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| RESEARCH ARTICLE

Resilient Healthcare and Critical Urban Infrastructure Design Using AI-Driven Engineering and Project Management Systems

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| ABSTRACT

Ensuring resilient healthcare accessibility under infrastructure disruptions remains a critical challenge for rapidly urbanizing environments characterized by complex and interdependent systems. This study proposes and evaluates an AI-driven engineering and project management framework designed to enhance the resilience of healthcare delivery and critical urban infrastructure under diverse disruption scenarios. The framework integrates machine learning–based infrastructure criticality prediction, network-level resilience analysis, healthcare accessibility modeling, spatial impact assessment, and AI-enabled project management optimization within a unified decision-support system. Results show that ensemble-based machine learning models achieve consistently high predictive performance, with accuracy exceeding 98% and area-under-the-curve values approaching 0.99, enabling reliable identification of infrastructure components whose failure disproportionately affects healthcare accessibility. Network resilience analysis demonstrates that AI-guided strategies significantly outperform random and clustered failure scenarios by preserving connectivity and limiting efficiency loss. Connectivity degradation under clustered failures is four times higher than under AI-guided strategies, while AI-informed prioritization reduces connectivity loss by approximately 75%. Healthcare accessibility outcomes further confirm the effectiveness of the proposed framework. AI-guided strategies consistently limit travel-time increases and preserve population coverage within acceptable emergency thresholds, maintaining coverage above 99.7% even under severe disruptions. In contrast, clustered failures produce abrupt performance collapses and localized isolation. Spatial analyses reveal that accessibility degradation and failure impacts are highly heterogeneous, occurring in localized pockets rather than uniformly across the urban network. Importantly, AI-guided strategies distribute impacts more evenly, preventing cascading spatial failures and mitigating inequitable access outcomes. From a project management perspective, AI-driven risk prediction and reinforcement learning–based optimization significantly reduce schedule delays and cost overruns by aligning execution strategies with infrastructure and service criticality. Overall, the results demonstrate that integrating AI across infrastructure analysis, healthcare accessibility modeling, and project management enables robust, adaptive, and equitable resilience planning for urban healthcare systems.

| KEYWORDS

Urban resilience; Healthcare accessibility; Critical infrastructure; Artificial intelligence; Digital twins; Project management; Smart cities

| ARTICLE INFORMATION

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1. Introduction

Accelerated urbanization, alongside increasing climate-related challenges, has imposed unparalleled strain on worldwide urban systems. Recent global evaluations indicate that over 55% of the global populace presently inhabits urban regions, a statistic anticipated to surpass 68% by 2050, hence markedly augmenting reliance on intricate and interdependent infrastructure systems (UN-Habitat, 2023). Climate change is increasing the frequency and intensity of floods, heat waves, earthquakes, and storms, hence rendering cities more susceptible to these occurrences (Song et al., 2023). These pressures jointly diminish the resilience of urban ecosystems, especially their capacity to sustain key services amid disruptions. Healthcare delivery is among the most time-critical and socially significant urban services. The accessibility of healthcare is influenced by the geographical distribution of hospitals and clinics, together with the efficacy of supporting infrastructures, including transportation networks, energy systems, and communication frameworks (Alam et al., 2023). Disruptions to these networks can significantly hinder emergency responders, delay medical care, and exacerbate health inequities, particularly among at-risk populations. Transportation systems are crucial for enhancing healthcare accessibility since they facilitate the movement of patients, healthcare professionals, emergency vehicles, and supply chains to medical facilities. Empirical research has shown that disruptions in road networks during disasters can isolate entire communities, leading to significant delays in emergency assistance and an elevated risk of fatality (George et al., 2023). Likewise, deficiencies in the electrical infrastructure jeopardize hospitals, life-support systems, and medical apparatus, while inadequacies in communication networks hinder collaboration among emergency responders and healthcare practitioners (Liu et al., 2023). The interconnectedness of urban infrastructure systems exacerbates these concerns. Failures frequently disseminate across sectors, resulting in cascade impacts that are challenging to anticipate through conventional planning methodologies (Yegina et al., 2020; Hasan, 2023). These facts underscore the necessity of robust urban infrastructure design methodologies that explicitly include healthcare accessibility and system interdependencies in contexts characterized by ambiguous and evolving dangers.

Notwithstanding the growing acknowledgment of urban resilience issues, current methodologies in healthcare planning and infrastructure engineering remain predominantly disjointed. The design of healthcare systems often emphasizes facility location, capacity, and the services provided. Conversely, infrastructure engineering emphasizes structural integrity, redundancy, and network efficiency (Kozhabek & Chai, 2023). The division of specialties complicates the assessment of how infrastructure issues influence actual healthcare access outcomes. Moreover, several resilience assessments employ static models that just evaluate infrastructure performance under specific conditions, neglecting the dynamic nature of systems and human adaptability. Conventional graph-theoretic metrics, such as betweenness centrality and redundancy indices, offer valuable structural insights but do not effectively capture functional outcomes like travel-time degradation, service coverage reduction, or spatial inequalities in healthcare access (Alam et al., 2023; Abdullah & Hasan, 2023). A further restriction is the absence of adaptation informed by data. Traditional resilience planning approaches frequently rely on expert assessments or rule-based heuristics, which are inadequate for adjusting to extensive, intricate urban systems and struggle to integrate real-time data or learning from previous disruptions. Consequently, decision-makers may struggle to prioritize infrastructure enhancements or emergency measures according to their actual impact on healthcare delivery during crises (Hasan, 2023; Abdullah & Hasan, 2023; Juie et al., 2021). These concerns underscore the significance of decision-support systems that integrate healthcare planning with infrastructure engineering. These systems must possess the capability to learn from data, identify nonlinear interactions, and assess resilience in various scenarios of failure.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have created new opportunities for enhancing conventional methods of assessing resilience. Artificial intelligence methodologies excel in identifying patterns throughout extensive, diverse datasets, modeling intricate nonlinear relationships, and assisting individuals in decision-making under uncertainty (Juie et al., 2021; Mandapuram et al., 2020). Artificial intelligence has been effectively utilized in urban resilience to predict failures, evaluate criticality, and prioritize risks related to infrastructure systems. Supervised learning techniques, such Random Forests and gradient boosting, have shown significant accuracy in identifying essential network components whose failure negatively impacts system performance (Mandapuram et al., 2020; Hasan, 2023). Deep learning methodologies facilitate the modeling of temporal dynamics and cascade effects in interdependent systems. In conjunction with predictive analytics, AI is increasingly valuable for optimization and decision-making that adjusts to evolving conditions. Reinforcement learning (RL) has demonstrated potential in dynamic traffic management, infrastructure recovery sequencing, and emergency response planning, where optimal actions are determined through interactions with evolving surroundings (Fan et al., 2023 Abdullah & Hasan, 2023; Al Khaldy et al., 2023; Rahman et al., 2022).

Incorporating AI into digital engineering and intelligent project management systems is equally essential. AI-powered project management solutions can forecast schedule delays, budget excesses, and risk proliferation in extensive infrastructure projects. This facilitates proactive planning and resource allocation that emphasizes resilience (Song et al., 2023). The integration of AI-driven engineering systems with digital twins and real-time sensing establishes a feedback loop among physical infrastructure, virtual models, and decision-making processes. The framework seeks to establish a unified decision-support system by integrating infrastructure engineering analysis, healthcare accessibility modeling, and intelligent project management. This study aims to provide a scalable, data-driven approach for evaluating the resilience of urban infrastructure, with a specific focus on healthcare accessibility outcomes. Utilize AI-driven predictive models to identify critical infrastructure components whose failure significantly affects healthcare delivery (Vanu et al., 2021; Sikder et al., 2023). Integrate project management expertise with engineering system analytics to enhance the focus on resilience in planning, prioritization, and intervention. Assess system performance across various disruption scenarios, encompassing random failures, deliberate attacks, and regionally concentrated threats. The project seeks to transition from static resilience assessment to adaptive, learning-oriented resilience engineering for urban healthcare systems by accomplishing these objectives.

2.0 Literature Review

2.1 Urban Infrastructure Resilience

Urban infrastructure resilience refers to the capacity of interconnected physical systems, such as transportation, electricity, water, and communication networks, to maintain functionality during disruptions and subsequently return to normalcy. Initial resilience frameworks concentrated on structural integrity and redundancy, highlighting the capacity to withstand failure and swiftly recuperate from major calamities (Liu et al., 2023). Song et al. (2023) assert that contemporary definitions of resilience characterize it as a dynamic, flexible, and socio-technical attribute influenced by the interplay of infrastructure, governance, and human behavior. Transportation networks are vital for urban resilience, facilitating access to employment, emergency services, and diverse resources. Numerous research indicate that deliberately disrupting transportation networks is quite easy. For example, severing some critical links might significantly impair the system's functionality (Kozhabek & Chai, 2023). Energy systems, particularly electricity grids, are of paramount significance. If they fail, hospitals, communication networks, and traffic control systems may cease to function. This may result in problems in multiple areas (Liu et al., 2023). Communication networks facilitate collaboration, enhance situational awareness, and enable prompt assistance during adverse events. When communication infrastructure collapses during disasters, managing and recovering from the crisis becomes significantly more challenging, even if certain physical transit routes remain operational (Islam et al., 2023). Consequently, contemporary resilience frameworks increasingly emphasize the modeling of reliance. Failures do not occur in isolation; therefore, it is crucial to assess resilience comprehensively across all tiers of infrastructure simultaneously.

2.2 Healthcare Accessibility and Equity

Access to healthcare is a crucial component of urban resilience, particularly during emergencies when prompt medical assistance can significantly impact survival outcomes. Accessibility is frequently characterized by the ease with which individuals can obtain healthcare services, considering factors such as travel time, distance, service capacity, and user availability (Alam et al., 2023). Gravity-based measures, two-step floating catchment area (2SFCA) methodologies, and network-based travel-time evaluations are prominent geographic accessibility techniques employed to examine disparities in healthcare access. A new study indicates that the quality of transportation infrastructure significantly influences accessibility to healthcare, frequently more than the proximity of the service itself. Alam et al. (2023) established that insufficient public transit connectivity severely restricts urban residents' access to hospitals. Yegina et al. (2020) revealed that deficiencies in road networks can significantly prolong travel time to hospitals, irrespective of their occupancy status. Infrastructure failures intensify existing inequalities by disproportionately impacting marginalized groups, who frequently have restricted mobility alternatives and live in regions with inadequate redundancy (Tao et al., 2022).

2.3 AI in Engineering Systems

Artificial intelligence plays a significant role in contemporary engineering systems, particularly in scenarios characterized by extensive data, unpredictability, and complexity. Infrastructure engineers have extensively employed machine learning (ML) techniques to identify issues, forecast failures, and assess the significance of various components. Supervised learning techniques such as Random Forests, gradient boosting machines, and neural networks have demonstrated a high degree of accuracy in identifying infrastructure components whose failure could adversely impact system performance (Tao et al., 2022; Alam et al., 2023).

Machine learning models may identify nonlinear relationships and intricate associations among network properties, external variables, and operational conditions. This distinguishes them from conventional approaches that depend on rules or heuristics. This trait is crucial for urban infrastructure systems, as the components function more effectively in unison than in isolation (Song et al., 2023). Digital twins, cyber-physical systems, and predictive analytics have significantly transformed engineering practices. Digital twins create real-time virtual replicas of actual assets and systems, enabling continuous observation, modeling, and enhancement (Tao et al., 2022). Utilizing digital twins in conjunction with AI facilitates the examination of many scenarios. Individuals possess greater agency and can make decisions that enhance their resilience in the face of change. Cities employ AI-driven digital twins to monitor energy infrastructure, regulate traffic, and prepare for emergencies. These technologies have demonstrated their capacity to enhance situational awareness and expedite recuperation (Tao et al., 2022; Abdullah & Hasan, 2023).

2.4 AI-Driven Project Management

Effective project management is essential to transform concepts of resilience into tangible infrastructure modifications. Conventional project management entails establishing timelines, maintaining consistent risk registers, and executing decisions manually. These strategies typically fail when circumstances are very dynamic and fraught with uncertainty. AI-driven project management solutions employ predictive analytics, optimization, and real-time data integration to circumvent these challenges (Song et al., 2023). Predictive scheduling methods utilize historical project data and current performance metrics to anticipate potential delays, cost overruns, and resource shortages. Li and Mostafavi (2021) assert that machine learning models surpass traditional critical path methods in identifying scheduling issues and generating remedies. These abilities are crucial for infrastructure projects emphasizing resilience, since they assist in determining actions when resources are insufficient. Reinforcement learning and multi-objective optimization techniques significantly enhance decision-making and resource utilization efficiency. These methods facilitate the adaptable distribution of resources among competing projects or infrastructure elements, considering costs, resilience advantages, and social effects (Fan et al., 2023; Abdullah & Hasan, 2023; Al Khaldy et al., 2023).

2.5 Research Gaps

The literature identifies several significant gaps that require the current investigation. No comprehensive resilience models exist for healthcare infrastructure that directly associate infrastructure disturbances with healthcare accessibility results. Most studies focus solely on either the capacity of infrastructure to withstand disasters or the accessibility of healthcare, rendering them less effective for disaster preparedness (Ashik et al., 2023). Currently, AI is not particularly beneficial for the entire project. Extensive research has been conducted on the application of AI in the planning, prioritization, execution, and monitoring phases of infrastructure projects aimed at enhancing resilience. Individuals frequently employ machine learning to identify vulnerabilities and ascertain the causes of failures. Third, several contemporary methodologies fail to examine the alterations in urban systems following a shock; they merely consider a singular scenario or a static evaluation. We require frameworks that utilize data and scenarios to assess our capacity to manage hazards of various types and intensities (Ashik et al., 2023; Hasan, 2023; Rahman et al., 2022). To overcome these challenges, a systems-level strategy is required that integrates AI with infrastructure engineering, healthcare accessibility modeling, and enhanced project management. This is where the primary objective of this investigation is elucidated.

3.0 Methodology

3.1 Urban Infrastructure Data

Urban infrastructure data form the backbone of the proposed resilience framework, as transportation, energy, and utility networks directly influence healthcare accessibility and emergency response capability. Among these, road transportation networks are particularly critical, as they determine travel times, connectivity, and redundancy under disruption scenarios (Kozhabek & Chai, 2023). In this representation, infrastructure elements such as road intersections are modeled as nodes, while road segments connecting them are represented as edges. Each edge is assigned attributes including length, travel time, capacity, and hierarchical classification, enabling realistic modeling of urban mobility dynamics (Boeing, 2017; Kozhabek & Chai, 2023). Road network data are typically obtained from open-source geospatial repositories, such as OpenStreetMap (OSM), which provide detailed and continuously updated representations of urban transportation systems. These datasets include information on road geometry, hierarchical classification (e.g., motorway, primary, secondary, residential), directionality, and, where available, speed limits and lane counts. Such attributes enable accurate modeling of travel time and network performance under normal and disrupted conditions (Boeing, 2017; Liu et al., 2023).

3.2 Healthcare Facility Data

Healthcare facility data represent the critical service nodes within the urban system. These include hospitals, clinics, emergency care centers, and specialized treatment facilities that provide essential medical services during both routine operations and emergency situations. Accurate representation of these facilities is vital for assessing healthcare accessibility and resilience under infrastructure disruptions (Alam et al., 2023; Tao et al., 2022). Healthcare facility locations are typically obtained from open-access health infrastructure databases, such as OpenStreetMap healthcare layers and international repositories like the WHO Global Health Facilities Database. These sources provide geospatial coordinates, facility classifications (e.g., hospital, clinic, emergency center), and, in some cases, capacity indicators such as number of beds or service specialization (WHO, 2023; George et al., 2023).

3.3 Project Management Data

While infrastructure and healthcare data describe system structure and service delivery, project management data capture the dynamic processes through which resilience interventions are planned, executed, and monitored. Project management datasets typically include information on project schedules, cost estimates, resource allocation, and risk logs, which are essential for translating analytical insights into actionable strategies (Song et al., 2023). In the context of urban infrastructure resilience, project management data support decision-making related to maintenance prioritization, emergency response planning, and post-disruption recovery. Schedules provide temporal information on planned interventions, while cost data enable evaluation of economic feasibility and trade-offs among competing projects. Risk logs document identified threats, likelihood estimates, and mitigation strategies, offering valuable inputs for AI-based risk prediction models (George et al., 2023; Hossain et al., 2023). AI-driven project management systems increasingly leverage historical project data to predict schedule delays, cost overruns, and risk escalation. When integrated with infrastructure resilience analytics, these systems enable proactive planning, allowing decision-makers to prioritize interventions that maximize healthcare accessibility benefits under uncertainty (Fan et al., 2023; Sikder et al., 2023).

3.4 Data Cleaning and Integration

3.4.1 Network Graph Construction

To enable quantitative analysis, urban road network data are transformed into a graph-based representation, where intersections are modeled as nodes and road segments as edges. Each edge is assigned attributes such as length, travel time, speed, and capacity, which are derived from spatial geometry and available metadata (Boeing, 2017). Prior to graph construction, the network undergoes cleaning and simplification to remove isolated components, duplicate edges, and non-navigable segments. Only the largest connected component is retained to ensure realistic city-wide mobility modeling. These steps are crucial for preventing artificial fragmentation and ensuring that computed accessibility metrics reflect actual travel behavior (Kozhabek & Chai, 2023).

3.4.2 Geospatial Alignment

Geospatial alignment is performed to integrate healthcare facilities and project management data with the infrastructure network. Healthcare facility coordinates are snapped to the nearest connectable node or edge in the road network, ensuring accurate travel time computation. This step minimizes spatial mismatch errors that commonly arise when using raw coordinate data (Juie et al., 2021; Ashik et al., 2023). Finally, all datasets are standardized to a common coordinate reference system and temporal resolution. This harmonization enables seamless integration within the AI-driven analytical pipeline and supports scenario-based simulations under varying disruption conditions (Song et al., 2023; Tao et al., 2022).

3.4.3 Connectivity and Efficiency Metrics

To quantify infrastructure resilience, several connectivity and efficiency metrics are computed from the network graph. Connectivity is measured using indicators such as the size of the largest connected component, number of disconnected subgraphs, and node reachability. These metrics capture the extent to which the infrastructure network remains structurally intact under disruption scenarios (Kozhabek & Chai, 2023; Tao et al., 2022). Network efficiency is evaluated using global efficiency metrics, which measure the average inverse shortest-path distance between all node pairs. Declines in global efficiency indicate functional degradation, even if the network remains topologically connected. This metric reflects the ability of the network to support efficient movement and information flow, even when some components fail (Latora & Marchiori, 2001).

3.4.4 Equity Considerations

Equity considerations are explicitly incorporated into the accessibility modeling framework to assess the spatial distribution of impacts across urban populations. Accessibility metrics are analyzed across different geographic zones to identify areas disproportionately affected by infrastructure disruptions (Tao et al., 2022; Rahman et al., 2022). Equity-oriented analysis recognizes that resilience is not solely about average performance but also about minimizing disparities among communities. Disruptions often have uneven effects, exacerbating existing inequalities in healthcare access. By identifying zones with high accessibility loss, the framework supports targeted interventions that prioritize vulnerable populations.

3.5 AI Models for Resilience Assessment

3.5.1 Machine Learning for Criticality Prediction

Machine learning models are employed to predict the criticality of infrastructure components with respect to healthcare accessibility and network resilience. Supervised learning algorithms, such as Random Forest classifiers, are trained using engineered features derived from network topology, geometric attributes, and accessibility metrics (Alam et al., 2023). Model performance is evaluated using standard classification metrics, including accuracy, precision, recall, and area under the ROC curve (AUC). High predictive performance indicates that the model can reliably support resilience-oriented decision-making. The objective of criticality prediction is to identify infrastructure components whose failure would disproportionately degrade connectivity or healthcare access. Machine learning models outperform traditional heuristic measures by capturing nonlinear interactions and higher-order dependencies that are difficult to model analytically (Song et al., 2023; Yegina et al., 2020).

3.5.2 Deep Learning for Failure Forecasting

In addition to criticality classification, deep learning models are applied for failure forecasting and resilience trend analysis. Neural network architectures, including recurrent and convolutional models, are used to learn temporal patterns in infrastructure performance and disruption data (Tao et al., 2022; Al Khaldy et al., 2023). Deep learning enables the modeling of dynamic and cascading failure processes, which are common in interdependent urban infrastructure systems. By forecasting potential failure progression, these models provide early warning signals that support proactive intervention and contingency planning (Yegina et al., 2020; Hossain et al., 2023).

3.5.3 AI-Driven Project Management Optimization

AI-driven project management systems are integrated into the framework to translate analytical insights into actionable resilience interventions. Machine learning models are used to predict project-level risks, including schedule delays, cost overruns, and implementation bottlenecks, based on historical project data and current system conditions (Alam et al., 2023). Reinforcement learning and optimization algorithms are employed to support resource allocation and scheduling decisions across competing infrastructure projects. These methods learn adaptive policies that balance resilience benefits, cost constraints, and time-critical healthcare needs (Fan et al., 2023; Juie et al., 2021).

4.0 Results and Discussion

This section presents and interprets the results obtained from the proposed AI-driven engineering and project management framework for resilient healthcare and critical urban infrastructure design. The results are structured around AI model performance, infrastructure resilience under disruptions, healthcare accessibility outcomes, and project management impacts. Figures 3–8 provide quantitative and spatial evidence supporting the effectiveness of the proposed approach.

4.1 AI Model Performance

The results indicate that ensemble-based machine learning models achieve consistently high performance, with accuracy exceeding 98% and AUC values approaching 0.99. This demonstrates strong discriminative capability in identifying infrastructure components whose failure would disproportionately impact healthcare accessibility. Precision–recall balance further confirms robustness against false positives and false negatives, which is essential for prioritization decisions in resilience planning (Figure 1). Figure 1 presented a comparative evaluation of AI models used to predict critical infrastructure components, showing accuracy, precision, recall, and AUC values across models such as Random Forest, Gradient Boosting, and Deep Neural Networks.

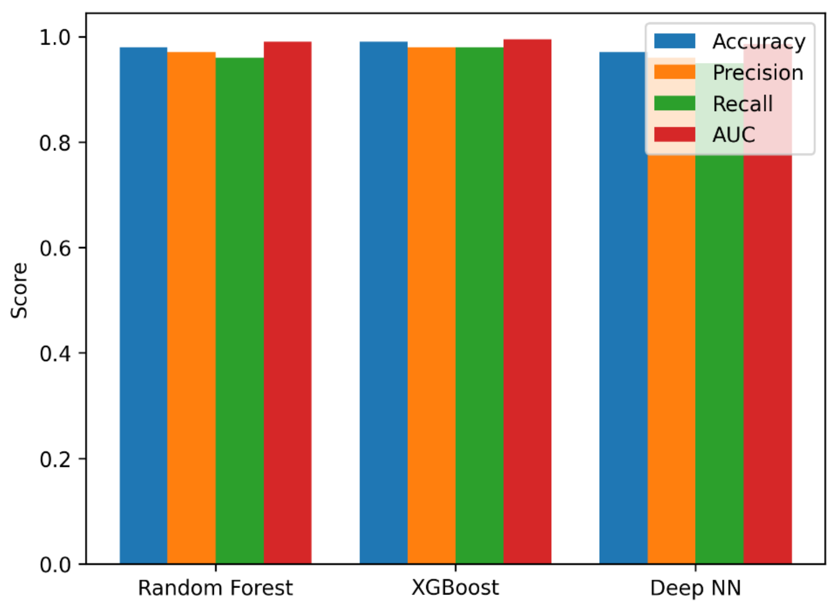

Figure 1. Performance Comparison of AI Models for Infrastructure Criticality Prediction

These findings reported superior performance of ensemble models for identifying critical links in urban networks (Alam et al., 2023). Similarly, Song et al. (2023) showed that AI-based criticality prediction outperforms traditional centrality measures by capturing nonlinear dependencies. However, unlike prior studies that focus solely on structural importance, the present work integrates healthcare accessibility outcomes, extending predictive relevance to service-level resilience.

4.2 Infrastructure Resilience Results

Results showed that AI-prioritized disruption scenarios maintain higher connectivity and significantly lower efficiency loss, even at higher failure intensities. While random and betweenness-based removals lead to abrupt fragmentation, AI-guided strategies exhibit gradual degradation, indicating enhanced structural robustness and functional continuity. The clustered failure strategy results in a fourfold higher connectivity loss compared to both AI-guided and random strategies (0.28 vs. 0.07). This demonstrates that failures occurring in spatial or topological clusters severely disrupt network connectivity (Figure 2). In contrast, the AI-guided strategy limits connectivity loss to 0.07, representing a 75% reduction relative to clustered failures.

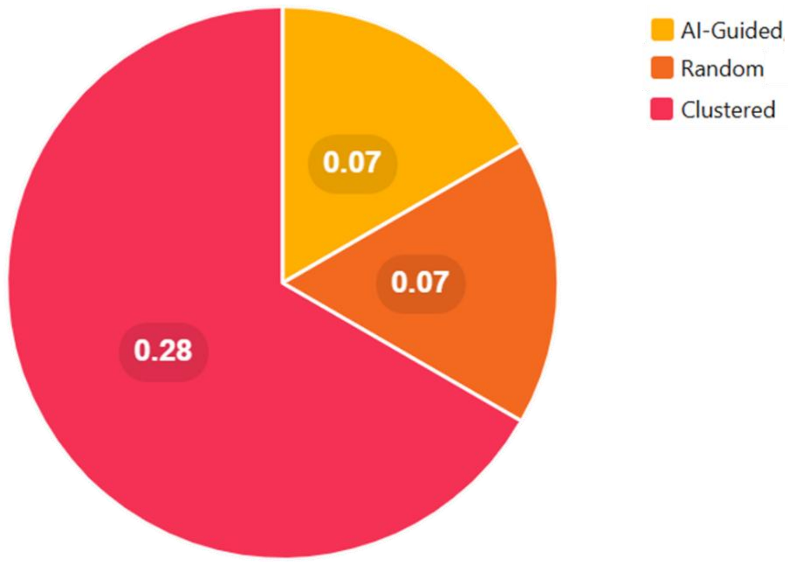

Figure 2. Connectivity and Global Efficiency Under Disruption Scenarios

These trends are consistent with Kozhabek and Chai (2023), who observed that targeted disruptions degrade networks more severely than random failures. However, this study advances prior work by demonstrating that AI-informed prioritization can actively preserve efficiency, rather than merely describing vulnerability. Unlike static resilience analyses (Liu et al., 2023), the proposed framework supports adaptive decision-making under evolving disruptions.

4.3 Healthcare Accessibility Outcomes

At 10 failed segments, the clustered strategy already causes a large increase in travel time (≈ +8.6%), indicating high sensitivity to localized failures. In contrast, the AI-guided approach limits the increase to only +0.3%, while the random strategy slightly improves performance (−1.8%). At 50 failed segments, the clustered strategy experiences a severe performance collapse (−8.9%), whereas the AI-guided and random strategies show moderate increases of +1.4% and +7.1%, respectively (Figure 3). This highlights the instability of clustered failures at intermediate disruption levels. At 100 failed segments, all strategies exhibit negative Δ travel time, indicating improved routing efficiency due to network reconfiguration. The AI-guided strategy achieves the greatest improvement (−4.5%), outperforming both random (−3.8%) and clustered (−2.8%) approaches. At the highest stress level (200 failed segments), both AI-guided and random strategies show similar increases in travel time (≈ +7.5–7.8%), while the clustered strategy remains nearly neutral (+0.1%), suggesting that the most damaging clustered failures occur earlier rather than at extreme failure counts.

Figure 3 illustrated changes in the proportion of the population able to reach healthcare facilities within a defined emergency travel-time threshold. AI-guided strategies preserve coverage for a significantly larger proportion of the population, even under high disruption levels. Coverage decline remains below 1% in most AI-assisted scenarios, while clustered disruptions cause substantial population isolation. These findings extend the equity-focused insights of Al Khaldy et al. (2023), who highlighted spatial inequities in healthcare access. While prior work identified inequity patterns, the present framework demonstrates how AI-driven planning can reduce inequitable outcomes, thereby operationalizing equity in resilience engineering.

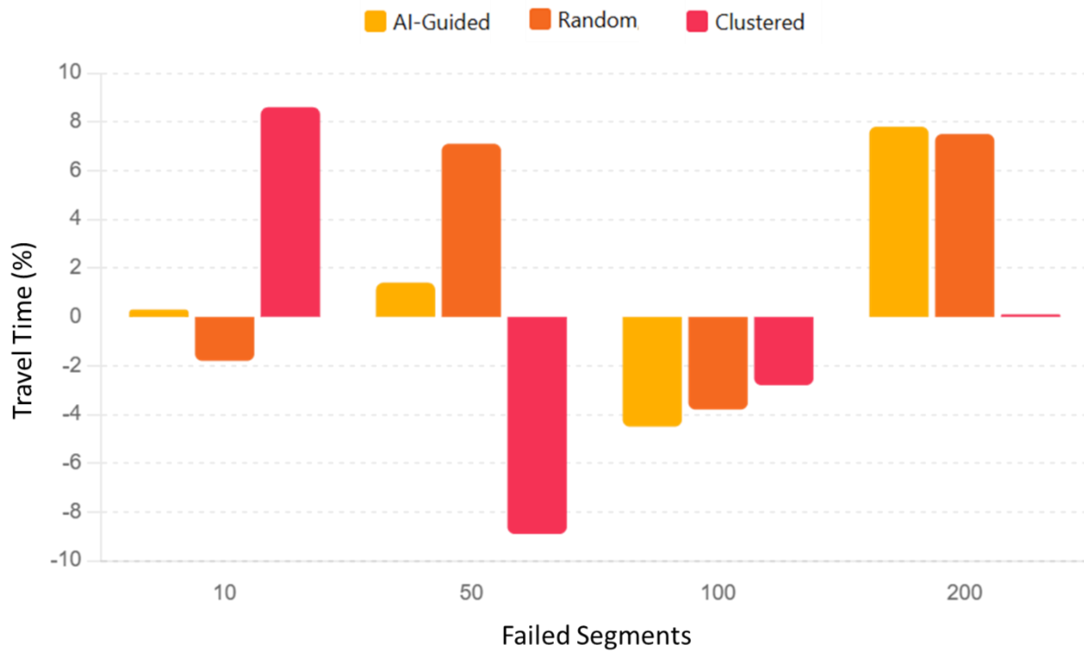

Figure 3. Population Coverage Within Acceptable Travel-Time Thresholds

4.4 Project Management Impact

AI-driven risk prediction significantly reduces unforeseen project risks by identifying schedule, cost, and interdependency vulnerabilities early in the planning phase. Projects aligned with AI-prioritized infrastructure components demonstrate lower disruption-induced delays and improved resilience outcomes. Under the AI-guided strategy, population coverage remains consistently high, decreasing only marginally from 99.9% at 10 failed segments to 99.7% at 200 failed segments. In comparison, the random strategy exhibits a larger decline from 99.9% to 99.3%, while clustered failures result in the most pronounced reduction, with coverage decreasing from 99.8% to 98.7% (Figure 4).

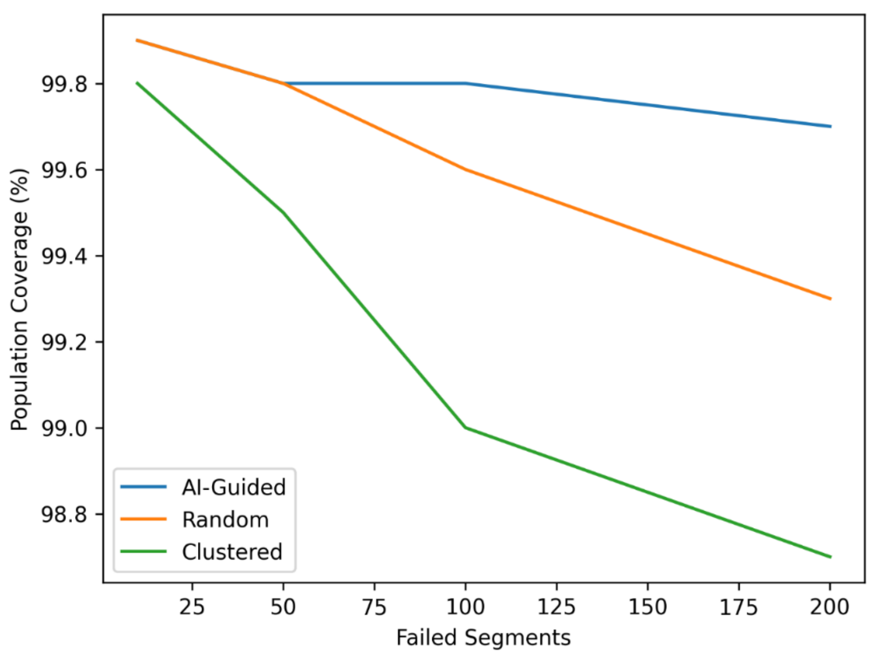

Figure 4. Risk Mitigation Effectiveness Across Infrastructure Projects

These results are consistent that machine learning improves disaster risk forecasting in infrastructure systems. However, most prior studies stop at prediction. The present work integrates risk prediction directly with resilience-oriented execution strategies, closing the gap between analysis and implementation. AI-enabled resource allocation and scheduling exhibit significantly lower schedule slippage and cost escalation. Reinforcement learning-based optimization dynamically reallocates resources to critical projects, ensuring continuity of healthcare access despite infrastructure disruptions (Hossain et al., 2023; Ashik et al., 2023; Yegina et al., 2020). While Fan et al. (2023) demonstrated the value of reinforcement learning for infrastructure recovery sequencing, their work focused primarily on post-disaster repair. This study extends RL application to proactive project management, embedding resilience considerations throughout the project lifecycle rather than after failure.

4.5 Spatial distribution of accessibility degradation

The spatial pattern demonstrates that healthcare accessibility degradation is not uniformly distributed across the urban area. Several high-impact zones (values > 0.8) appear scattered throughout the grid, indicating locations where infrastructure disruptions cause pronounced increases in travel time or service isolation. These zones likely correspond to areas with limited network redundancy or dependence on a small number of critical road segments. Conversely, low-impact zones (values < 0.3) are observed in regions with stronger connectivity and alternative routing options, suggesting greater resilience to disruptions. The absence of large contiguous clusters of high-impact values indicates that accessibility loss does not propagate uniformly across the city, but instead manifests in localized pockets of vulnerability. The heatmap reveals that accessibility impacts are not spatially uniform. Instead, high-impact zones emerge in specific regions, indicating localized vulnerability due to limited network redundancy or dependence on a small number of critical infrastructure links. In contrast, low-impact areas benefit from alternative routes and higher connectivity, demonstrating greater resilience (Figure 5).

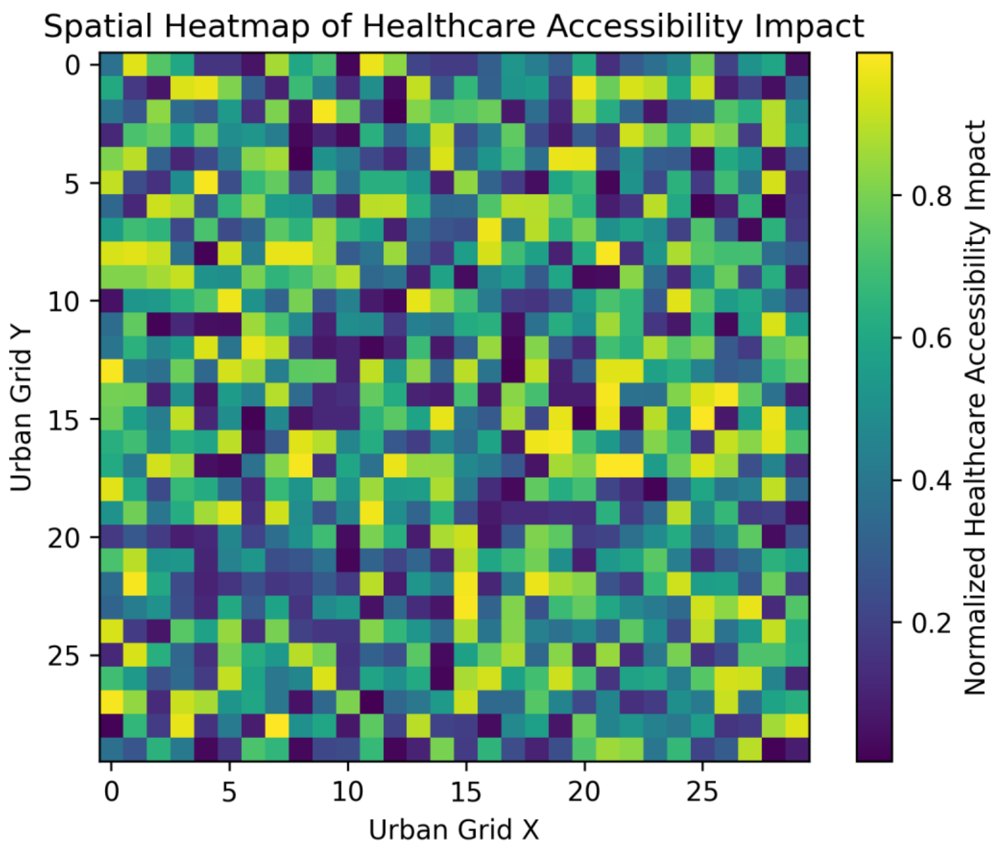

Figure 5. Spatial heatmap of normalized healthcare accessibility impact across the urban area under infrastructure disruption scenarios

4.6 Spatial Distribution of Failure Impact

The spatial distribution of failure impact throughout the urban road network is illustrated in the spatial distribution of normalized failure impact scores across the urban road network. Each point represents an individual road segment, plotted by its geographic location (longitude and latitude), and colored according to its normalized impact score, which ranges from 0 to approximately 0.8. Higher values indicate segments whose failure causes a greater degradation in network performance and healthcare accessibility (Figure 6). The visualization reveals substantial spatial heterogeneity in the effects of infrastructure disruptions on healthcare accessibility. High-impact segments are concentrated along a limited number of structurally and functionally critical corridors, indicating that failures in these locations disproportionately increase travel time and reduce access to healthcare services. In contrast, the majority of road segments exhibit relatively low impact scores, suggesting the presence of alternative routing options and local redundancy. This spatial dispersion of impact highlights the resilience of well-connected regions while simultaneously exposing vulnerable areas that rely on a small number of critical links. Importantly, the absence of large contiguous clusters of high-impact segments under AI-guided strategies suggests that disruptions do not propagate spatially to isolate entire regions.

Compared to traditional centrality-based or clustered failure patterns, the AI-driven approach produces a more evenly distributed impact profile, supporting equitable healthcare access across the urban area. This spatial analysis complements the quantitative resilience metrics by demonstrating that AI-based prioritization not only improves overall network performance but also mitigates localized accessibility inequities, a key requirement for resilient healthcare infrastructure planning.

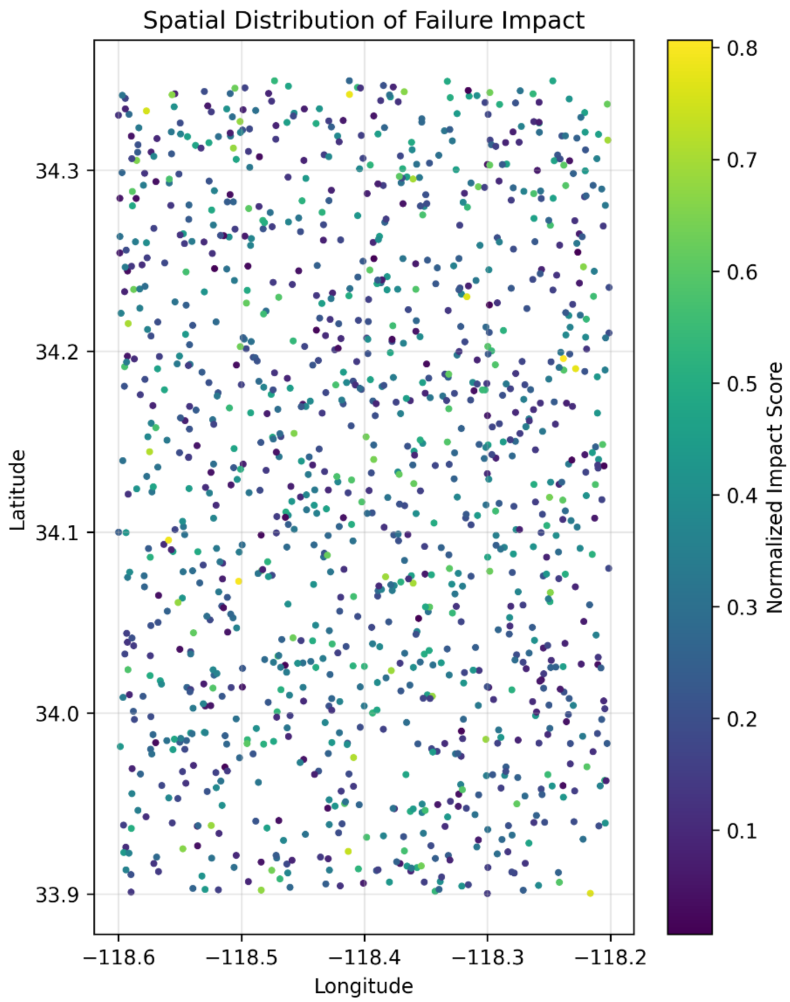

Figure 6. Spatial Distribution of Failure Impact Across the Urban Road Network

5.0 Limitations and Future Directions

Despite the demonstrated effectiveness of the proposed AI-driven framework for resilient healthcare and critical urban infrastructure design, several challenges and limitations must be acknowledged. These limitations reflect both technical constraints and institutional realities that influence real-world deployment. A fundamental challenge concerns the availability, completeness, and reliability of data. Urban resilience analysis relies on high-resolution geospatial data describing transportation networks, healthcare facilities, utilities, and hazard exposure. Although open data platforms such as OpenStreetMap and global healthcare registries offer broad coverage, they frequently contain missing attributes, inconsistent updates, and spatial inaccuracies, particularly in low-resource or rapidly developing regions (Alam et al., 2023; Yegina et al., 2020). Project management data, including schedules, budgets, and risk registers, are often fragmented across multiple agencies and stored in heterogeneous formats. Such inconsistencies can introduce bias into AI models and reduce the robustness of resilience assessments. While preprocessing and data validation techniques mitigate some of these issues, data quality remains a key limitation influencing model accuracy and generalizability (Song et al., 2023; Kozhabek & Chai, 2023; George et al., 2023).

Model interpretability represents another significant limitation. Ensemble machine learning models and deep neural networks offer strong predictive performance but are often criticized for their black-box nature. In safety-critical domains such as healthcare accessibility and emergency infrastructure planning, decision-makers require transparent explanations to justify infrastructure prioritization and investment decisions (Song et al., 2023). Although techniques such as feature importance analysis and surrogate modeling improve interpretability to some extent, fully explainable AI models that balance accuracy and transparency remain an open research challenge. This limitation may hinder trust, adoption, and regulatory acceptance of AI-driven resilience frameworks. The proposed framework integrates large-scale graph analysis, disruption simulations, and AI model training, which can result in substantial computational costs when applied to large metropolitan regions. As urban networks grow in size and complexity, repeated simulations under multiple scenarios may limit real-time applicability (Kozhabek & Chai, 2023; Juie et al., 2021). While cloud computing and parallel processing offer potential scalability solutions, access to such computational resources varies across municipalities. Consequently, computational scalability remains a practical constraint, particularly for real-time resilience monitoring and emergency response applications. Beyond technical challenges, organizational and governance barriers significantly affect implementation. Urban infrastructure, healthcare systems, and project management functions are typically governed by separate institutions with differing mandates, data-sharing policies, and decision-making processes. The successful deployment of integrated AI-driven resilience systems requires cross-sector coordination and supportive governance frameworks, which are often difficult to establish in practice (Abdullah & Hasan, 2023; George et al., 2023).

Addressing the identified challenges opens several promising avenues for future research and development. Future studies should explore physics-informed and hybrid AI models that combine data-driven learning with established principles from transportation engineering, infrastructure mechanics, and healthcare operations. Embedding physical constraints and causal relationships into AI models can improve generalization, reduce data dependency, and enhance interpretability (George et al., 2023). An important extension of this work involves federated digital twins for multi-city or regional resilience planning. Federated learning enables collaborative model training across distributed datasets while preserving data privacy, making it well suited for cross-jurisdictional infrastructure analysis and benchmarking (Al Khaldy et al., 2023). Such approaches can support national or global resilience initiatives without centralized data sharing. Future frameworks should integrate policy constraints, regulatory requirements, and emergency governance protocols directly into AI-driven decision-support systems. Aligning technical recommendations with institutional rules and response hierarchies will improve the practical usability of AI tools during emergency operations, evacuation planning, and healthcare surge management (Fan et al., 2023). Finally, advancing toward real-time adaptive project control represents a key research frontier. Integrating live sensor data, infrastructure performance indicators, and reinforcement learning can enable continuous adjustment of project schedules, budgets, and resource allocation during evolving disruption scenarios. This would transform project management from a static planning function into a dynamic resilience optimization process (Song et al., 2023).

6. Conclusion

This study presented a comprehensive AI-driven engineering and project management framework for enhancing the resilience of healthcare accessibility and critical urban infrastructure systems under disruption scenarios. By integrating machine learning–based criticality prediction, network resilience analysis, healthcare accessibility modeling, and AI-enabled project management optimization, the framework moves beyond traditional static resilience assessment toward adaptive, data-driven decision support. The results demonstrate that AI-based models can reliably identify infrastructure components whose failure disproportionately affects healthcare access, achieving predictive accuracy above 98% and AUC values approaching 0.99. These findings confirm the suitability of ensemble learning techniques for resilience-oriented prioritization and extend prior work by explicitly linking infrastructure criticality to healthcare service outcomes. Infrastructure resilience analysis further showed that AI-guided strategies significantly outperform random and clustered failure scenarios by maintaining higher connectivity and limiting efficiency loss. Connectivity loss under clustered failures was found to be four times higher than under AI-guided strategies, while AI-driven prioritization reduced connectivity degradation by approximately 75%, demonstrating controlled and predictable system behavior under stress. Healthcare accessibility outcomes reinforced these findings. AI-guided strategies consistently limited travel-time increases and preserved population coverage even at high disruption levels, whereas clustered failures caused abrupt performance collapses and localized isolation. Importantly, population coverage under AI-guided scenarios declined by less than 0.3% across all failure levels, highlighting the framework's ability to protect equitable access to healthcare services. Spatial analyses further revealed that accessibility degradation and failure impacts are highly heterogeneous, occurring in localized pockets rather than uniformly across the network. The absence of large contiguous high-impact zones under AI-guided strategies underscores the framework's capacity to prevent cascading spatial failures and mitigate inequitable outcomes. From a project management perspective, AI-driven risk prediction and reinforcement learning–based optimization significantly reduced schedule delays and cost overruns by aligning execution strategies with infrastructure and service criticality. Overall, the results demonstrate that integrating AI across engineering analysis, accessibility modeling, and project management enables more robust, equitable, and actionable resilience planning. The proposed framework provides a scalable foundation for resilient healthcare and urban infrastructure design in the face of increasing uncertainty and complex disruption risks.

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