2025 European Conference on Computing in Construction

CIB W78 Conference on IT in Construction

Porto, Portugal
July 14-17, 2025

ON ARTIFICIAL INTELLIGENCE APPLICATIONS FOR RESILIENT TRANSPORT INFRASTRUCTURE

Giuseppe Vega and Georgios Hadjidemetriou
School of Architecture, Building and Civil Engineering, Loughborough University, Loughborough, UK

Abstract

In recent decades, awareness of climate change challenges has grown across engineering disciplines, as has the interest of researchers and practitioners in incorporating AI technologies into engineering solutions. Yet, little has been discussed about the potential of AI in supporting societies to meet climate change challenges (e.g., resilience). A framework setting a pathway to achieve this is proposed, along with a methodology using a co-occurrence-based keyword strategy to tackle its first steps. Preliminary findings show that research in AI is being extensively developed for specific transport issues, but as a broader consequence, these can potentially increase the resilience of transport infrastructure systems.

Introduction

Transport infrastructure is the deliberate modification of the natural environment to meet the need of societies to move people and goods from one place to another. It encompasses physical assets, such as roads, bridges, railways, canals, and airports, but also the associated facilities such as vehicle signalling, communication, and management systems. However, it is also more than just physical constructs – it is a dynamic and evolving element essential for society's function and progress (National Geographic Society, 2023).

The development of transport infrastructure has been essential for economic and societal growth. It has enabled expanding capital productivity, accelerating industrial agglomeration, and reshaping market demand (Zhang and Cheng, 2023). Moreover, when transport infrastructure planning is conceived as inclusive, it can reduce inequalities, promote health, empower relegated groups, and help societies thrive (United Nations Office for Project Services et al., 2023).

Challenges of the transport sector

In the last decades, technological advances along with population growth and urbanisation have created several challenges for the transport systems. People living in dense population areas started facing increasing levels of congestion, travel costs, and even fatalities due to collisions (Goetz, 2019). For example, in 2023, it was estimated that an average driver in the UK lost 62 hours and 726 USD in fuel because of congestion, while 1624 people died due to road collisions (Pishue and Kidd, 2025).

Beyond these challenges, an additional significant concern has been increasingly raised. The climate crisis has been adding substantial pressure to the transport sector. On one hand, transport is one of the largest contributors to Green House Gas (GHG) emissions, accounting for around a quarter of all energy-related emissions (Ferrer and Thomé, 2023; United States Environmental Protection Service, 2024). Hence, world commitments have been made to cut transport-related emissions, increase investments in climate-resilient infrastructure, and expand low emissions mobility solutions by 2030, so that by 2050 net-zero transport is achieved along with enhanced resilience against climate impacts. On the other hand, as more intense and frequent extreme weather events are expected, transport infrastructure deteriorates faster, leading to higher maintenance costs, business interruptions, and increased health and public safety risks.

To address these issues, both researchers and practitioners have been increasingly focusing on resilience and sustainability across the transport sector (Bocchini et al., 2014). Resilient transport infrastructure can absorb disturbances from disruptive events while maintaining its basic structure and function and recovering rapidly to a required level of service within acceptable time and cost (United Nations, 1987). Sustainable transport infrastructure is about meeting the current needs without compromising the resources required to meet future needs (Wan et al., 2018). Still, the pursuit of sustainability and resilience may be often in conflict, so decisions must aim at the best possible balance (Bocchini et al., 2014).

Artificial Intelligence across the transport sector

Artificial Intelligence (AI) is a broad field and arguably the most significant area of modern Computer Science. In 1950, Alan Turing introduced the Turing test to assess whether a machine could exhibit intelligent behaviour. The term "Artificial Intelligence" is widely attributed to John McCarthy, who coined it in 1955 while proposing the Dartmouth Conference, which he organised in 1956 to explore ways to make machines exhibit intelligent behaviour (McCorduck, 2004). AI is a technology that enables computers and machines to replicate or simulate human cognitive abilities, such as learning, comprehension, problem-solving, and decision-making, among others (IBM, n.d.; Phusakulkajorn et al., 2023a).

In the transport sector, a wide range of AI applications have been proposed by researchers, and implemented by practitioners. The increasing complexities and interconnectedness of transport systems to other critical systems, as well as the challenges related to extensive and diverse sets of data have encouraged the implementation of this digital technology (McMillan and Varga, 2022). Hence, AI is currently being explored for applications such as forecasting transport demand (Ali, 2024; Subramanian et al., 2023), and predicting road accidents (Eskandari Torbaghan et al., 2022; Silva et al., 2020; Tselentis et al., 2023). It is also utilised for route optimisation (Vieira et al., 2025), logistics (Boršoša and Koman, 2025; Malhotra and Kharub, 2024), and monitoring the condition of infrastructure assets (Abu Dabous et al., 2025; Bunker et al., 2024; Chang et al., 2025; Zhang et al., 2025). Additionally, AI has been more broadly investigated for operation tasks such as traffic management and signalling (Ali Almansoori et al., 2022; Almatar, 2024), or those related to autonomous vehicles manoeuvring (Chen et al., 2023; Yang and Kim, 2025).

Some of the first studies of AI in transport took place in the 1980s and were related to the incorporation of expert systems in areas such as traffic engineering (Chang, 1987) and management (Taylor, 1990), networks and roads geometry design (Bryson and Stone, 1987), and maintenance and rehabilitation activities planning (Hajek et al., 1987). Later in the 1990s, other approaches, such as neural networks, were explored. These were found useful as a method of analysing extensive and complex data, often addressing non-linear problems. Driver behaviour, traffic management and forecasting, pavement maintenance, and operations efficiency were some of the investigated uses of neural networks (Dougherty, 1995). More recently, other potential uses, such as predictive maintenance have been explored further. Using automated data collection methods for both the operation and the physical aspects, AI tools can be used to analyse the data and set the plans of maintenance activities for bridges, tracks, and roads (Achillopoulou et al., 2020; Alsufyani and Gill, 2022; Dhada et al., 2020).

AI to meet the commitments of the transport sector

Beyond their many potential applications for improving the performance of transport networks, AI technologies can also support the sector in addressing global challenges related to resilience. Although many AI-based approaches are designed to address specific transport challenges without explicitly targeting resilience, they can contribute – directly or indirectly – to the development of resilient transport networks (John et al., 2024; Mohamed and Shen, 2024; Sharma and Singhal, 2025; Sun et al., 2024; Yang and Kim, 2025). In addition, since the concept of resilience has not reached a consensus within the scientific community, understanding how AI may have an impact on it becomes challenging and a pathway to do so remains unclear.

A critical research gap exists in developing a framework to understand how AI can enhance resilience across the transport sector. This paper aims to address this gap by, firstly, proposing a comprehensive framework and, secondly, focusing on the initial steps of that framework - specifically, understanding and linking AI with resilience properties and dimensions. The framework offers a structured approach to evaluating AI's contribution to resilient transport infrastructure, with the goal of identifying optimal technology combinations to enhance resilience in a holistic way, extending beyond purely technical or engineering considerations (Bruneau et al., 2003).

Proposed Framework

Resilient infrastructure has been a focus of research in engineering, particularly during the last twenty years. The concept popularity was presumably triggered by Holling in 1973, who introduced it in the context of ecological systems as a measure of systems' persistence and ability to absorb change and disturbance while maintaining their interdependencies and state variables (Holling, 1973). Thirty years later, Bruneau proposed a framework measuring resilience in the context of earthquake engineering; building and maintaining resilience depends on the ability to withstand a disruption, having alternatives when parts fail, being resourceful in the face of challenges, and recovering quickly. This is usually referred to as the 4Rs resilience framework, which stands for robustness, redundancy, resourcefulness, and rapidity (Bruneau et al., 2003). Depending on the context, additional concepts such as flexibility, redundancy, preparedness, and responsiveness, among others, are also referred (Bocchini et al., 2014b; Wan et al., 2018a). This paper develops a framework to measure the potential impact of AI technologies in transport infrastructure considering the 4Rs, which are widely acceptable in engineering and infrastructure management. Thus, a potential standardised pathway for the resilience of transport infrastructure assessment is offered.AI-driven resilient transport infrastructure framework

Figure 1 presents the proposed framework which defines a pathway to finding the optimal combination(s) of AI applications for resilient transport infrastructure. In step 1, the sources describing AI applications being used in the transport sector should be identified and compiled. Then, from step 2 to step 4, the compiled AI applications must be comprehensively analysed. Specifically, in step 2, the potential of the applications in transport infrastructure needs to be clarified (2a), along with the possible challenges for its implementation in real-world scenarios (2b). During step 2, it should be intended to answer the question 'what are the transport challenges the AI application addresses?'. In step 3, the link between the AI applications and the resilience properties (robustness, redundancy, resourcefulness, and rapidity), and dimensions (technical, organisational, social, and economic) must be established by understanding which

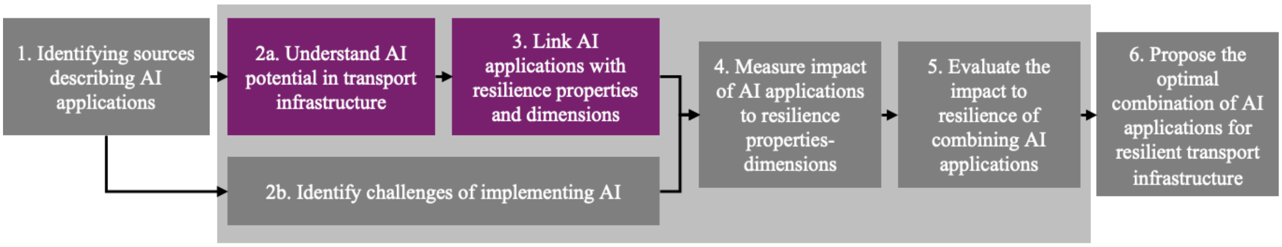

Figure 1: Resilient transport infrastructure framework for AI applications

direct or indirect resilience improvements the AI applications can undertake. For step 3, the link between AI applications and resilience should be stablished using the proposed framework in this paper, on which the definitions of Bruneau were adapted for the transport infrastructure context. In step 4, the impacts of AI applications to the resilience properties and dimensions should be measured through either quantitative or qualitative approaches. In step 5, after measuring the impact of compiled AI applications on the resilience of transport infrastructure, these are combined in different arrangements to evaluate the impact when these work together. The evaluation carried out in step 5 must consider not only the impacts of AI on the resilience but also the challenges of implementation in real-world scenarios, so that in step 6 an optimal combination of AI applications can be proposed.

4Rs resilience for transport infrastructure

Although the four properties of resilience as defined by Bruneau come from an earthquake engineering background, these are broadly applicable to other contexts. In the context of transport infrastructure, we propose the following modified definition of the 4Rs:

- Robustness: the capacity of the transport networks, assets, or interconnected systems to withstand a disruptive event without suffering degradation of or loss of its condition or functionality.
- Redundancy: the extent to which the functionality of degraded or damaged transport networks, assets, or interconnected systems can be substituted by others' in case of disruption.
- Resourcefulness: the capability to efficiently mobilize the resources to meet the required conditions to avoid disruptions or reduce their possible impacts.
- Rapidity: the capability to rapidly recover the functionality and conditions of the affected transport networks, assets, or interconnected systems.

Bruneau explained that resilience can also be comprehended regarding four interrelated dimensions: technical, organisational, social, and economic. The technical dimension is the capacity of the physical elements to perform at a level of service when facing the disruption. The organisational dimension is the capability of stakeholders to make decisions and take action to enhance the resilience efficiently. The social dimension is associated with the negative impacts that communities may suffer due to the reduced functionality given the disruption. The economic dimension is related to the direct and indirect monetary losses due to the impacts of the disruption (Bruneau et al., 2003).

Methodology

AI applications in the field of transport infrastructure are identified using Scopus. The search strategy includes keywords related to digital technologies, such as 'AI' OR 'artificial intelligence' OR 'machine learning' OR 'deep learning', but also (AND) keywords related to the target field, either (i) 'transport*' AND 'infrastructure', OR (ii) 'railway*' OR 'rail' OR 'rails' OR 'roads' OR 'road' OR 'highway*'. Additionally, the search is limited to document type article which have been published in English between 2020 and 2025.

After compiling these studies, the database containing their titles, abstracts, and keywords is analysed to address steps 2 and 3 of the proposed framework. A co-occurrence-based keyword strategy is carried out for both identifying AI potential in transport infrastructure, and linking these with resilience properties and dimensions, as stated in the proposed framework.

Classifying AI Applications in Transport Research

The titles, abstracts, and keywords of the collected papers are analysed with the co-occurrence strategy to determine whether the studies target the challenges of a particular subfield of transport research. To capture the widest range of studies, four subfields are defined: (i) road safety, (ii) infrastructure condition management, (iii) traffic management, and (iv) automated vehicles. For each subfield, a set of objective keywords is assembled. A paper is considered to target a subfield if any of its objective keywords appear in the title, abstract, or keywords of the paper. For example, if a paper contains in its abstract any of the following, it is considered to target the subfield of road safety: 'road safety', 'road collision', road crash', 'road accident', 'traffic safety', 'vehicle safety', 'transport safety', 'safe mobility', 'traffic collision', 'traffic crash', 'traffic accident', 'vehicle crash', 'vehicle collision', 'vehicle accident', 'car accident', 'car crash', 'car collision', 'road incidents', 'road fatalities', 'road injuries', 'road casualties', 'vision zero', or 'crash fatalities'

Linking AI in Transport Infrastructure to Resilience Properties and Dimensions

The links between AI potential applications in transport infrastructure and the properties and dimensions of resilience are stablished using a co-occurrence strategy with two or three sets of objective keywords. These sets are generated for every property (i.e., robustness, rapidity, redundancy, and resourcefulness) and dimension (i.e., technical, organisational, social, and economic). A scientific paper is considered to address a specific property or dimension only if it contains at least one keyword from each of the corresponding sets of objective words in its title, abstract, or keywords. For instance, a paper mentioning both ‘resist’ AND ‘failure’ is classified under robustness, as each word belongs to one of the two sets defining that property. Likewise, a paper mentioning ‘industry’ AND ‘growth’ is associated with the economic dimension of resilience.

To ensure the link between AI in transport infrastructure and resilience is captured, an additional co-occurrence analysis is carried out. Two sets of objective keywords are defined to effectively capture the studies addressing resilience. The two sets contain the following words:

1. 'resilien*', 'withstand', 'absorb', 'resist', 'recover', 'bounce back', 'adapt', 'respon*', 'mitigat*', 'coping', 'robust', 'flexib*', 'redundan*', 'prepare', 'maintain', 'persist', 'transform', 'continue'.
2. 'resilien*', 'disrupt', 'shock', 'stress', 'hazard', 'disturb', 'extreme event', 'weather event', 'extreme weather', 'disaster', 'emergency', 'threat', 'risk', 'fail', 'gault', 'breakdown', 'earthquake', 'flood', 'landslide', 'heatwave', 'delay', 'overload', 'accident', 'incident', 'storm', 'outage', 'blackout', 'collaps*'.

Preliminary findings

The implementation of the search strategy in scopus resulted in 13.240 papers, which were filtered for Q1 journals, reducing the number of papers to 9.547. From this, 1.513 were found to target road safety, 927 infrastructure condition management, 2.781 traffic management, and 1.310 automated vehicles (one paper can target two or more subfields). 4.530 papers remained without a targeted subfield.

During the analysis of objective words for the concept of resilience, only 233 papers contained the string ‘resilien*’. By using the co-concurrence strategy with two groups of objective words, it was possible to determine that 2.089 studies can potentially address resilience in transport infrastructure. It can be inferred that, despite numerous research do not mention resilience at all, they still show a potential for being relevant for contributing towards resilience. Likewise, when analysing the 2.089 studies regarding their subfield in transport infrastructure, 567 of them target road safety, 205 infrastructure condition management, 626 traffic management, and 267 automated vehicles. However, again, this might not mean that only 567 out of the 1.513 studies targeting road safety are addressing resilience. Instead, the 946 remaining studies might deliver significant contributions towards resilience. Thus, table 1 shows the results of the co-occurrence-based strategy, considering the four properties and dimensions of resilience.

Table 1: Studies targeting resilience properties and dimensions

	Technical	Organisational	Social	Economic
Robustness	1271	137	110	289
Rapidity	293	35	24	44
Redundancy	151	26	18	48
Resourcefulness	122	25	20	29

Figure 2 illustrates the data presented in Table 1. AI applications in transport infrastructure tend to emphasise the robustness property and the technical dimension, whereas the resourcefulness property and the social dimension remain the least explored. When analysing every explored subfield (i.e., road safety, infrastructure condition management, etc.), these trends do not change. Nevertheless, reviewing relevant studies in each subfield enables the identification of resilience properties and dimensions that are underexplored, highlighting areas where further research is needed.

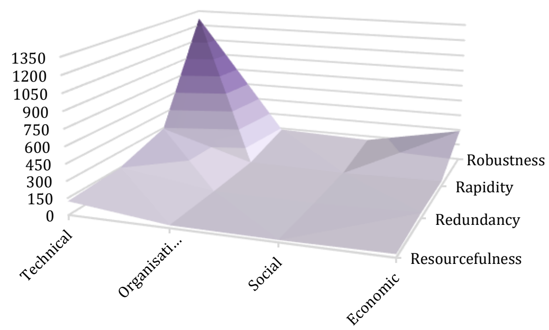

Figure 2: Studies of AI in transport infrastructure targeting resilience properties and dimensions

Transport safety

Due to its impact on societies, road safety has been a topic of extensive research in the transport sector (Bhattacharya et al., 2022). During the last years, an interest in using AI techniques for enhancing road safety instead of traditional statistics approaches has been growing (Abduljabbar et al., 2019). In particular, Machine Learning (ML) techniques have been found promising compared to traditional statistical models for identifying and predicting crash frequency and its classification according to the severity (Silva et al., 2020), but also for the accident hotspots (Eskandari Torbaghan et al., 2022). In the view of the proposed framework, these AI tools can improve resilience of transport infrastructure systems, especially across the technical, social, and economic dimensions. Predictive detection of road crash circumstances and hotspots allows planners to early implement measures to reduce the odds for disruption due to road accidents, increasing the capability of the network to avoid disruption (robustness) or road managers to allocate resources better (resourcefulness). Real-time detection and localisation of road accidents enable decision-making to reduce the impact of disruption and recover the degradation on the level of service rapidly, improving response speed (rapidity) and enabling more efficient resource mobilisation (resourcefulness). Overall, social, and economic impacts are lessened both for avoiding road casualties or injuries and keeping the technical conditions of the road infrastructure.

AI applications for safety have not been limited to road safety. The growing interest of researchers in this topic has led the academic sphere to investigate various applications using Artificial Neural Networks (ANN), Markov and Bayesian Models, and Support Vector Machine (SVM). Crash prediction, pattern identification, routing assistance, and incident or failure detection have been addressed across different transport modes (maritime, aviation, road, and rail) (Tselentis et al., 2023). Besides, AI applications are often incorporated as part of safety systems, like railways' (Chang et al., 2025).

Infrastructure condition management

As civil engineering projects become more complex, traditional inspection techniques can be considered as less accurate, slower and more expensive. In the view of a global shift to data-driven automation of processes and decision making, inspection of civil infrastructure has incorporated AI techniques and the interest of researchers in this area has significantly increased. Automated three-dimensional and two-dimensional imaging, radar detection, sound-based technologies, and ML data processing techniques are some of the tools that have been extensively explored for monitoring and assessing the conditions of civil infrastructure such as roads, railways, associated facilities, and interconnected systems (Abu Dabous et al., 2025; Gopalakrishnan et al., 2018; Zhang et al., 2025; Zhang and Cheng, 2023). Particularly, ML techniques are frequently part of detection systems supported by other technologies which can be supported or driven using AI tools, such as Unmanned Aerial Vehicles (UAVs) since this kind of equipment can facilitate the inspection tasks (Egodawela et al., 2024; Jin et al., 2023).

Using AI tools for more efficient monitoring techniques enables better resource allocation and mobilisation (resourcefulness) for maintenance and targeted interventions on infrastructure elements (robustness). This means that resilience of the transport infrastructure increases especially regarding resourcefulness across technical and organisational dimensions, and robustness across technical and economic dimensions. Moreover, as an indirect consequence, adequate maintenance helps ensuring operational safety and therefore, the improvements on resilience related to transport safety (stated before) are also reached.

Traffic management

Traditional traffic management is usually based on static rules and due to the increasing complexities of transport infrastructure networks and systems, these have been facing challenges to dynamically address common problems derived of congestion or disruptions (Khan et al., 2025). To improve the performance of traffic management systems, AI tools have been broadly incorporated, using ML techniques, pattern identification, reinforcement learning, and deep learning, among others, to deal with traffic congestion, intersections queuing, routing issues, or peak hour bottlenecks (Gazzawe and Albahar, 2024; Iyer, 2021; Skrabacz et al., 2024; Vieira et al., 2025; Yijing et al., 2023; Zhang and Zhang, 2023). Additionally, AI-driven traffic signalling has also been explored to reduce human intervention and enable traffic management at locations and circumstances such as roundabouts (Ali Almansoori et al., 2022) or junctions with regular light traffic which notably increases during peak hours (Kamasetty et al., 2022).

The implementation of AI tools for traffic management can assist the redundancy of transport networks across organisational and social dimensions by supporting the rerouting of traffic to reduce the impact of a disruption and therefore meeting the community needs, taking advantage of alternative routes. Resourcefulness is also supported across organisational and social dimensions by enabling real-time decision making and meeting the user's needs more easily. However, more importantly, the boosted efficiency provided by AI tools in traffic management can lead to a considerable increase in the rapidity across all four dimensions. The time to recover level of service of transport networks can be significantly diminished (technical dimension), the time needed for decision making to restore the performance of the network is also reduced (organisational dimension), and the general time to return to pre-disruption functional levels can be drastically optimised (social and economic dimensions).

Automated Vehicles

Use of AI applications and tools for Automated Vehicles (AV) is notably one of the most explored areas in the transport field. There is a consensus within researchers that AV can potentially make journeys safer and more efficient (Sayyad et al., 2024). However, more extensive research must be carried out to ensure the expected benefits of AV while their share in the automotive market grows rapidly and concerns within the customers spread (Muzahid et al., 2023). AI have a particular relevance for the AV take up, since these self-driving vehicles imply large challenges, such as objects classification, image recognition and analysis, changing driving decisions and even making choices in tough scenarios. Most of the applications of AI in this area are focused on the operational aspect of transport. However, broader improvements for resilient transport infrastructure can be obtained, particularly of the robustness across all four dimensions (Muzahid et al., 2023).

The analysis carried out for the reviewed studies in transport safety, infrastructure condition management, traffic management, and autonomous vehicles, enabled the linking of AI applications in these areas with the defined properties and dimensions of resilience. Table 1 presents the results of executing step 3 of the proposed framework.

Conclusion

Resilience is a widely used term across multiple fields, and no single, universal definition exists for the domain of transport infrastructure. This paper's first contribution is providing a framework with an adapted definition to understand and integrate different properties of resilience – robustness, redundancy, resourcefulness, and rapidity – with its various dimensions – technical, organisational, social, and economic. It includes the search of AI applications in transport infrastructure research and an analysis using a co-occurrence keyword strategy to understand the state-of-the-art of AI with a direct or indirect impact on resilience. These technologies are then categorised according to the relevant resilience properties and dimensions. This classification provides insights into the current capabilities of AI in enhancing transport infrastructure resilience and helps identify potential research gaps.

Presented herein are the preliminary steps of developing a comprehensive AI-driven framework for enhancing multiple properties and dimensions of resilience. A bibliometric analysis and a systematic literature review will be carried out to understand what properties and dimensions of resilience of transport infrastructure are being more commonly addressed by AI applications, and where potential gaps can be identified. Furthermore, metrics to assess the robustness, redundancy, resourcefulness, and rapidity across the technical, organisational, social, and economic areas need to be established. For this purpose, the quantitative approaches accepted in earthquake/structural engineering can also be a start point. However, considering transport dynamics inherent to human behaviour, qualitative approaches should also be explored. Overall, further research on the potential of AI addressing resilient transport infrastructure in the view of climate change and the growing challenges in this field can have a significant impact on modern societies.

Limitations and further research

This preliminary presented research work is characterised by some limitations which could potentially be addressed in future research. Particularly, the co-concurrence-based keyword strategy is not accurate to reveal the semantic meaning of what is stated in the analysed studies, and imply several assumptions that need to be addressed. For example, some objective keywords can mislead to classifying studies irrelevantly (e.g., 'road' is a string that can be taken as 'roadmap'). Additionally, only four subfields of AI in transport infrastructure were explored, but a vast number of studies remains out of these (e.g., urban planning can be considered as a subfield where many studies may focus on organisational property, and social and economic dimensions of resilience). Moreover, the subfields can be also divided regarding specific fields of research on each of them (e.g., demand modelling and forecasting in traffic management). Summarising, this study provides a foundation for understanding AI's role in enhancing transport infrastructure resilience, with further refinement and exploration of additional subfields essential to addressing the challenges posed by climate change and societal needs.

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