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APPLICABILITY OF ARTIFICIAL INTELLIGENCE FOR IMPROVING INFRASTRUCTURE RESILIENCE

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ABSTRACT

Infrastructure systems are susceptible to extreme weather events, climate change, ageing, interdependence and cyber threats, highlighting the inadequacy of conventional resilience approaches. This study aims to review and provide an integrated conceptual perspective on how artificial intelligence (AI) capabilities contribute to infrastructure resilience capacities and resilience lifecycle stages. To examine the relationship between AI capabilities and resilience characteristics, a qualitative narrative literature review was conducted following a thematic analysis. The review proposes an integrated conceptual framework linking AI technologies, AI-enabled capabilities, 4R resilience capacities, and resilience lifecycle stages. The findings imply that AI facilitates capabilities such as hazard prediction, real-time monitoring, damage detection, predictive maintenance, and optimised decision-making, supporting the core resilience capacities (4R: robustness, redundancy, resourcefulness, rapidity) to achieve different resilience lifecycle milestones, including prevention, absorption, recovery and adaptation. The findings also suggest that AI has the potential to bring a transition from conventional reactive, siloed approaches towards a more proactive, adaptive and data-driven resilience system. The findings further reveal the importance of AI integration in infrastructure planning, management, and disaster risk governance to enhance preparedness, monitoring, adaptation and decision-making. However, there are several constraints which limit AI performance in resilience, including data quality and availability, governance issues, cybersecurity risks, system interdependencies and complexity, and a lack of interdisciplinary integration. Future research must focus on ageing infrastructure systems, multi-sector interdependent infrastructure, and explainable AI approaches to enhance transparency and understanding of AI-enabled decision-making.

Keywords: *Artificial Intelligence; Infrastructure Resilience; Resilience Capacities; Resilience Lifecycle.*

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1. INTRODUCTION

Infrastructure systems often become vulnerable to various threats, disrupting their continuous and reliable functioning. This vulnerability arises from increasing stressors, including rapid urbanisation and ageing-induced deterioration (Val et al., 2019). In recent years, climate change has become a major driver of infrastructure vulnerability across various sectors (Zlateva & Hadjitodorov, 2022). These changing environmental conditions can reduce infrastructure performance, preventing systems from operating at the intended design capacity. (Neumann et al., 2015). The interdependence among infrastructure networks further complicates the vulnerability causing cascading failures, where disruption in one system affects multiple other sectors (Little, 2002). Together, these compounding effects increases the complexity of global infrastructure vulnerability.

Therefore, strengthening infrastructure resilience has become increasingly important to ensure the continuity of essential services, public safety and long-term sustainability. Infrastructure resilience is defined as the ability of a system to withstand, adapt and recover from various shocks and stresses whilst remaining operational (Ouyang et al., 2012; Sharma et al., 2018). The level of resilience is modelled using the cost of disruption and the duration it stays inoperable. These factors provide a basis for planning effective recovery (Pant et al., 2014). As a result, resilient infrastructure becomes a contributor for economic stability as well. Moreover, resilience has an interdependent relationship with sustainability. Resilience supports infrastructure to maintain continuous functioning and recovery during and after disruptions, while sustainability, ensures that resources are efficiently used with reduced environmental impact (Trejo & Gardoni, 2023).

There are challenges associated with the existing methods used in infrastructure resilience despite its growing demand and importance. Existing research focuses mostly on technical optimizations and discusses less on interdependent infrastructure systems and the strategies to enhance their resilience (Chang et al., 2014; Tong et al., 2025). Current resilience assessments depend on expert opinions, where the quality of results is affected by the subjective experience and their attitude (Bi et al., 2023). Additionally, the existing resilience assessments also rely on the static characteristics of physical systems, while disregarding their dynamic behaviour (Bi et al., 2023). Furthermore, it is highlighted that the resilience models consider resource allocation less frequently, affecting the overall performance of the system during compounding and cascading disaster events (Wells et al., 2022). Infrastructure retrofitting has often been neglected despite the significant societal benefits it offers. This is largely due to its perceived lack of cost-effectiveness and the limited direct benefits it provides to individual organisations (Chang et al., 2014). Consequently, not having a clear definition of resilience has constrained the understanding and meaningful application of it (Bi et al., 2023).

As a response to these limitations, in recent years, artificial intelligence (AI) and machine learning (ML) have emerged as popular transformative tools with the potential to redefine infrastructure resilience approaches. These technologies can process large datasets to identify patterns, predict failures and support decisions for optimized restoration of services (Afolabi et al., 2025). Unlike conventional techniques, AI and ML enable real-time analysis of data, creating a dynamic environment (Afolabi et al., 2025). AI and ML technologies also enhance resilience by supporting optimized decision-making and reducing socioeconomic losses (Alkhaleel, 2024). This is achieved through the identification and analysis of data patterns using ML enabled modelling. Moreover, these tools allow proactive decision making and response by recognizing unusual patterns, predicting system response and alerting operators in a timely manner (Alkhaleel, 2024). The integration of AI with digital twin, which are real-time digital replicas of physical systems, can further strengthen continuous monitoring, detection and response (Afolabi et al., 2025).

Accordingly, the focus of this study is on reviewing the applicability of AI in infrastructure resilience to understand how AI tools and techniques support resilience capacities and lifecycle stages to overcome the challenges in conventional methods. Existing studies are mainly built on separate AI applications, address individual resilience capacities, or focus only on a particular infrastructure sector. There is limited understanding of how AI capabilities collectively support infrastructure resilience capacities and lifecycle stages within an integrated infrastructure resilience framework. The paper is structured as follows: first, the research methodology adopted for the study is presented. This is followed by the literature review, a thematic discussion, and the key findings.

2. METHODOLOGY

This study adopts a qualitative research approach, grounded in a comprehensive narrative literature review to examine the intersection between infrastructure resilience and AI. Relevant literature was carefully identified from peer-reviewed journal articles and conference proceedings to ensure both academic rigor and inclusion of emerging developments in the field. The literature search was conducted using two primary databases, Scopus and Google Scholar. The search process primarily gathered studies published between 2015 and 2026, while several earlier publications were used for the foundational concepts. An iterative search strategy was used where search terms were refined according to the themes emerged during the search process. Representative search terms are "AI infrastructure resilience", "critical infrastructure resilience", "infrastructure vulnerability", "interdependent infrastructure systems", "infrastructure resilience lifecycle", "4R framework", "cascading failures", "structural health monitoring", "infrastructure resilience framework" and "predictive maintenance". Where appropriate, Boolean operator 'AND' was used for search term combinations. The selection process involved screening titles, abstracts, and full texts where necessary to ensure relevance to the research aim, prioritizing the studies based on relevance and recency, with particular attention given to studies addressing resilience characteristics and AI capabilities. The inclusion criteria considered publications related to resilience capacities, infrastructure vulnerability, resilience lifecycle stages and AI capabilities, including predictive analytics, real-time monitoring, damage detection and decision support systems. Studies unrelated to infrastructure resilience, non-English publications and duplicate publications were excluded from the literature review process. Initially, a pool of 183 records were identified. After screening titles and abstracts to remove duplicate and unrelated studies, 87 were reviewed. Ultimately, 49 core studies were selected for the final synthesis. The collected literature was then critically analysed and synthesised using a thematic approach to identify focused areas of the study, thereby providing a structured categorisation of the literature into five key themes, including infrastructure systems and their vulnerabilities, characteristics of resilience, conventional methods of ensuring infrastructure resilience and limitations, applications of AI enhancing infrastructure resilience and challenges and limitations of AI in infrastructure resilience.

3. LITERATURE REVIEW

3.1 INFRASTRUCTURE SYSTEMS AND THEIR VULNERABILITIES

Infrastructure systems are interdependent networks that improve economic stability and societal well-being (Rinaldi et al., 2001). These systems comprise both physical assets—such as transportation networks, energy supply systems, water and sanitation facilities, and communication networks, as well as the organizational and institutional frameworks required for their operation, management, and maintenance. The interdependency and interconnectedness of modern infrastructure systems lead to system vulnerability, as it has become difficult to isolate an individual infrastructure system when seeking solutions after disruptions (Jayasinghe et al., 2023). Interdependencies are classified into four principal types, physical (material or physical flow from one entity to another), cyber (transfer of information), geographic (physical proximity affecting components across multiple infrastructure systems) and logical (dependencies other than the above three categories). This indicates that there are multiple pathways for a disruption to occur (Jayasinghe et al., 2023; Rinaldi et al., 2001). Therefore, the functionality of interdependent infrastructure systems depends on the strength and stability of the connections between them (Mottahedi et al., 2021). However, the interdependency also increases vulnerability, since a failure in one system can trigger cascading impacts across the entire network. A prominent historical example occurred in 2011, when the Tohoku earthquake and tsunami in Japan damaged energy infrastructure, leaving 4.4 million households without electricity. This cascaded into water systems as well, affecting 1.5 million consumers without safe drinking water (Mottahedi et al., 2021). However, as shown by Jayasinghe et al. (2023), most research has focused on the bilateral relationship between infrastructure systems and has neglected the multi-directional dependence among them. Thus, in complex urban network systems, such approaches cannot fully capture the scale and dynamics of cascading effects. Importantly, the conventional silo-based approach used for infrastructure planning, design and operation is inadequate to achieve resilience and sustainability (Jayasinghe et al., 2023) in modern dynamic, and interdependent infrastructure systems.

The performance of infrastructure systems is affected by changing climatic conditions. Extreme events trigger floods, droughts and heatwaves, which may reduce the electricity generation and lead to cascading failures (Val et al., 2019). Although most research focuses on climate hazards, another important issue is the physical deterioration of infrastructure over time. However, the structural state due to ageing-related deterioration is often neglected in resilience assessment frameworks. Studies on seismic resilience of ageing bridges subjected to severe environmental conditions have reported a 52.64% reduction in resilience (Forcellini & Mitoulis, 2025). More recently, compounding threats, where two or more hazards occur simultaneously, have gained attention due to their impact on interdependent infrastructure systems. Yet, questions remain on how current models assess infrastructure resilience under such compounding threats (Wells et al., 2022).

Cyber-attacks can further complicate the infrastructure vulnerability, causing direct physical infrastructure degradation. As stated by Stellios et al. (2018), the Stuxnet attack in 2010 was a computer worm targeting Iran's nuclear program. It infected many industrial control systems and physically degraded approximately 1000 machines. Similarly, the Aurora attack in 2009 caused the circuit breakers to open and close at a fast rate, disrupting the operation of electric power generators that lead to physical damage. As a result of the increasing interdependency between cyber and physical networks, infrastructure becomes more vulnerable to both natural and man-made attacks (Islam et al., 2023).

3.2 CHARACTERISTICS OF RESILIENCE

The growing vulnerabilities of infrastructure highlight the importance of understanding resilience, a concept still with unclear and diverse theoretical foundations across different disciplines and perspectives. Bruneau et al. (2003) provide a definition for community seismic resilience from a functional and social perspective. It is viewed as the ability of systems and communities to mitigate hazards, absorb them and recover effectively to reduce social and economic impacts while limiting future risks. From a broader and more comprehensive perspective, resilience is a quality that controls vulnerability to threats, improving response and recovery, whilst enabling adaptation to disruptive events (Rehak et al., 2018). However, infrastructure resilience is often misapplied and overused in safety management concepts such as risk, reliability, robustness and vulnerability, where existing methods are merely relabelled as resilience (Bi et al., 2023a). Thus, existing methods, often lack strategies for recovery and adaptation after failure. Therefore, carrying out pre- and post-disaster planning with inadequate boundaries and scope can lead to insufficient and ineffective results, especially when using new concepts such as technological infrastructure resilience (Mottahedi et al., 2021).

Despite the many different definitions, there is some agreement across studies on four key resilience capacities. Bruneau et al. (2003) introduced the '4R' concept, which consists of robustness, redundancy, resourcefulness and rapidity as the key properties for physical and social resilience systems. Robustness is the ability to withstand stress without the loss of function, redundancy is the extent to which the systems and units are substitutable, resourcefulness is the capacity to identify problems, prioritize them and use resources efficiently. Rapidity is the ability to achieve recovery in a timely manner while preventing future disruption (Bruneau et al., 2003). Despite the wide use of 4R across studies, the framework faces most of the same limitations as existing resilience assessments. It often neglects the role of society (Mottahedi et al., 2021), and the challenges faced in quantifying resilience metrics, which can affect the accuracy of decision making (Mehvar et al., 2021).

The operation of the 4R capacities is explained in frameworks that view infrastructure resilience as a cyclic process. They propose a similar structure consisting of pre-event prevention, absorption, recovery and adaptation to enable the continual improvement of resilience (Ouyang et al., 2012; Rehak et al., 2018). Prevention is part of preparedness and refers to measures taken to resist potential impacts. Absorption is determined by robustness, which is the ability to absorb disruptive events without causing disturbance to services. Recovery is the ability to return to the original state and is governed by the available resources. Adaptation is the potential to withstand the recurrence of disruptive event (Rehak et al., 2018). When integrating these structured stages, important practical and conceptual challenges arise. Over time, resilience studies have evolved from a "bounce back" to a "bounce forward" approach. Bruneau et al. (2003) define rapidity as a step taken to recover and return to the original state upon disruption. In contrast, more recent studies emphasize transformative resilience which supports absorption, recovery and a bounce forward approach (Zhao et al., 2026). Another issue is the theory- practice gap, which is amplified by the lack of quantifiable resilience metrics (Mehvar et al., 2021). Similarly, many frameworks and principles are difficult to apply to practical scenarios due to the heavy theoretical nature (Labaka et al., 2016).

3.3 CONVENTIONAL METHODS OF ENSURING RESILIENCE OF INFRASTRUCTURE AND THEIR LIMITATIONS

One of the most common conventional approaches to improving infrastructure resilience is engineering design that achieves robustness and redundancy. Robustness allows the system to stay operational even during failure events (Bi et al., 2023), while redundancy brings backup components that support robustness (Bruneau et al., 2003). In practice, this is achieved through a notional infrastructure system with N-1 reliablility (a conceptual modelling used for system reliability, where N denotes the total number of components), where the loss of a single link does not interrupt the operation of other nodes in the network (Alderson et al., 2015). As a result, additional components and safety subsystems are implemented into the system (Labaka et al., 2016).

Another dominant approach is hazard-based risk assessment. This assumes that disruptions are from identifiable causes that can be eliminated or neutralized (Bi et al., 2023). To measure the risk associated with non-deliberate hazards, probabilistic risk analysis is widely used. It considers possible future scenarios, assigns probabilities and estimates their consequences (Alderson et al., 2015). Life-cycle management approaches can be used in three categories, condition-based Markov decision processes, reliability- and risk-based life-cycle management and renewal theory-based life-cycle cost models. These require intervention actions such as inspection, maintenance, repair and replacement during their design service life (Yang & Frangopol, 2019).

Despite the effectiveness of these methods, limitations can be seen due to their static, hazard-specific nature and their limited consideration of interdependent systems. Oversimplified disruption scenarios and the use of random failures to simulate disruptions are common across studies. Such approaches assume that all nodes face the same level of failure probability and successive failures. It is unfavourable in understanding location-specific hazard effects such as flooding (Bi et al., 2023). Moreover, the regulatory structure in most countries is based on a 'siloed' approach that focuses on individual systems, with minimal consideration on interdependence among them (Val et al., 2019). This can lead to cascading failures and unexpected disruptions across infrastructure systems. For instance, the Northeast blackout in 2003 was caused by a local software failure, which resulted in power outages, approximately affecting 50 million people (Bi et al., 2023). Modelling these cascading failures remains complex due to the scale of infrastructure systems and the lack of suitable benchmark studies for comparisons (Val et al., 2019).

A lack of adaptability and uncertainty is another limitation in conventional ex-post analysis approaches, where dynamic system behaviour is difficult to capture, particularly in climate change adaptation context (Mostafavi, 2018). Similarly, the growing digitalization, expose infrastructure systems to new risks, and increase interdependence. This makes them liable to cyber threats that are not addressed within conventional resilience frameworks (Osei-Kyei et al., 2021; Rathnayaka et al., 2022). Additionally, studies have shown that, severe deterioration significantly reduces the resilience performance within a few decades. Hence, the deterioration is neglected in resilience modelling (Forcellini & Mitoulis, 2025).

3.4 APPLICATIONS OF AI IN ENHANCING INFRASTRUCTURE RESILIENCE

This section covers the applicability of AI across five sectors that assist in improving infrastructure resilience, hazard prediction, monitoring, predictive maintenance, disaster response, recovery and adaptive systems. These represent key stages of the resilience lifecycle, including, prevention, absorption, recovery and adaptation (Ouyang et al., 2012; Rehak et al., 2018).

Hazard prediction and risk assessment have improved with the emergence of machine learning techniques. Particularly because AI identify and analyse complex, non-linear hazard patterns. In the context of risks associated with extreme weather events, AI can analyse historical climate data and real-time weather information to predict extreme rainfall events. This supports the planning and designing of infrastructure systems (Habib et al., 2024) by strengthening the proactive preparedness and prevention strategies. In flood assessments, Advanced Decision Tree models have shown significant predictive potential, compared with conventional models such as Frequency Ratio, Weights-of-Evidence and Analytical Hierarchy Process. However, they have limited ability to capture temporal variations (Khosravi et al., 2018), indicating the challenges AI models still face under dynamic environmental conditions. Similarly, in seismic hazard assessments, the integration of Internet of Things (IoT) and AI improves preparedness and early warning, through real-time data collection and analysis. This reduces the potential damage to infrastructure systems (Rosca & Stancu, 2024). These advancements demonstrate the emerging paradigm shift from conventional reactive approaches to proactive monitoring and risk management.

Continuous monitoring and automated observation of structures have become more efficient and accurate with the current advancements in AI, particularly due to its capability to process large datasets under minimal human involvement. In structural health monitoring, AI approaches such as machine learning, deep learning, and artificial neural networks analyse vast amounts of data to support data processing, damage detection and predictive maintenance. Furthermore, these approaches identify critical regions for optimal sensor placement to monitor the structural behaviour (Plevris & Papazafeiropoulos, 2024). This improves the speed and accuracy of infrastructure condition assessments, optimizing the monitoring efficiency and resource utilization. AI and IoT sensor systems support in proactive detection of infrastructure issues requiring maintenance, reducing response time compared with manual processes (Forkan et al., 2024). This supports the adaptive resilience and infrastructure management. Additionally, using deep learning with remote sensing broaden the field by allowing a wider spatial observation of infrastructure (Zhu et al., 2017). Although machine learning techniques using sensor data are widely used across studies, deep learning-based monitoring shows stronger performance, particularly in image-based damage detection (Plevris & Papazafeiropoulos, 2024; Zhu et al., 2017).

AI uses real-time and historical data for predictive maintenance analysis. In railway infrastructure, it is used to identify degradation trends and supports maintenance decision-making processes. Such efficient planning and reduced interventions lead to a greater system stability (Bris-Peñalver et al., 2026). Compared to degradation trend-based models, a more effective technique can be seen in water distribution networks. To identify water pipe deteriorations, artificial neural networks are widely studied due to its ability to cope with nonlinear relationships and uncertainty (Dawood et al., 2020). In addition, machine learning algorithms are promising for early detection of leaks and bursts in pipelines (Joseph et al., 2024). Unlike degradation and deterioration focused predictive maintenance models, anomaly detection models support faster identification and response, reducing the service disruptions.

AI has also enhanced the effectiveness of disaster response and recovery activities compared with conventional manual techniques. In damage assessment, AI-driven Geographic Information System (GIS) platforms automate the analysis of satellite and drone imagery for efficient and accurate damage detection. Similarly, machine learning and computer vision techniques use semantic segmentation, a pixel-based image classification, to rapidly assess the condition of damaged infrastructure (Kopiika et al., 2025). Deep learning-based frameworks such as ChangeOS demonstrate higher speed and accuracy in automated post-disaster damage assessments. This is done using remote sensing images and detecting semantic changes (Zheng et al., 2021). Therefore, deep learning techniques demonstrate strong potential for complex large-scale image analysis in post-disaster damage assessment. Following damage identification, reinforcement learning supports adaptive, sequential decision-making under dynamic, uncertain disaster environments. This facilitates optimized resource allocation and rescue operations during disaster relief activities (Xu et al., 2025).

Recent studies also highlight for the role of AI in adaptive and smart infrastructure systems for long-term resilience. Among them, AI-enabled smart grids optimise urban energy systems by managing the supply and demand in real-time (Almulhim, 2025). This becomes useful in improving operational and energy management in highly interconnected systems. Extending this, AI integrated digital twin systems enables adaptation to dynamic conditions through continuous monitoring, automated damage detection, dynamic hazard modelling and adaptive responses (Afolabi et al., 2025; Argyroudis et al., 2022). Unlike conventional static approaches, digital twin allows continuously updating system behaviour under changing environmental and operational conditions. However, implementation challenges such as data requirement, scalability and computational complexity exist in different scales.

3.5 CHALLENGES AND LIMITATIONS OF AI IN INFRASTRUCTURE RESILIENCE

Despite the capabilities AI provides, several interconnected challenges exist when incorporating AI for infrastructure resilience. Many studies highlight data quality and availability as a main constraint. Alkhaleel (2024) states that modelling complexity increases in interdependent systems when incomplete and uncertainty of data exists. Such issues arise when failure data goes unrecorded or unreported due to perceived insignificance or liability concerns (Val et al., 2019). In addition, Mostafavi (2018) claims that the complex adaptive behaviours and uncertainty of infrastructure systems, may pose challenges when AI-based models accurately represent real-world system behaviour. Weak governance further compounds the effective use of AI. The rapid growth of AI has surpassed regulatory frameworks, leading to governance uncertainties. Particularly, in AI-driven decision-making, there is lack of defined rules regarding responsibility (Androutsopoulou et al., 2025). This limits trust and creates barriers to AI implementation. Similarly, the lack of reporting of AI-related incidents constraints the use of such information for future learning (Agarwal & Nene, 2024). This can lead to repetitive occurrence of such issues. Moreover, AI with IoT increases cybersecurity risks, creating new vulnerabilities. For example, the attackers can manipulate input data, misleading AI models, causing inaccuracy in decision-making (Bonsu & Akekudaga, 2025).

Infrastructure resilience decisions require an interdisciplinary understanding of various sectors. Therefore, machine learning alone is insufficient to maintain such integrations. AI models often lack contextual knowledge required to represent the real-world scenarios. This requires expertise from a variety of disciplines to ensure that the AI model is tailored to the specific context (Ghaffarian et al., 2023). These challenges may become severe in the developing regions, where policy frameworks have not evolved with growing digitalization. In such environments, limited financial resources and technical skills further intensify the issue, slowing the progress and limiting the AI-based systems effectiveness (Ndiaye et al., 2025).

4. DISCUSSION

The conceptual framework illustrated in Figure 1 presents how AI technologies support infrastructure resilience through a sequential and interconnected process.

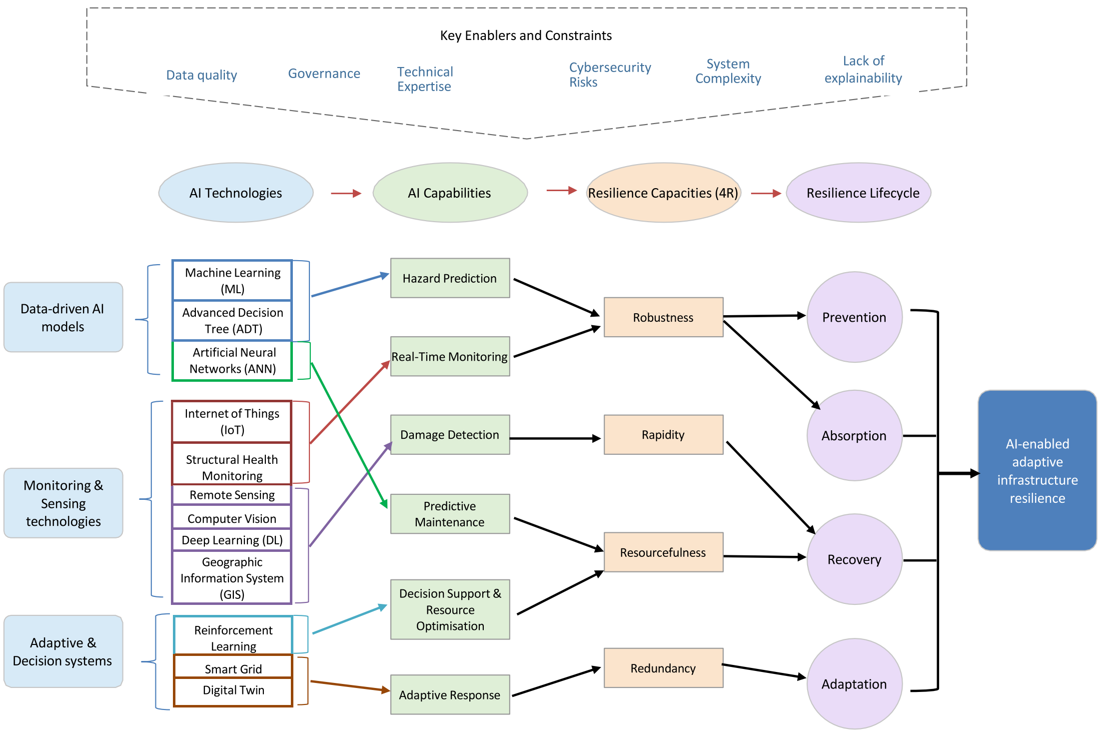

Figure 1: Conceptual framework for AI-enabled infrastructure resilience

The identified AI technologies were categorised based on their function, into data-driven AI models, monitoring and sensing technologies, and adaptive and decision systems. Collectively, these technologies enable six AI capabilities including hazard prediction, predictive maintenance, real-time monitoring, damage detection, decision support and resource optimisation, and adaptive response. These capabilities enhance 4R resilience capacities to achieve milestones across resilience lifecycle stages. The framework enables dynamic, adaptive, real-time resilience system compared to static, silo-based, hazard-specific conventional resilience approaches (Bi et al., 2023; Val et al., 2019).

The initial stages of the resilience lifecycle, prevention and absorption are primarily driven by the robustness of the system. As shown in figure 1, hazard prediction and real-time monitoring enhance the robustness by improving the system ability to withstand stress without a loss of function. In hazard prediction, machine learning and advanced decision tree models identify complex non-linear hazard patterns and deterioration trends (Bris-Peñalver et al., 2026; Habib et al., 2024; Khosravi et al., 2018), allowing proactive preparedness and prevention. This improves robustness allowing the system to prevent impacts before they occur and absorb disruptive events with less service interruptions (Ouyang et al., 2012; Rehak et al., 2018). Similarly, IoT and sensing technologies enable real-time monitoring, facilitating continuous situational awareness and identifies operational risks with minimal human involvement (Forkan et al., 2024; Plevris & Papazafeiropoulos, 2024; Zhu et al., 2017). This strengthens robustness by preventing cascading failures through early intervention and ensures that system absorb shocks through real-time system performance awareness.

The recovery stage is primarily supported by the resilience capacities of rapidity and resourcefulness. Figure 1 links damage detection to rapidity, which is the ability to achieve the timely recovery. This is achieved by reducing response time as a result of early identification of operational risks. For such identifications, deep learning, computer vision, remote sensing and AI-driven geographic information systems enable rapid, pixel-based assessment of damage using satellite and drone images (Kopiika et al., 2025; Zheng et al., 2021). Predictive maintenance and decision support and resource optimisation improve resourcefulness. Artificial neural networks help identify degradation trends and reinforcement learning enables organized decision-making under uncertain conditions (Dawood et al., 2020; Xu et al., 2025). These help to optimize resource allocation and maintenance planning.

The final stage of the lifecycle, adaptation, involves a “bounce forward” approach. Adaptation is the ability of infrastructure to withstand shocks in the future disruptive events (Rehak et al., 2018). This is supported by the adaptive response capability, which enables the redundancy. This can be achieved by smart grids and digital twins as they help manage supply and demand in real-time while adapting the system to changing operational and environmental conditions (Afolabi et al., 2025; Almulhim, 2025; Argyroudis et al., 2022). This reduces service interruptions and improves operational flexibility.

The reviewed literature also indicates a shift in infrastructure resilience, moving from “bounce-back” model toward an AI-enabled “bounce-forward” approach. AI supports transformative resilience through continuous learning, real-time analysis and proactive decision-making. This is particularly beneficial in highly interdependent systems where conventional approaches fail to capture cascading risks (Mottahedi et al., 2021). However, the reliability of AI-driven systems depends on data quality, governance, cybersecurity and system complexities (Alkhaleel, 2024; Androutsopoulou et al., 2025; Bonsu & Akekudaga, 2025). Despite the increasing adaptive capacity and system efficiency, digitalized infrastructure also becomes vulnerable to cyber threats and cascading risks due to system interdependencies (Androutsopoulou et al., 2025; Bonsu & Akekudaga, 2025; Islam et al., 2023; Stellios et al., 2018). Moreover, highly complex digitalized infrastructure may reduce transparency in decision-making (Ghaffarian et al., 2023; Alkhaleel, 2024) and requires interdisciplinary technical expertise and explainable AI for effective implementation (Androutsopoulou et al., 2025; Ghaffarian et al., 2023;

Ndiaye et al., 2025). Therefore, although AI shows greater potential for enabling proactive and resilience, its technological capabilities alone are insufficient for its successful implementation.

The findings highlight the importance of AI technologies in integrated infrastructure resilience planning, disaster risk governance processes and infrastructure management (Androutsopoulou et al., 2025; Argyroudis et al., 2022; Val et al., 2019). AI technologies have significant value when incorporated throughout the entire resilience lifecycle, rather than being limited to the recovery stage. This has the potential to create more integrated, adaptive infrastructure resilience systems capable of handling complex environmental, institutional and operational uncertainties (Argyroudis et al., 2022; Mostafavi, 2018). The review further indicates that AI applications are mature in disaster damage assessment, transportation and energy infrastructures. In contrast, ageing infrastructure and cross-sector infrastructure networks are underexplored, highlighting the need for future research.

5. CONCLUSIONS

The study reviews current literature to understand the applicability of AI in enhancing the resilience of infrastructure systems. The findings indicate that AI technologies bring strong potential to data-driven, dynamic, adaptive decision-making processes, which can be used to improve infrastructure resilience. The proposed framework demonstrates how AI capabilities such as hazard prediction, real-time monitoring, damage detection, predictive maintenance, and decision support link with 4R resilience capacities and resilience lifecycle, including prevention, absorption, recovery, and adaptation. The identified AI capabilities support continuous monitoring, predictive analysis, adaptive response, and decision-making, under dynamic environmental and operational conditions and uncertainties. Thus, AI tools facilitate both “bounce back” and “bounce forward”, addressing the conventional silo-based techniques by marking a transition in resilience paradigm. In practice, integration of AI technologies into infrastructure planning, management, and governance processes can advance and optimize preparedness, monitoring, adaptive resilience, and decision-making across the entire resilience lifecycle, rather than limiting them only to the conventional recovery stage. However, the performance of these AI models depends on the data quality, governance issues, cybersecurity risks, system complexities and resource limitations. Incorporating governance frameworks, strengthening cybersecurity, maintaining data quality and availability and understanding the system interconnectedness are essential to implement AI in infrastructure resilience successfully. Future research should examine AI-assisted resilience frameworks while addressing governance, cybersecurity, and data quality challenges. More attention is also needed in AI behaviour on ageing infrastructure and interdependent cross-sector systems, and on approaches such as explainable AI, to improve the transparency and AI-driven decision-making understanding.

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