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Risk Monitoring and Early Warning for Urban Critical Infrastructure: An Analytical Framework and Scenario Comparison

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Abstract

Risk monitoring and early warning for critical urban infrastructure face challenges such as infrastructure interdependence, data heterogeneity, cross-system risk propagation, and incomplete response chains. Existing research has yielded substantial results in areas such as urban lifeline monitoring, infrastructure interdependencies, digital twins, and intelligent early warning systems; however, the disparities in early warning capabilities across different application scenarios remain insufficiently explained. Based on a review of representative literature, this paper constructs an analytical path of "object layer - monitoring layer - early warning layer - scenario layer". Furthermore, it compares three categories of scenarios—flooding and urban drainage, road and rail transport, and energy storage, transport, and ports—across four dimensions: mechanistic clarity, data continuity, platform coupling, and closed-loop maturity. Research suggests that early warning capability does not depend on the specific name of an individual technology, but rather on whether the underlying risk mechanisms can be elucidated, whether monitoring data can consistently support the models, whether the model outputs can be integrated into platform rules, and whether the feedback from response actions can be used to iteratively refine the assessment process. This framework can serve as a reference for scenario assessment, system development, and the selection of technical roadmaps in the governance of urban safety risks.

Keywords

urban critical infrastructure, risk monitoring, early warning systems, maturity assessment, scenario comparison

1. Introduction

Urban critical infrastructure forms the foundation for maintaining the continuity of urban operations. Its importance comes not only from the function of a single facility, but also from the dependence formed between facilities in long-term operation. Water supply, drainage, gas, electricity, transportation, communication, underground space, energy storage and transportation, ports and other systems are often connected and constrained in high-density cities, forming a composite system jointly maintained by physical connection, functional dependence, information control and management coordination. Therefore, the risk will not always stay within a single device or a single system, but may spread along the chain of load transfer, spatial proximity and business interruption, resulting in service degradation, compounded risks, and even cascading failures.

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Urban safety governance not only needs to find abnormal points, but also needs to judge the systemic consequences that may be caused by abnormalities.

The theory of interdependence provides a basis for understanding this problem. Rinaldi et al. were among the first to distinguish the physical, network, geographical and logical interdependence between infrastructure [1], Ouyang systematically reviewed the interdependent infrastructure modeling and simulation paths [2], Buldyrev et al. revealed the formation mechanism of catastrophic cascading failure in interdependent networks from the perspective of complex networks [3]. In recent years, research has further turned to multilayer networks, resilience assessment and hybrid modeling, emphasizing the degradation of simultaneous function, recovery trajectory and uncertainty propagation under extreme event conditions [4-6]. These studies show that infrastructure early warning should not only answer "whether the fault has occurred", but also explain which dependencies the failure may be amplified through, and which nodes or links need priority intervention.

At the level of technical application, methods such as the Internet of Things, remote sensing, digital twins and machine learning have been introduced into the security management of urban critical infrastructure [7-11]. Among them, digital twin and post-disaster risk management research mainly supports the coupling between monitoring data, spatial model and scenario simulation [12-14]; Flood forecasting and urban flooding research focus on multi-source data integration and short-term forecasting ability [15-19]; The cascade transmission research of traffic and track scenarios is mainly used to explain network node disturbance and key component identification [20-21]; Knowledge graph, intelligent decision-making and crisis communication research support more early warning interpretation, response rules and multi-disaster decision-making [22-25]. From the perspective of actual governance, the improvement of monitoring capacity does not necessarily lead to the improvement of early warning ability; If the multi-source heterogeneous data cannot enter the model calibration and explain the cross-system impact, the early warning system is easy to stay at the technical detection level, resulting in disconnection from the actual actions of the response subject [26-29].

Focusing on the above problems, this article analyzes from two angles. One is the perspective of risk transmission, which examines how local anomalies extend into cross-system disturbances through facility dependence, spatial proximity and business connections; The second is the perspective of data governance, which examines how the monitoring data enters the risk research, judgment and response process through cleaning, organization, calibration and platform interface. In terms of comparative caliber, this article first examines the depth of mechanism modeling, the degree of coupling between the platform and data, and the breadth of the scene coverage, and then summarizes it into the four evaluation dimensions of mechanism clarity, data continuity, platform coupling degree and closed-loop maturity. Unlike simple listing monitoring technologies, this article focuses on why similar technologies form different early warning capabilities in different infrastructure scenarios.

The main work of this article includes three aspects: First, put forward a four-dimensional maturity evaluation framework for urban critical infrastructure monitoring and early warning. Include risk mechanisms, data conditions, platform interfaces and governance processes into the same analysis caliber to explain the differences in early warning capabilities; Second, build the analysis path of "object layer-monitoring layer-early warning layer-scene layer", Explain the basic process of operating status data entering the risk judgment and response process; Third, compare the three scenarios of flood and urban drainage, road and rail transit, energy storage and transportation and port, Analyze the differences in maturity of different scenarios in terms of mechanism interpretation, data continuity, platform embedding and response feedback.

In terms of literature selection, this article focuses on critical infrastructure, risk monitoring, risk early warning, digital twins, interdependence, urban lifeline and comprehensive early warning of urban safety. Focus on the research results in Chinese and English in recent years, and retain a small number of classic documents of foundational significance. Literature retrieval and screening mainly serve three analysis tasks: Explain infrastructure interdependence and cascade failure, sort out the main progress of state perception, platform integration and digital twin modeling, and compare the early warning differences in scenarios such as flood drainage, transportation rail transportation, energy storage and ports. This article does not pursue exhaustive listing, nor does it treat the samples as a strict systematic review, but carries out a framework comparison on the basis of representative literature review.

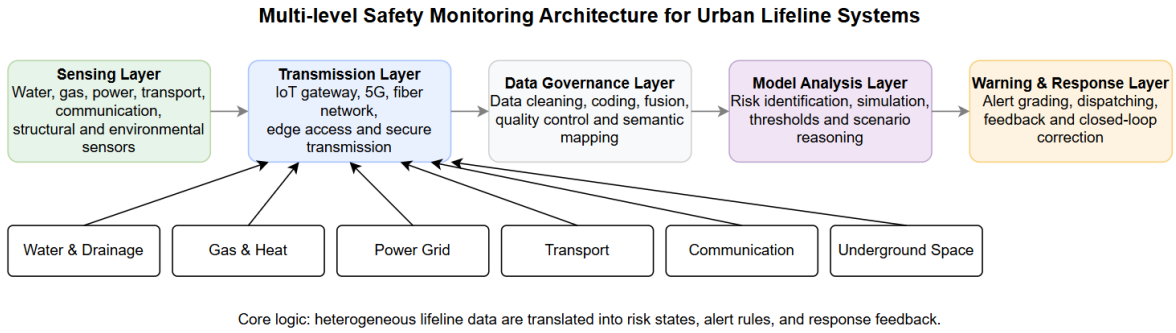
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2. Defining Urban Critical Infrastructure and the Analytical Framework

With the increasing complexity of urban space and industrial activities, underground space, new energy storage and smart ports have been intertwined and coupled with the traditional urban lifeline due to business continuity and risk spillover effects [7]. In order to avoid excessive expansion of the concept, this study defines the scope of analysis based on three criteria. First, the foundational importance, that is, the continuity of facilities directly maintains the core public services and economic activities of the city; The second is system interdependence, which emphasizes the physical and logical dependence between facilities due to power supply, communication or spatial proximity; The third is risk spillover, that is, the consequences of failure have the potential motivation to cause cross-system cascade failure along the conduction chain. The above judgment shows that "criticality" is not a static label of the facility name, but is determined by its network dependence location and dynamic spillover ability in the urban composite system.

The research basis of risk monitoring and early warning comes from both governance needs and technological evolution. At the governance level, urban safety management is shifting from single disaster response to comprehensive disaster prevention and mitigation, and from post-event feedback to front-end prevention and control [10]. At the technical level, monitoring and early warning is shifting from single-point collection and threshold alarming to multi-source perception, dynamic identification, model deduction and knowledge-assisted decision-making. The development of methods such as interdependent networks, resilience assessment, digital twins, machine learning and Knowledge graph allows cross-system risks to be transformed into analytical problems between structures, parameters, states and rules [4-6]. Figure 1 summarizes the multi-level monitoring logic of urban lifeline engineering from perception access, data governance to early warning response.

Figure 1: Multi-level safety monitoring architecture for urban lifeline systems (adapted from Ref. [11])



In order to make the follow-up comparison have a relatively stable caliber, this article adopts a four-layer analysis path of "object layer-monitoring layer-early warning layer-scene layer". The object layer focuses on facility attributes, failure mode and system coupling relationship, and clarifies which objects need to be included in critical infrastructure risk governance; The monitoring layer focuses on sensing, remote sensing, video, platform data and model compensation, explaining how the operating state forms analyzable data; The early warning layer focuses on mechanism models, machine learning and knowledge reasoning to explain how abnormal states enter risk risk assessment; The scenario layer combines data conditions, risk mechanisms and business processes to examine whether the early warning results can enter the actual governance process. Four levels constitute a continuous analysis process from object identification, state perception, risk explanation to governance response.

This framework is used to identify interlayer fractures in the process of monitoring and early warning. Unclear object boundaries will weaken the consistency of monitoring indicators and model input; The monitoring layer lacks semantic structure and quality control, and it is difficult for data aggregation to enter risk deduction; Without scene verification in the early warning layer, it is difficult for the model output to enter the governance process; The scene layer lacks a comparative scale, and it is difficult to judge the maturity of different technical routes. Therefore, this paper takes closed-loop integrity as the overall evaluation scale to examine whether the existing research has completed the continuous transformation from object identification, state monitoring, risk risk assessment to response decision-making.

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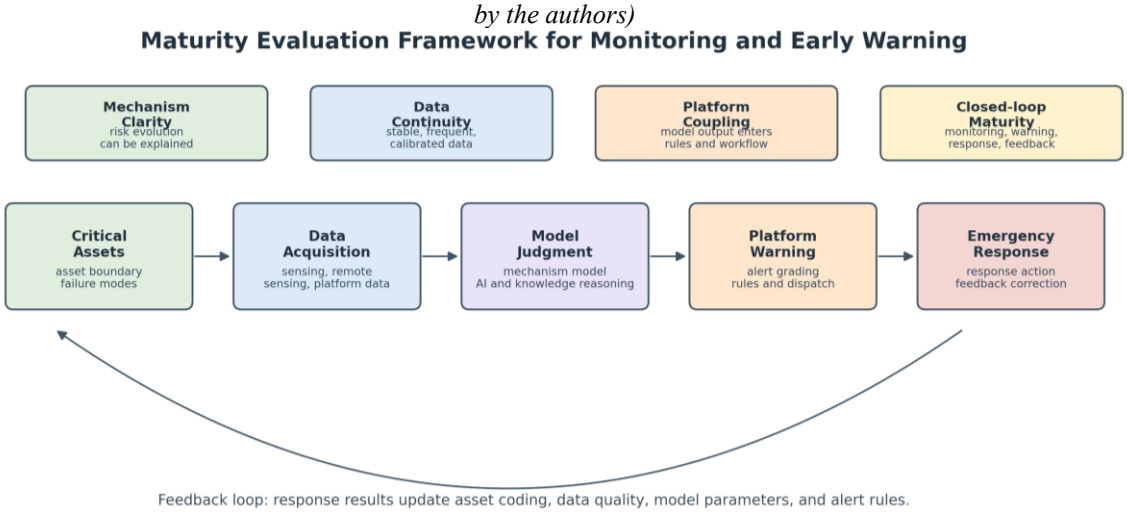
Specifically, closed-loop integrity can be developed from four dimensions. The clarity of the mechanism focuses on whether risk evolution has relatively clear physical, business or network dependence; Data continuity focuses on whether the monitoring data has a stable source, sufficient frequency, spatial coverage and calibrability; The platform coupling focuses on whether the model output can enter the platform data interface, alarm rules and governance processes; Closed-loop maturity comprehensively examines whether monitoring, judgment, alarm, response and feedback can be operated continuously. Resilience studies usually emphasize the importance of performance degradation, recovery speed and actionable indicators [28-29]. This article draws on this idea, but does not treat the four-dimensional framework as a strictly quantitative model, but uses it as an explanatory comparison caliber in the literature review. The four dimensions correspond to the four types of evidence: risk mechanism, data conditions, platform interface and response feedback.

In order to enhance the operability of comparison, the four evaluation dimensions are further divided into three levels: high, medium and low. The clarity of the mechanism means that the risk process can be explained by a clearer physical mechanism, business process or network dependency; Being at a medium level means that the local mechanism is relatively clear, but cross-system transmission still needs to rely on empirical inference; If it is lower, it means that the risk is often formed by the superposition of multiple subjects, multiple objects and multiple disturbances, which is difficult to explain by a single model. High data continuity is usually manifested as stable data source, high acquisition frequency and calibration quality; It is at a medium level, indicating that the local data is sufficient, but the spatial coverage or time continuity is still insufficient; If it is low, it is often manifested as data heterogeneity, obvious lack of measurement or inconsistent interface standards.

The high degree of platform coupling shows that the model output can support the platform's risk assessment and linkage response; It is at a medium level, indicating that the platform can gather data, but the model call and response linkage are still insufficient; If it is lower, it will stay in the display or archiving function. The high maturity of the closed loop means that monitoring, research, early warning, response and feedback can form a more complete operation process; It is at a medium level, indicating that monitoring and prediction are relatively mature, but the response feedback is insufficient; Low indicates that there is still an obvious disconnect between monitoring, model and governance actions. The above classification is mainly used for horizontal comparison, which does not mean that there is absolute superiority and inferiority between different scenarios.

Based on the above caliber, this article does not make accurate scoring of three types of scenarios, but makes hierarchical comparisons based on documentary evidence and the integrity of technical processes. Specific judgment mainly comes from four types of information: Whether the risk process has an explainable mechanism, whether the monitoring data is continuous and calibrable, whether the model results can enter the platform interface and alarm rules, and whether the response feedback can reversely correct the monitoring and model. This can not only preserve the operability of the review research, but also avoid making excessive quantitative judgments in the absence of unified samples and platform running data. Figure 2 shows the maturity evaluation framework on which the follow-up analysis is based.

Figure 2: Maturity evaluation framework for monitoring and early warning of urban critical infrastructure (compiled by the authors)



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3. Monitoring Technologies and System Architectures

The core task of the monitoring layer is to transform facility operation, environmental disturbance and structural changes into data that can be collected, transmitted, and analyzed. Due to the obvious differences in spatial scale, failure mode and operating environment of infrastructure, it is difficult for a single perception to cover all risk information. According to the observation layout method and data role, the existing monitoring technology can be summarized into three categories: point-based sensing, surface domain perception and model-assisted sensing. The first two categories mainly provide direct observation data, and the latter category is more used to estimate the insufficient observation area or the state that is difficult to directly measure. The three methods together form the data basis for risk risk assessment, but they themselves are not equivalent to the ability of early warning.

Point-based sensing is aimed at local objects such as pipe network nodes, structural parts and equipment compartments. In terms of structural health monitoring and high-voltage power equipment monitoring, scholars have developed a capacitor sensing damage identification system based on the Internet of Things and a switchgear remote monitoring architecture [30-31] respectively. The point-source perception sampling frequency is high, but the coverage is limited, and it cannot be explained alone whether the local signal will evolve into a cross-system cascading risk.

Area-based sensing is aimed at continuous space, linear corridors or regional objects. Satellite or aerial remote sensing, InSAR is more suitable for obtaining regional information such as surface coverage, water accumulation range and long-term deformation; Video and radar are more suitable for the continuous operation status recognition of roads and hubs. The advantage of area-based sensing is to reveal changes in spatial distribution, but its limitations come from factors such as light, weather, occlusion and coherence. Regional abnormalities still need to be explained in combination with inspection and engineering thresholds.

Model-compensated perception uses physical models, data assimilation or machine learning to estimate states that are difficult to observe directly. Relevant studies have proposed an infrastructure disaster simulation model based on multi-intelligent deep reinforcement learning to deduce state changes in flood situations [32]. Its value lies in transforming limited monitoring data into scenario simulation results, but the reliability depends on the consistency of the model assumption and the real scenario. Once the sample coverage is insufficient, the error will be amplified along the early warning chain.

After multi-source data acquisition, the key problem turns to state identification, that is, how to organize the distributed data into a interpretable operational states. Regional risk map can convert data such as basic geographic information, roads, buildings, pipelines, hazard sources and key protected objects into positionable and gradeable risk layers; Facility deformation monitoring can obtain the timing displacement and deformation rate with the help of SAR images, Digital Elevation Models (DEMs), differential interference and phase unwrapping; The identification of timing anomalies uses statistical models, deep learning or generation models to capture nonlinear changes and potential anomalies. The above methods improve the observability of the urban operation state, but whether the abnormal characteristics correspond to the real risk still needs to be checked back to the structural mechanism, on-site inspection and engineering threshold.

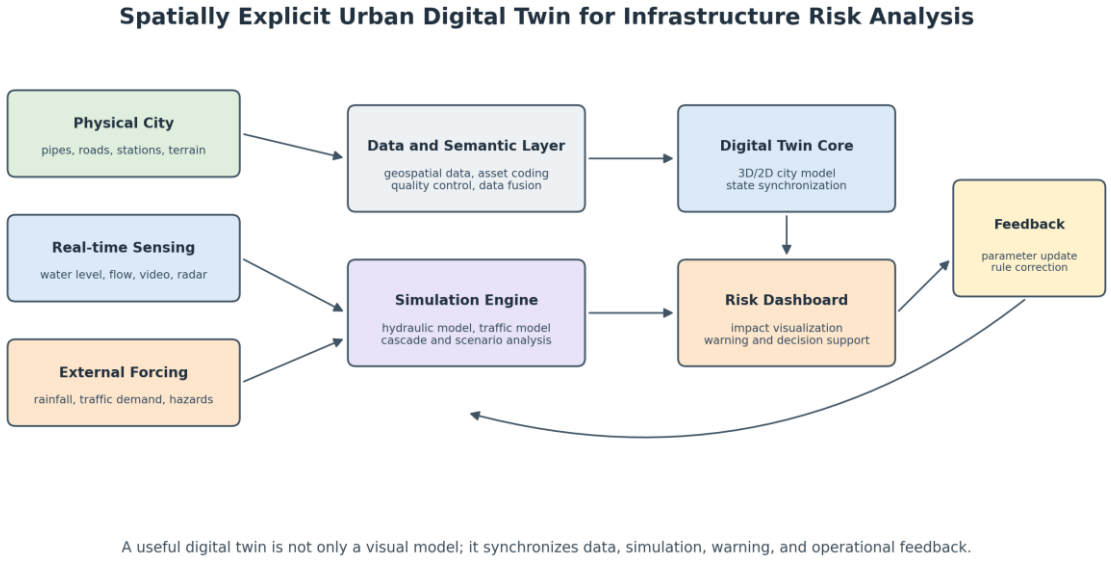
The platform architecture undertakes the functions of data access, governance arrangement and service call. The urban-level comprehensive monitoring and early warning platform usually adopts the hierarchical structure of perception layer, data layer, service layer and application layer: The perception layer is connected to heterogeneous monitoring data such as gas, water supply and traffic, The data layer completes the construction of convergence, governance and thematic library, The service layer provides model analysis and capability call, At the application level, business scenarios such as risk monitoring, early warning risk assessment, and joint defense linkage [8-9,11]. The hierarchical architecture improves scalability, but cannot automatically solve the problem of semantic consistency. There are differences in coding rules, indicator calibers and update frequencies in different industries. Without unified object coding, indicator caliber, quality control and model interface, the platform may stay at the level of data display and subsystem alarm, and it is difficult to support cross-system risk assessment.

Digital twins further link monitoring data, spatial models and simulation models for risk state expression and scenario simulation. In response to urban hydrological and waterlogging disasters, relevant studies integrate water infrastructure, hydrological sensors and three-dimensional geographic information models into

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urban-scale digital twin frameworks for flood impact analysis [13,17]; In industrial scenarios, digital twins can also assist abnormal detection and equipment status prediction [14]. What needs to be distinguished is that digital twins are not equivalent to a three-dimensional visualization platform. Its academic value lies in establishing a calibration relationship between the monitoring layer and the early warning layer through data synchronization, parameter update and scenario simulation. The process shown in Figure 3 reflects the continuous relationship from physical city, perceived data to risk dashboard and feedback correction. Its application bottlenecks mainly focus on data timeliness, model parameter update, high-precision modeling cost and edge computing pressure.

Figure 3: Spatially explicit urban digital twin framework for infrastructure risk analysis (adapted from Ref. [17])



4. Early Warning Methods and Intelligent Technologies

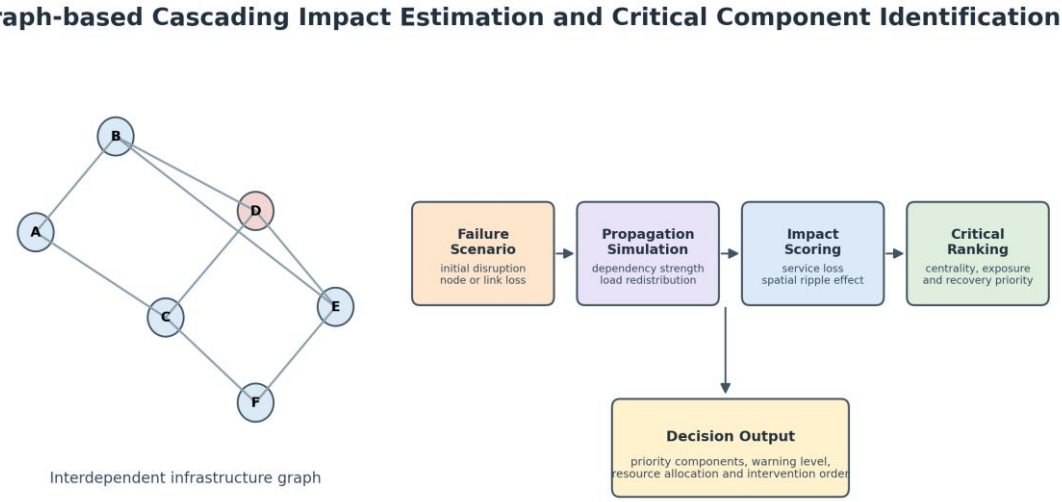
The task of the early warning layer is to transform status abnormalities into interpretable, gradeable and responsive risk signals. For urban critical infrastructure, crossing the boundary of a single indicator does not necessarily mean systemic risk; On the other hand, local minor anomalies may also be amplified in the dependent network. Early warning research therefore needs to move from threshold judgment to propagation-based explanation to explain how local faults extend to cross-system disturbances through physical connections, functional dependence or business associations.

The contribution of complex networks and dynamic models is to advance risk judgment from “abnormality” to “which connections the anomaly may spread and which nodes should be prioritized”. Liu and others built a cascading failure model for the fusion railway network, revealing the vulnerability of multi-layered coupling networks when high-connected nodes are attacked [20]; Lee et al. used graph theory and PageRank algorithm to estimate the cascading impact of local failure on relevant infrastructure components, providing a basis for key component identification and early warning prioritization [21]. This kind of model makes alarm grading no longer rely only on abnormal intensity, but can include node location, connection relationship and potential impact range. Figure 4 summarizes this logic as the analysis process of “failure scenario - propagation simulation - impact scoring – critical ranking”.

However, there is still a problem of engineering embedding between the cascade failure model and the city-level real-time early warning. Most models rely on relatively static network topology and idealized propagation parameters, and it is difficult to fully integrate load fluctuations, operation scheduling, emergency intervention and cross-departmental response mechanisms in the real system; The complexity of model calculation also limits its online update ability in high-frequency monitoring scenarios. Therefore, the improvement of risk identification and alarm logic not only improves the interpretation of the model, but also solves the problems of how the model absorbs new state data, how to dock with platform rules, and how to enter the governance process.

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Figure 4: Graph-based cascading impact estimation and critical component identification process (adapted from Ref. [21])



Machine learning and deep learning are good at processing high-dimensional, nonlinear and multimodal data. In the study of urban flooding and infrastructure resilience, it helps to reduce the computing cost of traditional models and improve the efficiency of short-term forecasting [6,16,32]. Knowledge graph and intelligent decision-making methods can transform expert experience, procedure standards and historical cases into computable and deductible knowledge structures [22-23], And deal with the relationship between multi-hazard, infrastructure interdependence and resilience goals through Bayesian networks or multi-criteria decision-making [24]. The weak link in the current early warning research is not the lack of a certain algorithm, but the lack of calibrable, traceable and executable connection mechanisms between multiple methods.

Knowledge graph and intelligent decision-making methods respond to another kind of problem: Early warning should not only give results, but also explain why the results are valid and how to deal with them. Unlike machine learning that focuses on statistical association, the Knowledge graph emphasizes the semantic relationship between organizational risk sources, disaster bearers, environmental conditions, failure modes and response rules. Transform expert experience, procedure standards and historical cases into computable and deductible knowledge structures. Chen and others proposed the management Knowledge graph method for critical infrastructure protection, emphasizing the role of ontological design, information extraction and relationship prediction in risk governance [22]; Xu et al. used Knowledge graph and case reasoning for bridge operation accident analysis, indicating that the knowledge structure can serve accident characterization and case retrieval [23].

Intelligent decision-making methods can further push the results of risk identification into governance actions. Bayesian networks and multi-criteria decision-making methods can deal with the relationship between multi-hazard, infrastructure interdependence and resilience goals [24], which can be used for alarm prioritization and response plan comparison. The limitation of the Knowledge graph is that there is tension between the static semantic relationship and the dynamic risk evolution. Existing knowledge graphs are effective in representing the logical chain of “object-attribute-relationship-rule”. However, state changes such as soaring water level, sudden changes in pipe network pressure, and sudden changes in traffic flow require real-time or quasi-real-time data to continuously correct the relationship intensity and reasoning results. Otherwise, the Knowledge graph may stay at the level of rule organization, and it is difficult to become a reasoning mechanism that effectively supports dynamic early warning.

Therefore, mechanism models, machine learning and Knowledge graph should not be understood as technical routes that replace each other. It should be examined in the same “data-model-decision-making” chain. The mechanism model explains the evolution of risk. Machine learning improves the efficiency of identification and prediction when the sample is sufficient. The Knowledge graph connects the model output,

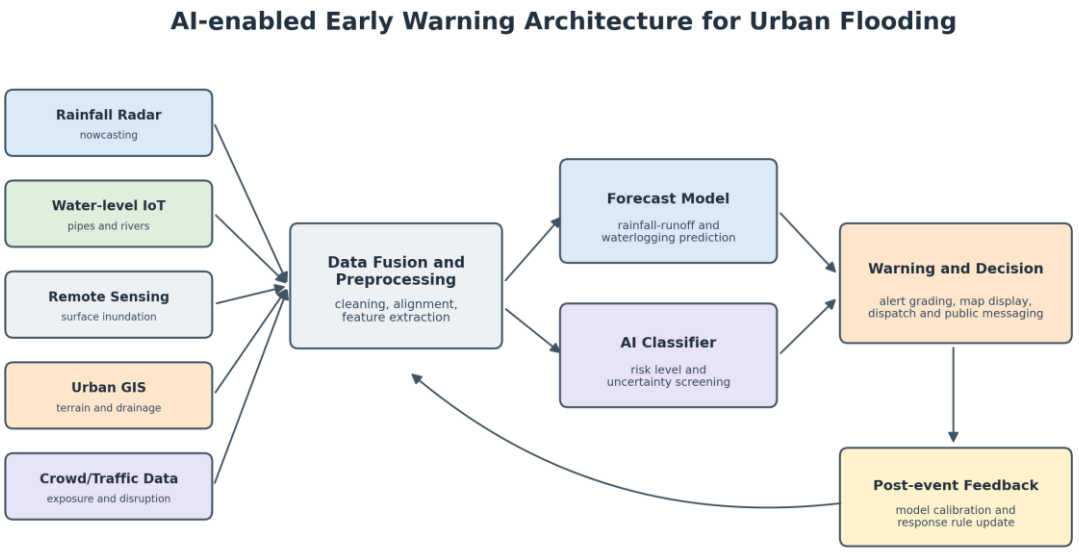
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response rules and governance semantics. The weak link in the current early warning research is not the lack of a certain algorithm, but the lack of calibrable, traceable and executable connection mechanisms between multiple methods. Follow-up research can improve the credibility of machine learning by monitoring data calibration mechanism models, and organize model output and response rules through knowledge graphs, thus improving the interpretability and enforceability of early warning decision-making.

5. Application Scenarios and Technology Adaptation

Selecting typical scenarios can test the explanatory power of the four-dimensional evaluation framework [12]. Flood and urban drainage scenarios have relatively clear physical processes and dynamic mechanisms. In recent years, artificial intelligence and digital twin research have further improved the prediction and perception ability of urban waterlogging [15-18]. The core feature of this scenario is the collaborative perception and dynamic input of multi-source data. As shown in Figure 5, heterogeneous data such as meteorological radar, Internet of Things, remote sensing and urban GIS, after fusion preprocessing, directly act as the continuous support of physical prediction models and AI classifiers, and finally access the alarm rules of the platform and form post-governance feedback [19]. According to the four-dimensional framework evaluation, the mechanism of the scene is highly clear, the data continuity is at a medium and high level, and the closed-loop maturity has taken shape, but the response feedback under extreme events is still a weakness.

Figure 5: AI-enabled early warning architecture for urban flooding based on multi-source data fusion (adapted from Ref. [19])



Road and rail transit scenarios show the characteristics of "data-intensive but insufficient risk explanation". Although video, radar and trajectory can continuously generate high-frequency state data, there is a lack of stable explanatory linkage between the perception results and the risk transmission logic such as congestion diffusion and facility cascading failure [20-21]. Judging from the four-dimensional framework, the data continuity of the scene and the coupling of the platform are relatively high, but the clarity of the mechanism is mostly at a medium level, and the closed-loop maturity is constrained by the disconnection of abnormal identification and risk propagation reasoning.

Energy storage and transportation and port scenarios are highly heterogeneous and highly coupled operation scenarios. The space of objects such as power batteries, dangerous goods storage and transportation, port operations and mobile ships is scattered, involving multiple subjects such as enterprises, port areas, transportation, fire fighting and emergency response, and it is difficult to unify data interfaces and response rules. The lithium-ion battery thermal runaway early warning study shows that this type of object needs to integrate temperature, voltage, gas, acoustics and other multi-source signals to obtain more reliable early risk

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identification [33]; The early warning research on hazardous chemical transportation risks also shows that accident data, environmental conditions and transportation process variables need to be continuously updated through machine learning models to support dynamic risk judgment [34]; The port digital twin research further shows that port safety management needs to integrate personnel, equipment, environment and logistics processes into a unified safety management and decision-making support framework [35]. Judging from the four-dimensional framework, the clarity of the scene mechanism is at a medium and low level. The data continuity and platform coupling are greatly affected by multi-subject barriers. The closed-loop maturity is relatively low. The key bottleneck is that the object coding, data interface and response rules have not been unified.

6. Research Gaps and Future Research Directions

The above comparison indicates that, research on monitoring and early warning of critical urban infrastructure has accumulated a wealth of technology, but this accumulation has not yet been stably transformed into urban-level risk governance capabilities. The current bottleneck is mainly reflected in the disconnect between object scope, data organization, model mechanism and platform application, rather than just the number of sensors or algorithm accuracy. Future research should focus on addressing the main shortcomings in different scenarios, rather than merely stating general technical improvements.

For scenarios with dispersed objects such as energy storage and transportation, ports, and underground spaces, infrastructure object standardization should be prioritized. Urban critical infrastructure includes not only traditional lifeline projects such as water supply, drainage, gas, electricity, transportation, and communication, but also new types of infrastructure such as energy storage facilities, hub ports, and data communication networks. Different studies are organized by industry system, risk scenario, or platform access scope. When the target criteria are different, it becomes difficult to align monitoring indicators, data standards, and model inputs, making it difficult to make horizontal comparisons of research conclusions. Therefore, object standardization is not only a data management issue, but also a prerequisite for cross-entity risk governance.

For high-frequency sensing scenarios such as roads and rail transit, online data coupling should be promoted. Existing research has been able to acquire relatively rich state data. Video, radar, trajectory, IoT sensor and platform data continue to improve state perception capabilities, but state observation results are not equivalent to risk assessment. Further research needs to explain how monitoring data is incorporated into model calibration, how state characteristics are transformed into propagation inferences, and how early warning results are written back to the platform and trigger the response process. Only by connecting anomaly identification, network propagation, and business response can high-frequency sensing data become an early warning capability, rather than just a display of operational status.

For scenarios such as flood drainage where the mechanisms are relatively clear but the uncertainties of extreme conditions are high, hybrid early warning models should be developed. Mechanistic models can explain risk propagation and cascading failure processes, but they are highly dependent on system boundaries, parameter settings, and topology. Machine learning methods can improve the efficiency of time series prediction, target recognition and state classification, but they are susceptible to sample distribution, rare events and cross-scene migration. Knowledge graphs facilitate the formal representation of expert knowledge and operational rules, but static semantic relationships are difficult to absorb in a timely manner the rapid changes in the physical risk field. Therefore, a more promising approach is to explain the evolution by mechanistic models, correct the state by data models, and organize the handling logic by knowledge structures, so that model prediction, rule interpretation and on-site feedback complement each other, rather than replacing the complete early warning process with a single model.

To address the issue of insufficient platform verification that exists across all three types of scenarios, a practical evaluation system should be established. Although a closed-loop system of “monitoring-simulation-prediction” has been initially formed for flood and urban drainage scenarios, the response and feedback under extreme events are still insufficient. Traffic scenarios are data-intensive, but lack a stable early warning reasoning chain; Energy storage, transportation, and port scenarios are constrained by factors such as dispersed objects, data barriers, and complex cross-system dependencies, resulting in lower closed-loop integrity. Therefore, future evaluations should not only focus on prediction accuracy, but also include response

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timeliness, cross-system propagation identification capability, robustness under extreme conditions, effectiveness of coordinated response, and feedback correction capability.

Overall, future research should shift from optimizing individual technologies to building system capabilities. Object standardization addresses the data entry problem in highly heterogeneous scenarios such as energy storage and transportation and ports; Online data coupling addresses the reasoning disconnect problem in high-frequency sensing scenarios such as transportation and rail transit; Model hybridization is suitable for scenarios with clear mechanisms but significant extreme uncertainties, such as flood drainage. The evaluation addresses the common issue of a lack of platform operation verification across three types of scenarios in practical application. Only when objects, data, models, and handling processes can be continuously calibrated on the same platform can monitoring and early warning move from status display to risk governance.

7. Conclusions

This paper focuses on the research of risk monitoring and early warning for critical urban infrastructure, and constructs a four-layer analysis path: "object layer - monitoring layer - early warning layer - scenario layer". A maturity evaluation framework consisting of mechanism clarity, data continuity, platform coupling degree, and closed-loop maturity is proposed. The findings suggest that related technologies have evolved from single-point perception and single-system monitoring to multi-source data fusion and platform integration, but there is still a structural gap between state observation and risk assessment. The monitoring layer is capable of continuously generating operational data, and the early warning layer has also formed multiple methods such as mechanism models, machine learning, and knowledge graphs. However, the two have not yet been stably connected into a city-level, multi-system, verifiable risk governance process. The primary contribution of this framework lies in providing a unified analytical approach for the evaluation of early warning systems, the determination of construction priorities, and the selection of technical routes for different infrastructure scenarios.

Comparative analysis across scenarios yields three key insights. First, the maturity of monitoring and early warning is primarily affected by the interpretability of risk mechanisms, rather than solely by the number of sensors; The scenarios of floods and urban drainage are relatively mature, mainly because the hydrological process and the drainage process have a relatively clear extrapolation relationship. Second, high-frequency data does not necessarily lead to high-quality early warnings; The road and rail transit scenarios illustrate a potential disconnect between data intensity and risk reasoning. Third, the main bottleneck in energy storage, transportation and port scenarios is not single-point monitoring capabilities, but rather the lack of sufficient cross-entity, cross-platform, and cross-scale collaboration. The evaluation framework presented in this paper is still an interpretive comparison based on literature review, and has not yet replaced empirical testing based on platform operation data. Future research should address the shortcomings of different scenarios by promoting standardization of objects, online data coupling, model hybridization, and practical evaluation, so that early warning models can be more effectively integrated into urban risk governance practices.

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Conflicts of Interest

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