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State-of-the-Art Analysis of Data Analytics Integration in Smart Systems for Cost-Effective Risk Mitigation in National Transportation Networks

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Abstract: The national transportation systems are increasingly faced with old infrastructure, climate-induced stressors, and increasing demands that are leading to untimely failures, safety concerns, and rising costs. Pervasive sensing, connectivity, and computation have been developed into smart systems that can be central to resolving these issues, but the effectiveness of their incorporation into architectures and decision processes depends on successful integration. This review synthesizes literature in sensing ecosystems, data integration and fusion, analytics typologies, and integration architectures, and identifies applications in asset health, traffic safety, network reliability, and resilience within national transportation networks, with a focus on the U.S. It considers the role of predictive and prescriptive analytics in maintaining risks, proactive safety, and adaptive traffic control, and how such tools can be used to measure economic effects, such as cost-benefit analysis and life-cycle analysis. The article cites some primary technical, organizational, and societal issues, such as data heterogeneity, model robustness, workforce capacity, governance fragmentation, privacy, and cybersecurity, that limit scalable deployment. Based on these insights, it presents future research and implementation priorities associated with advanced analytics and artificial intelligence; digital twins; uncertainty-aware decision frameworks; and standardized cost-efficiency analysis. The results highlight the potential and challenge of bringing data analytics to smart systems and emphasize the necessity of concerted research, practice, and policy actions to achieve long-term gains in safety, reliability, resilience, and economic performance. Transportation agencies can leverage integrated analytics to prioritize maintenance, enhance safety interventions, and allocate resources more efficiently for long-term, cost-effective network performance.

Keywords: Smart Transportation; Data Analytics; Risk Mitigation, Digital twins, predictive maintenance.

INTRODUCTION

The United States (U.S.) transport infrastructure is under growing pressure due to aging infrastructure, climatic stressors, and rising demand, which jointly give rise to delays, security risks, and persistent overrun costs in construction and operational activities (United States Department of Transportation (USDOT), 2024; Neumann *et al.*, 2021). These infrastructure management challenges are also exacerbated by climate stressors (flooding, sea level rise, landslides, washouts, wildfires, and extreme heat) and by exposure to service disruptions and asset damage (Lykou *et al.*, 2017). Pervasive sensing, connectivity, and computation have become key solutions to these issues, enabled by smart systems that can monitor the state of assets, traffic, and environmental loads across networks in real time (Sumalee & Ho, 2018). More recent reviews also describe smart transportation as an ecosystem that combines the Internet of Things, communication networks, edge and cloud computing, and data-centric intelligence to enable safer, more responsive mobility systems (Oladimeji *et al.*, 2023).

The real value of such smart systems, though, resides in their ability to turn diverse streams of data into useful insights through data analytics, helping predict risks, enable prompt interventions, and optimize life-cycle spending. The current literature on traffic safety, asset management, and intelligent transport services has shown considerable progress in specific application areas, yet these areas remain disjointed in terms of architectures, approaches, and assessment models (Tzika-Kostopoulou *et al.*, 2024). Relevant surveys of digital-twin-based smart transportation systems also note the swift rate of methodological progress, though the fragmentation of architectures, interoperability, evaluation rationale, and implementation approaches remains evident (Ge & Qin, 2024). Meanwhile, U.S. policy and technical debates go on to emphasize that transportation analytics should be evaluated on more than operational utility and that they have consequences for safety, security, privacy, reliability, and resilience (USDOT, 2024). This has led to the need for a synthesis that specifically concentrates on integrating data analytics into smart systems to deliver quantifiable risk mitigation and cost-effectiveness at the scale of national transportation systems.

The current paper fills this gap by providing a state-of-the-art discussion of data analytics integration in smart systems to mitigate cost-

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effective risks in national transit networks, with a focus on the U.S. context. By doing it, it explores the utilization of predictive and prescriptive analytics, such as machine learning and hybrid physics-data models, to aid risk-based maintenance, preventive safety management, and responsive traffic operations (Abbas & Humayun, 2023). These strategies enable transportation agencies to shift their operations toward proactive, rather than reactive, management techniques that boost infrastructure performance and improve resource-allocation efficiency. Other continuing issues that limit scalable and fair deployment, including data variation, model durability, workforce capacity, governance fragmentation, privacy, and cybersecurity, are also noted in the analysis (USDOT, 2024; Intelligent Transportation Society of America (ITS America), 2025; Mukhopadhyay *et al.*, 2024). The paper ends by summarizing future research and implementation priorities in advanced analytics, digital twins, uncertainty-aware decision frameworks, and cost-effectiveness assessment required to fully realize the potential of smart data-driven smart infrastructure monitoring in national transportation systems.

Methodology for literature review

To capture both the mature and emerging publications in data analytics integration in smart transportation systems to retain flexibility to incorporate agency reports and recent pilot studies, this paper is structured as a state-of-the-art review instead of a fully protocolized systematic review. To guide the review, four questions were used: 1) which data sources and sensing ecosystems support analytics-enabled smart monitoring; 2) what analytics typologies and methods address various risk and cost issues; 3) how analytics are integrated into architectures and decision processes; and 4) what evidence exists on risk mitigation and economic impacts. Peer-reviewed journal articles, conference proceedings, and official technical reports were considered in the fields of transportation engineering, computer science, and infrastructure management. Conceptual screening excluded studies not focused on transportation applications or on explicit analytical methods. It prioritized work connecting analytic outputs with decision-making concerning operations, asset management, or investment, and studies reporting risk or cost implications.

The search strategy involved the use of focused keyword searches on smart transportation, intelligent transportation systems, data analytics, predictive maintenance, safety analytics, resilience, and digital twins. No formal quality scoring rubric was utilized; however, empirically based studies, documented deployments, or large-scale pilots with clear methods and metrics were favored. The resulting synthesis offers an integrative view of the current conception and implementation of analytics-enabled smart systems for risk reduction in national transportation networks, highlighting where methodological and institutional gaps are most acute.

Conceptual foundations

Smart transportation systems may be conceptualized as cyber-physical systems that engage sensing, communication, computing, and control of various layers, such as field devices and vehicles, control centers and cloud platforms (Rathore *et al.*, 2021). In this paradigm, intelligent transportation systems (ITS), connected and cooperative systems, and smart corridors have a similar layered architecture that consists of sensing and data acquisition, communication and data management, analytics and decision support, and actuation or control (Guo *et al.*, 2024). All the layers have certain limitations to analytics, such as latency, reliability, and scalability, in particular when systems are deployed in regional or nationwide networks (Chowdhury *et al.*, 2018**)**. In this regard, data analytics covers both descriptive and diagnostic applications that generalize and explain past behavior and anomalies and predictive and prescriptive applications that forecast and prescribe behavior in the future given uncertainty (Gandomi and Haider, 2015). Descriptive and diagnostic analytics is based on statistical summaries, clustering and anomaly detection to describe the state of performance at the baseline and what the future trends are in connection to deterioration, crashes or disruptions. Predictive analytics can be used to predict failures, traffic conditions, or network outages using statistical models, machine learning, or hybrid physics-informed methods, whereas prescriptive analytics can propose interventions that balance risk mitigation and budget constraints, using optimization, simulation, and decision analysis (Hang *et al.*, 2025)

Risk in transportation networks is multi-dimensional and encompasses safety risk, structural and operational reliability, resilience to shocks, and cyber-physical security (USDOT, 2024; Gharaibeh *et al.*, 2017). The common safety risks are the rate and the intensity of crashes, unsafe interaction with vulnerable road users, and

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the possibility of secondary incidents. Structural reliability addresses the likelihood of failure of bridges, pavements, tunnels, and similar assets under uncertain loads and deterioration mechanisms (Frangopol *et al*., 2017), whereas operational reliability and resilience reflect the capability of the network to maintain and recover due to disruptions like congestion, incidents, extreme weather, and infrastructure outages (Wan *et al*., 2017) Cyber-physical security risk reflects vulnerabilities arising from increased connectivity of field devices, vehicles, and control systems, which can undermine data integrity or lead to unsafe control actions if exploited (USDOT, 2024; Ojo *et al*., 2024). These risk dimensions translate into both direct and indirect costs, including capital and maintenance expenditures, user delay costs, crash-related losses, environmental impacts, and broader economic damages from systemic disruptions (Sensemore, 2024). The concept of cost-effectiveness in this setting is therefore defined as the reduction in expected risk-related costs per unit of investment over the life cycle of infrastructure and operations.

The incorporation of analytics into smart systems should be considered both a technical and an institutional process. Technically, integration means developing architectures in which data flows and analytic results are systematically incorporated into planning, design, construction, maintenance, and operational decisions, rather than implemented as analytical activities in isolation (ITS America, 2025). To coordinate local processing and central analytics, architectures increasingly use edge, fog, and cloud computing to manage high-volume, high-velocity, and heterogeneous streams of data (Gharaibeh *et al*., 2017). Institutionally, integration involves the alignment of risk constructs, analytic products and decision levers; e.g., predicted pavement distress needs to map onto maintenance policies, budgetary allocations and performance targets to create tangible risk reduction and cost benefits (Makhoul *et al*., 2023). The conceptual scheme used in this paper thus focuses on the interaction among data sources, analytic typologies, risk and cost constructs, and system structures as the basis for a consistent state-of-the-art review of analytics-enabled smart transportation systems.

Data sources and sensing ecosystems

The richness, coverage and integration of underlying data sources and sensing technologies is of critical importance to the capability of smart systems to mitigate risk and manage costs. The traditional transportation data have been based on stationary sensors (loop detectors, traffic cameras, weigh-in-motion, periodical traffic counts) and complemented by crash data and asset catalogs maintained by the agencies (Davis *et al*., 2020). Although these data sets aid in long-term planning and safety studies, they are frequently unable to provide the temporal resolution, spatial coverage, and immediacy needed by real-time risk monitoring and predictive maintenance at network scale. Multi-year intervals of condition data on pavements and bridges are common, and this delay detection of the onset of deterioration, and limits the possibility of intervening before performance thresholds are violated (Wang *et al*., 2020). The resulting monitoring regimes are generally reactive, as opposed to proactive and offer little assistance to advanced analytics that rely on dense, continuous data.

The recent breakthroughs in sensing and the Internet of Things have augmented the transportation sensing ecosystem with structural health monitoring systems, connected and automated vehicles, mobile devices, and crowdsourced platforms. Structural health monitoring deployments use accelerometers, strain gauges, fiber-optic sensors and distributed sensing to continually monitor the dynamic response and condition of bridges, tunnels, pavements and other ancillary infrastructure (Makhoul *et al*., 2023). GPS-enabled probe vehicles connected vehicles and smartphones, as well as crowdsourced applications would generate high-frequency trajectory signals describing speed, travel time, and congestion patterns on the operations side (Markovic *et al* 2019). Radar, LiDAR, and camera-based computer vision systems are even more depthful as they identify vehicles, pedestrians, cyclists, and environmental conditions to provide situational awareness of intersection safety, work zones, and pedestrian environments (Mir *et al*., 2024). These various streams of data have the traditional volume, speed, variety, and veracity traits of big data, which pose both possibilities and challenges to integrate and analyze (Gandomi and Haider, 2015).

Agencies and vendors are building data integration and fusion systems to create coherent representations of heterogeneous data sources to be used in analytics and decision support to exploit this rich ecosystem. The data fusion methods synchronize the information between various timescales, space scales, and resolve the discrepancies between measurements, and

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integrate the supplementary data of sensors, vehicles, and external data sources like weather and events (Goumiri *et al*. 2023). An example is the fusing of probe vehicle data with fixed detectors and weather measurements to enhance incident detection and travel time prediction, or structural health monitoring data with traffic loads and environmental conditions to improve degradation models (ITS America, 2025). To achieve a strong integration, standardized data models, interoperability models, and metadata practices are needed to allow agencies and vendors to share and understand data consistently (Khan *et al*., 2016). Together with technical integration, data governance, privacy, security, and ethics have become key topics of concern, especially with detailed trajectory and video data becoming the new reality. Agencies should apply anonymization, access controls, and cybersecurity practices and make sure that data quality procedures like validation and cleaning are useful in providing reliable analytics. The leading edge in data sources and sensing is not only technological but institutional structures that facilitate responsible, high-quality data utilization in risk-conscious and cost-conscious transportation management.

State of the art in data analytics for risk mitigation

State-of-the-art risk mitigation data analytics are in the areas of predictive asset management, traffic safety and operations, network reliability and resilience, and prescriptive decision support. Predictive analytics in asset and infrastructure health utilize past condition experiences, structural health feedback, and environmental parameters to estimate deterioration and failure likelihood, which is used to plan risk-based maintenance and rehabilitation (American Association of Civil Engineers (ASCE), 2021; Congress & Puppala, 2021). Methods include statistical survival and Markov models, as well as machine learning methods, including random forests, gradient boosting, and deep neural networks, which have the ability to model nonlinear relations and interactions (Stevens *et al*., 2020). Other researchers propose hybrid or physics-informed models that incorporate domain knowledge into data-driven models to enhance interpretability and extrapolation outside of observed conditions (Congress & Puppala, 2021). Such predictive asset analytics, when it is combined with smart monitoring, promotes streamlined inspection plans, focused actions, and cost-efficient life-cycle management by lowering the chances of unexpected failures and related financial and safety costs. Recent analytical work further emphasizes that machine-learning models only yield meaningful maintenance benefits when explicitly embedded within risk-based decision frameworks, highlighting the need to couple predictive accuracy with consequence modeling and human-supervised evaluation (Adusei, 2026).

Analytics have developed in traffic safety and operations, becoming more extensive and proactive with the inclusion of spatial statistics, Bayesian and machine learning to explain complex interplay between roadway features, traffic exposure, weather, and behavioral factors (Skaug *et al*., 2025)**.** Proactive safety analytics make use of surrogate safety measures, near-miss detection, and trajectory-level analysis to predict high-risk locations and situations prior to crashes before they happen, usually based on computer vision and trajectory clustering of video and connected vehicle data (Abdel-Aty *et al*., 2023). Traffic management centers that implement real-time analytics estimate and predict traffic conditions, identify incidents, and inform responsive control mechanisms using time-series prediction, state-space modeling, and deep learning systems that learn spatiotemporal dependencies, including recurrent and graph neural networks (Ruan *et al*., 2025). Following the cooperative systems approach, information technology in cooperative intelligent transport systems combines the vehicle-to-vehicle and vehicle-to-infrastructure communications to facilitate the safety applications of cooperative adaptive cruise control and collision warnings. These analytics can take dynamic traffic management measures such as variable speed limits, ramp metering, and route guidance to reduce congestion, enhance safety, and minimize the risk of secondary incidents (Javed *et al*., 2019).

Network reliability and resilience analytics take the perspective of a network beyond individual assets or locations to the overall network performance both in normal and disrupted states. Network vulnerability is assessed using data-driven and simulation-based models to connect failures, capacity degradations, and demand spikes due to incidents, extreme weather, or other risks (Argyroudis *et al*., 2019). Integrating empirical traffic and infrastructure data with scenario analysis and Monte Carlo simulation enable analysts to measure reliability and resilience metrics, determine critical links and nodes, and evaluate alternative investment or operation

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strategies (Ahmed & Dey, 2020). The smart city viewpoint of Gharaibeh *et al*. (2017) explains that dynamic situational awareness in the event of extreme events and adaptive responses to evacuation, rerouting, and resource allocation can be achieved by linking real-time sensing data with hazard forecasts, and simulation models.

Prescriptive analytics and decision-support systems lie at the intersection of analytical insights and actionable interventions. These predictive risk models are then converted into maintenance scheduling, treatment prioritization, and investment decision models, with budget and resource limitations (Frangopol *et al*., 2017). Multi-objective formulations can allow for the balancing of competing goals: safety, mobility, environment, fiscal efficiency; and reinforcement learning can provide a principled approach to learning adaptive control policies for traffic management, incident response, and energy-efficient operations within prescribed limits of safety and regulations (Papageorgiou *et al*., 2003). Prescriptive analytics outputs are integrated into dashboards and decision support system, which display key performance indicators, risk indices and recommended actions in operationally accessible formats (Adeniji *et al*., 2023; González-Villa *et al*., 2024). Analytical costs must be offset by benefits, such as reduced unplanned downtime, longer asset service life and avoided crash costs in order to provide a return on the investment in analytics and continue institutional support for smart-system programs (Ouyang, 2014). However, there are still limitations to how well these benefits can be connected to specific parts of the analysis, how well model uncertainty can be communicated to operational decision-makers, and how well the distributional impact of analytics-driven actions can be quantified across different user groups and geographical settings (Frangopol *et al*., 2017). Overall, there is significant maturity in modeling approaches and pilot deployments, and a lack of standardized evaluation frameworks that can connect analytic performance with measurable risk and cost outcomes at the national scale (Tzika-Kostopoulou *et al*., 2024).

Integration architectures and smart system design

To enable concrete risk and cost reduction in national transportation networks, effective embedding of analytics in smart system architectures is key. Typically, reference architectures for ITS can be classified into five levels that include the following: field devices and edge computing, communication networks, data management platforms, analytics engines, and decision-support applications (Gharaibeh *et al*., 2017; Guo *et al*., 2024). The raw data streams at the field level include sensor data, connected vehicle data and legacy infrastructure devices, which can be pre-processed at the edge to minimize bandwidth usage and facilitate timely response to safety-critical events (Shi *et al*. 2016). Lightweight anomaly-detection models and predictive classifiers can be deployed on the edge platform at the road side or in the vehicle to trigger immediate warnings or local control actions without the need for a round-trip communication with any central systems (Papageorgiou *et al*., 2003). Data is then aggregated and filtered from the communication networks, either wired or wireless, and stored, indexed, accessed, monitored for quality assurance purposes in centralized or federated data management platforms (Khan *et al*., 2016). In the top tier of architecture, scalable cloud or hybrid cloud architectures enable the deployment and orchestration of heavy workloads for analytics such as batch-processing pipelines, streaming inference, and training of large models that meet the demands of national networks (Gharaibeh *et al*., 2017; Rathore *et al*., 2021).

Digital twin architectures are among the most impactful design patterns in this ecosystem, and they combine real-time sensor data, historical asset condition data, and physics-based or data-driven simulations into persistent, dynamic virtual models of physical assets and systems (Ge & Qin, 2024; ITS America, 2025). Transportation digital twins can be a single bridge, a highway corridor, or a multimodal urban network that can monitor the condition of the transportation system in real-time, simulate scenarios, and virtually evaluate proposed interventions before they are built into the physical transportation system (ITS America, 2025; Grieves & Vickers, 2017). Digital twin platforms can be used in conjunction with unmanned aerial vehicle (UAV) inspection data and instrumentation to enable predictive maintenance planning and asset life cycle cost optimization (Makhoul *et al*., 2023). Digital twins have been shown in the industry to provide better coordination, decreased design conflicts, and continue to provide a persistent data and analytics platform that flows naturally to operations and maintenance. Such architectures are typically designed to include edge sensing, cloud-based analytics and multi-stakeholder visualization environments enabling collaboration between

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infrastructure owners, operators and contractors (Lu *et al*., 2020).

Human-machine teaming and decision workflow compatibility are an integral part of the design of integration architectures. Decision-support tools need to be tailored to the roles, responsibilities, cognitive requirements, and time horizons of transportation professionals and need to provide results that are interpretable and reliable that can be implemented in real-world operational environments (Huang *et al*., 2025; Gunning & Aha, 2019). The next step in making complex model outputs actionable in the operational and managerial decision making process is through interface design, interactive dashboards, and scenario analysis. Explainability techniques such as feature importance attribution, sensitivity analysis, and generation of counterfactual scenarios can enhance the transparency of models and foster institutional trust that is crucial for effective analytics to drive critical decisions (Ribeiro *et al*., 2016; Ahmed & Khan, 2022). At the organizational level, integration means that analytic products are integrated into formal organizational processes like asset management plans, safety improvement plans, emergency response plans, and perhaps standard operating procedures, training programs and curricula, and performance management systems, which may in turn require revisions to the standard operating procedures, training programs, curricula, and performance management systems (ITS America, 2025). Multi-agency governance structures, data exchange hubs, and reference architectural standards provide institutional support to support interoperable, scalable, analytics-driven smart systems throughout national transportation networks (Oladimeji *et al*., 2023; USDOT, 2024).

Challenges, gaps, and barriers

While substantial technical advances and promising pilot deployments have been achieved, analytics-based smart transportation systems still have numerous challenges to overcome which limit the broad and cost-effective use of these systems. Technically, data heterogeneity is still a major challenge, as agencies need to harmonize the different formats, sampling rates and quality of data provided by the legacy sensing infrastructure, modern IoT platforms and external data providers before analytics can be applied in a reliable manner (Tzika-Kostopoulou *et al*., 2024). Network-scale real-time analytics put high demands on communication infrastructure and computing resources related to latency and throughput, often more than agency can currently deliver, and requiring significant capital investment (Chowdhury *et al*., 2018). The robustness and geographic transferability of the model are other challenges, as predictive models developed on data collected in specific corridors or climatic regions can suffer from significant decrease in performance when applied to different operational contexts, and systematic approaches to transfer learning, domain adaptation, and continual model performance monitoring (Ahmed & Khan, 2022) are needed. UQ is still not well developed in most practical applications, and decision-makers are not capable of interpreting the model outputs in the context of a sufficiently risk-informed framework, nor are they able to use probabilistic decision analysis in asset management and safety planning (Frangopol *et al*., 2017).

Restrictions are equally great at the institutional and organizational levels. Most U.S. transportation agencies have departmentalized structures that have silos for planning, operations, maintenance, and information technology, which makes it difficult to collaborate on cross-cutting data and analytics projects required for effective smart system integration (ITS America, 2025; USDOT, 2024). Data platforms and analytics services are constantly evolving, and a procurement approach that focuses on a single project deliverable doesn't make it easy to establish long-term vendor-agency relationships that support continuous system integration and improvement. Lack of expertise in data science, machine learning, and cyber-physical systems skills in public agencies, coupled with a lack of competitiveness in hiring and retaining these skills when compared to private sector employers (Sumalee & Ho, 2018), is still a common challenge. To address these workforce gaps, new programs of interdisciplinary training must be developed, structured pathways to the workforce must be created, and career frameworks must incorporate engineering, data analytics, and public policy skills.

There is an additional layer of complexity for regulatory, ethical, and societal issues. The collection and processing of detailed trajectory, video, and behavioural data from transportation networks can generate legitimate privacy and civil liberties concerns: empirical studies have shown that even anonymized mobility traces have a significant re-identification risk and must be addressed through effective governance structures and guided data minimization practices (Badu-Marfo, Farooq, & Patterson, 2019; Alanazi *et al*.,

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2025). The growing connectivity of field infrastructure and control systems creates an expanding cyber-physical attack surface and poses a new challenge for operational safety and system reliability, that requires careful risk management, continuous monitoring for security and incident response (Ojo *et al*., 2024). The liability issues arise when using analytics to make decisions results in a negative, but unanticipated, effect, especially when the analytics is based on opaque or proprietary models and therefore requires standards of explainability and auditability. Equity dimensions are becoming more central, with not only overall efficiency measures, but also the distributional impact on safety, accessibility and service quality in communities segmented by income, geography and mobility need (Ricord & Wang, 2023). Combined, these challenges reveal multiple weaknesses such as the lack of a unified framework that connects data, analysis, risk metrics, and economic assessment; lack of uncertainty-aware decision support; lack of data and architecture interoperability standards; and lack of long-term assessments of real-world deployments at a national scale (Gharaibeh *et al*., 2017; Oladimeji *et al*., 2023).

Future research and development directions

Progress along a number of mutually orthogonal fronts is necessary to take the methodological and translational steps needed for the integration of data analytics in smart transportation systems. Deep learning architectures, such as convolutional networks, recurrent networks, and graph neural networks, have exhibited impressive ability in modeling high-dimensional spatiotemporal patterns in traffic patterns, structural response signals and multimodal network dynamics (Ruan *et al*., 2025). Reinforcement learning provides an effective approach to learning adaptive control policies of traffic management, incident response, and energy-efficient operations as long as safety constraints and interpretability requirements are strictly considered (Haydari & Yilmaz, 2022). Predictive modeling can be enhanced with causal inference techniques that can differentiate between correlation and causation and offer stronger evidence on the effects of interventions, infrastructure modifications, or policy actions on safety and reliability (Hauer, 2024). The viewpoint of Gandomi and Haider (2015) states that scientific methods in complex infrastructure systems can enhance the explanatory power and generalizability with the help of hybrid analytics that merge physical models with data-driven elements. In all these developments, risk-informed decision frameworks will be necessary to be supported by explicit representation of uncertainty and probabilistic risk in models and optimization (Frangopol *et al*., 2017).

In the future, next-generation smart monitoring systems will be characterized by a closer connection between infrastructure and vehicles and an expanded urban system as connected and automated vehicles, smart cities, and digital twins merge. Scalable architectures and algorithms capable of combining data of connected vehicles, roadside sensors, and central systems to give more detailed, timely representations of network states and risks need to be researched (Oladimeji *et al*., 2023). Digital twins are expected to be scaled to multi-domain and multi-scale representations that combine structural performance, operations, environmental effects, and user behavior, which are continuously learning, and as new data is collected, and conditions evolve, they can be updated (Ge & Qin, 2024). Privacy-preserving analytics can be enabled through edge and federated learning methods where models can be trained and updated through distributed devices and agencies without centralizing sensitive data (Li *et al*., 2019). Similar methodological research on cost-effectiveness and risk reduction appraisal schemes is also essential. It involves standardized methods to estimate benefits and costs of analytics-enabled smart systems, taking into consideration agency, user, and societal views, and considering uncertainty. Stronger evidence of impact can be offered by longitudinal and quasi-experimental studies tracking outcomes before and after deployment, and inform adaptive management (Ouyang, 2014; Farhan & Chen, 2019).

The policy, capacity building and institutional change translational research will be pivotal in closing the gap between the research prototypes and operative systems. Policy frameworks can facilitate innovation by facilitating regulatory sandboxes and pilot programs whereby agencies can experiment with, and refine, analytics-enabled systems and manage risk (ITS America, 2025). Interoperability, data sharing, and shared evaluation metrics can be enabled by reference architectures and guidelines through the help of standards development bodies and professional associations (USDOT, 2024). Training and education programs must be developed to develop coherent skill sets which cut across different pertinent disciplines and place practitioners in a

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position to design, implement and manage analytics-enabled smart systems. Partnerships with other non-profit organizations, such as technology suppliers, startups, and educational organizations can help hasten innovation and ground it in practical limitations and societal goals. A combination of these research and development directions provides a way to a consistent ecosystem of technologies, approaches, and institutions capable of providing ongoing enhancements in safety, reliability, resilience, and cost-effectiveness of national transportation networks.

Implications for U.S. transportation infrastructure

The synthesis provided in this paper has significant implications to the design, management and governance of U.S. transportation infrastructure. The strategic implementation of data analytics into smart systems offers a route through which federal, state, and local agencies can shift their management models, which are currently based on reaction and time, to risk-informed and proactive management based on prioritizing resources where they can have the most significant reductions in risk and cost (Gharaibeh *et al*., 2017; USDOT, 2024). Predictive and prescriptive analytics can guide asset management plans, capital programming, and operating strategies with quantifications of anticipated performance, likelihoods of failures, and economic impacts in different scenarios of choice (Frangopol *et al*., 2017; Farhan & Chen, 2019). This is in line with the national policy goals of safety, resilience, and fiscal responsibility and can increase the capacity of the transportation networks to respond to climate change, changing travel trends, and emerging mobility technologies (Sharifi & Yamagata, 2022). Simultaneously, the U.S. governance setting, which has decentralized power and a variety of institutional potentials, highlights the necessity of federal leadership in establishing standards, financing common data and analytics infrastructure, and fostering knowledge sharing.

In terms of implementation, the reviewed case studies and analyses indicate that digital twins, predictive maintenance, and proactive safety analytics could have substantial operational and economic returns and need a long-term investment and cross-sector cooperation in order to scale (ASCE, 2021; Makhoul *et al*., 2023). The procurement models used by agencies will have to be new to support long-term support of data and analytics platforms, system integration, and iterative development (ITS America, 2025). This requires workforce development; multidisciplinary teams, which incorporate engineering, data science, human factors, and policy skills, can assist agencies to design and operate analytics-enabled systems that are technically well and socially acceptable (Quian et. al, 2025). Data governance, model transparency, accountability, and equity should be discussed in policy and regulatory frameworks, and the decisions made on the basis of analytics should be explainable, auditable, and reflect the shared values of the population (Huang *et al*., 2025). The use of analytics-based risk and cost metrics in performance management regimes can institutionalize them and provide incentives to constantly improve. Altogether, the implications to the U.S. are that analytics-based smart systems can greatly enhance safety and reliability and become more cost-effective, though achieving this promise will require a concerted effort on the research, practice, and policy levels.

CONCLUSION

This article has presented a state-of-the-art discussion on data analytics integration in smart systems to mitigate risks cost-effectively in national transportation systems with special consideration to the U.S. case. It has demonstrated how more proactive and targeted management of asset health, traffic safety, network reliability, and resilience can be achieved by increased sensing and data acquisition and more sophisticated analytics. Simultaneously, the synthesis focuses on the idea that the technical capabilities are not sufficient to achieve better results; risk and cost advantages are defined by the efficacy with which analytics are implemented in architectures, decision processes, and organizational lifestyles. Enablers of this integration are digital twins and multi-layer architectures that integrate edge, cloud, and federated analytics through the use of strong data governance and human-friendly decision-support tools.

The review also reports major gaps and challenges, which are heterogeneity of data, model robustness, workforce capacity, fragmentation of governance, privacy, cybersecurity, and incomplete evaluation frameworks that connect analytic performance with risk and cost outcomes. To overcome these issues, integrated research on higher-order and hybrid analytics, uncertainty-sensitive decision models, and cost-effectiveness assessment standards, policy, and capacity building translation will be necessary. The consequences of analytics-

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capable smart infrastructure are substantial to U.S. transportation infrastructure: smart infrastructure will be a potent driver of safety, reliability, and resilience as well as utilize scarce resources more efficiently, yet the delivery of their promise will require long-term, collaborative investments in technology, personnel, and institutions.

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