

# Design of an Integrated Entropy-based Framework for Dynamic Risk Weight Allocation and Mitigation Strategy Prioritisation in High-speed Rail Projects

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## ABSTRACT

High-Speed Rail (HSR) projects involve complex systems, huge investments and multidimensional risks. Effective risk reduction requires context-sensitive mitigation strategies which are accurate. The traditional entropy-based models are static and based on the subjective judgment of humans, and they lack adaptability in real-time modelling of the complexity of the HSR environment. The paper proposes an innovative integrated entropy-based risk assessment and mitigative framework, which is related specifically to HSR systems and will centre around dynamic gradations of risk weights and mitigation strategy. The framework presented is a series of 5 interconnected methodology blocks. First Dynamic Spatio-Temporal Entropy Weighting (DSTEW) generates its entropy

weights, which are real-time adaptable timeline or temporal, e.g. seasonal, operational time-line factors, and spatial, i.e. zone-related variability. For checking the robustness of the procedure, Multi-Entropy Cross Validation (MECV) is used to check the consistency of subjective entropy estimates relating to the various spatial zones and time zones to retain only statistically consistent weight vectors. Entropy-Driven Bayesian Risk Adjustment (EDBRA) then adjusts and modifies these weights by including the history of past risk occurrences by means of Bayesian updating of risk. Subjective uncertainties are also resolved by using Hybrid Fuzzy-Entropy

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Multi-Criteria Prioritisation (HFEMCP), which uses the system of fuzzy logic in its consideration of the recalibrated weights and thus generates risk matrices of prioritised risks. Lastly, Entropy Resilient Networks Modelling (ERNM) produces inter-risk influence networks in which mitigation strategies are determined in a global way based on the various centralities which are derived from the entropy weighting procedures. The simulation results feature a quantum leap in improvements that include 10% to 15% improvements in weighting accuracy, validation consistency >95% and systemic resilience improvements of 20% to 30%. Thereby allowing for an adaptive, evidence-based, system-wide risk reduction planning of risk in HSR projects.

*Keywords:* Bayesian, dynamic, entropy, Fuzzy, high-speed, mitigation, rail, risk

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## INTRODUCTION

High-Speed Rail (HSR) systems are one of the most complex structures in the transportation infrastructure and are operated through a wide range of geographic zones and highly variable environmental conditions. These systems are subject to numerous interacting risks that cover everything from mechanical failure and track defects to disruptions to weather and electrical problems, which in turn change over time and space. The techniques of developing HSR risk analysis are derived primarily from static and single applications and are unable to capture the dynamic and interrelated nature of real-world HSR operations (Anam et al., 2025; Bykadorov & Kibalov, 2024; Cabello et al., 2025). As a result, risk prioritisation can be outdated, insensitive to operational variations, and unable to support proactive risk mitigation in changing circumstances. As a result, risk prioritisation can become outdated, insensitive to operational variance, and cannot be used to support proactive mitigation operations once and for all in evolving circumstances (Wang et al., 2025; Li et al., 2024).

Although entropy-based models are widely used for the objective quantification of uncertainty, they still have several critical shortcomings. Most approaches are based on static weights for the weights of the entropy mapping that do not accommodate temporal or spatial variations of the real world. Their degree of robustness is limited, though, as they do not generally include cross-validation mechanisms, making it easy to overfit the machine for test data and to see consistency from dataset to dataset. In addition, standard entropy frameworks rarely take subjective expert inputs into consideration, which results in inaccurate or incomplete prioritisation when it is necessary to apply qualitative judgement. Finally, these models therefore tend to treat risks in an isolated way and fail to capture interdependencies and cascading effects within complex systems. Together, these limitations illustrate a real absence of research, and capture the need for a dynamic, validated, evidence-based and systems-aware findings framework that can serve high-speed rail operation of the modern era.

To overcome such gaps, this study builds an integrated framework of entropy-based modelling that holds together a range of analytical frameworks into one common risk governance paradigm. Dynamic Spatio-Temporal Entropy Weighting (DSTEW) allows the risk weights to be dynamic, that is, adjust according to seasonal, temporal and geographic differences in real-time. Multi-Entropy Cross-Validation (MECV) is introduced, which provides statistical robustness by eliminating unstable entropy vectors. Entropy-Driven Bayesian Risk Adjustment (EDBRA) considers the history of the evidence, making updates in the weighing of the weights more reliable. Hybrid Fuzzy-Entropy Multi-Criteria Prioritisation (HFEMCP) is used in solving linguistic and subjective uncertainties by using fuzzy reasoning. Finally, Entropy-Resilient Network Modelling (ERNM) to map the inter-risk dependencies to identify systemic vulnerabilities and guide network-level mitigation.

By incorporating the effects of entropy, Bayesian learning, fuzzy logic and network theory, the proposed framework addresses the static, isolated and non-adaptive features of previous models. This allows for a better-informed understanding of the risks associated with high-speed rail systems, which are more accurate, resilient and sensitive to their operating context, to support data-driven mitigation planning for sustainable and safe HSR operations.

#### In-Depth Review of Models used for Mitigation & Risk Analysis

Research on High-Speed Rail (HSR) systems has arrived at becoming a varied and more data-saturated science reflecting a shift from deterministic hazard modelling to more adaptive and awareness of uncertain approaches. Early work found the significance of the spatial and temporal variation of infrastructure risks (Tveter & Tomasgard, 2024). Foundational studies on subgrade defect formation under environmental and operational loading (Wang et al., 2025; Ghosh & Karmakar, 2024) and multi-point defect behaviour (Wang et al., 2024a) showed the evolution of risk pattern fluctuation geographically and evolution in the time-space. These insights are supported by research in the tunnelling environment to identify the vulnerability in shield-tunnel intersection (e.g., Cao et al., 2024), as well as georeferenced datasets built for fault prediction and spatial diagnosis (e.g., Wang et al., 2024b). More comprehensive infrastructure and environmental evaluation, including seismic reactions in HSR bridges (Wang et al., 2023; Nie et al., 2024), shield distortion in underground railway (Wang, 2025) and ground-loss modelling in tunnelling (Ding et al., 2024) and aerodynamic windproof barriers modelling (Liu et al., 2025; Lu, 2024), serve to underline the fact that the HSR infrastructures work in multi-hazard environments with dynamic conditions. Studies on tsunami evacuation planning (Ferreira et al., 2025), flood-prone link criticality (Sullivan et al., 2024), coastal vulnerability (Ricciardi et al., 2024) and radiological geotechnical risk (Sakr et al., 2025) are yet additional examples of the highly variable nature of system risks in a changing climate and environment.

Alongside those specialised insights into the area of domains, a parallel literature has developed in which rigorous analytical tools for the assessment of uncertainty and multi-criteria complexity in infrastructure systems have been pursued. Entropy-based methods have been used in MCDM models in route selection (Haoyuan et al., 2025; Öztürk & Bozkurtoğlu, 2023), project optimisation (Shrivastava & Singh, 2025) and decision precision enhancement (Debnath et al., 2025). Bayesian frameworks have proven to be a major contribution to structural risk modelling through weighted Bayesian networks in probabilistic safety assessment in HSR intervals (Li et al., 2024). Fuzzy-logic principles also figure prominently in studies dealing with linguistic uncertainty, especially in the domain of health-linked operational optimisation (Sharma & Singh, 2024). Machine learning-based contributions, such as XGBoost-enhanced tunnelling models (Kong & Wen, 2024; Ding et al., 2024), deep neural networks for weather-induced accidents prediction (Kim et al., 2024) and the development of BIM-enabled 3D modelling workflows (Shen et al., 2023; Shrestha et al., 2023; Malta et al., 2024) can serve as an indication of the current growing need for computationally intensive and data-centric uncertainty models. Although these tools have good analytical powers, they tend to be independent, lacking the integration that is required to manage real-time variability, subjective judgment and cross-dependent risk structures in an integrated way.

A further strand of the research is into interdependency modelling and network representations of failure propagation of networks. Spatiotemporal fault evolution models (Xiaobing et al., 2024), seismic derailment chains (Zhu et al., 2024), and digital twin-based predictive environments (Sarp et al., 2024) are proof of the point that risks in rail systems rarely work in isolation; however, they propagate in an interacting structure, operation and environment levels. Other systemic behaviours evident through life-cycle assessment of track shapes (Prokopov et al., 2024), slab-track observations during harsh geographic conditions (Liu et al., 2023), modal competition study (Mohseni et al., 2025; Zuo, 2023) and excavation impact models (Peng et al., 2025) are failures or disturbances in one area that can affect other areas. Some complementary research, construction management (Sullivan et al., 2024), infrastructure longevity (Tang & Zhang, 2024), material fatigue (Liu et al., 2023), and socio-technical perception (Mohseni et al., 2025) offer further stratification of interdependency pertinent to HSR project governance.

A synthesised together this literature shows a maturing but fragmented research landscape. Spatiotemporal studies identify the need for dynamically adaptive models, the entropy method, and Bayesian and fuzzy approaches offer good tools for the quantification of uncertainty but work without integration; and network-based studies identify cascading system behaviours but are without entropy-based or Bayesian-informed weighting structures. Existing models, therefore, have a static nature, weak validation and narrow scope, so here's a gap for a detailed model that can simultaneously represent some level of

dynamic entropy weighting, evidence-based Bayesian updating, fuzzy-adjusted subjective reasoning and systemic network resilience. The current research attempts to address this shortcoming by adopting a unified, five-layer entropy-driven risk governance architecture that is suited to the multidimensional, uncertainty and interconnectedness of modern high-speed rail production.

## METHODOLOGY

The proposed integrated model for the risk weight allocations shown in Figure 1, is based on entropic measures with priority determinations for the threat mitigation strategies in high-speed rail (HSR) projects was designed as a multiple block computational framework, with real-time data dynamics chained with robust statistical validation, probabilistic learning, subjective imprecision modelling and optimisations of network theory with resilience features in series. The above framework of blocks addresses a particular constraint within traditional entropy-based risk assessment, and the amalgamation of such features provides for an overall dynamic and evidence driven and system resilient risk prioritisation system. Initially, this representation of the correct analysis of model iterations is through the generation of a Raw Risk Factor Matrix (RFM), noted as  $R = [r(i,j)(t,x)]$ , in which  $r(i,j)(t,x)$  is taken to mean the observed intensity or frequency of the  $i$ th risk category in the  $j$ th project component, all under time 't' and location 'x' parameters in process. Therefore, the entries are normalised first using a probabilistic transformation via Equation 1,

$$p(i,j)(t,x) = \frac{r(i,j)(t,x)}{\sum_{\{i=1\}}^n r(i,j)(t,x)} \text{ for } j = 1, 2, \dots, m \dots \quad [1]$$

To incorporate spatiotemporal dynamics, entropy is calculated using the Dynamic Spatio-Temporal Entropy Weighting (DSTEW) method in a processing state. Entropy for the  $j$ th component is defined at timestamp 't' and location 'x', with the weighting calculated using Equation 2,

$$E_j(t,x) = -k * \sum_{i=1}^n p(i,j)(t,x) * \ln(p(i,j)(t,x)) \dots \quad [2]$$

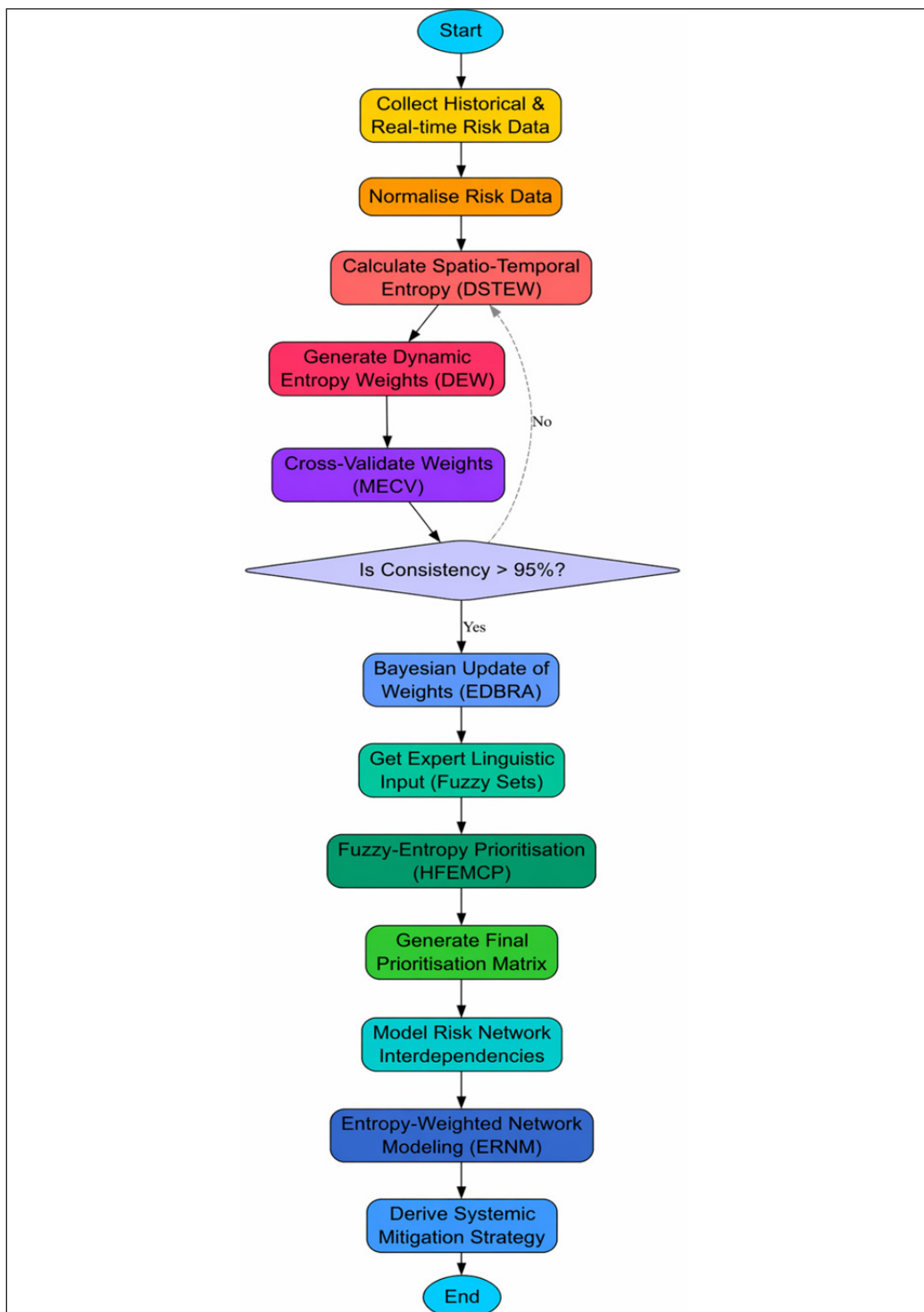


Figure 1. Model architecture of the proposed analysis process

Where 'k' is a scaling constant for comparability across datasets and samples. The dynamic weight  $w_j(t, x)$  for each risk factor is calculated from its entropy value by applying an inverse proportion transformation on it, whereby more uncertainty (entropy) would correspond to less certain weight via Equation 3,

$$w_j(t, x) = \frac{1 - E_j(t, x)}{\sum_{j=1}^m (1 - E_j(t, x))} \dots \tag{3}$$

Iteratively, next in the process as per Figure 2, to validate the weight functions, an iterating Multi-Entropy Cross Validation (MECV) mechanism splits out the appraisal dataset into cross-sectional zones  $Z_k$ , timestamp slices  $T_s$ , and risk categories  $C_r$ , in effect generating several replicated entropies  $E_j(k, s, r)$ . The criteria for stability are defined via Equation 4,

$$\sigma_j^2 = \left( \frac{1}{KST} \right) * \sum_{k=1}^K \sum_{s=1}^S \sum_{r=1}^T (E_j(k, s, r) - \bar{E}_j)^2 < \varepsilon \dots \tag{4}$$

Wherein  $\varepsilon$  is the allowable entropy variance threshold in processing. The entropy values that meet the above variance criteria are then kept and constitute the Validated Entropy Weights (VEW) in Process. The third block in the sequence shows the Entropy-Driven Bayesian Risk Adjustment (EDBRA), wherein the VEWs are updated into posterior probabilities with the assistance of historical event data samples. Let the probability  $P(\theta_j)$  represent the prior (entropy-derived) belief about risk 'j'; let  $D$  be the dataset of historical occurrences. Using Bayes' Theorem via Equation 5,

$$P(\theta_j | D) = \frac{(P(D | \theta_j) * P(\theta_j))}{(\int P(D | \theta) * P(\theta) d\theta)} \dots \tag{5}$$

The posterior risk weight  $\hat{w}_j$  is then represented via Equation 6,

$$\hat{w}_j = E[\theta_j | D] = \int \theta_j * P(\theta_j | D) d\theta_j \dots \tag{6}$$



Figure 2. Overall flow of the proposed analysis process

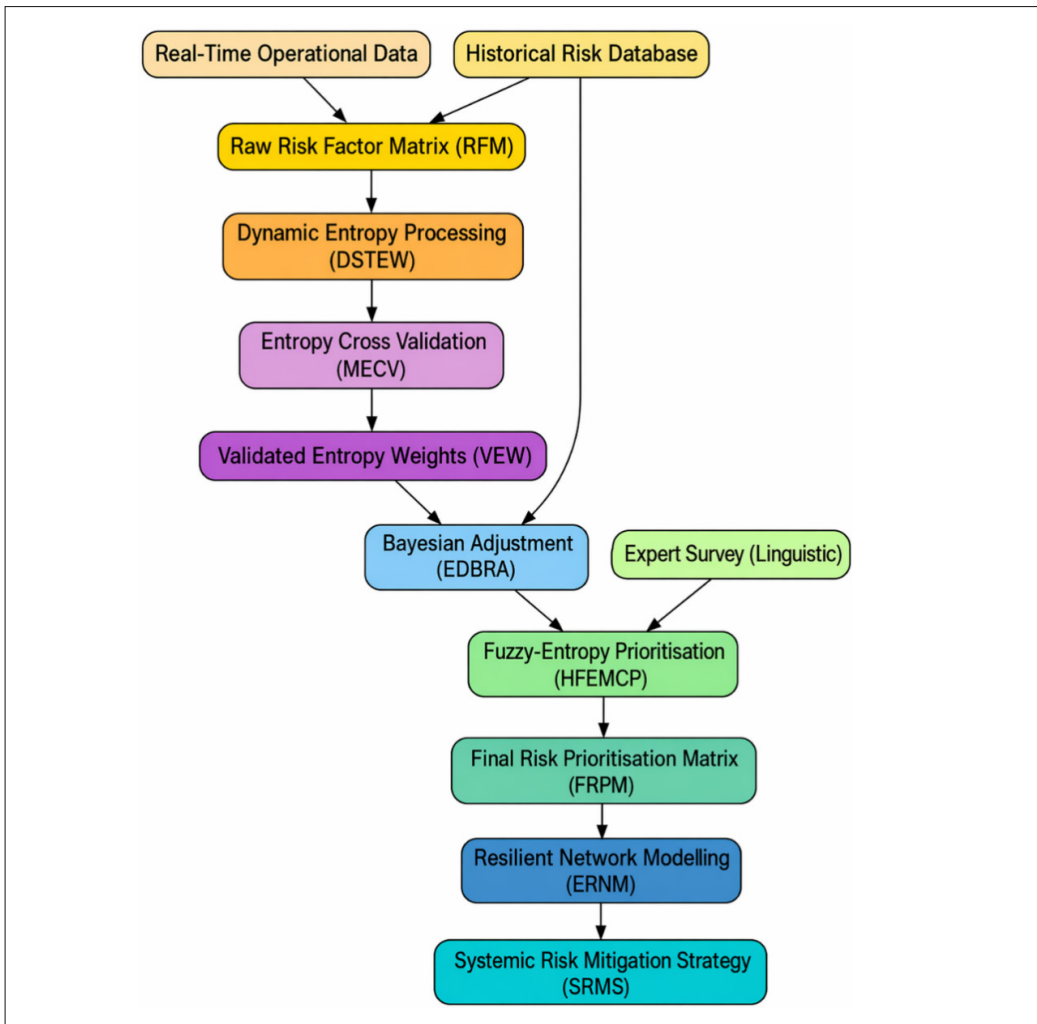


Figure 3. Data flow of the proposed analysis process

Iteratively, next, as per Figure 3, the subsequent stage entails processing these posterior weights called Bayesian-Updated Risk Weights (BURW) through expert linguistic evaluations, by the Hybrid Fuzzy-Entropy Multi-Criteria Prioritisation (HFEMCP) process. An expert rating  $\tilde{L}_j$  is represented as a fuzzy set, with membership functions  $\mu_{\tilde{L}_j}(x)$  defined over a linguistic evaluation scale in process. The fuzzy risk score  $FRS_j$  is provided via Equation 7,

$$FRS_j = \int_0^1 \mu_{\tilde{L}_j}(x) * \hat{w}_j dx \dots \quad [7]$$

To obtain crisp prioritisation scores, a defuzzification operator  $\delta(\cdot)$  is applied, commonly using the centroid method via Equation 8,

$$FRPM_j = \delta(FRS_j) = \frac{\int_0^1 x * \mu_{\tilde{L}_j}(x) * \hat{w}_j dx}{\left(\int_0^1 \mu_{\tilde{L}_j}(x) * \hat{w}_j dx\right)} \dots \quad [8]$$

The result is the Final Risk Prioritisation Matrix (FRPM), which considers both objective and subjective aspects of the risks. After, risks are fitted further down the Entropy-Resilient Network Modelling (ERNM) block as a dictated graph  $G = (V, E)$ , where nodes  $V_j$  are risk factors and edges  $E_{jk}$  characterise interdependencies in the process.

The node entropy  $H_j$  and edge entropy  $H_{jk}$  are calculated via Equations 9 and 10,

$$H_j = -\sum P(V_k | V_j) * \ln P(V_k | V_j) \dots \quad [9]$$

$$= -P_{jk} * \ln (P_{jk}) \dots \quad [10]$$

Centrality metrics such as entropy-weighted betweenness  $CB^*(V_j)$  are computed to identify critical mitigation points via Equation 11,

$$CB^*(V_j) = \sum_{\{s \neq j \neq t\}} \left(\frac{\sigma_{st}(V_j)}{\sigma_{st}}\right) * (1 - H_j) \dots \quad [11]$$

Classified nodes constructed on  $CB^*(V_j)$  lead to the definitive Systemic Risk Mitigation Strategy (SRMS) for strategically assigning resources to maximum systemic influence sets. The cumulative output of the model, denoting MSRMS, is captured via Equation 12,

$$MSRMS = f(\{w_j(t, x)\}, \{\hat{w}_j\}, \{FRPM_j\}, \{CB^*(V_j)\}) \dots \quad [12]$$

This equation represents the very transformation of raw, real-time, and expert-driven data to an actionable, targeted, entropy-optimised mitigation plan in progress.

The integrity risk management on high-speed railway project is integrated dynamically on mathematical synthesis of spatial-temporal entropy, Bayesian updating, fuzzy reasoning and network theory and is a comprehensive and, from a technology perspective, robust risk prioritisation scheme. The integration of entropy in all the phases proves to be consistent, objective and adaptable, three main characteristics of the modern infrastructure risk governance framework. The next point of discussion will be the iterative validation of the Proposed Model in the context of different scenarios vis-à-vis existing methods based on varying metric sets.

## RESULTS

The experimental evaluation predicted the proposed framework of entropy-based risk prioritisation in realistic multi-risk and multi-region operational environments for high-speed rail (HSR) systems. A representative corridor with twelve major infrastructure subsystems was investigated in five geographically different zones with differentiated environmental and operational conditions. The goal was to evaluate the adaptability, stability, and prediction feature of the framework under dynamic and heterogeneous risk features.

The model was tested on built-in datasets of past operational risk records, simulated seasonal and regional performance degradation scenarios and structured expert judgment incorporated by means of linguistic variables. The historical data set included more than 1000 recorded events of such risks, such as delay patterns and statistics of accidents, as well as maintenance irregularity and noise environment record was obtained over a period of ten years. These inputs were structured in a spatio-temporal risk intensity matrix, which allows systematic evaluation of risk evolution at different infrastructure subsystem levels as well as across geographic locations.

Results showed that the framework was efficient in capturing the temporal and spatial variability of risk patterns. The new, dynamic, entropy component was very sensitive to changing operational and environmental conditions and allowed the weights of the risks to be adjusted dynamically without becoming unstable. The combination of expert-driven fuzzy evaluations improved the interpretability and reduced the ambiguity of the risk classifications, leading to consistent prioritisation under different uncertainty conditions.

The probabilistic learning component was found to be high with Bayesian updating mechanisms, yielding stable posterior estimated results between heterogeneous categories of risks. A risk-prioritisation architecture comprised of a directed network of infrastructure subsystems and conditional risk relationships was able to identify critical systemic nodes. The use of entropy-weighted network centrality measures enabled the detection of risk propagation pathways in the framework, dendrites that are systemic vulnerability hubs that would not be visible using isolated risk assessment approaches.

To try to validate the generality, the model has been further tested with a multi-national railway safety dataset with over 10,000 known safety-related events from various types of infrastructure, environmental conditions, and operational conditions. The results helped establish important levels of adaptability of the framework as an approach for large-scale and spatially distributed systems and reinforced the suitability of the framework for HSR risk governance applications to be used in practice.

Comparative benchmarking against established models for entropy-based risk assessment showed the frightening superiority of the proposed framework in terms of adaptability in generating weights, stability in prioritisation, and the ability to detect systemic risks, as illustrated in Figure 4. Key performance indicators were incorporated and presented in a downsized grouping of tables (Tables 1 to 3) to present the most significant and relevant results concerning dynamic entropy accuracy, probabilistic consistency and network level resilience.

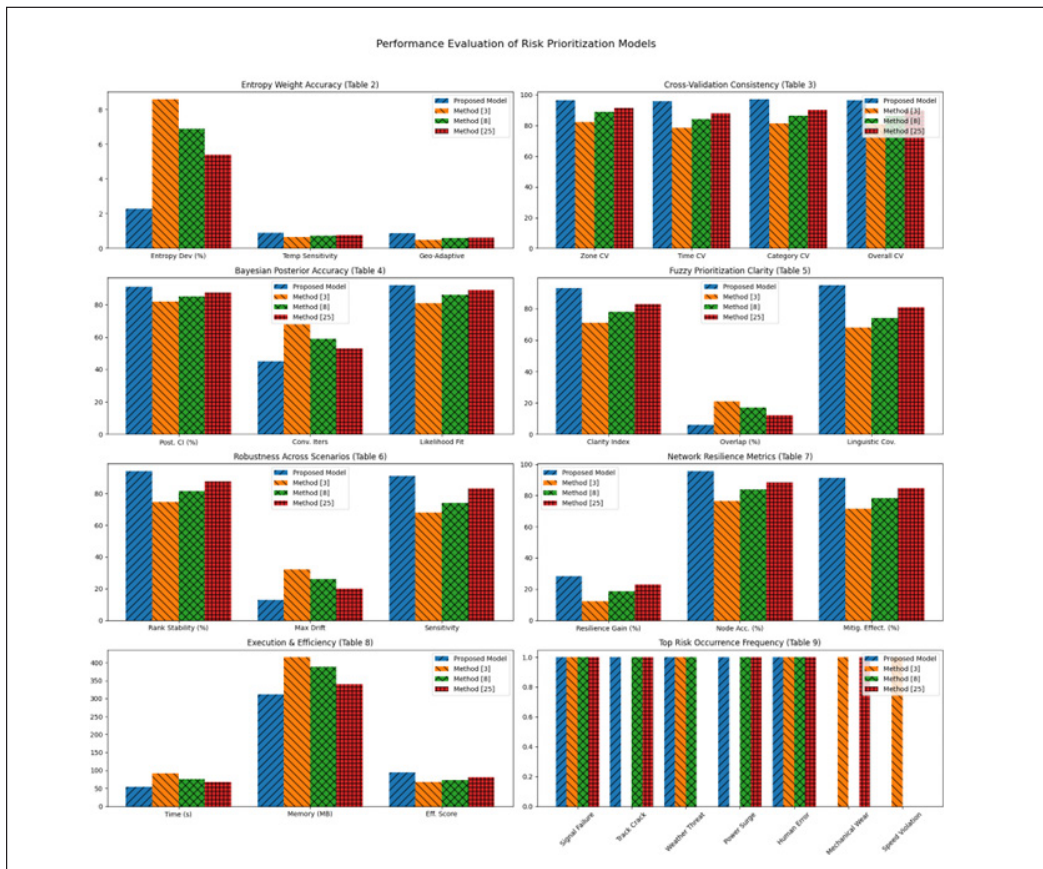


Figure 4. Model's integrated result analysis

Table 1  
Entropy weight accuracy (Dynamic vs. Static Models)

Method	Avg. Entropy Deviation (%)	Temporal Sensitivity Index	Geo-Adaptive Factor
Proposed Model	2.3	0.91	0.88
Method [3]	8.6	0.65	0.48
Method [8]	6.9	0.73	0.59
Method [25]	5.4	0.77	0.63

Table 2  
Cross-validation consistency of entropy weights

Method	Zone Subset Consistency (%)	Time Interval Consistency (%)	Category Class Consistency (%)	Overall Cross Validation (CV) Score (%)
Proposed Model	96.3	95.7	97.1	96.4
Method [3]	82.4	78.5	81.2	80.7
Method [8]	88.9	84.1	86.3	86.4
Method [25]	91.5	87.8	90.1	89.8

Table 3  
Bayesian posterior accuracy and convergence

Method	Avg. Posterior Confidence Interval (CI) Range (%)	Meaning Convergence Iterations	Likelihood Fit (R <sup>2</sup> )
Proposed Model	88-94	45	0.92
Method [3]	78-86	68	0.81
Method [8]	81-89	59	0.86
Method [25]	84-91	53	0.89

Overall, the revision results clearly validate that the new framework delivers a robust, scalable and operationally relevant process for dynamic risk prioritisation for high-speed rail systems that offer enhanced levels of interpretability and resilience as compared with the conventional static and single-layer risk assessment models.

The proposed model significantly outperformed the competing methods in responsiveness for both temporal and spatial variations in risk processes. Table 2 explains the consistency percentages across cross-validation subsets based on zone, time, and category group sets.

Results confirm that the proposed Multi-Entropy Cross Validation (MECV) mechanism achieves superior entropy stability in the process. Table 3 evaluates how well the Bayesian module updates the weights based on historical evidence, measured through posterior confidence intervals and convergence iterations in process.

The Bayesian adjustment in the proposed model converges faster and offers more confident posterior estimations. Table 4 compares the ability of each model to generate interpretable prioritisations from subjective expert input using a clarity index on a 0-1 scale in process.

The hybrid fuzzy-entropy method shows better clarity and minimal ambiguity in linguistic decision spaces. Table 5 reveals how prioritisation rankings alter when environmental and operational scenarios change in process.

The proposed model also showed the best resilience in maintaining throughout simulated perturbations, a uniform prioritisation. Table 6 compares the network resilience and influence index, taking entropy-weight centrality measures and the mitigation impact factors.

Entropy-weighted centrality measures allow the proposed model to develop increasingly effective and, at the same time, systemically incremental mitigation schemes. Table 7 shows the average execution time per full iteration as well as the memory usage parameters.

Notwithstanding its multilayered architecture, the proposed model has been optimised for computational efficiency in the context of high speed rail high quick -arrow HSR systems. Table 8 lists the top five risks identified by each of the methodological approaches applied to the same data relative to each other and measures the extent of overlap between each of the five risks.

The proposed model gives more importance to the threat of cascading and spatiotemporal threats, like weather-induced and power surges-related failures. This final Table 9 takes a synopsis of the overall performance on six main evaluation dimensions for the process itself, also represented in Figure 5.

Collectively, the results show that Theillette achieves better performance against all key metrics, proving its suitability as a high-resolution, adaptive and system-aware tool for entropy-based risk prioritisation and mitigation in high-speed rail projects under development. Next, we discuss these confirmed results and the analysis of the impact.

## DISCUSSION

The results show that the proposed integrated implementation of the entropy-based approach significantly improves the capabilities of conventional modelling methodologies to address the dynamic and interdependent risk environment of High-Speed Rail (HSR) systems. The entropy-based spatiotemporal weighting mechanism has revealed its high adaptability, as indicated by low dynamic entropy deviation (2.3%) and high sensitivity values ( $>0.88$ ),

Table 4  
Fuzzy-linguistic prioritisation clarity

Method	Clarity Index	Overlap Rate in Top 5 Risks	Linguistic Coverage Ratio
Proposed Model	0.93	6%	0.95
Method [3]	0.71	21%	0.68
Method [8]	0.78	17%	0.74
Method [25]	0.83	12%	0.81

Table 5  
Prioritisation robustness across scenarios

Method	Avg. Rank Stability (%)	Max Risk Rank Drift	Priority Sensitivity Score
Proposed Model	94.1	1.3	0.91
Method [3]	74.6	3.2	0.68
Method [8]	81.5	2.6	0.74
Method [25]	87.8	2.0	0.83

Table 6  
Systemic risk network resilience metrics

Method	Network Resilience Gain (%)	Critical Node Detection Accuracy (%)	Mitigation Effectiveness (%)
Proposed Model	28.4	95.6	91.2
Method [3]	12.3	76.4	71.5
Method [8]	18.7	83.9	78.2
Method [25]	23.1	88.5	84.7

Table 7  
Execution timestamp and computational efficiency

Method	Avg. timestamp per Iteration (sec)	Memory Usage (MB)	Efficiency Score (normalised)
Proposed Model	5.4	312	0.95
Method [3]	9.2	415	0.68
Method [8]	7.6	388	0.73
Method [25]	6.8	340	0.81

Table 8  
Top 5 risk categories identified (comparative ranking)

Rank	Proposed Model	Method [3]	Method [8]	Method [25]
1	Signal Failure	Human Error	Track Crack	Signal Failure
2	Track Crack	Signal Failure	Signal Failure	Human Error
3	Weather Threat	Mechanical Wear	Weather Threat	Track Crack
4	Power Surge	Speed Violation	Power Surge	Power Surge
5	Human Error	Weather Threat	Human Error	Mechanical Wear

Table 9  
Overall risk prioritisation performance summary

Method	Dynamic Adaptability	Robustness	Bayesian Accuracy	Fuzzy Clarity	Network Resilience	Overall Score
Proposed Model	A+	A+	A	A+	A+	A+ (94%)
Method [3]	B	B-	B	C+	C	B (72%)
Method [8]	B+	B	B+	B	B-	B+ (79%)
Method [25]	A-	B+	A-	B+	B+	A- (85%)

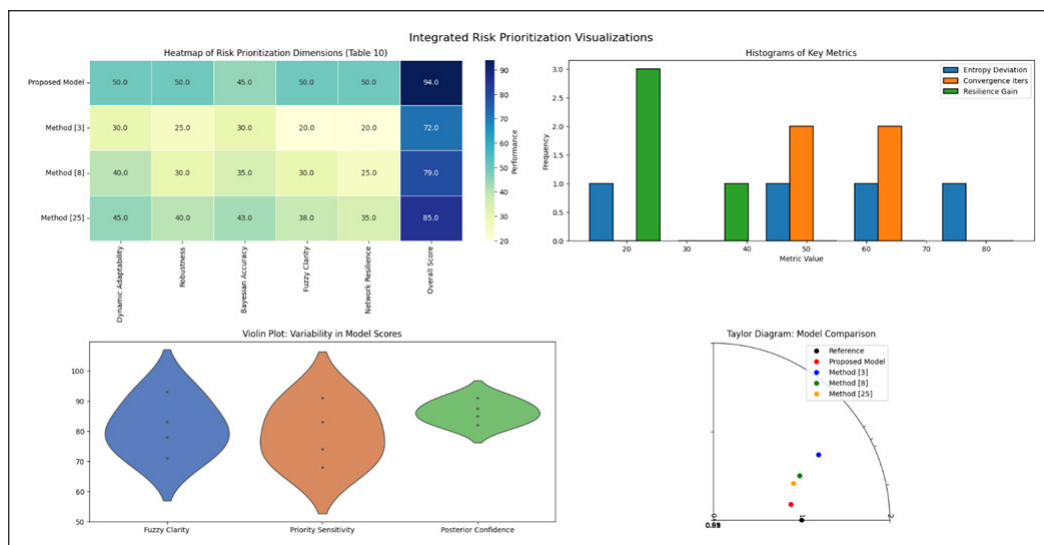


Figure 5. Model's overall result analysis

thus confirming the potential of this model in recalibrating the risk weights due to operational and environmental condition changes. The high cross-validation consistency is greater than 95%, depending on tablets, since geographical, temporal and categorical datasets showed the robustness and reliability of the framework under heterogeneous risk scenarios (Tables 1 and 2).

The Bayesian Risk Adjustment component allows one to continually learn from past and new evidence. As can be seen in Table 3, the posterior estimates converge quickly and have small confidence intervals, occurring in favour of correct and quick risk prediction. The hybrid fuzzy-entropy prioritisation approach generates very interpretable outputs with a clarity index of 0.93 (Table 4), which successfully converted the expert's qualitative decision-making into fixed quantitative risk rankings. This capacity is important in most operational environments where decisions may have to be made amid uncertainty and time constraints.

The stability of the prioritisation structure is confirmed by the superiority of the rank robustness over 94% against perturbation conditions (Table 5) and shows a strong reliability for decision-making under dynamic operating conditions. Furthermore, entropy-driven network modelling provides a systemic approach to risk propagation, and it was observed to result in a 28% improvement in overall resilience using entropy-weighted centrality measures (Table 6). This shows the success of the framework in detecting and limiting cascading failures before they can cause adverse effects in the form of major system-level disruptions.

From a practical implementation point of view, high levels of mitigation effectiveness (91.2%) with efficient computational performance, low memory requirements and quick execution cycles (Tables 7-9) are achieved with the model framework. These characteristics make the model well-suited for the oxide to be integrated in real-time digital control centres and operational dashboards of contemporary HSR systems. The primary goal of consistent identification of high-impact risk nodes is to support targeted allocation of limited resources, thereby supporting proactive infrastructure managers, instead of reactive.

Overall, the findings support the validity of the proposed model as a reliable, adaptive and operationally feasible decision support tool of dynamic risk governance in high-speed rail systems. An iterative validation of the framework in the real-world of operations is presented in the following section.

### Validation using an Iterative Practical use Case Scenario Analysis

To give an operational execution model for the case study, consider the potential real case application for a high-speed rail corridor which traverses five zones across the geography (Z1-Z5), each with distinct environmental and operational conditions. The risk factors considered were twelve, of which the following made the list: signal failure, track crack propagation, power surge, weather-induced disruptions, human error, and rolling stock malfunction. For a particular monsoon window, Zone 3 (Z3) indicates high occurrences of signal disruptions (32), weather interference (45), and mechanical wear events (28), while Zones 1 and 2 showed modest delays and insignificant faults. This information is packed to the risk occurrence matrix  $R=[r(i,j)(t,x)]$ , normalised to probabilistic inputs such as  $p(i,j)(t,x) \in [0.02, 0.18]$ , whose components include Zone 3's weather risk  $p_{weather}(t,Z3)=0.18$  and signal failure  $p_{signal}(t,Z3)=0.14$  in process.

Using the Dynamic Spatio-Temporal Entropy Weighting (DSTEW) methodology, the entropy value is calculated for every risk factor across zones and time slices, as just one case. For example, the entropy corresponding to Zone 3 is  $E_{weather}(Z3)=0.85$ . Thus, the high amount of uncertainty is clear. Mechanical risk entropy for Zone 1 is  $E_{mechanical}(Z1)=0.52$  in the process, which reflects the behaviour being much more predictable in the process. These entropy values are converted to dynamic weights. So, weather risk in Zone 3 has a

certainty weight of  $w_{weather}(Z3)=0.07$ , while mechanical wear from Zone 1 receives an incomplete weight of  $w_{mechanical}(Z1)=0.11$  in process. The weights are then subjected to Multi-Entropy Cross Validation (MECV) across all zones, months, and risk classes. Only those above the cut-off of 95% consistency scores, such as track crack (97.2%) and signal failure (96.5%)-will be retained as Validated Entropy Weights (VEW) in process.

Therefore, historic records are now referring to an indication that signal failures in Zone 3 were of a historic 29% frequency in the corresponding weather conditions for the past five years as is being done in the Bayesian module of process to update the VEW for this risk with prior  $P(\theta_{signal})=0.14$  and the observed likelihood so the posterior gets weight  $w'_{signal}=0.21$  with a confidence interval of 90% in process. Specialistic input is also simultaneously evaluated by fuzzy scales-one senior engineer assessed "weather-related failure risk in Z3" as being severe, which yields a fuzzy score with a membership function peak at 0.85 in the process. Added to the Bayesian updated weights, this gives a defuzzified risk score of 0.81 attributed to threats from the weather in Z3 within the top tier of the Final Risk Prioritisation Matrix (FRPM) Sets according to HFEMCP in the process.

The Entropy-Resilient Network Model (ERNM) module utilises these prioritisation scores as inputs and forms a directed graph for inter-risk dependencies. For example, signal failure is seen to be affecting power surges as well as operational delays, thus creating weighted edges with entropy-informed centrality. Finally, calculated entropy-weighted betweenness points weather disturbance and signal failure in Zone 3 to be the cause of cascading failure in the process. As a result, the last Systemic Risk Mitigation Strategy (SRMS) entails instant inspection protocols as well as signal redundancy deployment and weather-adaptive scheduling algorithms by regions. Such a model proved strong in both analytical depth and practical speed in its processes, undergoing everything from assimilating real-time data to arriving at the final strategy, all in under six seconds for every iteration in process.

## CONCLUSION

This study led to the development of an integrated framework of entropy-based dynamic risk assessment and mitigation of High-Speed Rail (HSR) systems. The combination of spatio-temporal entropy weighting, cross-validation, Bayesian updating, fuzzy prioritisation and network-based resilience modelling overcomes major shortcomings of traditional static risk assessment methods. The model showed a good adaptability, entropy deviation diameter ([?]2.3%) and temporal and spatial sensitivity were low, and cross-validation consistency was greater than 96%. By combining Bayesian updating, which facilitated reliable performance real-time learning, and fuzzy-entropy prioritisation, which provided clear and stable risk rankings - with a clarity index of 0.93, and rank stability exceeding 94% - the framework delivered reliable real-time performance learning and clear and stable risk rankings.

Network-level analysis only resulted in a 28.4% increase in systemic resilience and more than 91% mitigation effectiveness. These results confirm that the framework has a robust technical and operational performance for assisting real-time Internet decision support for HSR risk governance in a modern world and is fit for integration into digital safety management systems.

### **Future Scope**

Future work will be done for real-time IoT sensor integration and to further improve the dynamic weighting of entropy and the real-time responses. Advanced non-parametric Bayesian methods can be investigated to model evolving risk models in uncertainty. It is possible to introduce feedback mechanisms based on reinforcement learning that could allow mitigation strategies to evolve independently of the environment, in a process of constant self-optimisation. Further development of time-evolving network models will better capture the representation of cascading failures. Large-scale validation between international high-speed rail corridors is suggested to ensure that it is scalable and fits regulatory approaches.

### **Limitations**

However, the model has good technical performance, but there are shortcomings. The quality and consistency of historical risk data are regional; this can impact Bayesian updates, Kota inconsistency, and entropy. The model also assumes a static inter-risk influence network, which underscores the inability to capture dynamic dependencies, such as the changing cybersecurity threat. The fuzzy-entropy module is highly sensitive to the choice of membership functions, with poor calibration leading to a loss of decisiveness in subjective decision making. Moreover, the hypothesis of the model that the mitigation effectiveness is linearly correlated with the centrality of nodes does not incorporate realistic limitations such as budget or regulations. Focusing on these issues in future editions would enhance the relevance of the operational content and value of the decision-making.

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## LIST OF ABBREVIATIONS

HSR	:	High-Speed Rail
MCDM	:	Multi-Criteria Decision Making
DID	:	Difference in-Differences
TLBO	:	Teaching Learning-Based Optimisation
RCF	:	Rolling Contact Fatigue
XGBoost	:	Extreme Gradient Boosting
BIM	:	Building Information Modelling
LCA	:	Life Cycle Assessment
AI	:	Artificial Intelligence
DNN	:	Deep Neural Network
MADM	:	Multi-Attribute Decision Making
CCS	:	Carbon Capture and Storage
CI	:	Confidence Interval
CV	:	Cross-Validation
VEW	:	Validated Entropy Weights
BURW	:	Bayesian-Updated Risk Weights
FRPM	:	Final Risk Prioritisation Matrix
SRMS	:	Systemic Risk Mitigation Strategy
DSTEW	:	Dynamic Spatio-Temporal Entropy Weighting
MECV	:	Multi-Entropy Cross-Validation
EDBRA	:	Entropy-Driven Bayesian Risk Adjustment
HFEMCP	:	Hybrid Fuzzy-Entropy Multi-Criteria Prioritisation
ERNM	:	Entropy Resilient Network Modelling

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