applying physics-informed learning to $CO_2$ systems. While Shokouhi et al. [75] study $CO_2$ storage rather than pipeline transport, their physics-informed deep learning (incorporating mass conservation and Darcy's law into the loss) improves prediction of pressure and saturation versus purely data-driven baselines, suggesting a transferable pathway for thermofluid-aware anomaly detection and leak-sensitivity modeling in $CO_2$ pipeline contexts.

AI-enhanced DTs are emerging early in hydrogen applications. The safe hydrogen agile pipeline engineering (SHAPE) project demonstrates an extended reality (XR)- and AI-enabled DT tightly coupled to a hydrogen-pipeline test facility via OPC Unified Architecture, with bidirectional data exchange, AI-based leak detection/risk analysis, and immersive visualization/training for operators [76]. These capabilities illustrate how DTs can integrate real-time sensing with AI analytics when operational experience is still limited.

Looking ahead, the expansion of hydrogen and $CO_2$ pipeline networks creates opportunities to embed AI from the outset—combining data-driven learning with physical knowledge and operational constraints to achieve safer, more efficient, and more explainable pipeline management. Fig. 4 synthesizes AI application priorities and technical challenges for different energy carrier pipeline systems based on existing literature.

## 8. Conclusions and future perspectives

This review systematically synthesizes the current status, challenges, and future development trends of AI technologies in energy pipelines. By reviewing recent literature and case studies, we find that AI has demonstrated clear benefits in pipeline safety monitoring (e.g. more sensitive leak detection and automated defect recognition) and operational optimization (e.g. improved demand forecasting and compressor efficiency). Advanced models like transformers and GNNs show significant promise with verified accuracy improvements in controlled studies, while physics-informed approaches improve reliability and interpretability. At the same time, significant risks must be managed: Data biases, model opaqueness, cybersecurity threats, and human factors issues are all critical considerations when deploying AI in this safety–critical domain. Encouragingly, researchers are actively developing mitigation strategies—from data augmentation and explainable AI techniques to multi-layered cyber defenses and mixed-initiative

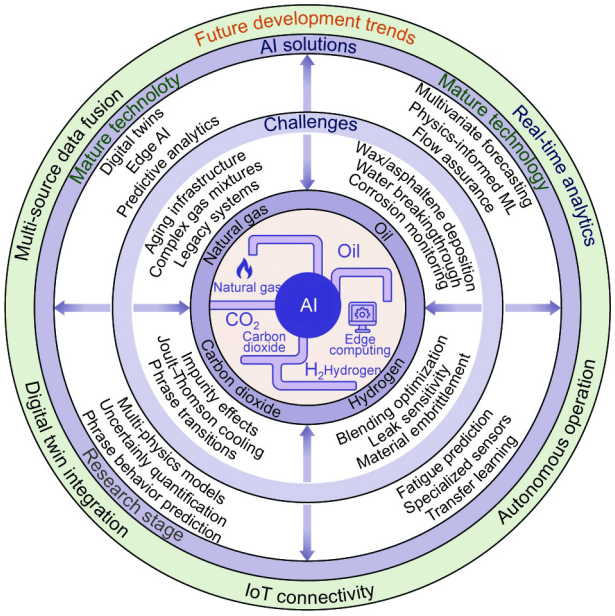


**Fig. 4.** AI application priorities and technical challenges for different energy carrier pipeline systems.

control regimes—to ensure AI can be adopted responsibly in pipeline operations.

Future research and development should focus on robust multimodal data fusion, addressing the significant research gaps in self-supervised learning for pipeline NDT, and developing verified applications of few-shot learning for pipeline defect detection. Integration of AI within DTs for emerging hydrogen and $CO_2$ pipeline systems represents a promising but underexplored area requiring substantial research investment. Collaboration between AI experts and pipeline engineers will be essential to tailor algorithms to real-world pipeline conditions and to embed domain knowledge. We recommend that industry stakeholders invest in pilot implementations of AI for specific use cases (such as an AI-assisted leak detection system or an optimization tool for a pipeline segment) under close monitoring, to build confidence and refine these technologies. In parallel, regulatory frameworks may need updating to provide guidance on AI validation and cybersecurity in pipeline applications.

In conclusion, AI offers substantial opportunities to enhance the safety, efficiency, and sustainability of energy pipeline infrastructure—from extending asset life via predictive maintenance to enabling the integration of new energy carriers. Realizing these benefits will require a balanced approach that amplifies human expertise with AI, under a strong governance of risk. With continued interdisciplinary efforts, AI can become a trusted component of pipeline engineering, supporting safer and smarter management of the pipelines that will continue to underpin the global energy system in the years to come.

## CRediT authorship contribution statement

**Hongfang Lu:** Writing – original draft, Investigation, Funding acquisition, Formal analysis. **Y. Frank Cheng:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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