© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1719447

AI-Driven Decision Support Systems for Regional Infrastructure Optimization and Sustainable Development

JITHESH CHANDRAN
ORCID: 0009-0001-0268-4982

Abstract- Artificial intelligence-driven decision support systems are becoming central to how regions plan, prioritize, operate, and renew infrastructure under sustainability pressure. This review examines how AI, geospatial analytics, Internet of Things data, digital twins, optimization models, and explainable dashboards can improve regional infrastructure decisions across transport, water, energy, utilities, public facilities, and climate-resilience assets. The aim is to synthesize recent literature from 2020 to 2025 and propose an integrated review framework for AI-enabled regional infrastructure optimization. Following a structured review design inspired by systematic literature review conventions, the paper groups evidence into five themes: data integration, predictive intelligence, optimization and simulation, governance and ethics, and sustainable development outcomes. The review finds that AI decision support systems add value when they connect fragmented asset data with transparent scenario evaluation, risk forecasting, and multi-criteria prioritization. However, adoption remains limited by data silos, uneven regional capacity, model opacity, cybersecurity concerns, and weak links between technical analytics and public accountability. The paper contributes a practical framework that aligns AI-enabled decision support with regional planning objectives, Saudi Vision 2030 priorities, and global sustainable development goals. It concludes that AI should not replace professional judgement or community consultation; rather, it should create a disciplined evidence layer for faster, fairer, and more resilient infrastructure choices.

Keywords: Artificial Intelligence, Decision Support Systems, Regional Infrastructure, Sustainable Development, Optimization, Smart Cities

I. INTRODUCTION

Regional infrastructure systems are under growing stress from urbanization, climate risk, demographic change, service demand, fiscal limits, and public expectations for faster delivery. Transport corridors, water networks, energy grids, drainage systems, digital connectivity, health facilities, logistics hubs, and public spaces are no longer isolated assets. They function as interdependent regional platforms that shape productivity, quality of life, environmental performance, and social inclusion.

Because decisions about one network often create consequences for another, infrastructure planning requires more than engineering calculations or static feasibility studies. It needs decision support systems that can combine technical evidence, spatial priorities, financial constraints, sustainability indicators, and stakeholder preferences within a common analytical environment.

Artificial intelligence offers a timely response to this complexity. Machine learning can detect patterns in asset failure, travel demand, energy use, flood exposure, maintenance history, and construction performance.

Optimization algorithms can compare investment packages under budget, carbon, service, and equity constraints. Natural language processing can extract signals from policy documents, citizen feedback, inspection notes, and procurement reports. Digital twins and simulation models can test scenarios before projects are delivered.

When these capabilities are embedded into decision support systems, regional authorities and infrastructure organizations can move from fragmented reporting toward evidence-based, predictive, and adaptive decision-making (Gupta et al., 2022; Smith, 2022).

The topic is particularly relevant to sustainable development. Infrastructure decisions lock regions into long-term patterns of land use, energy consumption, mobility behavior, water security, public health, and economic opportunity.

Poorly prioritized infrastructure can increase emissions, widen spatial inequality, expose communities to climate hazards, or create costly stranded assets. Conversely, optimized regional infrastructure can reduce lifecycle costs, improve resilience, support compact development, and align public expenditure with national transformation strategies.

For Saudi Arabia, this logic connects directly with Vision 2030, the National Strategy for Data and AI, smart city investments, and the wider effort to strengthen regional competitiveness through high-quality, technology-enabled public services (SDAIA, 2020; Vision 2030, 2024).

This review paper therefore investigates how AI-driven decision support systems can support regional infrastructure optimization and sustainable development.

The review does not present a single empirical case study; rather, it synthesizes current scholarship and policy-oriented evidence to define the architecture, benefits, limitations, and governance requirements of AI-enabled infrastructure decision support.

The paper is organized in the style of a journal review article, with an introduction, literature synthesis, review methodology, thematic findings, proposed framework, discussion, recommendations, limitations, future research agenda, and conclusion.

The central argument is that AI creates value only when technical modelling is connected to accountable planning processes, transparent criteria, domain expertise, and measurable sustainability outcomes.

II. LITERATURE REVIEW

Decision support systems have long been used in planning, operations research, construction management, and public administration. Traditional systems usually relied on structured databases, geographic information systems, multi-criteria decision analysis, and expert judgement.

Their strength was formalization: they made assumptions visible and helped decision-makers compare alternatives. Their weakness was limited adaptability. Many systems could not easily absorb high-frequency sensor data, unstructured documents, real-time operational changes, or nonlinear relationships across infrastructure networks.

Recent AI-enabled DSS research addresses this limitation by combining automated learning with scenario simulation, optimization, and interactive visualization (Gupta et al., 2022).

In infrastructure contexts, AI-enabled DSS can be understood as a layered system. The first layer collects data from asset registers, GIS platforms, satellite images, traffic counters, smart meters, supervisory control systems, weather feeds, project controls systems, and public feedback channels.

The second layer cleans, links, validates, and governs these data sources. The third layer applies AI and analytical models to predict demand, detect deterioration, estimate risk, simulate interventions, and optimize decisions.

The fourth layer presents result through dashboards, maps, alerts, and recommendation engines. The fifth layer captures human review, stakeholder negotiation, policy adjustment, and performance learning after implementation.

The literature from 2020 to 2025 shows strong growth in AI applications for smart cities, construction sustainability, public works, climate resilience, energy systems, and urban planning.

Smith (2022) reviewed AI-based DSS techniques in construction and found that they increasingly support project sustainability through predictive analytics, risk assessment, and decision automation.

Gupta et al. (2022) mapped the relationship between AI, operations research, and decision support, showing that AI strengthens traditional optimization by improving learning from data. Recent smart city

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1719447

studies also emphasize digital twins, edge-cloud architectures, IoT integration, and AI-based recommendation engines for mobility, environmental monitoring, and public services (Sacoto-Cabrera et al., 2025; Shulajkovska et al., 2024).

Despite this progress, regional infrastructure optimization remains a more demanding task than single-asset analytics. A road pavement model may predict deterioration accurately, but regional optimization must decide where renewal creates the greatest public value across multiple districts and asset classes.

A flood model may identify high-risk zones, but planning authorities must prioritize interventions that balance drainage capacity, land availability, cost, social vulnerability, and future development.

An energy model may forecast load, but regional authorities must coordinate renewables, grid resilience, demand response, and industrial growth. AI-enabled DSS must therefore support integrated choices rather than narrow technical predictions.

Sustainable development also requires attention to equity and governance. AI models can reproduce historical bias if training data reflect unequal service provision or underreported community needs. Infrastructure optimization can favor already-developed areas when algorithms maximize short-term economic returns.

Automated recommendations can become difficult to challenge when model logic is opaque. These risks are why explainable AI, participatory planning, privacy-by-design, cybersecurity, and human-in-the-loop governance are repeatedly emphasized in recent literature (Du, 2024; OECD, 2025). A responsible DSS must show not only the recommended option but also the assumptions, trade-offs, uncertainty ranges, and distributional impacts behind that recommendation.

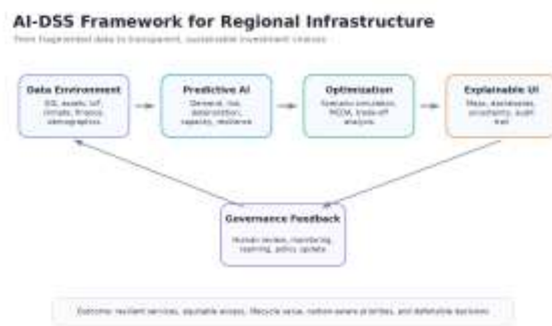

Figure 1: AI-driven regional infrastructure decision support framework

III. AIM, OBJECTIVES AND RESEARCH QUESTIONS

The aim of this review is to examine how AI-driven decision support systems can improve regional infrastructure optimization while advancing sustainable development outcomes.

The specific objectives are: first, to identify the core data, analytical, and governance components of AI-enabled infrastructure DSS; second, to synthesize recent applications across transport, water, energy, utilities, urban services, and climate-resilient infrastructure; third, to evaluate the sustainability benefits and implementation challenges associated with these systems; fourth, to propose a practical framework for regional infrastructure decision support; and fifth, to outline recommendations for policymakers, infrastructure owners, consultants, and technology providers.

The review is guided by three research questions. How are AI-driven DSS being applied to regional infrastructure planning and optimization? What sustainability outcomes are most commonly supported by these systems? What governance conditions are required to make AI-enabled infrastructure decisions transparent, accountable, and implementable? These questions keep the review focused on decision usefulness rather than technology novelty alone.

Contribution of the Review

This review contributes to the literature and to professional practice in five ways.

First, it reframes artificial intelligence in infrastructure as a decision governance capability rather than a narrow modelling technique. Much writing on smart infrastructure focuses on algorithms, sensors, platforms, or individual use cases.

Regional authorities, however, need a broader logic that explains how data moves from asset systems into investment decisions, how recommendations are questioned, and how outcomes are monitored after implementation.

By connecting data integration, prediction, optimization, explainability, and governance feedback, the review offers a practical structure for agencies that must justify infrastructure priorities under public scrutiny.

Second, the review connects regional development with sustainability in a way that avoids treating sustainability as a separate reporting category. Infrastructure decisions shape mobility, housing access, industrial competitiveness, water security, energy efficiency, climate exposure, and public service quality.

A decision support system that optimizes only cost or delivery speed may produce technically efficient but socially weak outcomes. The contribution here is to position sustainability indicators inside the decision model itself. Carbon, resilience, accessibility, equity, lifecycle value, and resource efficiency should be part of the comparison between alternatives, not decorative measures added after a preferred project has already been selected.

Third, the paper clarifies the difference between prediction and decision support. Many AI applications in infrastructure successfully forecast demand, deterioration, delay, leakage, congestion, or hazard exposure. Forecasts are valuable, but they do not automatically answer which project should be funded, which district should be prioritized, or which service standard is acceptable.

Decision support requires a further layer that translates predictions into scenarios, trade-offs, constraints, and choices.

This distinction is important for regional infrastructure because public value depends on selecting combinations of interventions across places and sectors, not merely identifying isolated risks.

Fourth, the review offers a framework that can be adapted to Saudi Vision 2030 and similar national transformation programs. Large-scale regional development requires disciplined capital allocation, transparent project selection, resilient service networks, and technology-enabled public administration.

AI-driven DSS can support these aims when it is aligned with institutional roles and legal responsibilities. The proposed framework therefore emphasizes human-in-the-loop review, audit trails, data quality, model monitoring, cybersecurity, and stakeholder communication.

These governance elements make the framework more realistic for ministries, municipalities, consultants, utilities, and infrastructure owners that operate within formal approval processes.

Fifth, the review identifies research gaps that should guide future scholarship. The literature still contains limited longitudinal evidence on whether AI-enabled DSS improves actual infrastructure outcomes after implementation. There is also insufficient comparative research on regional capacity, data maturity, procurement models, and public trust.

Further work is needed on explainable optimization, open benchmarking datasets, participatory AI tools, and evaluation methods that measure sustainability impact rather than only model accuracy. By identifying these gaps, the review supports a research agenda that is useful for both academic publication and real-world infrastructure transformation.

Sixth, the review highlights the importance of spatial fairness. Regional infrastructure optimization can easily become dominated by high-volume corridors, large economic zones, or locations where data are already abundant. Such outcomes may appear efficient while overlooking rural areas, informal service gaps, vulnerable communities, and environmental buffers. AI-driven DSS should therefore include geospatial equity checks, vulnerability layers, and service-access indicators.

This helps decision-makers examine who benefits, who bears risk, and whether infrastructure investment supports balanced regional development rather than reinforcing historical concentration.

Seventh, the paper provides a usable bridge between technical specialists and decision-makers. Data scientists often speak in terms of models, parameters, and accuracy, while infrastructure executives focus on budget, risk, delivery, compliance, and public value.

The framework translates technical outputs into decision questions: which assets are most critical, which interventions produce the strongest lifecycle value, which risks are unacceptable, and which assumptions require political or professional judgement.

This bridge is essential because AI systems fail when their outputs are technically impressive but not understandable or actionable for the people responsible for approvals.

Eighth, the review underlines that implementation should be phased. A region does not need a complete digital twin before it can benefit from AI decision support. It can begin with asset data cleaning, targeted predictive maintenance, geospatial risk mapping, or a capital prioritization dashboard.

Each stage should strengthen governance and data quality for the next stage. This staged approach reduces cost, builds confidence, and prevents unrealistic expectations. It also allows organizations to learn from pilot projects before scaling into integrated regional platforms.

Ninth, the review gives attention to accountability. Infrastructure decisions involve public money, safety, service reliability, land use, and intergenerational consequences. For that reason, an AI-driven DSS must preserve a clear line of responsibility.

The system may recommend, rank, forecast, and simulate, but accountable professionals and public authorities must decide, justify, and monitor. This principle protects trust and keeps AI aligned with democratic and professional responsibilities.

Finally, the contribution is practical because it turns a broad technology discussion into a review-based implementation logic. It shows what data are needed, what models can do, what decision criteria should be visible, and what governance safeguards must be in place.

This makes the paper suitable for researchers, regional planners, infrastructure engineers, public-sector transformation teams, and consultants preparing evidence-based programs for sustainable development. It also supports defensible research alignment for infrastructure applications linked to national transformation agendas and regional competitiveness.

IV. REVIEW METHODOLOGY

This paper uses a structured narrative review methodology suitable for an emerging and interdisciplinary topic. The approach follows systematic review logic by defining search boundaries, inclusion criteria, thematic categories, and synthesis procedures, while allowing conceptual integration across engineering, planning, data science, public policy, and sustainability literature.

The review period was limited to 2020-2025 to capture recent advances in AI, digital twins, smart infrastructure, sustainable development governance, and regional transformation. Earlier foundational concepts are acknowledged only where necessary to explain the evolution of decision support systems.

Relevant literature was identified through academic databases and professional sources, including Scopus-indexed and Web of Science-indexed journals, IEEE, ScienceDirect, Springer, MDPI, Taylor and Francis, Emerald, OECD, UN-Habitat, World Bank, Saudi Vision 2030 materials, and SDAIA policy documents. Search terms combined technology concepts, infrastructure concepts, and sustainability concepts.

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1719447

Examples included artificial intelligence decision support system, infrastructure optimization, smart cities, digital twins, regional planning, sustainable infrastructure, predictive maintenance, multi-criteria decision analysis, geospatial analytics, climate resilience, public infrastructure, explainable AI, and AI governance.

Studies and reports were included when they addressed AI, data analytics, or decision support in relation to infrastructure planning, operations, sustainability, smart city management, regional development, or public service optimization.

Sources were excluded when they focused only on software development without infrastructure relevance, presented unsubstantiated commercial claims, lacked methodological transparency, or fell outside the review period.

The final synthesis prioritized peer-reviewed studies and authoritative policy documents. The evidence was coded into five analytical clusters: data integration, predictive intelligence, optimization and simulation, governance and ethics, and sustainable development outcomes.

The review methodology is intentionally transparent but not limited to bibliometric counting. A purely quantitative bibliometric review could identify publication patterns, yet it would not sufficiently explain how AI-enabled DSS should be designed for real infrastructure decisions.

Therefore, thematic synthesis was used to compare concepts, extract recurring barriers, and build a framework that links technology capabilities with planning value. This approach matches the applied nature of the topic, where decision quality depends on institutional workflow, data maturity, and sustainability accountability as much as model performance.

Figure 2: Structured review methodology and thematic coding approach

V. FINDINGS AND THEMATIC SYNTHESIS

The first major finding is that data integration is the foundation of effective regional infrastructure DSS. Infrastructure organizations often hold valuable information in separate asset databases, project control systems, utility models, planning documents, contractor reports, inspection records, and geospatial layers.

AI models cannot generate reliable recommendations when these sources are incomplete, inconsistent, or disconnected. Recent literature therefore emphasizes data lakes, interoperable standards, spatial data infrastructures, cloud platforms, and metadata governance as prerequisites for AI-enabled decision-making. In regional infrastructure, integration is not a technical luxury; it is the condition that allows trade-offs between sectors, districts, and time horizons to be evaluated fairly.

The second finding concerns predictive intelligence. Machine learning is increasingly used to forecast demand, asset deterioration, traffic congestion, flood exposure, energy load, water leakage, construction delay, and maintenance risk. Predictive analytics improves regional planning by showing where future pressure is likely to emerge before service quality declines.

It also helps decision-makers shift from reactive repair to preventive intervention. However, prediction alone is not optimization. A model that predicts a pipe failure or road bottleneck must be connected to cost, service criticality, social impact, and implementation feasibility before it can guide investment priorities.

The third finding is that optimization and simulation are the decision engine of AI-enabled DSS. Regional infrastructure choices involve multiple objectives that may conflict with one another. Authorities may need to reduce carbon while increasing capacity, minimize cost while improving equity, or accelerate delivery while protecting environmental assets.

Multi-objective optimization, genetic algorithms, reinforcement learning, agent-based simulation, and digital twins can help test alternative packages under these constraints. The strongest DSS designs combine predictive models with scenario tools so that users can ask practical questions: what happens if growth concentrates in one corridor, if extreme rainfall increases, if a bridge is delayed, or if maintenance budgets are reduced?

The fourth finding is that geospatial intelligence is essential for regional value. Infrastructure problems are spatially distributed, and their impacts vary by neighborhood, corridor, watershed, economic zone, and service catchment. GIS-linked AI models allow decision-makers to identify clusters of vulnerability, underserved communities, land-use conflicts, and network interdependencies.

This is especially relevant for regional development because sustainability is not achieved only by improving average performance. It is achieved when infrastructure investment improves access, resilience, and opportunity across places. Spatial decision support therefore helps convert abstract sustainability goals into location-specific priorities.

The fifth finding is that explainability and trust determine adoption. Infrastructure decisions affect public budgets, land, communities, contracts, safety, and long-term development. Stakeholders are unlikely to accept an AI recommendation unless the system can explain why a project was prioritized, which data were used, what uncertainty exists, and who remains accountable.

Explainable AI methods, transparent scoring criteria, audit trails, and human-in-the-loop review reduce the risk of blind automation. In practice, the most useful DSS is not the most complex model; it is the system that allows engineers, planners, finance teams, environmental specialists, executives, and communities to understand the decision logic.

The sixth finding is that AI-enabled DSS supports Saudi and regional transformation agendas when deployed as part of institutional modernization. Vision 2030 emphasizes economic diversification, digital government, quality of life, infrastructure excellence, and sustainable urban development.

AI-driven DSS can support these priorities by improving capital allocation, accelerating project prioritization, reducing lifecycle cost, supporting smart city management, and enhancing environmental resilience.

The same logic applies to other countries pursuing regional development: AI strengthens the evidence base for investments that connect people, industries, services, and ecosystems.

Table 1: Thematic synthesis of AI-enabled DSS applications in regional infrastructure

Theme	Main DSS capability	Infrastructure use	Sustainability value
Data integration	Unifies asset, GIS, sensor, climate, cost and demographic data	Regional asset planning and cross-sector coordination	Creates a shared evidence base
Predictive intelligence	Forecasts risk, demand, failure, congestion and exposure	Maintenance, capacity planning and resilience preparation	Reduces reactive spending and service disruption
Optimization and simulation	Compares project packages and policy scenarios	Capital prioritization, corridor planning	Balances cost, carbon, resilience and equity

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1719447

		and utilities renewal	
Geospatial intelligence	Maps vulnerability, access gaps and network interdependencies	Regional development and service accessibility planning	Targets investment to places of greatest need
Governance and explainability	Shows assumptions, uncertainty, audit trails and trade-offs	Executive approvals, public accountability and regulatory review	Improves trust and defensibility

VI. PROPOSED AI-DSS FRAMEWORK FOR REGIONAL INFRASTRUCTURE OPTIMIZATION

The proposed framework for AI-driven regional infrastructure decision support has six connected components. The first component is a trusted regional data environment that integrates asset, project, financial, environmental, demographic, and geospatial data. The second component is diagnostic analytics that identifies current service gaps, bottlenecks, condition risks, and spatial inequalities.

The third component is predictive analytics that estimates future demand, deterioration, climate exposure, and operational performance. The fourth component is optimization and scenario simulation that compares alternative investment packages against cost, carbon, resilience, service, and equity objectives.

The fifth component is an explainable decision interface that presents maps, dashboards, confidence levels, trade-off curves, and audit trails. The sixth component is governance feedback, where implemented decisions are monitored and lessons are returned to the model and planning process.

This framework is deliberately circular rather than linear. Regional infrastructure optimization is not a one-time exercise performed before a project starts.

It is a continuous learning process that links planning, delivery, operation, renewal, and policy review. Data from completed projects should improve future cost estimates. Sensor data from operating networks should improve maintenance models.

Community feedback should improve service priorities. Climate observations should update resilience assumptions. A circular DSS creates institutional memory and prevents each planning cycle from starting again with disconnected evidence.

A practical example illustrates the framework. A region experiencing population growth, road congestion, water stress, and flash-flood risk could integrate transport counts, land-use forecasts, drainage models, utility condition data, satellite imagery, and development approvals.

AI models could identify growth corridors, predict service failures, and map exposed communities. Optimization tools could compare packages such as transit improvements, stormwater upgrades, water reuse networks, road capacity enhancements, and green infrastructure. Decision dashboards could show expected cost, carbon reduction, resilience benefit, travel-time improvement, water savings, and equity impact. Decision-makers would then use the DSS output as structured evidence, not as an automatic verdict.

VII. DISCUSSION

The review demonstrates that AI-driven DSS can improve regional infrastructure decisions in four main ways. First, it increases analytical coverage by linking datasets that were previously reviewed separately. Second, it improves foresight by predicting future pressures and risks.

Third, it strengthens prioritization by comparing alternatives through transparent criteria. Fourth, it accelerates learning by monitoring outcomes after implementation. These benefits align closely with the needs of regional development, where investment decisions must balance growth, sustainability, resilience, and fairness over long time horizons.

At the same time, the technology is not a substitute for governance. AI models may give precise outputs based on incomplete assumptions. Optimization can hide value judgements inside mathematical weights. Digital twins can create a false sense of certainty if calibration data are weak.

Dashboards can oversimplify political, social, and environmental trade-offs. For these reasons, AI-enabled DSS should be treated as a decision-support layer within a broader planning institution. Engineers, planners, economists, environmental specialists, legal teams, and community representatives must remain part of the decision process.

Implementation capacity is another decisive factor. Wealthier regions and large infrastructure agencies may have the budget, data infrastructure, and specialist staff required to deploy advanced AI platforms. Smaller municipalities or regional authorities may lack clean data, cybersecurity capacity, procurement skills, or internal analytics teams.

This creates a risk that AI widens regional capability gaps instead of reducing them. Scalable deployment models should therefore include shared data standards, national cloud services, open architectures, training programs, and phased adoption pathways. The goal is not to purchase the most advanced platform immediately, but to build decision maturity progressively.

The sustainability dimension also needs careful measurement. Many AI infrastructure tools claim sustainability benefits, yet evaluation often focuses on model accuracy, processing speed, or cost efficiency. Sustainable development requires broader indicators: emissions reduction, resilience improvement, service accessibility, lifecycle value, public health, biodiversity protection, and distributional fairness.

A regional DSS should therefore include sustainability indicators at the design stage rather than adding them after technical optimization. When sustainability metrics are embedded into the objective function, the system can compare options according to long-term public value rather than short-term delivery convenience.

VIII. RECOMMENDATIONS

Policymakers should establish infrastructure data governance standards before scaling AI-enabled DSS. These standards should define data ownership, quality rules, update cycles, metadata requirements, privacy protection, cybersecurity controls, and interoperability expectations. Without common standards, each agency or consultant may create a separate digital system that cannot support regional optimization.

National and regional authorities should also publish clear guidelines on explainability, auditability, and human responsibility for AI-supported infrastructure decisions.

Infrastructure owners should begin with high-value use cases that address real planning pain points. Examples include capital project prioritization, predictive maintenance, flood resilience planning, utility leakage reduction, traffic corridor optimization, energy demand forecasting, and regional service accessibility analysis.

Starting with specific use cases helps organizations prove value, improve data quality, and build trust before moving toward fully integrated digital twins. Each use case should include measurable success indicators, such as reduced downtime, better budget allocation, improved response time, lower emissions, or clearer investment justification.

Consultants and technology providers should design DSS platforms that are explainable, modular, and compatible with existing workflows. Infrastructure professionals need systems that support engineering judgement rather than black-box outputs. Dashboards should allow users to inspect assumptions, compare scenarios, adjust weights, and export evidence for reports and approvals.

© JUL 2026 | IRE Journals | Volume 10 Issue 1 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I1-1719447

Vendors should avoid presenting AI as a universal solution and should instead demonstrate how models were trained, validated, monitored, and governed. Ethical and sustainability safeguards should be built into platform design rather than treated as optional features.

Academic researchers should expand empirical evaluation of AI-enabled DSS in real regional infrastructure settings. More longitudinal studies are needed to measure whether these systems actually improve investment outcomes over time.

Comparative research across regions would also help identify how governance culture, data maturity, procurement models, and institutional capacity affect adoption. Researchers should pay special attention to the link between technical accuracy and decision adoption, because a model can be statistically strong yet organizationally unused.

Table 2: Governance maturity requirements for responsible AI-DSS adoption

Maturity area	Basic practice	Advanced practice	Expected outcome
Data governance	Defined owners and validation rules	Interoperable regional data architecture	Reliable and reusable decision evidence
Model governance	Documented model purpose and training data	Continuous monitoring and independent audit	Reduced bias and model drift
Explainability	Visible scoring criteria and assumptions	Interactive trade-off and uncertainty dashboards	Greater stakeholder trust
Cybersecurity and privacy	Access control and compliance checks	Privacy-by-design and threat modelling	Protected infrastructure information
Sustainability accountability	Basic cost and service KPIs	Carbon, resilience, equity and lifecycle value metrics	Long-term public value alignment

IX. LIMITATIONS AND FUTURE RESEARCH

This review has limitations. The topic spans multiple disciplines, and no single database captures all relevant work across infrastructure engineering, urban planning, public policy, computer science, operations research, and sustainability.

The review also emphasizes recent literature from 2020 to 2025, which strengthens currency but may omit older foundational DSS studies. Because the paper is a review rather than an empirical deployment, it does not test a model on primary infrastructure data. The proposed framework should therefore be interpreted as a synthesis-based contribution that requires validation through case studies, pilot projects, and regional implementation trials.

Future research should develop measurable maturity models for AI-enabled regional infrastructure DSS. Such models could assess data readiness, model readiness, governance readiness, sustainability readiness, and organizational readiness. Future studies should also investigate responsible use of generative AI for infrastructure planning documents, procurement analysis, citizen engagement, and technical reporting.

Another priority is the development of open benchmarking datasets for regional infrastructure optimization, allowing models to be compared under common assumptions. Finally, future research should explore how AI can support participatory planning without replacing democratic deliberation or professional accountability.

X. CONCLUSION

AI-driven decision support systems can make regional infrastructure planning more integrated, predictive, transparent, and sustainability-oriented.

The review shows that the greatest value arises when AI is connected to data integration, geospatial analysis, predictive intelligence, optimization, scenario simulation, explainable dashboards, and governance feedback.

These systems can help regions prioritize investments, anticipate risks, improve resilience, reduce lifecycle cost, and align infrastructure delivery with sustainable development objectives. For Saudi Arabia and other transformation-focused economies, AI-enabled DSS can support regional development by turning fragmented infrastructure information into actionable evidence.

The central conclusion is that AI should support, not replace, human decision-making. Regional infrastructure optimization involves public values, spatial equity, environmental responsibility, financial discipline, and long-term uncertainty. These matters cannot be solved by algorithms alone.

A responsible DSS combines machine intelligence with engineering expertise, planning judgement, stakeholder participation, and policy accountability. When designed in this way, AI-driven decision support becomes more than a technical tool; it becomes a governance capability for sustainable regional development.

REFERENCES

[1] Aldoseri, A., Al-Khalifa, K., and Hamouda, A. (2024). AI-powered innovation in digital transformation: Key pillars and industry implications. Sustainability, 16(5), 1790.

[2] Ali, M., Naeem, F., Adam, N., Kaddoum, G., Huda, N. U., Adnan, M., and Tariq, M. (2023). Integration of data-driven technologies in smart grids for resilient and sustainable smart cities: A comprehensive review. Energy Reports, 9, 4593-4621.

[3] Bibri, S. E. (2021). Data-driven smart sustainable cities of the future: An evidence synthesis approach to a comprehensive state-of-the-art literature review. Sustainable Futures, 3, 100047.

[4] Bibri, S. E., Krogstie, J., and Kaboli, A. (2020). Smart sustainable cities of the future: An extensive interdisciplinary literature review. Sustainable Cities and Society, 62, 102407.

[5] Bibri, S. E., Alexandre, A., Sharifi, A., and Krogstie, J. (2023). Environmentally data-driven smart sustainable cities: Applied innovative solutions for energy efficiency, pollution reduction, and urban metabolism. Energy Informatics, 6, 1-35.

[6] Chen, Z., Chen, M., and Lee, J. (2022). Digital twin-enabled smart infrastructure management: A review of technologies, applications, and challenges. Automation in Construction, 141, 104399.

[7] Dias, T., Fonseca, T., Vitorino, J., Martins, A., Malpique, S., and Praca, I. (2023). From data to action: Exploring AI and IoT-driven solutions for smarter cities. Smart Cities, 6(4), 2030-2056.

[8] Du, J. (2024). Artificial intelligence enabled participatory planning: A review. International Journal of Urban Sciences, 28(1), 1-22.

[9] Gupta, S., Modgil, S., Bhattacharyya, S., and Bose, I. (2022). Artificial intelligence for decision support systems in the field of operations research: Review and future scope of research. Annals of Operations Research, 308, 215-274.

[10] Haleem, A., Javaid, M., Qadri, M. A., and Suman, R. (2022). Artificial intelligence applications for sustainable development. Environmental Technology & Innovation, 27, 102520.

[11] Jiang, F., Ma, L., Broyd, T., and Chen, K. (2021). Digital twin and its implementations in the civil engineering sector. Automation in Construction, 130, 103838.

[12] Karam, H., and Afiouni, R. (2025). A systematic review for AI in government. Open Research Europe, 5, 101.

[13] Kumar, H., Singh, M. K., Gupta, M. P., and Madaan, J. (2020). Moving towards smart cities: Solutions that lead to the smart city transformation framework. Technological Forecasting and Social Change, 153, 119281.

[14] Masoumi, Z., van Genderen, J., and Maleki, J. (2024). Artificial intelligence for sustainable development of smart cities: Multi-objective optimization approaches for urban land-use allocation. Geocarto International, 39(1), 2184729.

[15] OECD. (2025). Artificial intelligence for advancing smart cities. OECD Programme on Smart Cities and Inclusive Growth, Paris.

[16] Saudi Data and Artificial Intelligence Authority. (2020). National Strategy for Data and AI. SDAIA, Riyadh.

[17] Sacoto-Cabrera, E. J., Gomez, J., and Alvarez, R. (2025). IoT, AI, and digital twins in smart cities: A systematic literature review. Smart Cities, 8(5), 175.

[18] Shulajkovska, M., Ackovska, N., and Koceski, S. (2024). Artificial intelligence-based decision support system for smart city mobility planning. Electronics, 13(18), 3655.

[19] Smith, C. J. (2022). Advancements in artificial intelligence-based decision support systems for improving construction project sustainability. Information, 9(2), 43.

[20] UN-Habitat. (2020). World Cities Report 2020: The Value of Sustainable Urbanization. United Nations Human Settlements Programme, Nairobi.

[21] UN-Habitat. (2022). World Cities Report 2022: Envisaging the Future of Cities. United Nations Human Settlements Programme, Nairobi.

[22] United Nations. (2023). The Sustainable Development Goals Report 2023. United Nations, New York.

[23] Vision 2030. (2024). Saudi Vision 2030 annual report and national transformation progress resources. Government of Saudi Arabia, Riyadh.

[24] World Bank. (2021). World Development Report 2021: Data for Better Lives. World Bank, Washington, DC.

[25] World Economic Forum. (2022). Digital Twin Cities: Framework and Global Practices. World Economic Forum, Geneva.

[26] Yigitcanlar, T., Butler, L., Windle, E., Desouza, K. C., Mehmood, R., and Corchado, J. M. (2020). Can building artificial intelligence into smart cities improve urban sustainability? International Journal of Environmental Research and Public Health, 17(3), 971.

[27] Yigitcanlar, T., Desouza, K. C., Butler, L., and Roozkhosh, F. (2020). Contributions and risks of artificial intelligence in building smarter cities: Insights from a systematic review. Energies, 13(6), 1473.

[28] Yigitcanlar, T., Kankanamge, N., and Vella, K. (2021). How are smart city concepts and technologies perceived and utilized? Cities, 107, 102878.

[29] Zhang, Y., Pan, Y., and Li, H. (2021). Deep learning-based infrastructure asset management: A review of applications and future directions. Journal of Infrastructure Systems, 27(4), 03121002.

[30] Zhu, Z., and Lin, L. (2023). Explainable artificial intelligence for infrastructure systems: Opportunities, risks, and governance requirements. Advanced Engineering Informatics, 57, 102066.