IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

From Reactive Management to Trustworthy Autonomy: An Explainable, Digital-Twin-Assisted Framework for AI-Native 6G Networking

Kolekar Rushikesh Dnyaneshwar[1], Prof. M. S. Diighe[2], Prof. P. A. Sawant[3], Dr. H. B. Jadhav[4]
Student, Department Of Computer Engineering[1]
Guide, Department Of Computer Engineering[2]
Co-Guide, Department Of Computer Engineering[3]
HOD, Department Of Computer Engineering[4]
Adsul's Technical Campus, Chas, Ahilyanagar, India

Abstract: *Future communication networks will need to manage increasingly diverse services, fluctuating traffic demands, and complex operating conditions with minimal manual intervention. Artificial intelligence (AI) offers useful capabilities for predicting network behaviour, identifying faults, and recommending resource-allocation decisions. However, making a prediction is only one part of reliable network management. Operators must also understand why a recommendation was produced, assess its possible consequences, and determine whether it is safe to apply. This paper proposes an explainable, digital-twin-assisted framework for trustworthy AI-native networking, particularly in the context of sixth-generation (6G) communication systems. The framework combines network telemetry, AI-based prediction, digital-twin simulation, explainable recommendations, policy validation, and monitored execution. A virtual representation of the network is used to examine candidate actions before deployment, while the explainability component presents the factors influencing each recommendation. A policy-control layer checks operational restrictions and identifies actions requiring human approval. The proposed design is informed by a focused review of research published during 2024, 2025, and 2026 on AI-enabled digital twins, autonomous network management, generative AI, and AI-native 6G architectures. The review indicates that integrating prediction, simulation, explanation, and feedback offers a promising direction for more transparent network automation. Nevertheless, the framework remains a proposed design and requires implementation and experimental validation. The paper therefore defines research questions, evaluation metrics, and test scenarios for investigating its effectiveness, while discussing the challenges associated with model reliability, digital-twin accuracy, cybersecurity, privacy, and computational overhead..*

Keywords: AI-native networking, sixth-generation communication, explainable artificial intelligence, network digital twins, autonomous network management, trustworthy AI, network optimization, closed-loop control

I. INTRODUCTION

A. Background and motivation

Modern communication networks support applications that differ considerably in their requirements. A connected sensor may transmit small amounts of data periodically, whereas an industrial control application may require predictable latency and high reliability. Video services, connected transportation, cloud computing, and emerging immersive applications introduce further demands on network capacity and resource management.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

Managing these environments through fixed rules and manual configuration can become difficult as the number of devices, services, and network parameters increases. A configuration that works well during normal traffic conditions may become unsuitable when demand changes suddenly or a network component fails. Consequently, future networks need management approaches that can interpret changing conditions, anticipate potential problems, and evaluate possible responses.

Artificial intelligence can contribute to this objective by learning patterns from operational data. Predictive models can estimate future traffic, classification models can identify suspicious behaviour, and optimization techniques can recommend changes to routing or resource allocation. These capabilities are relevant to the development of AI-native networks, in which intelligence is integrated into network operation rather than being used only as an external analytical tool.

Network digital twins provide another useful capability. A digital twin maintains a virtual representation of a physical network or selected components, allowing researchers and operators to examine possible operating conditions and evaluate alternative configurations. Recent studies have explored the combination of AI and digital twins for 6G network management, simulation, optimization, and autonomous operation [1]–[4].

Despite these advances, an operational recommendation still needs to be assessed before it is applied. An AI model may identify a potentially useful action without providing sufficient information about its reasoning or the conditions under which its prediction may fail. A digital twin may also produce misleading results when its representation is outdated or incomplete. These concerns make transparency, validation, and controlled execution important parts of trustworthy network automation.

B. Problem definition

The central problem addressed in this paper is the separation between AI-generated network recommendations and the evidence needed to evaluate those recommendations before deployment.

A reliable management process should answer three questions. First, what is likely to happen if the current network conditions continue? Second, what action could improve the situation, and what evidence supports that recommendation? Third, what checks are necessary before the proposed action is applied to the physical network?

Addressing these questions requires more than a prediction model. It requires an integrated process connecting network observations, AI-based analysis, virtual testing, understandable explanations, operational policies, and post-deployment monitoring.

C. Research objectives

The objectives of this study are:

1. To examine recent research on AI-native networking and digital-twin-assisted network management published during 2024–2026.
2. To identify practical challenges associated with transparency, simulation accuracy, and automated network control.
3. To design an architecture that combines AI prediction, digital-twin evaluation, explainable recommendations, and policy validation.
4. To define measurable criteria for evaluating the proposed architecture.
5. To identify the implementation requirements and open research questions associated with trustworthy network automation.

D. Main contribution

This paper proposes a unified workflow in which an AI-generated recommendation is treated as a candidate action rather than an instruction that must be executed automatically. The candidate action is evaluated in a digital twin, accompanied by an explanation, and checked against operational constraints before authorization.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

The contribution lies in the integration of these functions into a clearly defined architecture and evaluation plan. The paper does not claim to introduce a new machine-learning algorithm or demonstrate a measured improvement over existing systems. Such claims would require an implemented prototype and reproducible experiments.

E. Paper organization

Section II reviews relevant literature from 2024–2026. Section III presents the proposed architecture and explains its components. Section IV describes the methodology and evaluation plan. Section V discusses potential benefits, limitations, and deployment challenges. Section VI concludes the paper and outlines future work.

II. RELATED WORK AND RESEARCH TRENDS

A. Developments in 2024

Research published in 2024 provides important foundations for combining artificial intelligence with network management and digital-twin technology.

Sheraz and colleagues examined AI-enabled digital-twin networks for 6G, discussing the role of digital representations in network optimization and connectivity management [1]. Their work supports the idea that a virtual network model can help assess operating conditions and investigate alternative decisions.

Li and colleagues presented a digital-twin architecture for 6G that moves from design considerations toward practical implementation [2]. Their work is relevant because a digital twin must be connected to real network observations and evaluated against the behaviour of the physical environment. A virtual model that is not sufficiently synchronized with the network cannot be assumed to produce dependable predictions.

Mekrache, Ksentini, and Verikoukis examined machine learning and machine reasoning within the FCAPS network-management framework [3]. Their discussion highlights the importance of combining data-driven prediction with reasoning that can support more understandable network-management decisions.

Wu, Huang, and Luan also proposed an AI-native network digital-twin framework for intelligent 6G management [4]. Their work connects digital-twin models with network-state prediction, pattern abstraction, and decision-making.

Taken together, these studies establish a foundation for AI-supported network management. They also suggest that network intelligence should be considered alongside the mechanisms used to represent, interpret, and control network behaviour.

B. Developments in 2025

Research in 2025 extended the discussion of digital twins toward generative AI, native network architectures, and integrated network optimization.

Li and colleagues surveyed generative AI-enabled network digital twins, examining their use in data processing, network monitoring, digital replication, simulation, optimizer development, and the transition from virtual experiments to physical network control [5]. This work is particularly relevant because it treats the digital twin as part of a broader operational lifecycle rather than as an isolated simulation tool.

Liu and colleagues proposed a native design for 6G digital-twin networks, covering use cases, architecture, functions, and key technologies [6]. Their work emphasizes the importance of integrating digital-twin capabilities into network design and management.

These studies suggest that the relationship between virtual experimentation and operational control deserves particular attention. A simulated action may appear beneficial under the assumptions of a model but perform differently when exposed to real traffic, unexpected failures, or incomplete observations. For this reason, the proposed framework treats simulation as an important validation step, not as an unconditional guarantee of safety.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

C. Developments in 2026

Recent work has continued to examine the functional architecture and lifecycle requirements of network digital twins for AI-native 6G systems.

Zaki-Hindi and colleagues presented a reference functional architecture for network digital twins in 6G systems [7]. Their study discusses functional requirements, simulation, data management, orchestration, and the integration of network digital twins with AI-native networks. This provides a useful reference for considering how separate network-management functions can be organized into a coherent architecture.

A 2026 survey by Sanjalawe and colleagues examines AI-driven digital-twin networks for future wireless systems, including the roles of deep learning, reinforcement learning, federated learning, and explainable AI across the digital-twin lifecycle [8]. This work is especially relevant to the present study because it connects intelligence with twin creation, synchronization, prediction, decision-making, and feedback.

The 2026 literature reinforces the importance of treating AI-enabled network management as a lifecycle problem. Prediction, simulation, explanation, and feedback are interdependent functions. Their effectiveness depends not only on the quality of individual models but also on the accuracy of the information exchanged between them and the controls placed around automated decisions.

D. Comparative analysis

The reviewed literature contributes to several closely related areas:

Research direction	Contribution to the field	Relevance to the proposed framework
AI-enabled digital twins, 2024 [1]	Examines AI-supported digital-twin networking for 6G	Motivates virtual evaluation of candidate actions
Digital-twin architecture, 2024 [2]	Connects digital-twin design with practical network operation	Highlights the need for synchronization and validation
Machine reasoning in FCAPS, 2024 [3]	Examines learning and reasoning for network management	Motivates understandable and auditable recommendations
AI-native digital twins, 2024 [4]	Connects AI with network-state prediction and management	Supports integrated AI and digital-twin workflows
Generative AI and digital twins, 2025 [5]	Reviews data generation, simulation, optimization, and control	Highlights the importance of validating simulated outcomes
Native 6G digital-twin design, 2025 [6]	Addresses architecture and operational functions	Supports system-level integration of network intelligence
Reference digital-twin architecture, 2026 [7]	Organizes functional requirements and lifecycle management	Provides architectural context for orchestration and validation
AI-driven digital-twin survey, 2026 [8]	Examines multiple AI approaches across the digital-twin lifecycle	Motivates evaluation of explainability, synchronization, and feedback

The reviewed work provides substantial foundations for AI-based network management and digital-twin design. The opportunity pursued in this paper is to specify a single operational workflow that makes the relationship between an AI recommendation, its explanation, its simulated consequences, and its authorization explicit.

The proposed framework focuses on five requirements:

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

1. **Traceability:** Each recommendation should be linked to the network observations and model output that produced it.
2. **Virtual evaluation:** Candidate actions should be assessed in an appropriately calibrated digital twin where feasible.
3. **Explanation and uncertainty:** The system should communicate influential factors and limitations rather than presenting predictions as certain outcomes.
4. **Policy-constrained control:** Recommendations should be checked against service, security, and operational requirements.
5. **Post-action verification:** The physical network should be monitored after execution so that unexpected results can be detected.

This is an integration-focused research opportunity. It should not be interpreted as proof that previous systems lack these capabilities; individual studies may already address some or all of them. A more detailed systematic review would be required to establish the precise novelty of the proposed combination.

III. PROPOSED FRAMEWORK

A. Design principle

The proposed framework is based on a simple principle: an AI recommendation should be evaluated before it is allowed to influence a live network.

In a conventional automated workflow, a model may identify a problem and pass a recommended configuration directly to a controller. This approach can be effective when the task is well understood and the permitted actions are carefully restricted. However, it offers limited protection when the model receives unreliable data, encounters an unfamiliar situation, or proposes a change with unintended consequences.

The proposed framework introduces additional stages between prediction and execution. A recommendation is first associated with the relevant network state, examined in a digital twin, and accompanied by an explanation. A policy-validation component then determines whether the proposed action satisfies the required constraints. Depending on its impact and uncertainty, the action may be rejected, returned for further analysis, or submitted for human approval.

The framework also monitors the physical network after an approved action is applied. The observed outcome is compared with the predicted outcome so that deviations can be identified and investigated.

B. Proposed system architecture

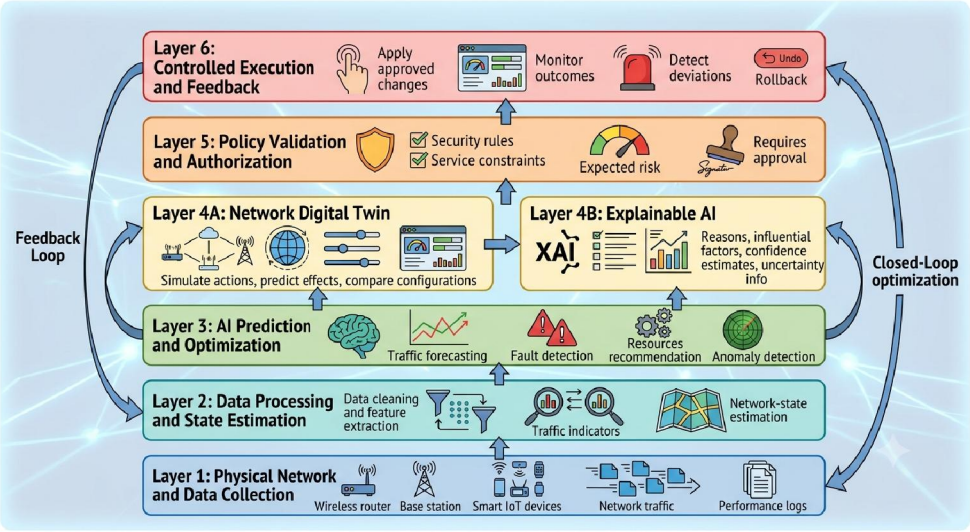


Fig. 1. Proposed architecture for explainable, digital-twin-assisted AI-native network management.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

C. Description of the architecture

1) Physical network and telemetry collection: The process begins with information collected from the network and its management systems. Depending on the application, the data may include throughput, latency, packet loss, queue length, resource utilization, fault events, and energy consumption. The framework should retain the time and source of each observation so that later recommendations can be traced to their inputs.

2) Data preparation and network-state estimation: Measurements are checked for missing values, inconsistent timestamps, duplicate records, and implausible readings. The processed information is converted into features representing the current network state. Data-quality information is retained because a prediction produced from incomplete or unreliable measurements should be treated cautiously.

3) AI analysis and candidate-action generation: An appropriate model analyses the available information and estimates future traffic, possible faults, congestion risk, or resource demand. Depending on the task, the implementation may use supervised learning, time-series forecasting, anomaly detection, or reinforcement learning. The model generates candidate actions rather than directly modifying the network.

4) Network digital twin: The digital twin represents the relevant network topology, components, operating state, and constraints. Candidate actions can be tested against representative traffic conditions to estimate their possible effects. For example, alternative routing configurations can be compared according to expected latency, throughput, and resource use. The usefulness of this stage depends on the fidelity, synchronization, and calibration of the twin.

5) Explainable AI: The explanation module identifies the factors that influenced a recommendation. Depending on the model and task, this may involve feature attribution, rule-based reasoning, local surrogate explanations, or counterfactual analysis. The explanation should be checked for fidelity to the underlying model and should not imply causation merely because a variable is influential.

6) Policy validation and authorization: Each candidate action is checked against defined operational boundaries, security requirements, service-level objectives, and access permissions. Actions that violate mandatory constraints are rejected. Actions involving significant uncertainty or service impact can be referred to an operator for approval.

7) Controlled execution and feedback: Approved actions are applied through authorized management interfaces. The system then monitors actual network behaviour and compares it with the expected outcome. If a predefined safety condition is violated, the system can stop further changes or invoke a tested recovery procedure. The feasibility of rollback depends on the particular network operation and must be verified during implementation.

D. Illustrative example

Suppose that traffic measurements indicate increasing congestion in part of a mobile network. The proposed framework first checks the available measurements and uses an AI model to estimate whether the congestion is likely to continue. The optimization component then generates candidate actions, such as adjusting a permitted routing policy or reallocating available resources.

Rather than applying the first recommendation immediately, the system evaluates the alternatives in the digital twin. It compares their predicted effects on service quality and resource use. The explainability module identifies the observations that influenced the recommendation and reports relevant uncertainty. The policy-validation component then checks whether the selected action complies with operational constraints.

If the action passes validation and any required approval is obtained, it can be applied through the authorized controller. The system subsequently measures the actual outcome. If the physical network behaves differently from the simulation, the deviation is recorded and may trigger further analysis or recovery.

This example illustrates how the proposed architecture is intended to operate. It is a conceptual scenario, not a report of a completed experiment.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

E. Comparison with conventional approaches

Criterion	Conventional or basic AI-assisted management	Proposed framework
Decision input	Rules, monitoring data, or model outputs	Validated network observations and AI outputs
Candidate evaluation	Depends on the existing system	Digital-twin evaluation where suitable
Decision explanation	May be limited or model-dependent	Explicit explanation stage
Safety controls	Existing rules and permissions	Dedicated policy-validation stage
Execution	Manual or automated	Authorized and monitored execution
Feedback	Monitoring and periodic adjustment	Explicit comparison of predicted and observed outcomes
Evidence required	Depends on the implementation	Comparative experiments needed to establish benefits

Copyright to IJARSCT
www.ijarsct.co.in
DOI: 10.48175/IJARSCT-38850

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

F. Decision workflow

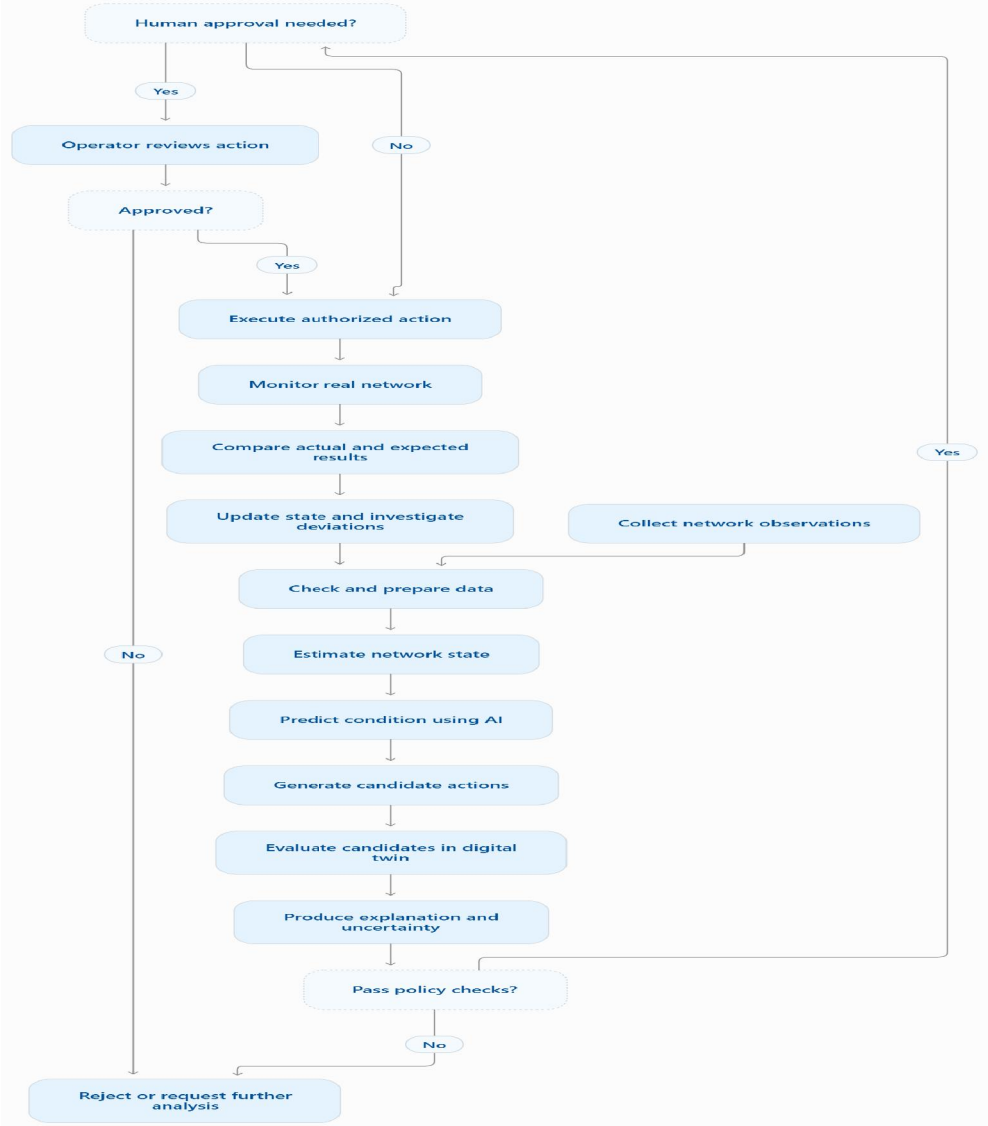


Fig. 2. Decision workflow showing how candidate network actions pass through simulation, explanation, validation, and feedback.

F. Comparison with conventional approaches

Criterion	Conventional or basic AI-assisted management	Proposed framework
Decision input	Rules, monitoring data, or model outputs	Validated network observations and AI outputs

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

Candidate evaluation	Depends on the existing system	Digital-twin evaluation where suitable
Decision explanation	May be limited or model-dependent	Explicit explanation stage
Safety controls	Existing rules and permissions	Dedicated policy-validation stage
Execution	Manual or automated	Authorized and monitored execution
Feedback	Monitoring and periodic adjustment	Explicit comparison of predicted and observed outcomes
Evidence required	Depends on the implementation	Comparative experiments needed to establish benefits

IV. RESEARCH METHODOLOGY AND EVALUATION PLAN

A. Methodological approach

This study uses a literature-informed system-design methodology. Research published during 2024–2026 is examined to identify developments in AI-native networking, network digital twins, intelligent management, and explainable AI. These findings inform the requirements and components of the proposed framework.

The methodology follows five stages:

1. **Literature examination:** Identify relevant approaches, reported contributions, limitations, and open questions.
2. **Requirement specification:** Define the need for data validation, prediction, simulation, explanation, policy enforcement, and feedback.
3. **Architecture development:** Specify the system components and their interactions.
4. **Evaluation planning:** Define suitable baselines, test scenarios, and performance measures.
5. **Critical assessment:** Examine deployment risks, computational requirements, and the limits of the proposed design.

The literature selection presented here is focused rather than exhaustive. A formal systematic review would require a documented search protocol, selected databases, explicit inclusion and exclusion criteria, and reproducible screening of retrieved publications.

B. Data and implementation requirements

A future prototype could be evaluated using a public network dataset together with a network simulator or a digital-twin platform. Traffic datasets can support prediction and anomaly-detection experiments, but a dataset alone cannot demonstrate the effectiveness of a complete network-control workflow.

The implementation should, where appropriate, include:

- Network throughput, latency, packet loss, and queue measurements.
- Resource utilization and traffic-demand observations.
- Network topology and permitted configuration changes.
- Fault and congestion scenarios.
- Service requirements and policy constraints.
- Time-stamped actual and predicted outcomes.

The selected dataset, simulator, model settings, and network scenarios should be documented. If the data contain sensitive operational or user information, appropriate access controls and privacy safeguards must be applied.

Copyright to IJARSCT
www.ijarsct.co.in
DOI: 10.48175/IJARSCT-38850

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

A. Evaluation metrics

Area	Metrics	Purpose
Prediction	MAE, RMSE	Measure numerical forecast error
Fault detection	Precision, recall, F1-score	Assess classification performance
Service quality	Latency, throughput, packet loss	Measure network behaviour
Resource efficiency	Energy consumption, utilization	Assess resource use
Digital-twin quality	State-estimation error, synchronization delay	Measure the reliability of the virtual representation
Explainability	Fidelity, stability, operator usefulness	Assess explanation quality
Safety	Constraint violations, recovery events	Assess operational risk
Scalability	Processing time, computational overhead	Measure cost as the system grows

The metrics should be selected according to the task. For example, MAE and RMSE measure different aspects of numerical prediction error, whereas precision and recall describe different aspects of classification performance. Explanation fidelity and stability also measure different properties and should be evaluated separately.

B. Experimental design

A future experimental study should compare three configurations under equivalent conditions.

Baseline 1 — Rule-based management: Uses predefined thresholds and permitted operational policies.

Baseline 2 — AI-assisted management: Uses prediction or optimization models without the complete proposed workflow.

Proposed configuration — Explainable digital-twin-assisted management: Combines AI-based recommendations, virtual evaluation, explanation, policy validation, and controlled execution.

The test environment should include representative traffic patterns and events such as sudden demand increases, link failures, incomplete telemetry, and resource shortages. Each configuration should be evaluated with the same network topology, traffic traces, and resource constraints wherever applicable.

The study should report the actual measurements, repeated-trial results where appropriate, uncertainty intervals, and implementation settings. Simulation findings should be clearly distinguished from results measured on a physical testbed.

Because the proposed framework has not yet been implemented and tested in this paper, no numerical performance improvement is claimed. The evaluation plan specifies how such improvements could be investigated.

V. DISCUSSION

A. Expected benefits

The proposed framework is intended to improve the quality of network-management decisions by connecting AI-based analysis with validation and feedback. Its main potential benefit is not simply greater automation, but a clearer process for deciding when an automated recommendation should be trusted.

First, explainable AI can help operators identify the factors that influenced a recommendation. This information may support troubleshooting and make it easier to investigate unexpected model behaviour. However, explanations must be evaluated because a plausible explanation is not necessarily a faithful representation of the model's internal decision process.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

Second, digital-twin-based evaluation can provide an opportunity to examine candidate actions before applying them to a live network. This may reduce exposure to unnecessary configuration changes, provided that the virtual model represents the relevant operating conditions accurately.

Third, policy validation introduces a defined boundary between an AI recommendation and an authorized operational action. This distinction is particularly important when network changes may affect service availability, security, or critical communication functions.

Finally, feedback from the physical network can help identify differences between predicted and observed behaviour. These differences may reveal model drift, inaccurate simulation assumptions, or unexpected environmental changes.

The benefits described above are hypotheses about the proposed design. Their practical value must be established through comparative experiments.

B. Technical challenges

Digital-twin accuracy: A virtual network representation may omit important physical details or fail to reflect recent changes. Synchronization and calibration are therefore essential.

Model uncertainty: AI predictions can become less reliable when operating conditions differ from the training data. The system should identify uncertain cases and avoid treating every recommendation as equally dependable.

Explanation reliability: Some explainability techniques provide approximate descriptions of model behaviour. Their fidelity, stability, and usefulness should be tested before they are used to justify consequential actions.

Computational overhead: Running simulations and producing explanations may introduce additional processing time. The design must balance the value of validation against the time available for operational decisions.

Security and privacy: Network telemetry and management interfaces may expose sensitive operational information. Authentication, access control, secure data handling, and protection against manipulated inputs are necessary.

Safe execution: Even a well-tested recommendation can fail under unexpected conditions. Automated control must operate within clearly defined permissions, with monitoring and tested recovery mechanisms.

C. Practical applications

1. Mobile and 6G communication networks

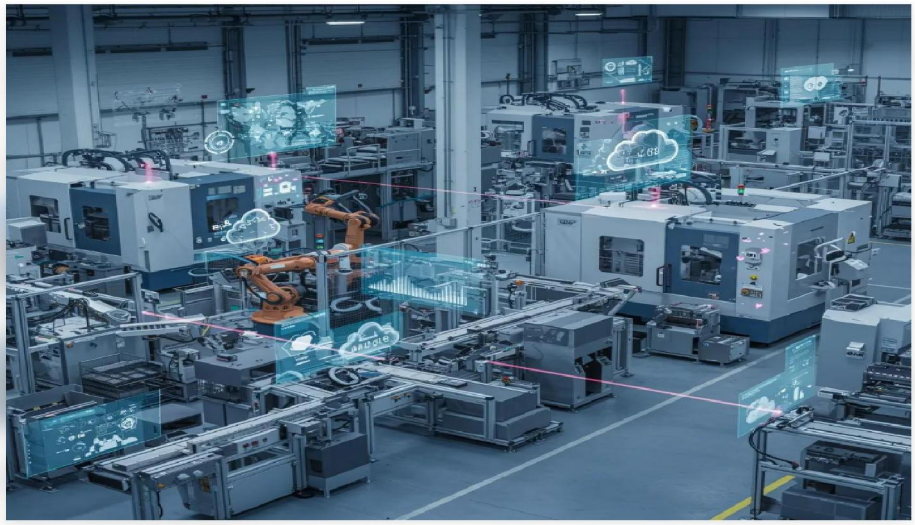
Predict congestion, evaluate resource allocation, and examine routing or configuration changes before deployment.



IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

2. Industrial IoT

Examine network conditions supporting connected machines and assess the potential effect of network changes on industrial services.



3. Smart-city infrastructure

Support communication between connected traffic systems, public sensors, and distributed urban infrastructure.



4. Cloud and edge computing

Compare workload-placement and resource-allocation options while considering network latency and capacity.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

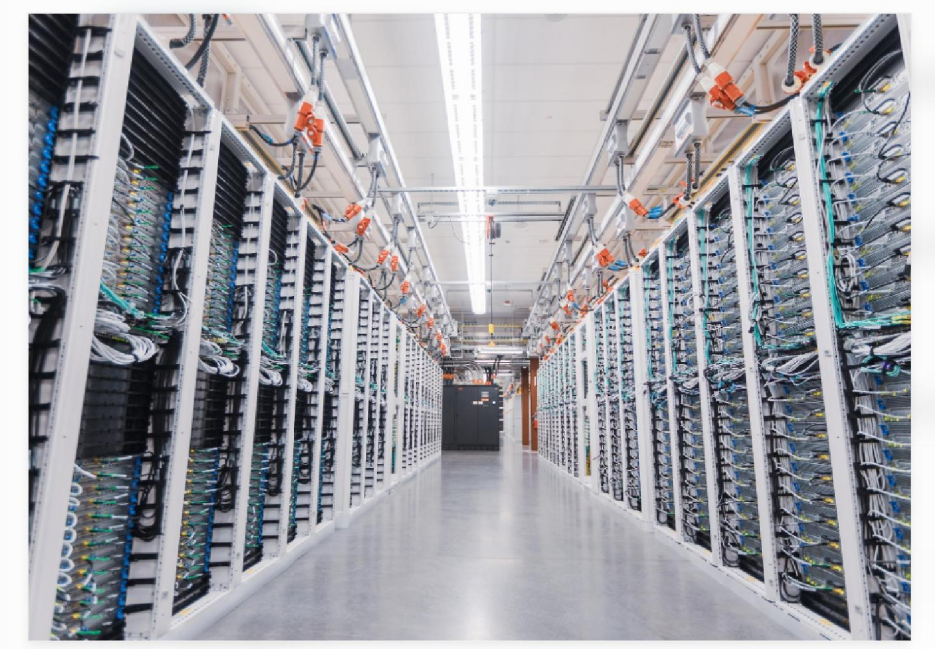


Fig. 3. Potential application areas of explainable, digital-twin-assisted network management.

D. Future research directions

The immediate next step is to develop a prototype that connects a network simulator or digital-twin platform with an AI prediction model and a policy-controlled decision module. The first implementation should focus on a manageable task, such as congestion prediction and the evaluation of alternative routing policies.

Subsequent experiments could investigate graph neural networks for topology-aware prediction, reinforcement learning for resource allocation, and federated learning for distributed environments. Generative AI could also support scenario generation and natural-language interaction with network operators. However, generated outputs should be treated as proposals and subjected to validation before they influence operational control.

Future studies should measure how accurately the digital twin reflects the physical network, whether explanations help operators make better decisions, and how much processing overhead the additional validation stages introduce. Security testing should also investigate the effects of missing, delayed, or manipulated telemetry.

A reproducible evaluation using public datasets, documented simulator configurations, and clearly defined baselines would provide a stronger basis for determining whether the proposed framework offers measurable advantages over simpler network-management approaches.

VI. CONCLUSION

This paper proposed an explainable, digital-twin-assisted framework for trustworthy AI-native networking, motivated by the growing complexity of future 6G network management. The literature review examined developments from 2024, 2025, and 2026 in AI-enabled digital twins, network architecture, machine reasoning, and autonomous management. Based on these developments, the proposed framework connects network observations, AI-based prediction, virtual evaluation, understandable explanations, policy validation, and monitored execution. Its central idea is that an AI recommendation should be assessed before it is permitted to change a live network. The framework provides a basis for investigating how transparency and virtual validation can be integrated into network automation, but its benefits have not yet been established experimentally. Future work will focus on prototype development,

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 2, October 2026
Impact Factor: 8.2

comparison with conventional and AI-assisted baselines, and evaluation of network performance, explanation reliability, digital-twin accuracy, computational overhead, and operational safety. Such evidence will be necessary to determine whether this approach can contribute to reliable and accountable AI-native networking.

ACKNOWLEDGMENT

The author acknowledges the researchers and organizations whose published work and technical resources informed this study. Any additional institutional support or funding acknowledgment should be included only where applicable.

REFERENCES

[1] M. Sheraz et al., "A Comprehensive Survey on Revolutionizing Connectivity Through Artificial Intelligence-Enabled Digital Twin Network in 6G," *IEEE Access*, vol. 12, pp. 49184–49215, 2024, doi: 10.1109/ACCESS.2024.3384272.

[2] Q. Li et al., "Native Network Digital Twin Architecture for 6G: From Design to Practice," *IEEE Communications Magazine*, vol. 63, no. 4, pp. 24–31, 2025, doi: 10.1109/MCOM.001.2400216. First published online in 2024.

[3] A. Mekrache, A. Ksentini, and C. Verikoukis, "Machine Learning in FCAPS: Toward Enhanced Beyond 5G Network Management," *IEEE Communications Surveys & Tutorials*, vol. 26, no. 4, pp. 2769–2797, 2024, doi: 10.1109/COMST.2024.3395414.

[4] W. Wu, X. Huang, and T. H. Luan, "AI-Native Network Digital Twin for Intelligent Network Management in 6G," arXiv:2410.01584, 2024. [Online]. Available: https://arxiv.org/abs/2410.01584.

[5] T. Li et al., "Generative AI Empowered Network Digital Twins: Architecture, Technologies, and Applications," *ACM Computing Surveys*, vol. 57, no. 6, Art. no. 157, pp. 1–43, 2025, doi: 10.1145/3711682.

[6] G. Liu et al., "Native Design for 6G Digital Twin Network: Use Cases, Architecture, Functions, and Key Technologies," *IEEE Internet of Things Journal*, vol. 12, no. 15, pp. 29135–29151, 2025, doi: 10.1109/JIOT.2025.3553500.

[7] A. Zaki-Hindi et al., "A Reference Functional Architecture for Network Digital Twins in 6G Systems," *IEEE Open Journal of the Communications Society*, vol. 7, pp. 2068–2101, 2026, doi: 10.1109/OJCOMS.2026.3668035.

[8] Y. Sanjalawe et al., "Bridging the Gap: A Comprehensive Survey on AI-Driven Digital Twin Networks for Future Wireless Systems," *Journal of King Saud University Computer and Information Sciences*, 2026, doi: 10.1007/s44443-026-00522-y.

[9] Y. Huang, M. Kang, Y. Zhu, N. Li, G. Liu, and Q. Wang, "Digital Twin Network-Based 6G Self-Evolution," *Sensors*, vol. 25, no. 11, Art. no. 3543, 2025, doi: 10.3390/s25113543.

[10] H. Zhou et al., "Large Language Model (LLM) for Telecommunications: A Comprehensive Survey on Principles, Key Techniques, and Opportunities," *IEEE Communications Surveys & Tutorials*, 2024, doi: 10.1109/COMST.2024.3465447.

[11] International Telecommunication Union, "Focus Group on Artificial Intelligence Native for Telecommunication Networks (FG-AINN)," ITU-T, established July 2024. [Online]. Available: https://www.itu.int/en/ITU-T/focusgroups/ainn/Pages/default.aspx.