

Systematic Review

Navigating Fragmented Research: A Model–Data–Scenario Adaptation (MDSA) Framework for Sustainable Accident Prediction and Risk Governance in High-Risk Industries

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Abstract

Proactive accident prediction is a fundamental prerequisite for the environmental and social sustainability of high-risk sectors. Accident prediction research has expanded rapidly across transportation, construction, fire safety, chemical/process industries, and mining, yet many models that perform well in offline benchmarks fail in field deployment because algorithm capability, data regime, and operational constraints are misaligned. This review synthesizes cross-industry evidence on how accident prediction is practiced under distinct data conditions, including spatiotemporal, multimodal, and data-scarce settings, and compares mainstream methods from statistical baselines to machine learning and deep learning in terms of deployability rather than accuracy alone. Building on this synthesis, we propose the Model–Data–Scenario Adaptation (MDSA) framework, a systems-level protocol that operationalizes deployment-aware model selection through a multi-dimensional scoring rubric and an iterative validation loop. MDSA balances predictive performance with interpretability, robustness, data dependency, and implementation cost. A chemical industry case study demonstrates how accuracy-centric selection can fail operationally and how MDSA yields a more viable choice under real constraints. The framework ultimately facilitates long-term sustainable risk governance by balancing predictive performance with operational constraints, thereby contributing to the United Nations Sustainable Development Goals (SDGs 3, 8, 9, and 11).

Keywords: accident prediction; artificial intelligence; sustainable risk governance; MDSA framework; sustainable development; high-risk industries



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1. Introduction: The Fragmented Landscape of Accident Prediction Research

The rapid pace of industrial and technological development has brought about unprecedented productivity but also complex, high-risk operational environments. Incidents occurring in industries like transportation, construction, chemical production, and mining still present major risks to human safety, industrial resilience, and sustainable development. Catastrophic events in high-risk industries not only cause economic loss but also lead to irreversible ecological damage and social instability, directly hindering the United Nations Sustainable Development Goals (SDGs), particularly Goal 3 (Good Health and Well-being),

Goal 8 (Decent Work and Economic Growth), Goal 9 (Industry, Innovation and Infrastructure), and Goal 11 (Sustainable Cities and Communities) [1]. Data from the World Health Organization indicate that around 1.19 million fatalities result from road crashes each year worldwide, averaging roughly 3300 deaths daily [2]. According to the National Fire Protection Association, fire departments across the United States handled approximately 1.39 million fire incidents in 2023. These incidents caused an estimated 3670 civilian deaths and 13,350 injuries. Associated property damage was valued at approximately 23 billion USD [3]. In mining, the International Council on Mining and Metals notes that fatalities still occur despite safety improvements. In 2023, ICMM's 25 member companies recorded 36 deaths. Comparatively, 33 deaths occurred in 2022, 45 in 2021, and 44 in 2020 [4].

Beyond highlighting urgency, these domains differ fundamentally in their data regimes, which directly constrain what “effective prediction” means in practice [5]. Transportation often provides high-frequency, large-volume records that support spatiotemporal learning [6,7], whereas data-scarce sectors such as mining may offer limited and highly imbalanced samples, favoring sample-efficient and robust methods [8]. Chemical and process industries frequently sit between these extremes: datasets are moderate in size but must satisfy strict requirements on interpretability, traceability, and regulatory accountability [9]. This coupling motivates a central premise of this paper: accident prediction is not only an algorithmic competition, but an adaptation problem shaped jointly by models, data, and deployment scenarios.

Predictive analytics is increasingly used to shift safety management from reactive reporting to proactive prevention, thereby supporting safer production, lower disruption costs, and reduced accident-related environmental burdens. Yet the literature has grown in a fragmented manner. Studies either refine traditional statistical models or advocate advanced AI architectures, but comparisons are often conducted in offline or laboratory-style settings that overlook real deployment constraints such as data drift, maintenance burden, interpretability, and safety assurance requirements [10,11]. Consequently, methodological progress can remain detached from practical data conditions, interpretability demands, and human–machine collaboration needs.

A recurring issue is a three-way mismatch among: (i) the Model (what the algorithm can represent), (ii) the Data (scale, quality, imbalance, heterogeneity, and temporal structure), and (iii) the Scenario (constraints such as latency, accountability, cost, and operational workflows). Models that excel on large, clean datasets may degrade under sparse, noisy, or heterogeneous inputs, especially when explanations are required for decisions [12,13]. To address this gap, we propose the Model–Data–Scenario Adaptation (MDSA) framework, a compact three-dimensional tool that aligns modeling capability (Model), data characteristics (Data), and operational context (Scenario). MDSA reframes model selection from accuracy-centric ranking to deployment-aware adaptation.

This review synthesizes accident prediction approaches from traditional methods, such as regression and grey models, to artificial intelligence techniques, including machine learning methods like random forests and support vector machines, as well as deep learning architectures, as shown in Figure 1 [14–18]. To systematically address the challenges mentioned above, Figure 1 provides a conceptual overview of the study, illustrating how the subsequent research questions are logically derived. As depicted in the top tier of Figure 1, the current methodological landscape remains highly fragmented across different algorithmic families. The middle tier highlights our core theoretical diagnosis: the inherent three-way mismatch among model capabilities, data regimes, and scenario constraints. To bridge this gap, the middle tier also introduces the proposed Model–Data–Scenario Adaptation (MDSA) framework as a systems-level solution. Guided by this framework, the bottom tier of Figure 1 outlines the three core research questions and corresponding contri-

butions that drive this review toward sustainable safety governance. It further examines how diverse inputs, including operational logs, sensor streams, environmental monitoring, human behavior records, meteorological variables, and road-condition information, support risk prediction across different domains.

Classification of accident prediction methods and the Model–Data–Scenario Adaptation (MDSA) conceptual overview

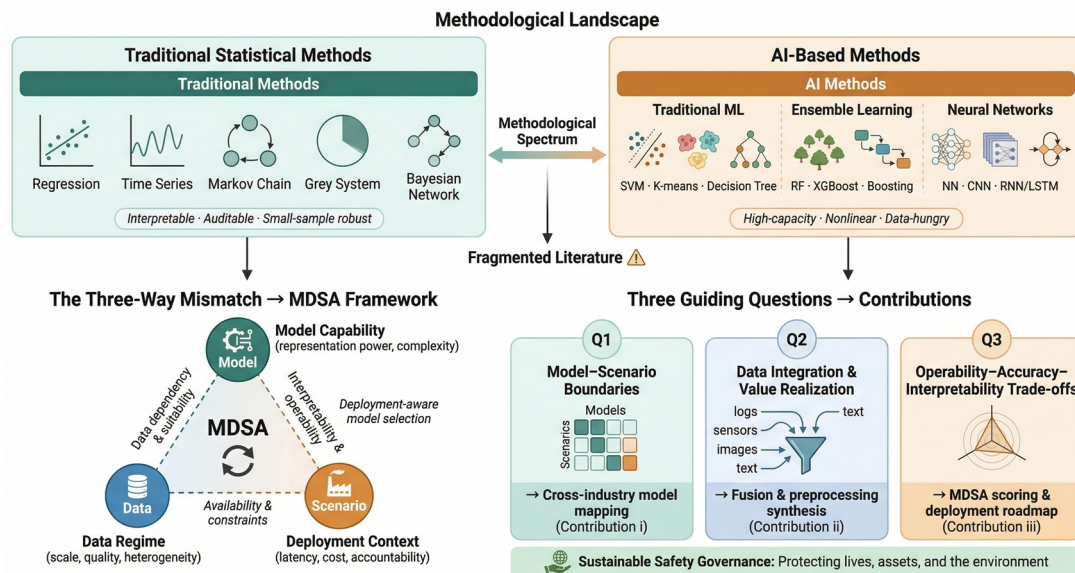


Figure 1. Conceptual overview of the study. The figure illustrates the transition from a fragmented methodological landscape (top tier) to the identification of the three-way mismatch among model, data, and scenario. The proposed Model–Data–Scenario Adaptation (MDSA) framework (middle tier) bridges this gap, guiding the three core research questions and corresponding contributions (bottom tier) toward sustainable safety governance.

To motivate MDSA, we pose three guiding questions:

- (1) **Model–Scenario Boundaries.** Given diverse accident types and industrial contexts, what are the practical adaptability boundaries of mainstream methods, from lightweight baselines to deep multimodal models (MDSA → Model × Scenario mapping)?
- (2) **Data Integration and Value Realization.** How can heterogeneous inputs (structured logs, sensor streams, images, text) be efficiently fused to realize predictive value across industries and data regimes (MDSA → data strategies and matching)?
- (3) **Operability–Accuracy–Interpretability Trade-offs.** Can we construct an operational guideline that balances prediction accuracy, explainability, and deployment cost for end-to-end system design (MDSA → cross-dimension scoring)?

In the context of this study, sustainability in accident prediction does not refer only to environmental protection in a narrow sense, nor merely to the prolonged functioning of algorithms. Rather, it refers to the long-term viability of accident prediction systems in high-risk industries across three interconnected dimensions: (i) social and environmental sustainability, achieved by reducing accident-related environmental risks and protecting human lives through reliable early warning; (ii) economic sustainability, reflected in avoiding costly production disruption, excessive warning burden, and resource-wasting misdeployment; and (iii) technological and governance sustainability, ensured by selecting models that remain feasible under hardware and data constraints while satisfying accountability and interpretability requirements. From this perspective, sustainable accident prediction is not simply a question of which model is most accurate, but of how model families match concrete deployment scenarios, how heterogeneous data can be effectively integrated, and how accuracy, interpretability, and operational feasibility can be balanced in practice. This

understanding directly motivates the three guiding questions of this review and underpins the contribution of the proposed MDSA framework as a deployment-oriented approach to sustainable safety governance.

Accordingly, this review makes three contributions: (i) it provides a cross-industry mapping of model families under concrete data and deployment constraints (Q1); (ii) it synthesizes data fusion patterns and preprocessing strategies for heterogeneous data scenarios (Q2); and (iii) it proposes the MDSA framework as an actionable evaluation and deployment tool, with a concrete implementation roadmap presented in Section 6 (Q3).

The remainder of this paper is organized into four logical phases, structurally corresponding to the conceptual flow illustrated in Table 1. Phase I (Research Foundation and Methodology) establishes the basis of this review. Following this introduction, Section 2 details the PRISMA-guided methodology used for the literature search and screening. Phase II (Literature Synthesis and Gap Analysis) systematically maps the current research landscape. Section 3 critically analyzes traditional statistical baselines and performance-driven AI architectures. Section 4 explores scenario-based applications across five high-risk sectors and provides a cross-domain quantitative synthesis of model usage. Building on this evidence, Section 5 critically discusses the inherent capabilities and deployment limitations of current AI applications, highlighting the inevitability of a paradigm shift from purely accuracy-centric to deployment-oriented model selection. To bridge these identified gaps, Phase III (Framework Development and Operationalization) is presented in Section 6. This core section formally introduces the multi-dimensional MDSA framework, details its implementation protocol, and demonstrates its practical utility through an illustrative application and comprehensive value analysis. Finally, Phase IV (Critical Discussion and Conclusion) synthesizes the overarching insights. Section 7 provides a critical discussion on specific methodological constraints—such as the limits of grey systems and the evolving nature of edge computing—alongside the review’s limitations. Section 8 concludes the study and outlines future research prospects toward sustainable safety intelligence.

Table 1. Structural roadmap of the manuscript illustrating the four-phase logical organization.

Phase I: Foundation	Phase II: Synthesis & Gaps	Phase III: MDSA Framework	Phase IV: Discussion & Outlook
Introduction (Section 1) Fragmented Landscape	Methodologies (Section 3) Stat. Baselines (Section 3.1) AI Architectures (Section 3.2)	MDSA Concept (Section 6) Three Dimensions (Section 6.1)	Discussion (Section 7) Method Limits & Dynamics (Sections 7.1 and 7.2) Review Limitations (Section 7.3)
Methods (Section 2) PRISMA Protocol	Sector Scenarios (Section 4) Transport, Construction, Fire, Chem, Mining (Sections 4.1–4.5)	Implementation (Section 6.2) Scoring Protocol	Conclusion (Section 8) Sustainable Safety Intelligence
	Paradigm Shift (Section 5) AI Limitations (Section 5.3) Deployment Needs (Section 5.4)	Validation (Section 6.3) Illustrative Case Study	

2. Methods

This systematic review followed the PRISMA guidelines. The complete protocol, including search strings, screening rules, and the full list of references, is provided in the Supplementary Materials. We queried Web of Science, Scopus, PubMed, and IEEE Xplore, complemented by Google Scholar, for studies published between 1 January 1990 and 31 December 2025.

After removing duplicates, two independent reviewers screened 4410 records based on titles/abstracts and full texts. Studies were included if they: (1) focused on high-risk industrial sectors; (2) proposed a predictive modeling approach; and (3) reported quantitative evaluation metrics. Non-predictive research and articles lacking methodological details were excluded. A total of 253 studies were selected for qualitative synthesis, as shown in

Figure 2 [19]. Due to the substantial heterogeneity in data regimes and evaluation metrics across industries, a narrative systematic review with structured quantitative coding and comparative synthesis was conducted, rather than a pooled quantitative meta-analysis.

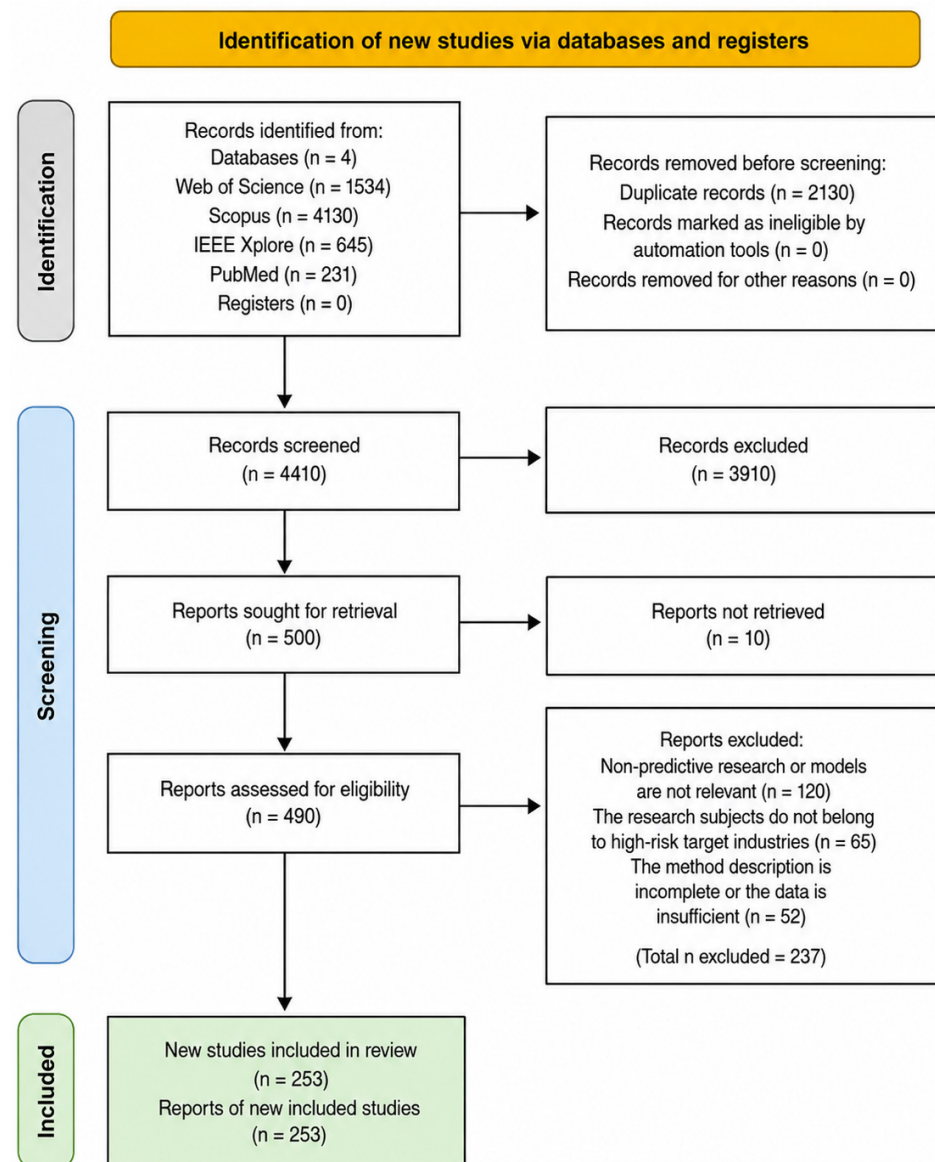


Figure 2. PRISMA flowchart outlining the sequential steps of the article selection process.

3. Accident Prediction Methodologies: A Critical Analysis

Accident prediction research spans a broad spectrum of methodological families, from interpretable statistical baselines to performance-driven AI architectures. For deployment-oriented safety applications, the key question is rarely “which algorithm is most advanced,” but rather “which method family remains reliable under the given data regime and operational constraints.” This section therefore reframes the methodological review around three deployment-relevant dimensions: data suitability, deployment constraints, and representative evidence. The synthesis in Section 6 (MDSA) builds directly on these method–data–scenario patterns. Due to space constraints and to avoid redundant citations with the industry-specific analyses in Section 4, only representative studies are cited here. For a comprehensive overview, a detailed 2D mapping matrix categorizing all 253 reviewed articles by their respective model families and industrial scenarios is provided in Supplementary Materials Table S6.

3.1. Traditional Statistical Methods: Interpretable Baselines

Traditional models remain widely used in safety-critical domains because they are transparent, auditable, and often robust under limited data. Their main limitation is restricted representational capacity when accident mechanisms are strongly non-linear, spatiotemporal, or multimodal.

3.1.1. Regression Prediction Method

Regression-based accident prediction is most appropriate when the task can be expressed through structured covariates and count outcomes, such as crash frequency or fatality counts. It is particularly effective when covariates are well defined and the dataset is sufficiently large to support stable estimation. For early-stage traffic safety modeling, empirical studies reported clear relationships between accident frequency and factors such as traffic flow, road type, and meteorological conditions [20].

These models are attractive in regulated environments due to strong interpretability and straightforward validation. However, naïve linear formulations can be mis-specified when accident mechanisms involve non-linear interactions. For count outcomes, the main operational risk is statistical mismatch: accident data often show overdispersion and excess zeros, which can undermine reliability if not modeled explicitly.

Regression variants explicitly designed for accident count data provide strong, defensible baselines. Greibe reported that a Poisson GLM explained over 60% of system variability in urban crash data, while negative binomial models better handled overdispersion [21]. For low-frequency accident events with many zeros, zero-inflated models improved fit and captured the underlying generating mechanism more realistically; this was shown for railway crossing accidents in South Korea [22]. These findings justify a practical rule: regression baselines should be selected by data regime (dispersion and zero inflation) rather than by convenience.

3.1.2. Time Series Method

Time-series methods are most suitable when accident risk evolves with clear temporal structure, such as trends, seasonality, or periodic volatility. They are typically most effective for univariate forecasting tasks where historical dynamics dominate and covariates are limited. Exponential smoothing families provide simple but stable short-term forecasting options [23], while ARIMA-type models support trend and seasonality modeling under relatively stable dynamics.

These methods are often easy to deploy and computationally light, which is valuable for routine monitoring. Their main limitation in practice is sensitivity to data quality and difficulty in representing multi-factor interactions when accident risk is driven by multiple coupled variables.

For settings characterized by high volatility and small samples, hybridization can improve robustness. A combined ARIMA and fractional grey approach was proposed for municipal construction accidents in China, achieving high accuracy for monthly and quarterly fatality forecasts under small-sample, high-volatility conditions [24]. The evidence suggests a practical boundary: time-series models are strong when temporal dynamics are dominant and data are relatively consistent; they weaken when risk is driven by complex multivariate interactions.

3.1.3. Markov Chain Prediction Method

Markov models are appropriate when accident risk is naturally described as transitions among discrete states, such as safety levels, operational conditions, or clustered risk regimes.

They can be useful for capturing regime switching and short-term fluctuations when state definitions are meaningful.

A key operational challenge is that state definition and transition estimation can be unstable under sparse data; moreover, standard Markov chains treat multi-step transitions in a simplified manner that may not reflect differentiated influence across orders.

To address the limitation of equal contribution assumptions across transition orders, weighted Markov chain prediction was proposed [25]. In practice, Markov components are more often embedded in hybrids, such as Grey–Markov models that combine long-term trend estimation with fluctuation state prediction for improved expected values [26]. This supports a pragmatic use pattern: Markov models are most reliable as fluctuation modules within hybrid frameworks, rather than as standalone predictors.

3.1.4. Grey Prediction Method

Grey models are designed for “grey systems” where information is incomplete and samples are small, which aligns with many safety datasets characterized by sparse events and uncertain measurements. Grey forecasting is particularly suitable for trend prediction when data volume is limited and noise is non-negligible [27].

The primary advantage is feasibility under limited data and modest computation. The main risk is reduced adaptability to non-stationary or strongly nonlinear patterns, which can be mitigated through dynamic updating mechanisms and hybridization.

A dynamic non-homogeneous grey model with metabolic updating and optimal sliding windows improved responsiveness to fluctuations in fatality data; reported minimum prediction errors reached 7.29% for construction and traffic accident forecasting [28], as shown in Figure 3. Hybridization further strengthened performance in volatile, small-sample contexts, as demonstrated by combining ARIMA with a fractional grey model for municipal engineering accident datasets [24]. These results justify grey forecasting as a practical option when “data scarcity” is the dominant constraint.

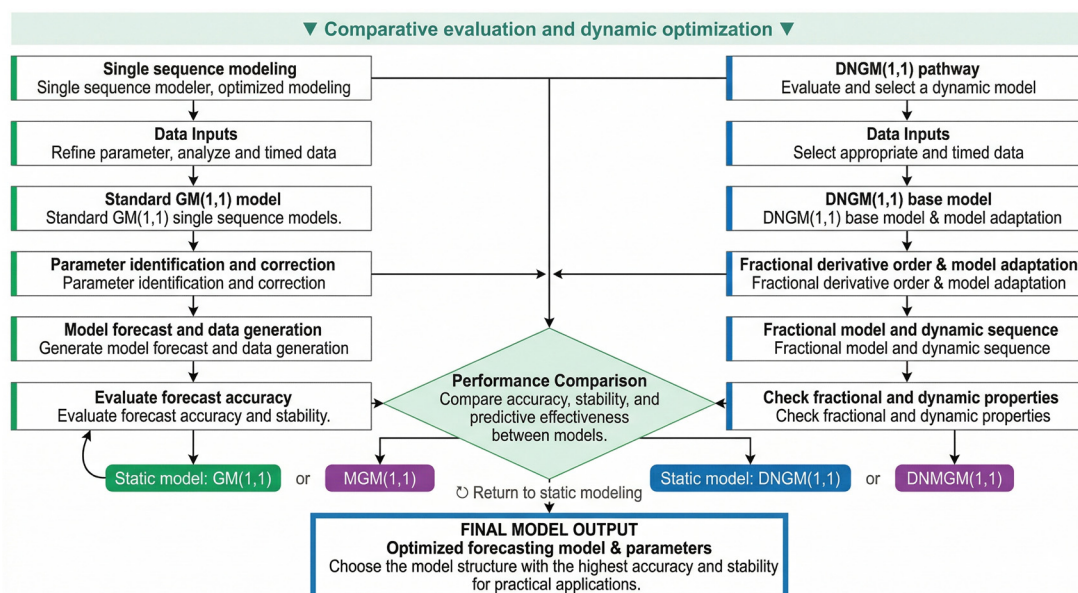


Figure 3. Flowchart illustrating the data preprocessing steps and model selection process for the grey forecasting model.

3.1.5. Bayesian Prediction Method

Bayesian networks and Bayesian inference are well suited to accident prediction settings where uncertainty is intrinsic and causal or conditional dependencies must be

represented explicitly. They are particularly valuable when expert knowledge can be incorporated and when missing or imprecise information is unavoidable.

Bayesian approaches align well with safety decision support because they provide interpretable structures and support probabilistic reasoning. Their deployment burden often lies in structure learning and parameter estimation under limited data, which can be alleviated by combining data-driven learning with informed priors.

A Bayesian network was used to estimate injury probabilities in construction projects, providing interpretable pathways among working conditions, experience, and environment [29]. Bayesian methods were applied to classify highway accidents with support for dynamic updates as new data arrived, improving classification performance while maintaining structural interpretability [30]. In mining, hierarchical Bayesian inference combined with prior knowledge improved responsiveness to infrequent gas explosion events [31]. Collectively, these studies position Bayesian methods as a strong choice when interpretability and uncertainty quantification are hard requirements.

To better synthesize their core principles, advantages, disadvantages, and practical trade-offs, the main traditional accident prediction models are critically compared in Table 2.

Table 2. A critical comparison of traditional accident prediction models.

Model Category	Core Principle	Advantages	Disadvantages	Primary Trade-Off
Regression Models	Statistical relationship between dependent and independent variables	High interpretability; easy to implement	Assumes linear relationships; sensitive to multicollinearity	Interpretability vs. Performance
Time Series Models	Historical data patterns	Captures temporal dynamics; requires limited data	Assumes stationarity; difficult to model non-linear trends	Simplicity vs. Non-linearity
Markov Chain Models	State transitions and probabilities	Captures system evolution; low computational cost	Relies on the Markov assumption (memoryless)	Efficiency vs. Accuracy
Grey System Models	Weakens randomness through data processing	Effective with small, incomplete, or sparse datasets	Poor generalization; low long-term accuracy	Small Data vs. Generalization
Bayesian Networks	Probabilistic graphical model for causal relationships	Models causality and uncertainty; high interpretability	Requires expert knowledge for network structure; computationally intensive	Causality vs. Scalability

3.2. Artificial Intelligence (AI) Methods: Performance-Driven Architectures

AI methods are increasingly adopted because they can capture complex non-linear relationships and high-dimensional interactions. Their practical value, however, depends on whether the available data regime and deployment setting can support the model's training demands, stability requirements, and interpretability expectations.

Rather than tracing historical developments in detail, this section focuses on how AI method families behave in accident prediction under realistic constraints. Nevertheless, to situate this shift within the broader methodological trajectory of the field, Figure 4 presents the evolution process of accident prediction research [32–36]. Canonical work on support vector machines and deep learning provides representative anchors for this shift toward learning-based modeling.

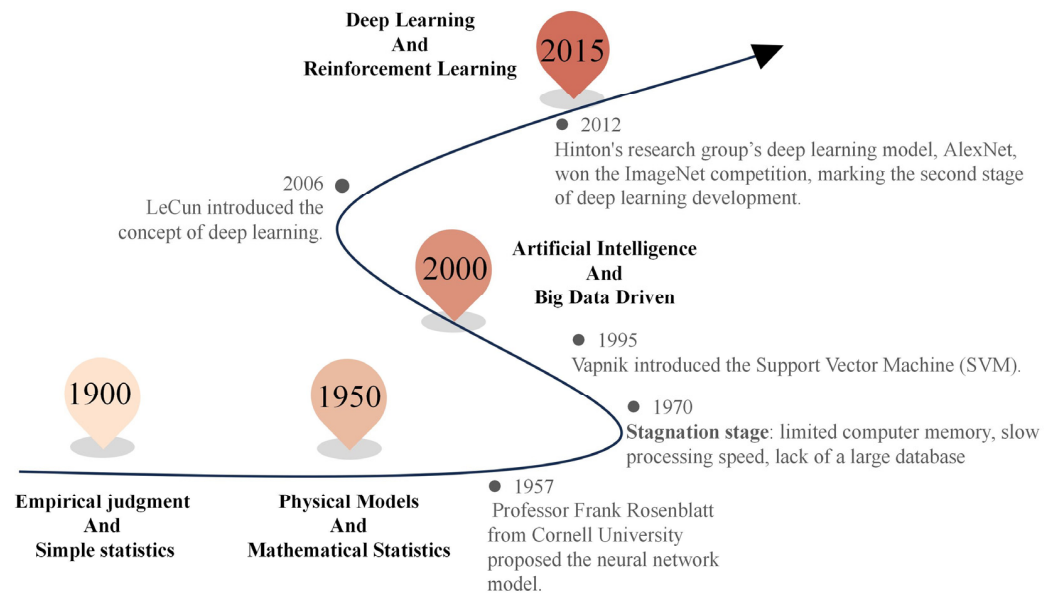


Figure 4. Accident prediction evolution process.

This paper categorizes machine learning approaches into three types based on core methodological principles: traditional machine learning, ensemble learning, and neural networks. Traditional machine learning relies on statistical theory, optimization techniques, and probabilistic models to directly map input–output relationships through mathematical formulations. Ensemble learning enhances generalization by aggregating multiple weak learners, leveraging “collective intelligence” to reduce overfitting risk. Neural networks employ layered nonlinear transformations to automatically extract high-level feature representations, reflecting the brain’s hierarchical information processing. To better summarize their core principles, strengths, limitations, and deployment trade-offs, the major AI-based accident prediction models are critically compared in Table 3.

Table 3. A critical comparison of AI-based accident prediction models.

Model Category	Core Principle	Advantages	Disadvantages	Primary Trade-Off
Traditional ML	Learns patterns from feature vectors	High efficiency; good for structured data	Limited capacity for high-dimensional data; requires extensive feature engineering	Simplicity vs. Feature Engineering
Ensemble Learning	Combines multiple models to improve robustness	Highly accurate; robust against overfitting	High computational cost; reduced interpretability	Accuracy vs. Computational Cost
DNNs	Multilayer network for hierarchical feature learning	Excellent for complex, high-dimensional data; end-to-end learning	High data dependency; low interpretability (black-box)	Performance vs. Interpretability

3.2.1. Traditional Machine Learning

(1) Support Vector Machine (SVM).

In accident prediction, SVM is most competitive when the dataset is limited in size but features are informative and potentially high-dimensional. This matches many safety datasets where labeled accident events are scarce but structured covariates are available.

SVM offers a relatively controlled training pipeline and can be easier to validate than complex deep models, which supports deployment in resource-constrained or audit-sensitive settings. Its main constraint is scalability when data become large-scale and strongly spatiotemporal.

In rural traffic accident forecasting, an SVM-based model achieved higher accuracy and faster computation than NB regression and BPNN under small-sample conditions (below 2000 cases) [37]. For long-term traffic accident prediction in China (1970–2006), a PSO–SVM approach outperformed BPNN in MAPE, supporting its robustness under non-trivial temporal dynamics [38]. For coal mining, a hybrid SVM approach improved the assessment of human-factor accidents, demonstrating applicability beyond transportation [39]. These results support a clear deployment rule: SVM is a strong choice for structured, limited data, but it is not the default answer for large-scale spatiotemporal streams.

(2) K-means algorithm.

Clustering supports tasks such as hotspot identification, risk stratification, and pattern discovery when labels are limited or when the aim is to structure heterogeneous accident records before downstream prediction.

Clustering is lightweight and often deployable as an analytical module. The operational risk is sensitivity to noise and cluster initialization, which can affect stability when datasets are imbalanced.

K-means has been integrated with GIS to identify traffic accident hotspots and support targeted interventions [40]. It has also been used to classify hazardous chemical accidents and improve the precision of risk categorization [41]. Large-scale application was shown on more than 350,000 UK highway accident records, where clustering identified high-risk zones and time periods, followed by decision trees to extract interpretable rules for intervention [42]. These studies indicate that clustering is best treated as a front-end structure discovery step that can strengthen interpretability and operational decision-making.

3.2.2. Ensemble Learning

(1) Random Forest.

RF is well suited to heterogeneous structured features, missing values, and non-linear interactions—conditions common in safety datasets combining operational, environmental, and contextual variables. It is often reliable under moderate sample sizes and noisy features.

RF offers a favorable accuracy–robustness trade-off and supports partial interpretability through feature importance, which can be acceptable in many operational settings. Its limitations emerge in modeling long-range spatiotemporal dependencies unless combined with richer representations.

In railway–road crossing incident prediction, RF achieved higher accuracy and specificity than single decision trees while reducing false positives, indicating practical value under limited and imbalanced data [43]. In industrial safety, an RF-based model for coal and gas outburst hazard achieved 100% sensitivity and 97.5% accuracy after integrating correlation analysis and outlier filtering, supporting real-time warning potential [44]. These results position RF as a strong deployment candidate when robustness and stable performance matter more than end-to-end representation learning.

As shown in Figure 5, the Random Forest mechanism combines bagging-based tree aggregation with favorable deployment properties, making it a practical option for accident prediction in safety-critical settings.

(2) XGBoost.

XGBoost is frequently effective for severity classification and risk identification with structured features, particularly when interactions are complex but the data remain tabular. It is also practical when feature engineering can be curated and data quality is manageable.

Although XGBoost is not inherently transparent, it can be paired with post hoc explanation tools, which improves acceptability in operational decision-making. Its main limitation is handling complex spatiotemporal dependencies without specialized architectures.

In hazardous chemical transportation accident severity classification across seven regions in China, XGBoost was identified as the most effective method and revealed regional differences in contributing factors [45]. A highway accident severity model integrating XGBoost with Bayesian networks used SHAP interpretation and achieved 89.05% accuracy, demonstrating compatibility with interpretable AI toolchains [46]. For crash detection on Chicago expressways, XGBoost maintained 99% overall accuracy with a false alarm rate of 0.16%, highlighting its potential for high-precision operational detection [47]. These findings justify XGBoost as a strong option when structured data dominate and decision-makers require both performance and explainability support.

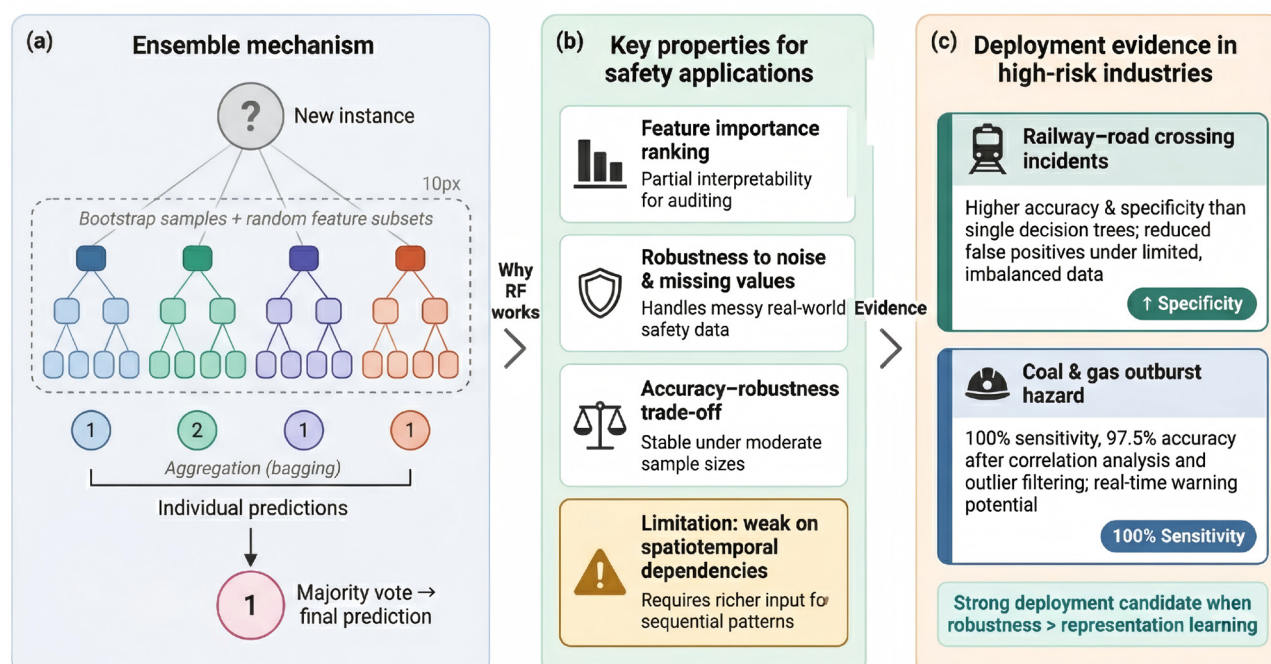


Figure 5. Random Forest ensemble mechanism and its deployment suitability for accident prediction: (a) bagging-based aggregation of diverse decision trees, (b) key properties relevant to safety-critical applications, and (c) empirical evidence from high-risk industry case studies. In panel (a), the numbers 1 and 2 indicate example class predictions, and the colors distinguish different base learners. In panel (c), the upward arrow indicates improvement in the corresponding reported performance indicator.

3.2.3. Neural Networks

Neural networks become advantageous when accident risk is driven by complex spatiotemporal patterns, multimodal signals, or relational structures. This includes injury severity prediction from heterogeneous predictors, regional crash risk forecasting with spatial heterogeneity, and safety modeling where accident records form networks of related events.

The main operational barrier is data and resource demand: neural models often require larger datasets, careful validation to avoid leakage, and stable deployment environments. Interpretability is also a persistent concern in safety-critical settings, which increases the value of architectures and analysis that support explanatory reasoning.

ANN models have been used for traffic accident prediction with substantive datasets; for example, an ANN built on 7780 highway accident cases identified vertical curvature as a key determinant of accident frequency, demonstrating practical feature sensitivity [48]. For temporal dependence and severity classification, RNN/LSTM modeling outperformed traditional methods on highway datasets [49]. To capture heterogeneous spatiotemporal crash patterns, a ConvLSTM-based model achieved predicted distributions closely

aligned with real accident data in Iowa, highlighting its capacity to represent spatial heterogeneity [50]. Beyond grids and sequences, graph neural networks offer a natural fit for network-structured safety systems; a graph attention approach constructed sparse accident networks and improved predictive stability while supporting interpretability through attention mechanisms [51]. These studies collectively indicate that neural networks offer their strongest gains when the data regime provides sufficient signal complexity, and when scenario constraints can accommodate higher development and validation effort.

The fundamental distinctions between traditional prediction methods and artificial intelligence methods in terms of interpretability, data requirements, adaptability, computational complexity, and real-time capability are summarized in Table 4.

Table 4. Comparative analysis of traditional prediction methods and artificial intelligence methods.

Dimension	Traditional Methods	AI-Based Methods
Interpretability	High; principles are transparent and logically intuitive	Low; complex architectures with prominent “black-box” issues
Data Requirements	Can be applied to small datasets	Requires large volumes of high-quality training data
Model Adaptability	Suitable for linear, univariate prediction problems	Capable of modeling nonlinear, high-dimensional, and spatiotemporal dynamic data
Computational Complexity	Low; ideal for rapid deployment	High; demands substantial computational resources
Real-Time Capability	Limited; infrequent updates	Strong; supports real-time forecasting with sensors and streaming data
Application Limitations	Poor generalization in complex scenarios	Strong generalization capacity, though prone to overfitting if not properly regularized

3.3. Method–Data–Scenario Implications for MDSA

The above evidence suggests a consistent pattern: traditional models deliver strong transparency and stability under constrained data regimes, whereas AI methods provide superior representational capacity when data are rich enough and deployment constraints can be satisfied. Importantly, the “best” method family changes as the dominant constraint shifts—from zero-inflated sparsity (favoring ZINB/grey hybrids) to heterogeneous tabular features (favoring RF/XGBoost) to spatiotemporal heterogeneity and relational structure (favoring ConvLSTM/GNN). These patterns motivate the MDSA framework in Section 6, which operationalizes method selection as an adaptation task rather than an accuracy-only ranking.

4. Scenario-Based Analysis of AI Applications in Accident Prediction

AI techniques have advanced rapidly in accident prediction research, particularly in transportation and building construction. While existing reviews have examined machine learning and deep learning architectures and reported performance trends, many remain confined to a single domain or focus on algorithmic categories in isolation. This leaves a practical gap: accident prediction is deployed under strongly heterogeneous data regimes and operational constraints, and model suitability cannot be inferred from algorithm labels alone. Therefore, this section conducts a cross-industry scenario-based synthesis across five high-risk sectors—transportation, construction, firefighting, chemical/petrochemical industries, and mining—highlighting how AI methods align (or fail to align) with domain-

specific data characteristics and deployment requirements. The analysis is organized to directly support the “Scenario” and “Data” dimensions of the MDSA framework.

4.1. Transportation Sector: Harnessing Spatiotemporal Dynamics

Traffic accident prediction is a prototypical safety application where the demand for early warning is high and data streams are increasingly available at scale.

Transportation datasets are often high-frequency and spatiotemporal, combining traffic flow, speed, occupancy, GPS trajectories, road geometry, weather, and incident logs. This richness enables learning complex patterns, but it also introduces challenges that are central to deployment: accident events remain rare relative to exposure, labels can be delayed or noisy, and data distributions drift with seasonal effects, infrastructure changes, and policy interventions. Practical datasets may also mix heterogeneous sources collected under different standards, creating multi-source inconsistency.

Operational deployment typically requires low-latency inference and stable performance under changing traffic conditions. False alarms incur real costs, while missed alarms can have severe consequences, creating a high-stakes precision–recall trade-off. Many use cases also require explainability, at least at the level of factor attribution, to support traffic management decisions and policy actions. Finally, because traffic systems evolve continuously, robust generalization and re-calibration are often more important than peak retrospective accuracy.

Early work relied on statistical models that linked crash frequency to explanatory variables such as traffic flow and meteorological conditions, establishing interpretable baselines for prediction and inference [52–55]. As data volume and feature diversity increased, machine learning approaches became attractive for handling multifactor interactions and non-linear relationships; early decision-tree-style models demonstrated measurable gains over conventional statistical techniques and improved coverage across more complex datasets [56,57]. Spatial analytics also became a practical bridge between data and intervention: GIS-based approaches were used to identify hotspots and characterize spatiotemporal patterns for risk management [58,59]. More recently, deep learning and multi-modal fusion have been used to exploit large-scale datasets and integrate GPS, meteorology, and traffic flow to enhance robustness and predictive power [60–62].

At the deployment frontier, real-time prediction is increasingly linked to intelligent transportation systems, where live data streams support dynamic risk assessment and traffic control [63–67]. Vehicle networking and vehicle-to-vehicle communication further enable near-real-time warning; for example, traffic-networking data combined with machine learning has been used to identify key risk factors and improve predictive accuracy in operational settings [68]. In parallel, prediction research is increasingly aligned with automated driving and ADAS evaluation, reflecting a broader system-level shift toward proactive safety technologies [69].

The transportation sector illustrates a typical “data-rich yet non-stationary” regime: strong spatiotemporal signal, high real-time demand, and persistent distribution drift. These features map directly to MDSA’s emphasis on spatiotemporal capability, data dependency, and deployment constraints.

4.2. Construction Sector: Navigating Human and Environmental Factors

Construction accident prediction is dominated by heterogeneous hazards and strong human factors, where prevention depends on actionable risk identification rather than retrospective explanation alone.

Construction data are often fragmented and heterogeneous. Core sources include incident reports (often text-heavy), worker attributes, work scheduling and task descriptions,

site environment measurements, and increasingly IoT streams and digital engineering artifacts. Labels can be inconsistent because event definitions vary across projects, and many hazards are context-dependent (site layout, work-at-height, temporary structures). Compared with transportation, construction data are typically less continuous and less standardized, and cross-project transfer is difficult.

Construction safety decisions are operational and responsibility-sensitive, which creates a strong requirement for interpretability and accountability. Risk alerts often trigger onsite interventions, so false positives carry tangible costs, while missed risks can cause severe harm. Deployment also faces practical constraints: data collection coverage differs across sites; sensor and reporting practices vary; and human behavior introduces non-reproducible variability. As a result, robust models must tolerate incomplete data and remain stable under heterogeneous contexts.

Early-stage construction risk assessment leaned heavily on practitioners' experience and checklist-like heuristics [70], followed by attempts to formalize predictors using statistical approaches and regression analyses that incorporated worker demographics and project factors [71–76]. With broader digitization and more structured data collection, machine learning models have been used for risk classification, feature selection, and predictive assessment, including RF, SVM, ANN, and XGBoost [77–80]. Representative evidence shows strong performance when datasets are sufficiently structured: RF achieved high accuracy and robustness in a large accident dataset from Malaysia [79], while RF-based modeling for fatality risk prediction reported high accuracy and highlighted interpretable determinants such as seasonality and worker age [81]. XGBoost has also been used for disability risk identification with improved interpretability through SHAP analysis [82].

Beyond supervised learning, optimization and probabilistic reasoning approaches have been integrated into construction safety modeling to improve factor identification and decision support [82–85]. Meanwhile, the adoption of BIM and IoT is shifting construction prediction toward data-rich, context-aware monitoring: BIM provides a digital representation of project geometry and activities, supporting proactive risk identification [86–89], and IoT sensors enable real-time measurement of environmental and operational conditions [90–93]. A representative integrated system is the CoSMoS framework, which combined BIM with wireless sensors to monitor confined spaces and support accident prediction [94], as shown in Figure 6.

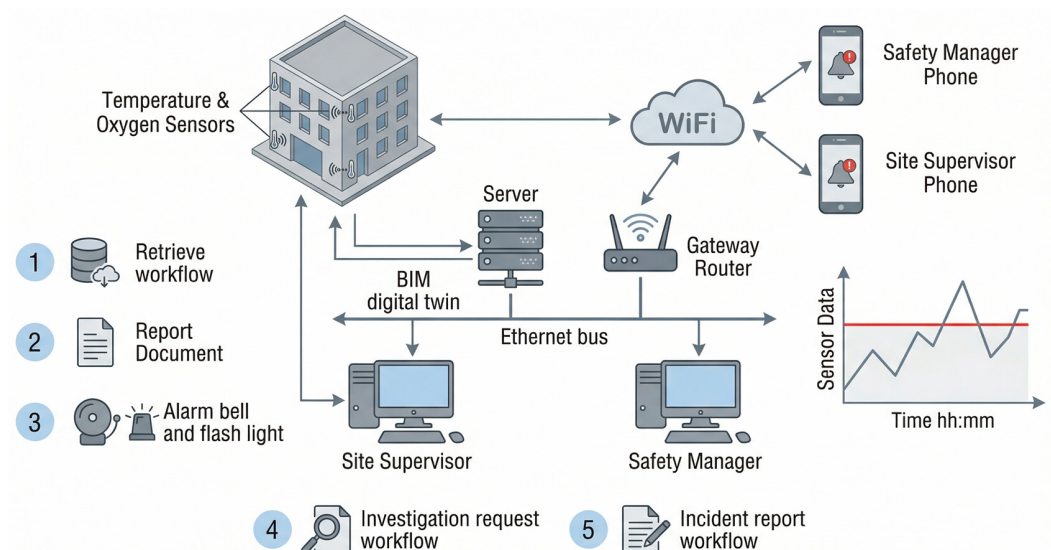


Figure 6. System architecture of a BIM-integrated wireless sensor network for real-time confined space safety monitoring and incident management in construction sites.

Construction emphasizes the “scenario-heavy” side of accident prediction: data heterogeneity, strong human factors, and high accountability requirements. This motivates MDSA-style matching that prioritizes interpretability, robustness under incomplete data, and deployment feasibility over purely accuracy-driven selection.

4.3. Fire and Electrical Power Industries: Predicting Rare Events

Fire prediction focuses on rare but high-consequence events and aims to provide early warnings that are actionable under uncertainty.

Fire-related prediction commonly relies on heterogeneous, multi-scale signals, including meteorology, drought-related indicators, and spatial context from remote sensing/GIS, together with increasing streams from distributed sensing and visual monitoring [95–98]. Data quality is often uneven across space and time, labels may be delayed or uncertain, and the predictors of ignition and escalation can differ, which complicates feature alignment and validation.

Deployment is dominated by high-stakes asymmetric costs: missed alarms can escalate rapidly, while excessive false alarms waste resources and erode trust. Practical systems therefore prioritize timeliness, robustness to missingness/noise, and outputs that map to concrete actions (e.g., hotspot alerts or risk maps). Integration with monitoring and response workflows further raises the bar for reliability and minimally sufficient explainability.

Meteorological variables remain foundational drivers of fire risk and propagation tendency [99,100], and drought indices provide additional early-stage risk signals [101]. Remote sensing and GIS-based integration enable scalable monitoring and support mapping and pattern analysis at operational scales [102–104]. Thermal infrared sensing strengthens early warning by improving hotspot identification [105].

With richer data streams, learning-based models have been used to capture non-linear interactions (e.g., ANN/GIS risk forecasting and probabilistic ignition mapping) [106], while CNN-based recognition has been explored for real-time visual detection settings [107].

In parallel, simulation-driven approaches—particularly CFD-based modeling and FDS toolchains—support scenario evaluation and decision support where physical dynamics and evacuation considerations matter [108–112].

Fire prediction exemplifies a rare-event, high-consequence regime where suitability depends on the joint fit between model capability, data regime, and deployment constraints—especially multi-source fusion, robustness under uncertainty, and timely integration with response workflows—making it a natural target for MDSA-style matching and scoring.

4.4. Chemical and Petrochemical Industries: Analyzing Complex Processes

Chemical and petrochemical accident prediction targets complex, tightly coupled industrial processes where monitoring is continuous and safety decisions are strongly regulated.

Chemical process safety data are typically multivariate time series collected from sensor networks and control systems, including temperature, pressure, flow rates, and alarm records. Data are high-frequency, but failures can be rare and mechanism-driven, creating imbalance and making generalization challenging. Signals may drift with equipment aging, operational changes, and maintenance practices, requiring continuous monitoring and recalibration.

Deployment demands are shaped by high accountability and strict operational constraints. Models must support reliable early warning, often under real-time requirements, and provide evidence that can be audited and acted upon. False alarms can disrupt pro-

duction and create alarm fatigue, while missed detection can be catastrophic. Therefore, robustness and interpretability are frequently as important as accuracy.

The increasing integration of sensor networks and automated monitoring enables real-time measurement of essential process indicators [113–116]. A representative example is a wireless gas leak detection and localization system using distributed sensor nodes and probabilistic localization, which improved localization performance while reducing false alarms [113]. With the growth of process data, data mining and machine learning have been applied to extract patterns from historical accident cases and identify dominant contributing factors; classification and regression tree modeling has been used to analyze petrochemical accident cases and reveal associations with equipment failure and safety management factors [117]. Machine learning has also been used for risk assessment in storage and fire-related hazards, including SVM-based models with optimized kernels and parameters [118]. Beyond prediction, integrated decision support and emergency management platforms have been proposed to support situational awareness and coordinated response, including GIS-enabled decision support systems for chemical facilities [119].

Chemical industries represent a “data-rich but regulation-heavy” environment where suitability hinges on real-time stability, alarm control, interpretability, and integration with operational decision processes—direct inputs to MDSA’s scenario and data dimensions. In chemical processing, the MDSA framework prioritizes models that minimize leak-related environmental footprints, treating pollution prevention as a core sustainability mandate.

4.5. Mining Sector: Dealing with Remote and Unstructured Environments

For mining operations, robust prediction ensures the social sustainability of the workforce, fulfilling the ethical requirement to protect human lives in hazardous, remote environments. Mining accident prediction operates in remote, harsh environments where events are rare but severe and where sensing and communication can be constrained.

Mining safety data often combine sparse accident records with sensor measurements (e.g., gas, ventilation, temperature), equipment operation logs, and sometimes geological information. Datasets can be small, noisy, and incomplete; labels may be limited; and the operational context varies across mines, hindering cross-site transfer. Some tasks rely on physics-based simulation outputs (gas dispersion, fire propagation), while others rely on statistical incident records and monitoring streams.

Traditional mining risk management has included structured hazard identification and assessment methods. HAZOP-style approaches have been used for risk classification and hazard identification, but can remain complex and less quantitatively grounded [120]. Quantitative risk assessment methods, supported by probabilistic and fuzzy techniques, have been used to estimate likelihood and consequence distributions [121], and Monte Carlo simulation has supported scenario-based risk estimation [122].

Physics-based simulation has contributed detailed modeling of hazardous processes; gas explosion modeling approaches have been categorized into correlation, phenomenological, and CFD types, with trade-offs between fidelity and computational cost [123]. Fire propagation simulation also provides mechanism-informed insights, including large-scale coal fire simulation with sensitivity to permeability and spread behavior [124–127].

AI approaches have been adopted to improve prediction and early warning when data are limited but monitoring signals are available. SVM has been recognized as suitable for small-sample, high-dimensional settings [39,128,129]. Neural-network approaches have also been applied to capture non-linear risk patterns [130–133], including early warning frameworks that improve training and convergence through optimization [132] and CNN-based identification models for specific hazards such as water inrush sources [130].

Bridge to MDSA. Mining highlights a “data-constrained, high-stakes” regime where suitability is determined by robustness under missingness, feasibility under resource constraints, and the integration of domain knowledge with data-driven learning—exactly the type of scenario MDSA is designed to formalize.

4.6. AI Model Suitability Analysis and Deployment Recommendations

AI methods have demonstrated strong predictive capability across multiple accident prediction contexts, but deployment suitability depends on more than accuracy. Across the five sectors reviewed above, model choice must reflect the coupling between data regime and operational constraints. In practice, selection should consider (i) whether the available data support the model’s training and validation requirements; (ii) whether the model can operate under the intended latency and resource limits; and (iii) whether the outputs are interpretable enough to drive safety decisions and satisfy accountability requirements.

Based on cross-domain evidence, a practical pattern emerges. For structured, moderate-size datasets with heterogeneous features and a need for stable performance, classical machine learning models and ensemble methods often provide a strong balance between accuracy and operational feasibility. When the primary signal is spatiotemporal and data are rich and continuously collected, deep learning architectures become more competitive, provided that sufficient validation rigor and maintenance capacity exist. In contrast, in data-scarce, high-uncertainty settings, models that are robust under small samples and that allow incorporation of expert knowledge or uncertainty reasoning may be preferable.

To make these considerations actionable, this paper proposes a model–accident-type matching framework with six evaluation dimensions: prediction accuracy, interpretability, spatiotemporal modeling capability, data dependency, applicable production domain, and typical use case. Together, these dimensions provide a structured basis for comparing AI methods in realistic deployment settings, rather than treating model selection as a single-objective accuracy ranking. Detailed suitability results are summarized in Tables 5 and 6.

The qualitative assessments are defined by the following boundary criteria:

Accuracy: Evaluates relative predictive precision. Rated “High” for state-of-the-art performance on complex, non-linear tasks; rated “Low/Weak” for sub-optimal baseline precision.

Interpretability: Evaluates structural transparency. Rated “High” for explicit mathematical coefficients or trackable decision paths; rated “Low” for opaque, “black-box” processing.

Spatiotemporal Processing: Evaluates the capacity to handle multidimensional spatial and temporal data. Rated “High” for natively capturing spatiotemporal dependencies; rated “Weak” for treating inputs as isolated, static tabular vectors.

Data Dependency: Measures the minimum sample size needed for stable generalization. Rated “High” for requiring massive datasets ($>10^5$ samples); rated “Low” for robust learning from small, sparse, or incomplete datasets.

The categorizations reported in Tables 5 and 6 were developed through a three-step interpretive process. First, evidence was extracted from the reviewed literature, including reported model performance, data conditions, and deployment-related characteristics. Second, these findings were compared across sectors to identify recurring patterns in how different model families behave under typical accident prediction scenarios. Third, these patterns were synthesized into relative suitability labels to support structured cross-sector comparison within the MDSA framework. Accordingly, labels such as “High,” “Medium,”

and “Weak” should be understood as comparative summaries grounded in the reviewed evidence, rather than as purely impressionistic judgments or fixed universal ratings.

Table 5. Adaptability analysis of artificial intelligence methods in accident prediction.

Model Method	Accuracy	Interpretability	Spatiotemporal Processing Capability	Data Dependency	Typical Scenarios	Applicable Production Areas
Random Forest (RF)	Medium–high	High	Weak	Medium	Structured data prediction, e.g., injury record analysis, traffic accident classification	Transportation, construction, manufacturing
XGBoost	High	Medium–high	Weak	Medium	Accident severity ranking, risk level assessment	Construction, Transportation, Chemical
Support Vector Machine (SVM)	Medium	Medium	Weak	Low–Medium	Small sample fault diagnosis, accident type classification	Coal mine, electric power, manufacturing
K Nearest Neighbor (KNN)	Medium	High	Weak	Low	Hazardous Behavior Classification, Matching of Similar Working Conditions	Light industry, warehousing, manufacturing
Neural network (ANN)	High	Low	Medium	Medium High	Multi-dimensional variable fitting and prediction, e.g., accident modeling for construction environments or coal mine ventilation systems	Construction, mining, manufacturing
LSTM/GRU	High	Low	High (time series)	High	Time-series data modeling, e.g., sensor accident warning, equipment behavior prediction	Power, chemical, mining
ConvLSTM	High	Very low	Very high (spatiotemporal)	Very high	Intelligent traffic prediction, spatio-temporal accident risk distribution modeling	Intelligent transportation, intelligent mining
Graph Neural Network (GNN)	High	Low	High (topology)	High	Prediction of accident propagation in network structures, e.g., analysis of accident impact paths in power grid, transportation network structures	Power grid, pipeline network, transportation

Table 6. Adaptive analysis of AI models in accident prediction by industry.

Industry Sector	Typical Scenario & Data Characteristics	Applicable AI Models	Key Strengths of Model in This Context	MDSA Framework Perspective
Transportation	High-volume, spatiotemporal data from sensors, GPS, cameras	ConvLSTM, Hybrid CNN-RNN	Captures complex spatiotemporal patterns effectively	Data-intensive models are justified due to data richness.
Construction	Diverse, heterogeneous data with human and environmental factors	XGBoost, Random Forest, LightGBM	Handles mixed data types and identifies important features	Balancing accuracy with a degree of interpretability is key.
Chemical & Petrochemical	Complex process networks, sensor data with interdependencies	GNNs, Hybrid models	Models topological structures and complex causal links	Model must reflect the underlying physical and network structure.
Fire & Electrical	Sparse, imbalanced, and high-stakes data	Imbalanced learning techniques, Anomaly Detection	Effective for predicting rare, critical events	Prioritizing robustness for imbalanced data is crucial.
Mining	Sparse, unstructured, and sensor data from remote sites	CNNs, NLP models, Traditional ML	Adapts to different data modalities (e.g., image, text)	Model choice is dictated by the heterogeneous data format.

Note: The model–industry matching relationships reported in this table are based on the literature synthesis and scenario-based comparison developed in Sections 3 and 4.

This scenario-based synthesis provides the empirical grounding for Section 6, where these qualitative patterns are operationalized into a unified MDSA-based matching and scoring procedure that supports model selection, deployment design, and iterative adaptation.

4.7. Cross-Domain Quantitative Synthesis of Model Usage and Deployment Implications

To complement the scenario-based narrative synthesis, a metadata-based quantitative synthesis was conducted to examine how accident prediction models are distributed across high-risk industries. The purpose of this analysis was not to rank models by a single accuracy metric, but to determine whether model adoption patterns vary systematically with industrial data regimes and deployment requirements. The results provide additional empirical support for the MDSA framework by showing that different sectors rely on different model families, reflecting differences in data availability, interpretability requirements, physical process complexity, and real-time deployment constraints.

4.7.1. Industrial Distribution of Accident Prediction Studies

Table 7 summarizes the industrial distribution of the coded literature. Transportation accounted for the largest share of the collected records, followed by fire/electrical safety and construction. Mining and chemical/petrochemical safety were less represented, reflecting the relative scarcity, confidentiality, and high acquisition cost of accident and process safety data in these sectors.

Table 7. Industrial distribution of accident prediction studies in the coded literature.

Industrial Domain	Number of Records	Percentage
Transportation	92	36.4%
Fire/Electrical safety	34	13.4%
Construction	32	12.6%
General/Review/Methodological studies	25	9.9%
Mining	19	7.5%
Chemical/Petrochemical safety	9	3.6%
Other/Unclear	42	16.6%
Total	253	100%

The distribution indicates that accident prediction research remains strongly concentrated in transportation, where large-scale structured and spatiotemporal datasets are more accessible. By contrast, chemical/process safety and mining are underrepresented in the bibliographic dataset, although they are among the most safety-critical sectors. This imbalance itself supports the need for an adaptive framework: model selection rules derived from data-rich transportation settings cannot be directly transferred to data-scarce, regulation-heavy, or physically constrained industrial scenarios.

4.7.2. Frequency Analysis of Model Families

A frequency analysis of model families was then conducted. Because one study may contain more than one model, the model counts in Table 8 represent model occurrences rather than mutually exclusive paper counts.

The frequency distribution shows that accident prediction research is not dominated by a single best-performing model family. Instead, traditional statistical models, classical machine learning, deep learning, expert-based methods, and physics-based simulation all remain active. This finding supports a central premise of MDSA: model choice is shaped not only by predictive performance, but also by data structure, domain mechanism, interpretability requirements, and deployment constraints.

Table 8. Frequency of model families in accident prediction studies.

Model Family	Frequency of Occurrence	Main Implication for MDSA
ANN/BPNN	39	Frequently used for nonlinear fitting, but requires careful control of overfitting and interpretability limitations
SVM	32	Suitable for small- to medium-scale structured datasets and high-dimensional safety features
Deep learning/CNN/RNN/LSTM	32	Increasingly used in data-rich, image-based, sensor-based, and spatiotemporal scenarios
Simulation/CFD/physics-based models	31	Important in fire, explosion, gas dispersion, and physically governed accident processes
KNN/K-means/clustering	27	Useful for hotspot detection, pattern discovery, and preliminary risk stratification
Fuzzy/AHP/expert-based methods	25	Common in domains requiring expert judgment, interpretability, and qualitative risk reasoning
Random Forest	25	Provides a balanced trade-off among accuracy, robustness, and partial interpretability
Regression/GLM	25	Remains an important interpretable baseline, especially for count-based accident modeling
Bayesian/Bayesian networks	24	Suitable for causal reasoning, uncertainty modeling, and interpretable safety decision support
Time-series/ARIMA	23	Useful for temporal accident trend forecasting and short-term warning tasks
XGBoost/boosting models	17	Effective for structured tabular data and severity classification, especially when combined with explanation tools
Hybrid/ensemble models	15	Reflect attempts to combine complementary strengths of multiple model families
Decision tree	14	Provides interpretable classification rules but may suffer from limited generalization
Grey models	13	Suitable for small-sample and incomplete-information forecasting problems
Markov models	8	Useful for state transition and risk evolution modeling
GNN/graph-based models	4	Emerging approach for networked, relational, and propagation-based accident prediction

4.7.3. Cross-Domain Comparison of Model Adoption Patterns

To further examine industry-specific preferences, model families were mapped to industrial domains. Table 9 summarizes the most frequently observed model families in each sector.

This cross-domain pattern provides quantitative support for the MDSA framework. Transportation studies show a stronger tendency toward deep learning and spatiotemporal modeling because of richer data availability. Construction studies more frequently involve Bayesian, fuzzy, tree-based, and ensemble methods, reflecting the need for interpretability and managerial usability. Fire and electrical safety studies rely more heavily on physics-based simulation because ignition, spread, and propagation processes are strongly governed by physical mechanisms. Mining and chemical/process safety remain more constrained by data scarcity, sensor reliability, regulatory accountability, and the need for domain knowledge.

Table 9. Cross-domain model adoption patterns in accident prediction.

Industrial Domain	Frequently Observed Model Families	Data and Scenario Characteristics	MDSA Interpretation
Transportation	ANN/BPNN, clustering, deep learning, regression/GLM, time-series models, SVM, XGBoost	Large-scale, structured, spatiotemporal, and relatively accessible data; strong demand for real-time or near-real-time prediction	Data-rich conditions justify more complex models, but distribution shift and transferability remain key deployment risks
Construction	Bayesian networks, fuzzy/AHP, clustering, Random Forest, XGBoost, hybrid models	Fragmented project-level data, strong human and environmental factors, inconsistent labels, and high managerial accountability	Interpretability, actionability, and robustness across sites are often more important than marginal accuracy gains
Fire/Electrical safety	Simulation/CFD/physics-based models, time-series methods, regression, decision trees	Rare but high-consequence events, strong physical mechanisms, and asymmetric false-negative costs	Physics-informed modeling and recall-oriented early warning are critical
Chemical/Petrochemical safety	Simulation/physics-based models, hybrid models, fuzzy/expert methods, time-series models, neural networks	Sensor-driven, regulation-heavy, process-dependent, and drift-prone operating environments	Alarm credibility, interpretability, robustness, and regulatory auditability dominate model suitability
Mining	SVM, ANN/BPNN, deep learning, simulation, fuzzy/expert methods, clustering	Sparse, noisy, incomplete, and high-risk data; harsh sensing conditions and strong domain knowledge dependence	Small-sample robustness and expert knowledge integration are essential
General/Methodological studies	ANN/BPNN, deep learning, Bayesian models, Random Forest, SVM, fuzzy/expert methods	Cross-domain or methodological focus	Useful for methodological transfer, but direct deployment requires scenario-specific adaptation

4.7.4. Performance Reporting and Limitations of Pooled Meta-Analysis

The coded literature also showed that performance reporting is highly heterogeneous. Some studies reported classification metrics such as accuracy, precision, recall, F1-score, AUC, sensitivity, and specificity; others used forecasting metrics such as MAPE, RMSE, MAE, or relative error; simulation-oriented studies often focused on physical consistency, scenario reproduction, or spatial-temporal evolution rather than conventional prediction accuracy. This heterogeneity prevents meaningful pooling of model performance into a single statistical effect size.

Therefore, the present study does not claim that one model family is universally superior in terms of pooled accuracy. Instead, the performance evidence was interpreted in relation to model family, data regime, and deployment context. As shown in Table 10, model families differ not only in predictive tendency, but also in computational burden, interpretability, data dependency, and deployment suitability. This approach is more appropriate for accident prediction research because a model with high retrospective accuracy may still be unsuitable for field deployment if it requires excessive training data, lacks interpretability, performs poorly under distribution shift, or cannot satisfy real-time and regulatory constraints.

This table clarifies why accuracy alone is insufficient for deployment-oriented accident prediction. Deep learning models often show strong predictive potential, but their high data dependency, computational burden, and limited interpretability constrain their applicability in safety-critical settings. Conversely, classical and expert-based models may be less powerful in complex nonlinear tasks but remain valuable when data are limited, decisions require explanation, or deployment resources are constrained. Ensemble methods such as Random Forest and XGBoost occupy an intermediate position and frequently provide favorable trade-offs between performance and deployability.

Table 10. Deployment-oriented summary of model performance tendencies.

Model Family	Typical Predictive Tendency	Computational Burden	Interpretability	Data Dependency	Deployment Suitability
Regression/GLM	Moderate for structured count or severity data	Low	High	Low to medium	Strong baseline for interpretable and regulated settings
Grey models	Moderate for small-sample temporal forecasting	Very low	Medium–high	Low	Suitable for sparse accident trend prediction
Bayesian networks	Moderate to high when causal structure is meaningful	Medium	High	Low to medium	Suitable for uncertainty reasoning and safety decision support
SVM	Medium to high for small- and medium-scale structured data	Medium	Medium–low	Low to medium	Suitable for small-sample classification and fault diagnosis
Random Forest	High and robust for heterogeneous tabular data	Medium–low	Medium–high	Medium	Strong balance between accuracy, robustness, and deployability
XGBoost/boosting	High for structured tabular data and severity classification	Medium	Medium with post hoc explanation	Medium	Suitable when accuracy and feature-level interpretation are both needed
ANN/BPNN	High for nonlinear fitting	Medium to high	Low	Medium to high	Useful but requires overfitting control and explanation support
LSTM/RNN/deep learning	High in data-rich temporal or multimodal scenarios	High	Low	High	Suitable for sensor-rich and spatiotemporal systems, but deployment burden is high
GNN/graph models	High potential for networked and relational accident propagation	High	Low to medium	High	Promising for transportation networks, pipelines, and power grids
Simulation/CFD/physics-based models	Strong for mechanism reproduction and scenario analysis	High	Medium–high	Scenario-dependent	Suitable for fire, explosion, dispersion, and physically governed hazards
Fuzzy/AHP/expert-based methods	Moderate but transparent	Low to medium	High	Low	Useful when expert knowledge and qualitative indicators dominate

5. The Inevitability of Paradigm Shift: A Critical Analysis of AI’s Capabilities and Limitations

This section clarifies why a paradigm shift in accident prediction is increasingly inevitable and what this shift means in practice. The shift is not simply the replacement of traditional models with deep learning. Rather, it reflects a move from model-centric development toward deployment-centric adaptation, where success depends on whether a method can operate reliably under real data regimes and operational constraints. This perspective also motivates the Model–Data–Scenario Adaptation (MDSA) framework introduced in Section 6.

5.1. Drivers of the Paradigm Shift

Accident prediction is being reshaped by two concurrent changes. First, data regimes have expanded from sparse retrospective records to continuous streams that combine operational logs, sensors, spatial context, and environmental dynamics. Second, the expected output has shifted from offline explanation to early warning that supports intervention under latency, reliability, and accountability constraints. As a result, “best model selection” can no longer be treated as an accuracy-only ranking; it must be framed as an adaptation problem that explicitly accounts for the mismatch between model capacity, data availability, and deployment requirements.

5.2. What AI Uniquely Adds in Modern Accident Prediction

AI contributes several capabilities that are difficult to achieve with classical approaches when data are rich, high-dimensional, or strongly structured.

Spatiotemporal representation at scale. When accident risk emerges from coupled spatial and temporal dynamics, learning-based architectures can capture patterns that are hard to express with manual feature design. A representative example is the multi-view multi-task spatiotemporal modeling strategy used to predict accident risk at both fine-grained and aggregated levels within a unified framework [134].

Multi-source fusion for situational understanding. Safety prediction increasingly depends on heterogeneous signals rather than single-factor predictors. AI models can integrate trajectories, contextual factors, and perception signals into a coherent representation of risk. This is exemplified by collision-risk prediction efforts in connected and multimodal traffic settings, where multi-source perception and communication jointly support risk inference [135].

Real-time integration with sensing and alerting systems. The practical value of AI is often realized at the system level, where inference is coupled with sensing and response. IoT- and edge-oriented deployments illustrate how predictive components can support continuous monitoring and timely warnings, including mining safety monitoring systems that integrate sensing, learning, and wireless communication to trigger alerts under hazardous conditions [136].

Adaptation through transfer and reinforcement learning. Transfer learning can reduce labeled-data dependence and support regional adaptation with lower retraining cost [137]. Reinforcement learning can optimize decision policies under dynamic environments, such as distributed learning for multi-UAV wildfire detection and response planning [138]. These approaches signal that the emerging frontier is not only prediction accuracy but adaptive capability under evolving conditions.

5.3. Why AI Fails in Safety-Critical Deployment

AI systems can fail even when retrospective performance is strong, because the deployment environment exposes structural weaknesses that are not visible in offline evaluation.

Rare-event data and imperfect labels. Accidents are inherently imbalanced and often underreported or inconsistently labeled. Under extreme imbalance, models can appear accurate while failing on the very events of interest. Reports show that when the rare-event rate drops below 1%, recall can fall below 5% for standard classifiers [139]. This is a central mechanism behind fragile deployment.

Distribution shift and cross-scenario degradation. Operational environments drift as infrastructure, equipment, and procedures change. Correlations learned from historical data can become unreliable under new conditions. This makes cross-site transfer and long-term stability a core risk, not a corner case.

Mismatch between evaluation metrics and real costs. Real deployments face asymmetric costs: false alarms produce operational disruption and alarm fatigue, while missed alarms can be catastrophic. Standard metrics alone are therefore insufficient unless thresholds, costs, and decision workflows are explicitly considered.

Operational and organizational constraints. Prediction does not automatically translate into prevention. Failures can occur when organizations do not act on warnings or lack governance mechanisms for intervention. The Beirut port explosion and the Vale dam collapse have been discussed as reminders that risk recognition is not equivalent to risk control; organizational response and accountability are decisive [140].

Compliance and privacy constraints. Safety systems often touch sensitive operational or personal data. Legal and regulatory requirements can limit data collection, sharing, and

processing, shaping what models are feasible in practice. The Cybersecurity Law and regulations on critical information infrastructure protection exemplify such constraints [141].

5.4. Implications for Deployment-Oriented Model Selection and the Link to MDSA

The above analysis yields three practical implications. First, AI offers genuine advantages in spatiotemporal modeling, multi-source fusion, and real-time system integration when data regimes support these capabilities [135]. Second, the dominant deployment failures are predictable: rare-event imbalance and label uncertainty [139], drift and cross-scenario degradation, metric–cost mismatch, opacity, organizational gaps [142], and compliance limitations [141]. Third, these trade-offs cannot be resolved by selecting a “best” algorithm in the abstract. They must be managed through explicit matching between model properties, data regimes, and scenario constraints.

These deployment trade-offs are also sustainability trade-offs. In high-risk industries, an accident prediction system that requires excessive data, frequent retraining, unstable infrastructure, or black-box decisions that cannot be acted upon may perform well in laboratory settings but remain unsustainable in practice. By contrast, models that balance predictive power with interpretability, robustness, and feasible operating costs are more likely to support long-term safety governance, reduce false-alarm burden, limit production disruption, and lower the environmental and social consequences of accidents. In this sense, sustainability in accident prediction is inseparable from deployability, resource efficiency, and accountable decision support.

The preceding analysis establishes the theoretical rationale and the operational imperatives for sustainability that underpin the MDSA framework detailed in Section 6. MDSA operationalizes deployment-centric adaptation by translating capabilities and failure mechanisms into a structured matching and scoring procedure, supporting model choice, deployment design, and iterative adjustment under real-world constraints.

6. The Model–Data–Scenario Adaptation (MDSA) Framework: A Systems-Level Concept for Sustainable Safety Governance

It should be emphasized that MDSA is not a predictive algorithm and therefore does not generate standalone accuracy, AUC, F1-score, or runtime values. Rather, MDSA is a deployment-oriented decision framework for selecting and adapting accident prediction models under heterogeneous data regimes and operational scenarios. Accordingly, the validation target of MDSA is not predictive accuracy per se, but whether it can improve model selection decisions compared with an accuracy-only selection strategy. In this study, accuracy, training time, inference latency, deployment cost, interpretability, robustness, and data dependency are treated as attributes of candidate models and are incorporated into the MDSA decision matrix.

6.1. The Three Dimensions of the MDSA Framework

MDSA treats accident prediction as a coupled system defined by three interdependent dimensions, as shown in Figure 7. The goal is not to judge models in isolation, but to evaluate the synergy among:

Model (Capability): not only predictive power, but structural attributes that govern deployability, including training stability, interpretability mechanisms (e.g., feature attribution support), robustness, and inference latency.

Data (Constraint): the practical “data regime” available for training and operation, including sample scale, modality complexity, missingness/noise, temporal dynamics, and spatial coupling.

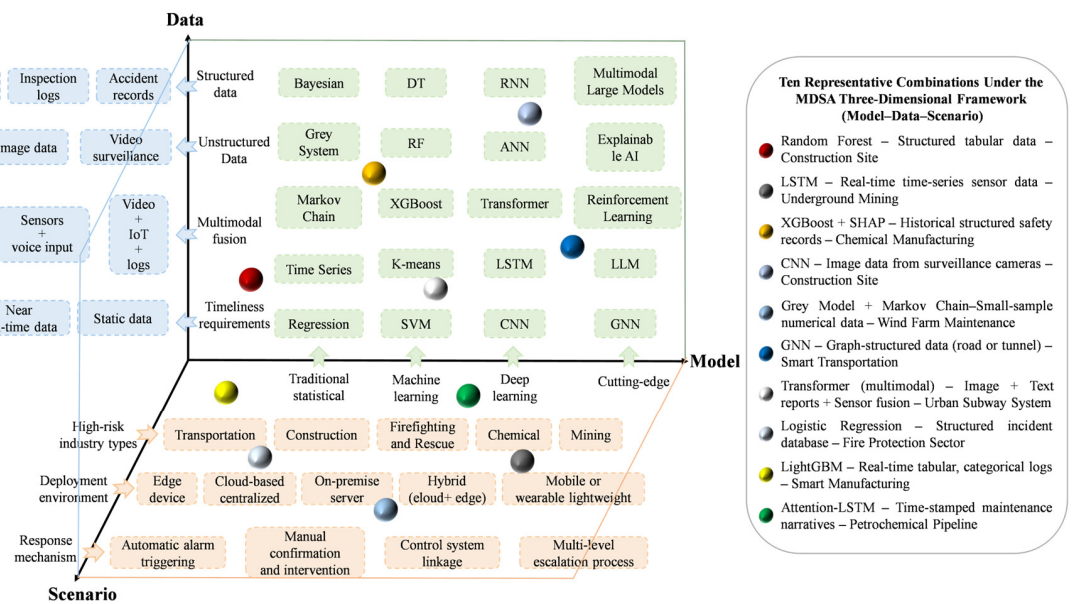


Figure 7. Schematic diagram of the Model-Data-Scenario Adaptation (MDSA) three-dimensional framework. The framework integrates three interdependent dimensions—Data (input modality and timeliness), Model (algorithmic capability ranging from traditional statistical to cutting-edge approaches), and Scenario (industry type, deployment environment, and response mechanism)—to guide the systematic selection of accident prediction models in high-risk industrial settings. Ten representative model-data-scenario combinations are annotated as colored spheres.

Scenario (Requirement): deployment boundary conditions, especially the cost of error (false positives vs. false negatives), response window (real-time vs. offline), infrastructure limits (edge/cloud/hybrid), and accountability (black-box acceptable vs. audit required).

These three dimensions interact through a quantitative protocol: scenario constraints determine what is feasible and what must be prioritized; data regimes determine what can be learned reliably; model properties determine what trade-offs are acceptable. This interaction is operationalized by the MDSA scoring and validation loop below.

6.2. The MDSA Implementation Protocol

The MDSA framework provides a practical method for selecting accident prediction models that match real-world deployment needs. Unlike traditional approaches that focus only on prediction accuracy, MDSA considers three factors together: what the model can do, what data is available, and what the application requires. This section presents a four-stage protocol that guides researchers through the model selection process.

(1) Stage 1: Define Deployment Requirements.

The first step is to clarify the intended use of the prediction system. Three key questions must be answered. First, what is the prediction timeline? Early warning systems forecast accidents days or weeks ahead to support planning, while real-time systems detect imminent risks within minutes to trigger immediate response. Second, what computing resources are available? Edge devices such as roadside sensors have limited processing power, cloud platforms offer substantial computational capacity, and hybrid systems combine both. Third, how will predictions be used? Some systems trigger automated safety actions, others provide decision support for human operators, and regulatory applications require detailed documentation.

These choices establish boundaries for model selection. For example, real-time systems on edge devices cannot support computationally intensive deep learning models, regardless of their accuracy. Similarly, regulatory reporting mandates interpretable models that explain their predictions, even if black-box alternatives perform better.

(2) Stage 2: Characterize Available Data.

The second step examines the data that will train and operate the model. Five characteristics determine which models are viable. Data volume is measured by sample count: fewer than 1000 samples is considered small-scale, 1000 to 100,000 is medium-scale, and more than 100,000 is large-scale. These thresholds reflect practical experience showing when different model types achieve reliable performance. Data modality describes the input format, ranging from simple tabular records to complex combinations of images, sensor streams, and text reports. Data quality is assessed through missing values, measurement errors, and inconsistencies. Temporal properties distinguish one-time surveys from ongoing monitoring systems with varying update frequencies. Spatial structure identifies whether accidents cluster geographically or occur independently.

This analysis produces a data profile that limits model choices. Small datasets cannot support deep learning, which requires large samples to learn patterns. Multimodal data demands specialized fusion techniques. Poor data quality favors robust methods over sensitive ones.

(3) Stage 3: Score Model Suitability.

After identifying feasible models, the third step evaluates each candidate across six dimensions using a 1–5 scale. Accuracy measures how well the model predicts accidents using task-appropriate performance metrics. Training time reflects the computational effort required to train the model, which is particularly relevant when frequent retraining or limited computational resources are involved. Inference speed assesses how quickly the model can generate predictions in operational settings, especially under real-time or edge-deployment constraints. Data dependency evaluates the extent to which stable model performance relies on large, high-quality datasets, with higher scores assigned to methods that remain effective under limited or imperfect data conditions. Interpretability assesses whether users can understand why the model makes specific predictions: transparent methods such as regression receive high scores, partially interpretable ensemble methods receive moderate scores, and opaque neural-network-based methods receive lower scores unless supported by explanation tools. Robustness reflects the extent to which model performance remains stable when data quality declines, such as in the presence of missing values, noise, or shifting operating conditions.

The six evaluation dimensions of the MDSA framework are not merely technical metrics; they are direct operationalizations of sustainable risk governance requirements. Specifically, accuracy and robustness map directly to environmental and social risk reduction, because high-consequence hazards can only be effectively prevented when prediction systems remain reliable under noisy, incomplete, or shifting real-world conditions. Training time and inference speed reflect resource and operational sustainability, since excessively heavy models may impose unnecessary computational burden, energy consumption, and maintenance costs, particularly in scenarios where lightweight or edge-deployable solutions are sufficient. Interpretability supports governance sustainability and accountability by ensuring that safety alerts can be understood, audited, and translated into timely human-led interventions. Data dependency affects deployment scalability and long-term sustainability, because models that require massive volumes of high-quality labeled data may be difficult to maintain across sectors where accident data are sparse, heterogeneous, or costly to curate. In this sense, the MDSA scoring criteria are designed not only to compare technical performance, but also to capture whether a prediction system can remain viable, efficient, and governable over time in high-risk industrial settings.

To make these abstract dimensions concrete, Table 11 presents a systematic comparison of eight representative model families across the six evaluation criteria. Scores range from

1 (poor) to 5 (excellent), reflecting empirical performance patterns documented in the literature synthesis from Sections 3 and 4.

Table 11. Multi-dimensional performance comparison of accident prediction models.

Model Family	Accuracy	Training Time	Inference Speed	Data Dependency	Interpretability	Robustness
Linear Regression	2	5	5	5	5	3
Grey Systems (GM)	2	5	5	5	4	2
Bayesian Networks	3	3	4	4	5	4
Random Forest (RF)	4	4	4	3	4	5
Support Vector Machine (SVM)	3	3	3	3	2	4
XGBoost	4	3	3	3	3	5
Deep Neural Networks (DNN)	5	2	2	2	1	3
Long Short-Term Memory (LSTM)	5	2	3	2	2	3
Graph Neural Networks (GNN)	5	1	2	1	1	2

Note: The 1–5 scores are based on the literature synthesis in Sections 3 and 4 and are structured according to the six evaluation dimensions of the MDSA framework.

Scores reflect relative performance within typical accident prediction contexts. Accuracy measures predictive power; Training Time indicates computational efficiency during model development; Inference Speed measures real-time prediction capability; Data Dependency reflects minimum sample requirements (higher scores = lower dependency); Interpretability assesses explanation transparency; Robustness measures resilience to data quality issues.

This matrix reveals fundamental trade-offs that drive model selection under MDSA. Three patterns are particularly notable. First, the accuracy-interpretability trade-off is stark: Linear Regression and Bayesian Networks score highest on interpretability but lowest on accuracy, while LSTM and GNN show the reverse pattern. This explains why regulatory-driven applications in mining and chemical industries continue to rely on classical methods despite their performance limitations. Second, computational efficiency inversely correlates with accuracy: models achieving scores of 5 for accuracy require the longest training and slowest inference, making them unsuitable for resource-constrained deployments. Third, ensemble methods like Random Forest and XGBoost occupy a strategic middle ground, sacrificing neither interpretability nor robustness while achieving competitive accuracy.

To convert these priorities into a decision, each criterion is assigned a scenario-dependent weight determined in Stage 1. The overall suitability score of model m is then computed as a weighted sum:

$$S(m) = \sum_{k=1}^6 \omega_k \cdot s_k(m) \quad (1)$$

$$\sum_{k=1}^6 \omega_k = 1 \quad (2)$$

where $S(m)$ denotes the overall suitability score of model m , $s_k(m)$ denotes the score (1–5) of model m on criterion k as reported in Table 11, and ω_k denotes the scenario-dependent weight assigned to criterion k . In this study, the six criteria correspond to the six evaluation dimensions listed in Table 11: accuracy, training time, inference speed, data dependency, interpretability, and robustness. The resulting score provides a ranked recommendation explicitly conditioned on deployment constraints, rather than identifying an absolute “best” model across all settings.

(4) Stage 4: Validate and Refine.

The fourth step tests the selected model in controlled pilot deployments before full implementation. Operational metrics are tracked, including false alarm rates, response

times, and user acceptance. When pilot performance differs substantially from predicted scores, earlier stages are revisited to identify incorrect assumptions about requirements or data characteristics. This feedback enables continuous improvement.

6.3. MDSA Decision Space and Illustrative Application

To make the MDSA framework more tangible, this section presents a visual representation of the decision space and illustrates its practical use through an application-oriented case example.

6.3.1. Visualizing the Decision Space

The three MDSA dimensions can be mapped onto a three-dimensional space where the X-axis represents data availability from sparse to abundant, the Y-axis represents scenario urgency from offline analysis to real-time response, and the Z-axis represents interpretability needs from performance-focused to explanation-required, as shown in Figure 8. Different model families naturally occupy distinct regions within this space.

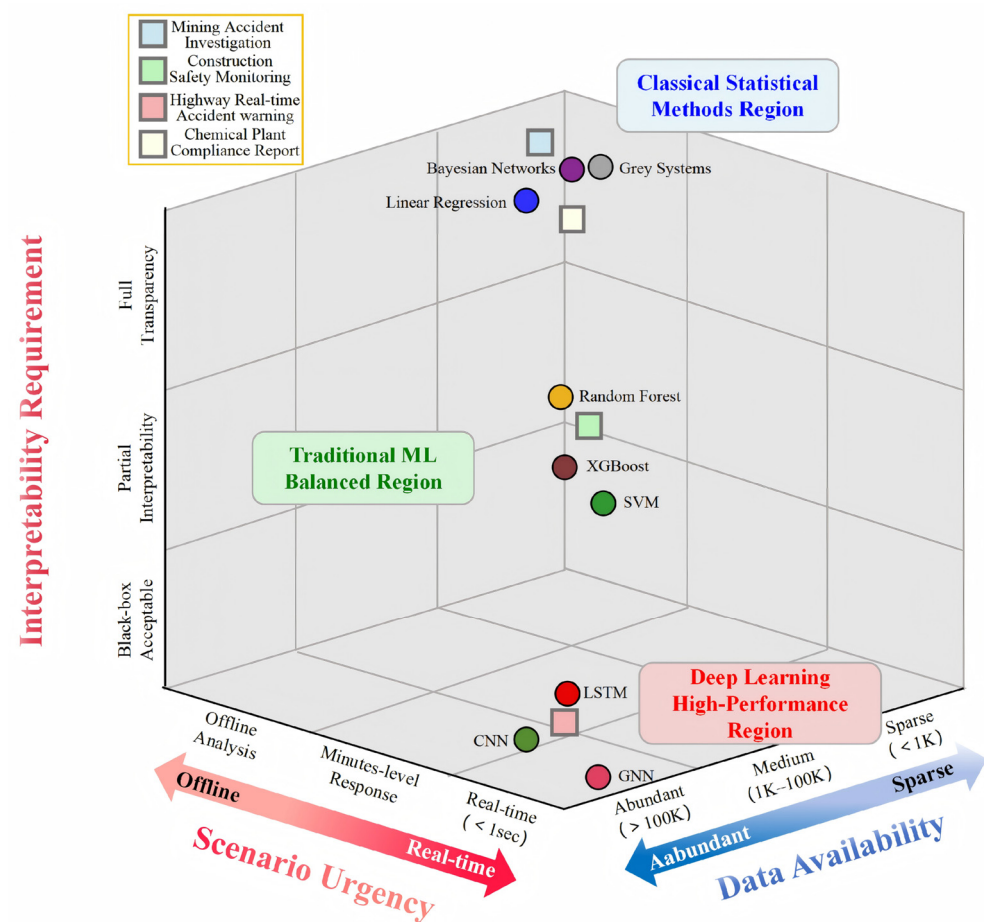


Figure 8. Three-dimensional decision space of the MDSA framework for model selection in accident prediction. The X-axis represents data availability (sparse to abundant), the Y-axis represents scenario urgency (offline analysis to real-time response), and the Z-axis represents interpretability requirements (black-box acceptable to full transparency). Three model families occupy distinct regions: classical statistical methods (Bayesian Networks, Grey Systems, Linear Regression) suit sparse-data, high-interpretability contexts; traditional machine learning methods (Random Forest, XGBoost, SVM) occupy the middle ground; and deep learning methods (LSTM, CNN, GNN) dominate abundant-data, real-time deployment scenarios.

Classical statistical methods, including grey models and Bayesian networks, suit contexts with limited data, low urgency, and high interpretability requirements. These

methods function reliably with hundreds of samples and provide clear reasoning chains, making them appropriate for regulatory reporting in small-scale operations like individual mine sites. However, their predictive power is limited in complex scenarios.

Traditional machine learning methods, including Random Forest and Support Vector Machines, occupy the middle ground with moderate data requirements of several thousand samples, balanced urgency, and partial interpretability. These methods achieve good performance across diverse applications while maintaining some transparency through feature importance or decision boundaries.

Deep learning methods, including Convolutional and Recurrent Neural Networks, dominate the region of abundant data, high urgency, and low interpretability requirements. These approaches excel with hundreds of thousands of samples and can capture intricate patterns, but their black-box nature limits transparency.

6.3.2. Illustrative Application: Chemical Plant Gas Leak Detection

A petrochemical facility illustrates both the consequences of ignoring MDSA principles and the multi-dimensional trade-offs that govern model selection. The facility initially selected a Deep Neural Network for gas leak prediction based solely on its high accuracy in offline testing. This choice prioritized the accuracy dimension while neglecting five critical factors.

Because gas-leak warning is a safety-critical task, predictive accuracy was treated as an initial screening condition rather than the sole decision criterion. Based on Table 11, only models with relatively high accuracy scores were retained as primary candidates for further evaluation, namely Random Forest, XGBoost, LSTM, and GNN. However, high predictive accuracy alone was not sufficient to justify deployment in this scenario.

Among these four candidates, GNN was not retained as a primary deployment option despite its high accuracy score. First, its interpretability score of 1 was incompatible with the regulatory and human-supervised requirements of the application scenario. Safety engineers could not clearly understand why specific alarms were triggered, and the black-box structure made it difficult to identify which sensor readings or process parameters drove the risk predictions. This opacity substantially undermined operator trust, with more than 60% of alerts reportedly dismissed even when many of them reflected legitimate warnings. Second, its training time score of 1 and inference speed score of 2 imposed substantial operational burdens. Minor adjustments in production parameters led to performance degradation, requiring frequent retraining and thereby placing excessive pressure on the site's computing infrastructure. Third, its data dependency score of 1 indicated strong reliance on large-scale datasets, whereas the facility had only 8000 historical incident records, which was insufficient to support stable deployment of such a data-intensive model. These limitations were further amplified by the edge-computing context, in which continuous cloud connectivity could not be assumed to remain reliable in the industrial environment.

After excluding GNN on feasibility grounds, the remaining candidate models—Random Forest, XGBoost, and LSTM—were compared using the six MDSA criteria defined in Table 11 and the scenario-dependent weighting scheme described above. For the present gas-leak warning scenario, the criterion weights were specified as follows: accuracy = 0.15, training time = 0.10, inference speed = 0.15, data dependency = 0.10, interpretability = 0.25, and robustness = 0.25. This weighting scheme reflects the strong regulatory and human-supervised nature of the scenario, which increases the importance of interpretability; the presence of missing sensor readings and process variation, which elevates the importance of robustness; and the edge-computing deployment context, which makes inference efficiency more important than training efficiency.

Using the criterion scores reported in Table 11, the weighted suitability score for Random Forest was calculated as:

$$S(\text{RF}) = 0.15 \times 4 + 0.10 \times 4 + 0.15 \times 4 + 0.10 \times 3 + 0.25 \times 4 + 0.25 \times 5$$

$$S(\text{RF}) = 0.60 + 0.40 + 0.60 + 0.30 + 1.00 + 1.25 = 4.15$$

For XGBoost, the weighted suitability score was calculated as:

$$S(\text{XGBoost}) = 0.15 \times 4 + 0.10 \times 3 + 0.15 \times 3 + 0.10 \times 3 + 0.25 \times 3 + 0.25 \times 5$$

$$S(\text{XGBoost}) = 0.60 + 0.30 + 0.45 + 0.30 + 0.75 + 1.25 = 3.65$$

For LSTM, used here as a representative deep learning model, the weighted suitability score was calculated as:

$$S(\text{LSTM}) = 0.15 \times 5 + 0.10 \times 2 + 0.15 \times 3 + 0.10 \times 2 + 0.25 \times 2 + 0.25 \times 3$$

$$S(\text{LSTM}) = 0.75 + 0.20 + 0.45 + 0.20 + 0.50 + 0.75 = 2.85$$

The final ranking was therefore Random Forest (4.15) > XGBoost (3.65) > LSTM (2.85). This result indicates that the most suitable deployment option in this scenario was not the model with the highest standalone accuracy score, but the model that achieved the best balance across interpretability, robustness, computational feasibility, and data requirements. Random Forest emerged as the most appropriate deployment choice because it combined relatively high predictive performance with stronger interpretability and robustness, while maintaining acceptable training and inference efficiency. XGBoost remained a viable alternative, particularly when predictive performance was prioritized more strongly. By contrast, although LSTM retained high predictive accuracy, its lower interpretability, stronger data dependency, and weaker deployment efficiency reduced its overall suitability in this specific context. This case should therefore be understood as an illustrative application of the MDSA framework rather than as a fully validated empirical deployment study.

More importantly, the comparison between the accuracy-only DNN baseline and the MDSA-guided Random Forest recommendation provides quantitative evidence of decision improvement. For DNN, which represents the accuracy-only baseline in this illustrative case, the weighted suitability score was calculated as:

$$S(\text{DNN}) = 0.15 \times 5 + 0.10 \times 2 + 0.15 \times 2 + 0.10 \times 2 + 0.25 \times 1 + 0.25 \times 3$$

$$S(\text{DNN}) = 0.75 + 0.20 + 0.30 + 0.20 + 0.25 + 0.75 = 2.45$$

If the facility followed an accuracy-only selection strategy, DNN would be selected because it had the highest accuracy score. However, under the MDSA-based deployment evaluation, Random Forest achieved a weighted suitability score of 4.15, whereas DNN achieved only 2.45. The decision improvement rate can therefore be calculated as:

$$DIR = \frac{S(\text{RF}) - S(\text{DNN})}{S(\text{DNN})} = \frac{4.15 - 2.45}{2.45} \times 100\% = 69.4\%$$

This means that, compared with the accuracy-only DNN baseline, the MDSA-guided selection improved the deployment-oriented decision utility by 69.4%. This value should not be interpreted as an improvement in predictive accuracy; rather, it represents the improvement in overall deployment suitability after incorporating interpretability, robustness, computational feasibility, and data dependency into the decision process.

This illustrative case highlights that the value of MDSA lies not in identifying the “best” model in absolute terms, but in revealing which model is most suitable under the competing constraints of real-world deployment. However, the chemical gas-leak case represents only one deployment scenario. To further generalize the failure logic of accuracy-centric model selection, the following section extends the analysis to multiple high-risk industries and identifies measurable quantitative impact indicators for each sector.

6.3.3. Case-Based Failure Analysis and Industry-Specific Quantitative Impact Indicators

To further clarify the practical value of MDSA, this section adds a case-based and industry-specific failure analysis. The purpose of this analysis is not to evaluate MDSA as a predictive algorithm, but to examine how accuracy-centric model selection may fail when model capability, data regime, and deployment scenario are misaligned. Since MDSA is a deployment-oriented decision framework, its contribution should be assessed by whether it can reduce the risk of selecting a locally accurate but operationally unsuitable model.

Across high-risk industries, the failure modes of accident prediction models are not identical. In transportation, a model may achieve high retrospective accuracy on historical traffic data but degrade significantly when transferred to new road networks, traffic policies, or weather conditions. In construction, a model trained on one project may not generalize well to another because accident reports, worker behaviors, site layouts, and management practices differ substantially across projects. In fire and electrical safety, high overall accuracy may conceal poor recall for rare but catastrophic events, leading to missed alarms. In chemical and petrochemical industries, a black-box model may be rejected by operators or regulators even when its offline performance appears strong. In mining, data-hungry models may become unstable when applied to sparse, noisy, and incomplete monitoring data.

Therefore, the quantitative impact of model–data–scenario mismatch should not be understood only through predictive accuracy. It should also be evaluated using deployment-related indicators, including recall degradation, false-alarm rate, missed-alarm rate, warning delay, inference latency, retraining frequency, operator acceptance, regulatory documentation burden, and maintenance cost. These indicators provide measurable pathways for evaluating whether a model can actually support accident prevention in real-world safety governance.

The table does not provide pooled numerical estimates of quantitative impact across industries, because the reviewed studies differ substantially in accident type, dataset structure, validation protocol, deployment condition, and performance metric. Directly aggregating impact values such as recall, false-alarm rate, warning delay, or deployment cost across heterogeneous domains would therefore be methodologically inappropriate. Instead, Table 12 identifies the measurable quantitative indicators through which deployment failures can be evaluated in future empirical studies.

Together with the illustrative chemical gas-leak case in Section 6.3.2, this analysis provides a two-level response to the issue of quantitative impact. At the case level, Section 6.3.2 provides a weighted suitability calculation comparing the accuracy-only DNN baseline with the MDSA-guided Random Forest recommendation, thereby offering numerical evidence of deployment-oriented decision improvement. At the cross-industry level, Table 12 identifies measurable impact indicators for different high-risk sectors and explains how MDSA can redirect model selection toward more deployable, interpretable, and robust solutions.

Table 12. Industry-specific failure modes and quantitative impact indicators of accuracy-centric model selection.

Industry	Typical Model–Data–Scenario Mismatch	Case-Based Failure Mechanism	Quantitative Impact Indicators	MDSA-Based Correction
Transportation	Models trained on historical traffic patterns are deployed under changed road networks, weather conditions, or traffic policies	High offline accuracy may degrade under temporal or spatial distribution shift	Recall/F1 degradation; false-alarm rate; warning delay; cross-site transfer error	Increase weights for spatiotemporal generalization, drift monitoring, recalibration, and real-time inference
Construction	Models trained on fragmented project-level data are transferred to sites with different reporting standards, worker behaviors, and management practices	Site-specific models may fail to generalize across projects, and alerts may be difficult for managers to interpret	Transfer accuracy drop; false intervention rate; user acceptance; interpretability score	Increase weights for interpretability, data-quality tolerance, cross-project robustness, and managerial actionability
Fire/Electrical safety	Rare ignition or fault events are hidden within large volumes of normal observations	High overall accuracy may mask poor detection of rare but catastrophic events	Rare-event recall; missed-alarm rate; false-negative cost; warning lead time	Prioritize recall, imbalance handling, early-warning lead time, and physics-informed reasoning
Chemical/Petrochemical safety	High-performing black-box models are deployed in regulated, sensor-driven, and human-supervised environments	Operators may not trust alarms; regulators may require auditable explanations; process drift may require frequent retraining	Alarm acceptance rate; inference latency; retraining frequency; documentation burden; maintenance cost	Increase weights for interpretability, robustness, edge feasibility, auditability, and process-drift tolerance
Mining	Data-hungry models are applied to sparse, noisy, incomplete, and harsh underground monitoring environments	Models may become unstable under missing sensors, small accident samples, and site-specific geological conditions	Missing-data sensitivity; false-negative rate; unstable generalization; sensor failure sensitivity; maintenance cost	Prioritize small-sample robustness, expert knowledge integration, uncertainty reasoning, and missing-data tolerance

This failure analysis further supports the central logic of MDSA: the value of a prediction model cannot be judged by accuracy alone. A model that performs well in offline testing may still fail in deployment if it lacks interpretability, requires excessive data, cannot meet latency constraints, or is unstable under changing operating conditions. MDSA addresses this problem by converting industry-specific deployment requirements into explicit decision criteria, thereby reducing the risk of selecting models that are accurate in isolation but unsuitable for real-world accident prevention.

6.3.4. Indicative Trade-Off Boundaries for Deployment-Oriented Model Selection

The decision space and comparison matrix also suggest several indicative trade-off boundaries that may help readers interpret model suitability under different deployment conditions. These boundaries are not intended as universally fixed decision rules; rather, they serve as practical reference points derived from the semi-quantitative scoring structure of Table 11 and the cross-sector literature synthesis underlying the MDSA framework.

For example, when interpretability is assigned a particularly high weight, models with very low transparency become less suitable in regulation-heavy and human-supervised settings, even if they perform well in terms of predictive accuracy. Likewise, in edge-deployment scenarios, models with low inference efficiency and high computational burden become more difficult to justify operationally, especially when real-time warning is required. Similarly, when data availability is limited, models with stronger data dependency become less attractive, and classical or ensemble approaches may provide a more feasible balance between predictive performance and deployment stability.

These indicative boundaries are therefore best understood as scenario-sensitive guidance rather than rigid thresholds. For instance, a researcher working on construction site safety with 2000 accident records, edge-computing constraints, and moderate interpretability requirements may infer from Table 11 that ensemble methods occupy the most

viable part of the solution space under such conditions, whereas deep learning models may require stronger data support and deployment infrastructure to become competitive. In this sense, MDSA does not replace expert judgment with fixed rules; instead, it provides a structured way to reason about trade-offs under realistic deployment constraints.

6.4. Innovative Value and Comprehensive Advantages of MDSA Framework

In summary, MDSA contributes: (i) a three-dimensional systems lens (Model–Data–Scenario) to formalize deployable model selection; (ii) a reproducible scoring-and-weighting protocol (Table 11) that converts priorities into ranked recommendations; and (iii) practical trade-off guidance and an illustrative application (Section 6.3) showing how multi-dimensional constraints can change the most suitable model under real deployment requirements. By preventing costly deployment failures and promoting resource-efficient, interpretable solutions, MDSA directly supports the sustainability imperative of high-risk industries: protecting workers, communities, and ecosystems while maintaining economic viability.

7. Discussion

While the MDSA framework provides a structured basis for deployment-oriented model selection, several issues merit further discussion, including the treatment of low-generalization models in sparse-data settings, the evolving role of deployment infrastructure, and the conceptual as well as empirical limits of the present review.

7.1. Mitigating the Generalization Limits of Grey Systems Within MDSA

Grey systems models remain valuable in safety prediction when data are small, incomplete, or sparse, particularly in early-stage deployment contexts or sectors where large, high-quality datasets are not yet available. Their main strength lies in their low data requirement and fast operationalization. However, as noted in this review, their generalization ability is often limited, especially when prediction models are transferred across regions, facilities, or operational scenarios with different underlying dynamics.

Within the MDSA framework, this limitation is not treated as a reason to reject grey systems models outright, but rather as a signal that their suitability is strongly scenario-dependent. In practical safety-critical deployments, MDSA suggests mitigating weak generalization through several strategies. First, grey models are better positioned as local or context-specific predictors rather than as universally transferable solutions. Second, their outputs may be used in combination with more adaptive models, for example in hybrid or staged architectures, where grey systems provide robust first-pass estimation under sparse data conditions and other models refine predictions when richer data become available. Third, frequent recalibration and scenario-specific updating are important when grey systems are used in environments with changing operational patterns. In this sense, MDSA reframes poor generalization not as an absolute defect, but as a manageable deployment constraint that should be balanced against low data dependence and strong practicality in sparse-data settings.

7.2. The Dynamic Nature of Deployment Suitability: Deep Learning Under Evolving Edge-Computing Conditions

In Table 11, deep learning models such as LSTM and GNN receive the highest scores for predictive accuracy, but lower scores for training time and inference speed. These lower scores reflect current deployment realities in many safety-critical contexts, especially where computational resources, latency tolerance, and maintenance capacity remain constrained. However, these evaluations should not be interpreted as permanent or technology-

invariant. Rather, they reflect the present balance between algorithmic capability and deployment infrastructure.

As edge computing hardware, model compression methods, and lightweight deployment frameworks continue to improve, the practical viability of deep learning models may increase in resource-constrained scenarios. Faster on-device inference, quantization, pruning, and hardware acceleration could reduce the operational penalty currently associated with deep architectures. Under such conditions, the relative disadvantage of deep learning in training and inference efficiency may narrow, especially for applications that require high-dimensional spatiotemporal modeling.

For this reason, the MDSA framework should be understood as adaptive rather than static. The scores reported in Table 11 represent a structured comparison under current mainstream deployment conditions, but they may shift over time as hardware ecosystems and engineering practices evolve. This also highlights an important strength of MDSA: it does not hard-code model superiority, but instead supports periodic re-evaluation as data environments, deployment infrastructure, and operational requirements change.

7.3. Limitations of the Review and the MDSA Framework

This study has several limitations that should be acknowledged. First, as a cross-industry review, it synthesizes evidence from sectors that differ substantially in accident types and characteristics. Although this broad scope supports comparative insight, it also means that direct comparability across sectors remains imperfect. Accordingly, this study explicitly adopts a narrative systematic review approach rather than a quantitative meta-analysis. This choice is primarily due to the substantial heterogeneity of datasets, evaluation metrics, accident definitions, model outputs, and deployment scenarios across industrial domains, which makes pooled quantitative comparison or effect-size synthesis methodologically inappropriate.

Second, the scoring structure used in the MDSA framework is partly based on literature synthesis and comparative interpretation rather than on unified benchmark experiments. The resulting scores are therefore best understood as semi-quantitative decision-support guidance, not as universally fixed ratings. Their value lies in making trade-offs explicit, but they remain sensitive to context and to the evolving state of data and deployment infrastructure.

Third, while this study includes an illustrative application to demonstrate how MDSA can guide model selection, the framework has not yet been validated through a large set of real-world prospective deployments across multiple industries. The current case-based illustration shows how MDSA can improve deployment-oriented reasoning, but more extensive empirical application would be needed to test its robustness in diverse operational settings.

Finally, the review itself remains subject to the limitations of the available literature, including heterogeneous reporting quality, inconsistent performance metrics, and uneven maturity across sectors. Future work should therefore combine broader empirical benchmarking with sector-specific implementation studies to further refine the scoring logic and improve the operational precision of the framework.

8. Conclusions and Future Prospects Toward Sustainable Safety Intelligence

This review systematically analyzed 253 accident prediction studies (screened from 4410 records via PRISMA) across five high-risk industries. The synthesis reveals that the field lacks a universally optimal model; rather, suitability strictly depends on specific operational contexts. For instance, while transportation heavily utilizes data-driven spatiotemporal models, the mining and chemical sectors are constrained by sparse data,

process drift, and strict accountability, necessitating highly interpretable approaches. These cross-domain patterns confirm that accident prediction must be treated as a model–data–scenario adaptation problem rather than an accuracy-only ranking task.

To operationalize this, the proposed Model–Data–Scenario Adaptation (MDSA) framework integrates multi-dimensional deployment constraints—such as inference speed, interpretability, deployment cost, and data dependency—into a structured decision matrix. In the illustrative petrochemical case, transitioning from an accuracy-only DNN baseline to the MDSA-guided Random Forest increased the weighted suitability score from 2.45 to 4.15. This represents a 69.4% improvement in deployment-oriented decision utility, effectively preventing the operational failure of purely accuracy-driven models.

Based on this literature synthesis, future research toward sustainable safety intelligence should prioritize three directions:

(1) Trustworthy and resource-aware AI: Future models must address distribution shifts and edge-deployment limits. Prioritizing computationally economical models over power-hungry deep learning architectures aligns continuous safety monitoring with Green AI principles.

(2) Human–AI collaborative decision-making: Prediction systems must be embedded in expert-in-the-loop workflows. Integrating AI alerts with accountable human escalation protocols reduces harmful errors under ambiguous conditions.

(3) Data governance and privacy: Breaking data silos across sectors requires “usable but not visible” privacy-preserving sharing mechanisms, alongside ethical boundaries to restrict the high-risk misuse of AI.

Ultimately, the value of MDSA lies in enhancing the rationality and transparency of model selection under real-world constraints. Future research should empirically validate this framework using standardized operational indicators (e.g., false-alarm rates, inference latency, and operator acceptance) to transform predictive algorithms into deployable, sustainable risk governance tools.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18136606/s1>, Table S1: Summary of the final search strategies applied across all databases included in this review; Table S2: Keyword modules used for specific high-risk industries (Block A); Table S3: Study inclusion criteria defined according to the PICOS framework; Table S4: Study exclusion criteria defined according to the PICOS framework; Table S5: Quality appraisal rubric for accident prediction modeling research; Table S6: A comprehensive cross-domain mapping matrix of the 253 reviewed articles, categorized by specific methodological families and high-risk industrial applications. The supplementary references provide the full PRISMA-based evidence base used for screening, coding, and cross-domain mapping. Because the main manuscript is written as a structured cross-sector review with representative citation rather than as a study-by-study annotated catalogue, not all references listed in the Supplementary Materials are cited individually in the main text. Instead, the main text cites the most directly relevant and representative studies, while the supplementary file preserves the complete review corpus for transparency, reproducibility, and traceability.

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