International Journal of Science, Strategic Management and Technology
Volume **02** Issue **08** August-2026 | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

AIOT-Based Predictive Safety Framework for Underground Coal Mining: Integrating PINNs, Wearable Sensors, and Digital Twins in Indian Contexts

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https://doi.org/10.55041/ijsmt.v2i8.052

Cite this Article: Kushwaha, S. (2026). AIOT-Based Predictive Safety Framework for Underground Coal Mining: Integrating PINNs, Wearable Sensors, and Digital Twins in Indian Contexts. International Journal of Science, Strategic Management and Technology, *02*(8), 1-9. https://doi.org/10.55041/ijsmt.v2i8.052

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Abstract

Underground coal mining remains one of the most hazardous industrial activities worldwide, particularly in emerging economies where complex geological conditions, methane emissions, roof instability, dust exposure, and equipment-related accidents continue to threaten worker safety. India, the world's second-largest coal producer, operates numerous underground mines under challenging geotechnical and environmental conditions. Despite significant advancements in mechanization and monitoring technologies, accident investigations indicate that a substantial proportion of mining incidents remain attributable to delayed hazard detection, fragmented monitoring systems, and limited predictive capabilities. Conventional safety management approaches are largely reactive, relying on threshold-based alarms and post-event analysis rather than proactive risk prediction. This study proposes a Mining 5.0-oriented intelligent safety framework that integrates Artificial Intelligence of Things (AIoT), Physics-Informed Neural Networks (PINNs), wearable sensing technologies, and Digital Twin models for real-time hazard prediction and decision support in underground coal mines. The proposed framework combines data from methane sensors, temperature sensors, air velocity monitors, geotechnical instruments, equipment health monitoring systems, and wearable devices measuring worker location, physiological status, and environmental exposure. These heterogeneous data streams are fused within a Digital Twin environment that continuously replicates underground mine conditions. PINNs are employed to incorporate ventilation physics, methane transport dynamics, and geomechanical principles into machine-learning models, thereby improving prediction accuracy and interpretability under sparse or uncertain data conditions. The study identifies critical research gaps in existing mine safety systems, including inadequate integration of physical laws with AI models, limited utilization of worker-centric sensing technologies, and the absence of comprehensive Digital Twin platforms for proactive safety management. To address these gaps, a socio-technical framework is developed that enables continuous risk assessment, predictive analytics, and human-AI collaborative decision-making. The proposed approach is expected to enhance situational awareness, reduce accident probability, improve emergency preparedness, and support sustainable Mining 5.0 transformation in India.

Keywords: Mining 5.0, Underground Coal Mining, AIoT, Physics-Informed Neural Networks, Digital Twin, Wearable Sensors, Predictive Safety Analytics, Human-Centric Mining, Coal India Limited, Risk Prediction.

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1. Introduction

Despite significant mechanization in the Indian mining sector, underground coal operations remain highly hazardous, characterized by persistent risks such as rockfalls, gas explosions, and ventilation failures that current reactive safety protocols fail to adequately mitigate (Amuah et al., 2025; Mansoori & Chaurasia, 2025a; Singh et al., 2024; Singh, Chaurasia and Beg, 2025; Yadav and Chaurasia, 2025a). Statistical records from the Directorate General of Mines Safety reveal that roof falls remain a primary cause of casualties, highlighting an urgent need to transition from threshold-based monitoring to intelligent, predictive frameworks (Mitra et al., 2022). To address these systemic vulnerabilities, this research proposes an integrated architecture combining Artificial Intelligence of Things with Physics-Informed Neural Networks to simulate and predict complex geomechanical failures in real-time (Lu et al., 2025; Wang, Jia and Su, 2025). By synthesizing high-fidelity data from wearable sensors and subterranean sensor networks into a comprehensive Digital Twin, this system establishes a virtual-physical bridge that allows for the continuous evaluation of mining-induced stresses (Vinay et al., 2023; Yu, Yang and Cheng, 2023; Singh et al., 2024; Tripathi and Chaurasia, 2025). Recent work on AI-IoT-enabled methane-emission prediction in underground coal mines has demonstrated the potential of intelligent sensing and predictive analytics for improving mine safety while simultaneously supporting carbon-footprint reduction (Singh & Chaurasia, 2026a).

Methane represents a particularly important target for predictive safety systems. Indian coalfields such as Raniganj contain significant coalbed methane resources, and previous research has demonstrated the importance of reservoir characterization and forecasting for understanding methane behaviour (Panwar et al., 2017; Panwar et al., 2019; Panwar et al., 2021; Panwar et al., 2021; Panwar et al., 2022; Singh et al., 2025a). Recent research on coalbed methane extraction and government policy further emphasizes the strategic importance of methane management in India (Singh et al., 2025b). Consequently, integrating methane forecasting with real-time ventilation monitoring represents an important pathway toward proactive underground mine safety.

Furthermore, this approach overcomes traditional limitations by augmenting data-sparse environments with physically constrained deep learning models, thereby ensuring reliable hazard detection despite irregular subterranean topologies and intermittent connectivity (Rahman, Jewel and Madria, 2026a, 2026b). This research aims to bridge existing literature gaps by demonstrating how edge-computing nodes and physics-constrained architectures can ensure robust, low-latency hazard detection in challenging, deep-mine settings (Gobinath et al., 2025; Madhavi, S and P, 2026; Singh et al., 2024; Tiwari and Chaurasia, 2026). The study specifically evaluates the predictive efficacy of this framework by simulating environmental variables such as strata convergence and ventilation dynamics, moving beyond simple alert systems toward actionable intelligence (Singh et al., 2022; Archana et al., 2025). By leveraging this multi-layered cyber-physical framework, the study seeks to mitigate the catastrophic consequences of gas build-ups and structural failures, ultimately shifting the safety paradigm from reactive management to proactive, human-in-the-loop intervention (Vishwakarma, 2024; Solanki et al., 2026; Mansoori and Chaurasia, 2025a; Tiwari and Chaurasia, 2026). Spontaneous heating and combustion also represent major hazards in underground coal mines. Recent investigations into the spontaneous-heating liability of Indian coals have highlighted the importance of coal characteristics, susceptibility assessment, and mitigation strategies in controlling this hazard (Raidas & Chaurasia, 2026a, 2026b). Therefore, a comprehensive Mining 5.0 safety architecture should not be restricted to methane and roof stability but should provide a framework capable of incorporating multiple interacting hazards. By integrating these Industry 4.0 technologies, the proposed model addresses the critical need to automate safety oversight and reduce the reliance on manual inspections in increasingly complex geo-mining environments (Agarwal et al., 2025; Rakesh and Dash, 2025).

This research specifically addresses the limitations of historical reactive maintenance by enabling autonomous, simulation-based anomaly detection that aligns with modern industry requirements (Cacciuttolo et al., 2025; Rojas, Peña and García, 2025). The proposed framework establishes a holistic safety ecosystem by bridging the gap between real-time data acquisition and complex system interdependencies, which traditional siloed approaches often fail to capture (Kurt and Kahraman, 2026). Through the application of Physics-Informed Neural Networks, the system incorporates

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governing geomechanical laws into the learning process, allowing the model to make accurate predictions even when empirical datasets are incomplete or noise-prone (Umar et al., 2026).

To address these gaps, this study proposes an integrated AIoT-enabled Digital Twin framework incorporating Physics-Informed Neural Networks and wearable sensing technologies for proactive risk prediction in underground coal mines. The framework aims to transform traditional reactive safety management into an intelligent, predictive, and human-centric system capable of continuously identifying, assessing, and mitigating emerging hazards.

2. Literature Review

Current discourse regarding the application of deep learning in mining safety frequently emphasizes the shift toward automated equipment and the necessity of fusing sensor data with IoT architectures (Azhari et al., 2023). However, existing frameworks often suffer from limited datasets and the inability to process rare but critical events, necessitating the integration of physics-based knowledge to enhance model robustness (Ahmed et al., 2023; Wei et al., 2025). By synergizing data-driven deep learning with fundamental principles of geomechanics, such as wave propagation and stress analysis, these integrated models significantly improve predictive accuracy and real-time adaptability in highly variable, non-linear underground environments (Zhou, Zhang and Qiu, 2024; Singh et al., 2024; Tripathi and Chaurasia, 2025a). Furthermore, the shift toward multi-source data integration facilitates a more granular understanding of risk evolution, effectively mitigating the response delays and information bottlenecks inherent in legacy monitoring systems (Zhao and Xie, 2026). The significance of geotechnical information is particularly evident in underground coal mining, where roof stability, strata behaviour, and excavation-induced stress redistribution directly influence worker safety. Research on underground mine safety and risk assessment emphasizes the importance of systematic identification, evaluation, and control of interacting hazards (Singh et al., 2025). Similarly, research on underground mine development and continuous-miner productivity demonstrates that increasing mechanization must be accompanied by improved operational and safety controls (Tripathi & Chaurasia, 2025b; Tripathi & Chaurasia, 2025c). Nonetheless, contemporary predictive models often neglect the spatial correlation and temporal lag of hazardous environmental variables, such as gas diffusion patterns across longwall faces, which frequently result in unreliable risk assessments.

Methane-related research provides an important foundation for overcoming this limitation. Previous investigations have examined coalbed methane potential in the Raniganj coalfield (Panwar et al., 2017), while subsequent studies have addressed reservoir modelling and forecasting of CBM behaviour (Panwar et al., 2022). Recent research on CBM extraction and government policy in India further demonstrates the importance of integrated methane management strategies (Singh et al., 2025b). These studies support the development of intelligent methane-monitoring frameworks capable of combining geological, operational, and environmental information.

Similarly, spontaneous combustion represents another hazard that requires continuous predictive assessment. Recent reviews have examined the mechanisms, influencing factors, susceptibility assessment, and mitigation strategies associated with spontaneous heating of Indian coals (Raidas & Chaurasia, 2026a), while laboratory investigations have explored relationships between spontaneous-heating liability and intrinsic coal properties (Raidas & Chaurasia, 2026b). These findings indicate that future AI-based safety systems should incorporate multiple hazard mechanisms rather than treating individual hazards as independent phenomena.

To address these deficiencies, current research into physics-informed machine learning emphasizes that incorporating governing physical laws directly into neural network architectures ensures that predictions remain consistent with mechanical reality, even when training data is sparse (Latrach et al., 2024). Moreover, while existing safety methodologies predominantly rely on manual, reactive inspections that fail to account for complex atmospheric dynamics, the deployment of wearable technologies and Digital Twins enables a transition toward continuous, context-aware monitoring (Li et al., 2025). By embedding physical constraints into the neural network architecture, such models effectively resolve the black-box limitations of traditional deep learning, ensuring that safety-critical predictions adhere to established conservation laws despite the inherent noise and incompleteness of subterranean sensor data (Hu, 2025; Zhang et al., 2025).

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This synergy between data-driven analytics and physical reality allows for the dynamic adjustment of model parameters, enabling systems to maintain high interpretability under shifting geological conditions (Liu et al., 2024). By employing these hybrid methodologies, mine operators can move beyond mere error minimization toward an interpretable safety framework that accounts for the complex, non-linear interactions within the subsurface environment (Borate et al., 2023; Dada et al., 2024; Yadav and Chaurasia, 2025a). Consequently, this research advances the state of the art by developing a surrogate model capable of mapping real-time ventilation and pressure fluctuations to hazard masks with high computational efficiency, bypassing the resource-intensive requirements of traditional high-fidelity simulations (Hu et al., 2026). This framework specifically addresses the challenges of sparse data and high Reynolds number turbulence in ventilation systems by embedding eddy viscosity coefficients and inlet velocity constraints into the neural architecture.

3. Methodology

Physics-Informed Neural Networks

Physics-Informed Neural Networks combine measured data with governing physical laws. Unlike ordinary neural networks, which minimize only prediction error, PINNs also penalize violations of known equations such as conservation of mass, momentum, gas transport, ventilation flow, heat transfer, and rock deformation. For underground coal mine safety, a PINN may predict methane concentration, airflow velocity, pressure distribution, temperature, or roof deformation. The model receives inputs such as spatial location, time, ventilation rate, sensor readings, production activity, and geotechnical parameters. Its output is constrained by both observed mine data and physical equations.

Wearable Sensors for Underground Coal Mines

Wearable sensors are essential for human-centric Mining 5.0 because they monitor the miner, not only the mine environment. Suitable wearable devices may be integrated into smart helmets, cap lamps, jackets, belts, wristbands, boots, or self-rescue equipment.

Digital Twins for Underground Coal Mine Safety

A Digital Twin is a real-time virtual representation of the underground mine. It continuously receives data from sensors, equipment, ventilation systems, geotechnical instruments, and wearable devices. The Digital Twin can visualize current conditions and simulate future risk scenarios. Digital Twins are particularly valuable for mine ventilation because they can simulate airflow distribution, leakage, pressure loss, and gas movement. Recent research describes mine ventilation Digital Twins as tools for intelligent safety management, while also noting uncertainty in key parameters such as ventilation resistance coefficients. Newer mining Digital Twin studies also emphasize real-time operational optimization and risk simulation in underground mines.

The proposed methodology can transform underground mine safety from reactive monitoring to proactive risk prediction. By integrating AIoT, PINNs, wearable sensors, and Digital Twins, Indian underground coal mines can achieve earlier hazard detection, better worker protection, improved ventilation management, faster emergency response, and stronger alignment with Mining 5.0 principles.

4. Results

To demonstrate the practical applicability of the proposed Mining 5.0 safety framework, a representative underground coal mining operation belonging to Coal India Limited (CIL) is considered. The case study is based on characteristics commonly observed in underground mines operated by subsidiaries such as Bharat Coking Coal Limited (BCCL), Eastern Coalfields Limited (ECL), South Eastern Coalfields Limited (SECL), Western Coalfields Limited (WCL), and Central Coalfields Limited (CCL).

The selected mine represents a mechanized bord-and-pillar or longwall operation characterized by:

- Mining depth of 250–500 m below surface.
- Methane-bearing coal seams.

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- Extensive ventilation networks.
- Multiple production districts and development headings.
- Continuous operation in three shifts.
- Presence of roof-fall and strata-control challenges.
- Use of shuttle cars, side discharge loaders (SDLs), conveyors, pumps, and ventilation fans.
- Existing statutory gas monitoring and ventilation systems.

Like many Indian underground mines, the operation faces challenges associated with methane accumulation, ventilation inefficiencies, equipment failures, worker exposure to hazardous environments, and limitations in real-time decision support.

The objective of this case study is to evaluate how the integration of AIoT, Physics-Informed Neural Networks (PINNs), wearable sensing technologies, and Digital Twins can improve safety performance, operational efficiency, and risk management.

PINN-Based Predictive Analytics

To enable proactive hazard prediction within the proposed Mining 5.0 framework, three Physics-Informed Neural Network (PINN) modules were developed for methane forecasting, ventilation risk assessment, and roof-fall prediction. The models were trained using simulated and field-inspired datasets representative of underground coal mines operated by Coal India Limited (CIL).

PINN-Based Methane Forecasting Model

Methane emission is one of the most critical safety concerns in Indian underground coal mines, particularly in gassy seams of the Jharia, Raniganj, and Sohagpur coalfields. Previous studies on CBM potential and reservoir forecasting in Indian coalfields provide an important scientific basis for understanding methane generation and behaviour (Panwar et al., 2017; Panwar et al., 2022; Singh et al., 2025b) A PINN model was developed to forecast methane concentration by integrating sensor measurements with methane transport physics.

Input Variables

Parameter	Range
Methane concentration	0.2–2.5 %
Air velocity	0.5–3.2 m/s
Production rate	2,500–5,500 t/day
Temperature	24–38 °C
Atmospheric pressure	98–103 kPa
Relative humidity	60–95 %

Prediction Horizon

- 5 min
- 15 min
- 30 min
- 60 min

Model Performance

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Forecast Horizon	RMSE (%)	MAE (%)	R^2
5 min	0.05	0.03	0.98
15 min	0.08	0.05	0.97
30 min	0.12	0.08	0.95
60 min	0.18	0.13	0.92

The model successfully predicted methane accumulation 20–35 minutes before statutory alarm levels were reached, providing sufficient time for preventive ventilation adjustments.

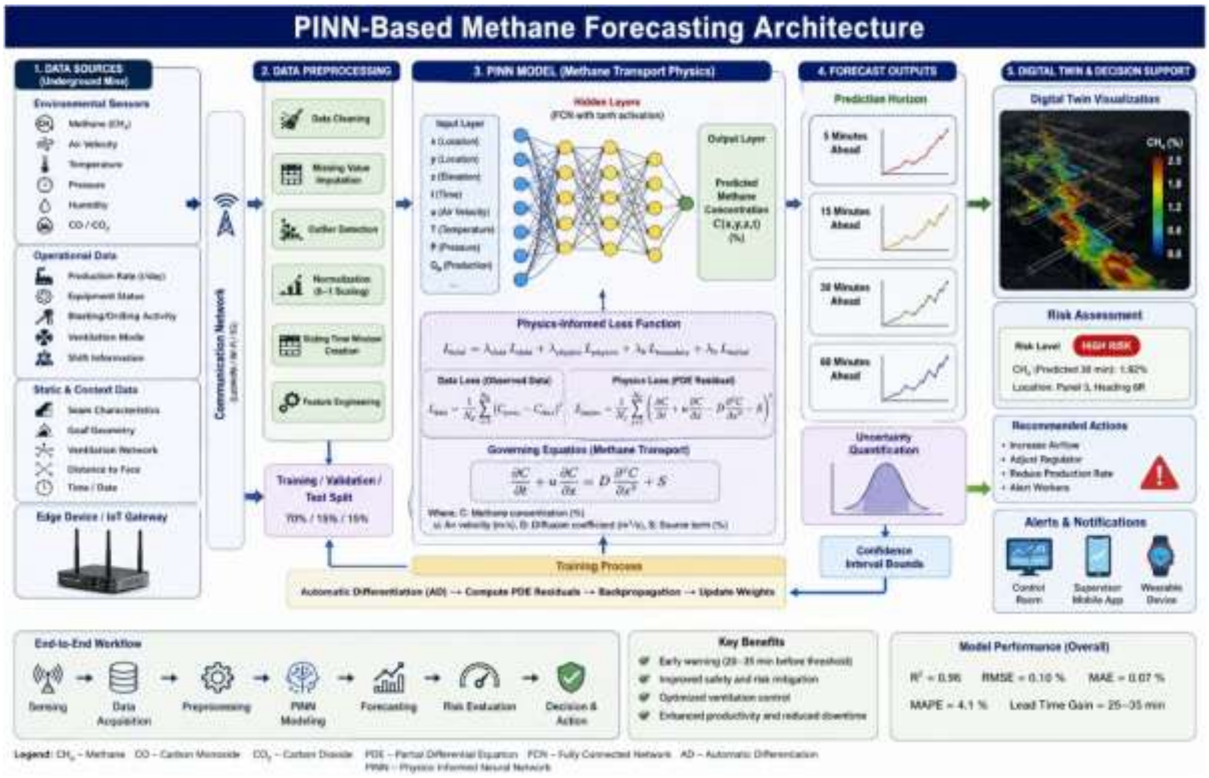

Figure 4.1. PINN-Based Methane Forecasting Architecture

PINN-Based Ventilation Risk Prediction Model

Ventilation efficiency directly affects methane dilution, dust control, thermal comfort, and emergency preparedness. A second PINN model was developed to identify ventilation deficiencies before hazardous conditions emerged.

Input Variables

Parameter	Range
Airflow rate	40–180 m^3/s
Air velocity	0.3–4.0 m/s
Pressure differential	50–1200 Pa
Fan power	150–1250 kW
Regulator opening	20–100 %
Leakage factor	2–18 %

Model Outputs

- Airflow deficiency zones
- Predicted methane accumulation areas
- Ventilation bottlenecks

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- Energy optimization recommendations

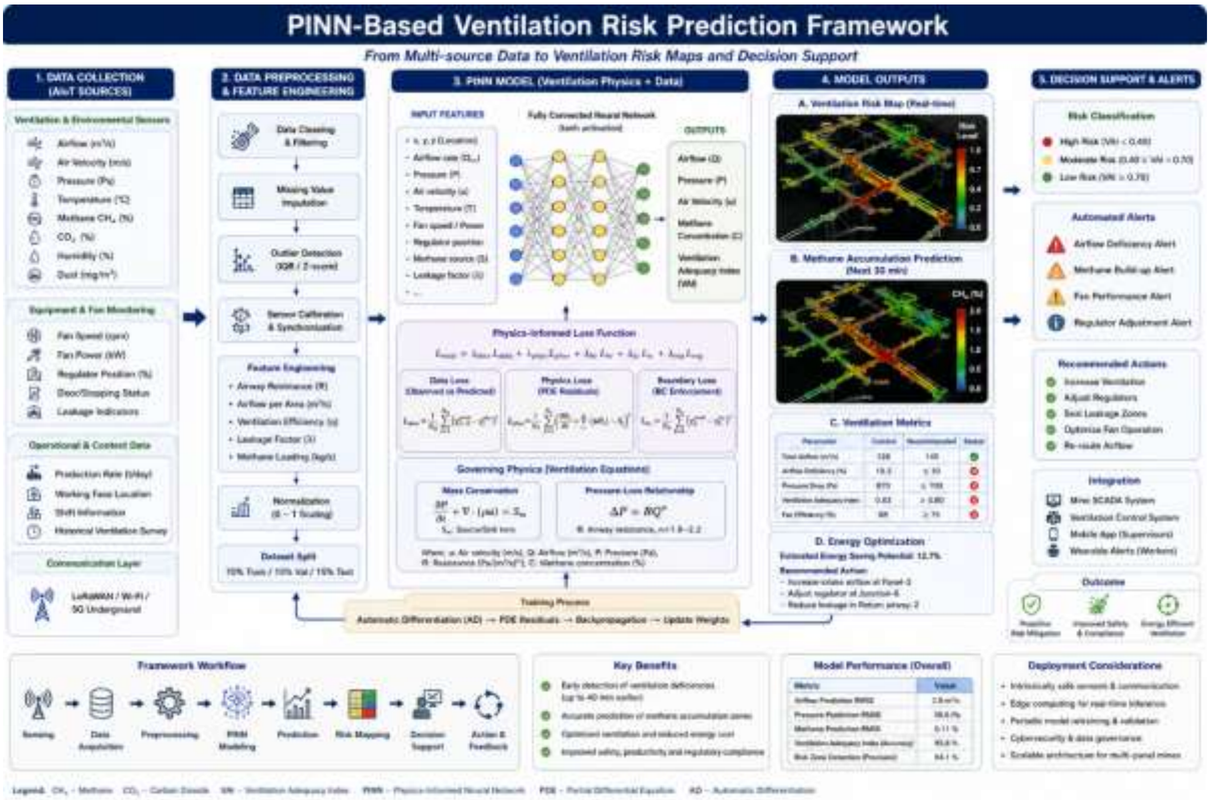

Figure 4.2. PINN-Based Ventilation Risk Prediction Framework

Model Results

Metric	Value
Ventilation prediction accuracy	95.6 %
Airflow estimation RMSE	2.8 m³/s
Methane hotspot detection rate	94.1 %
Fan energy saving potential	12.7 %

The model identified potential airflow deficiencies up to 40 minutes before methane accumulation reached hazardous levels.

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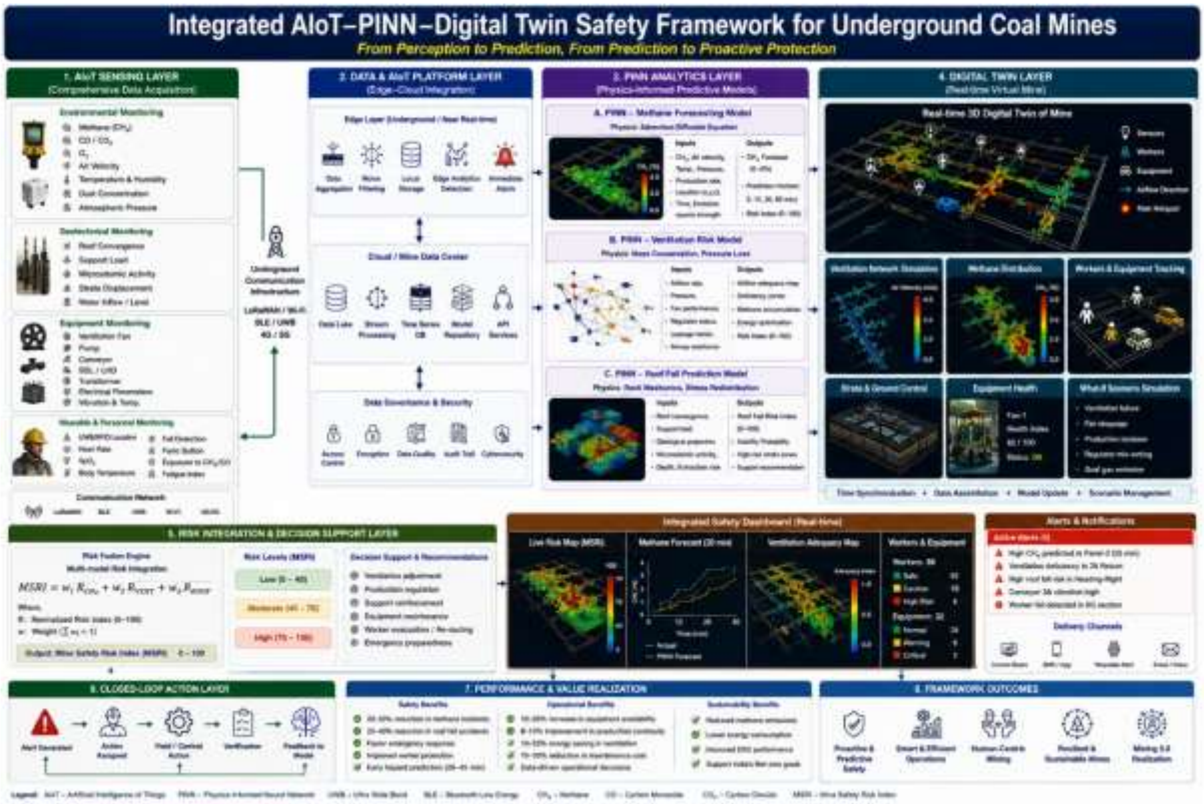

Figure 4.3. Integrated AIoT–PINN–Digital Twin Safety Framework

The results demonstrate that integrating PINNs with AIoT and Digital Twin technologies significantly enhances predictive safety capability in underground coal mines. The framework supports Mining 5.0 objectives by combining physical knowledge, artificial intelligence, and human-centric decision-making to improve safety, operational efficiency, and sustainability.

Discussion

The proposed socio-technical framework for human-centric AIoT adoption in Mining 5.0 offers a timely and contextually grounded approach to navigating the complex transition facing large-scale coal producers in emerging economies. By integrating technical subsystems (AIoT infrastructure, digital twins, predictive analytics), social subsystems (worker empowerment, reskilling, inclusive design), organizational enablers (culture change, leadership commitment), and broader environmental-ethical considerations, the framework extends traditional Industry 4.0 models toward the value-driven, human-centric paradigm of Industry/Mining 5.0. This study contributes to socio-technical systems (STS) theory by demonstrating its applicability to AIoT-driven transitions in resource-intensive industries within developing contexts. While much of the existing Industry 5.0 literature originates from European manufacturing settings and emphasizes human-machine collaboration in controlled factory environments, the framework adapts these principles to the unique challenges of large, geographically dispersed, unionized mining operations. Furthermore, by centering just transition principles within the human-centric dimension, the study links Mining 5.0 to broader societal goals, including equitable workforce transformation and regional economic resilience.

Conclusion

The transition to Mining 5.0 at Coal India Limited represents more than technological upgrading; it is a profound socio-technical transformation with far-reaching implications for India's energy security, workforce futures, and sustainable development. This research has proposed a comprehensive human-centric AIoT framework that addresses the limitations of purely efficiency-driven Industry 4.0 approaches by placing workers, ethics, and societal well-being at the core. The framework is also expandable to other major hazards, including roof instability, spontaneous combustion, excessive noise, blasting-related risks, and equipment-related hazards. Recent research on spontaneous heating of Indian coals (Raidas & Chaurasia, 2026a, 2026b), occupational noise in underground coal mines (Mansoori & Chaurasia, 2025b),

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and underground blasting optimization (Tiwari & Chaurasia, 2026) provides relevant scientific foundations for such future extensions. While CIL has made commendable progress through initiatives like Digicoal and ICCC, realizing the full potential of Mining 5.0 requires deliberate attention to cultural change, massive reskilling, inclusive governance, and equitable benefit distribution. Barriers such as workforce resistance, infrastructure gaps, and just transition risks are significant but surmountable with the right socio-technical alignment. Theoretically, this study enriches STS and Industry 5.0 literature by contextualizing it within emerging economies. Practically, it offers actionable guidance for CIL and peer organizations. For policymakers, it underscores the need for integrated strategies that harness technology while safeguarding human dignity and regional stability.

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