Global Academic Journal of Economics and Business

Available online at https://www.gajrc.com
DOI: https://doi.org/10.36348/gajeb.2026.v08i04.037

ISSN: 2706-9001 (P)
ISSN: 2707-2584 (O)

Original Research Article

AI-Enabled Fault Prediction and Performance Optimization in 5G Optical Transport Networks

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Article History
Received: 16.06.2026
Accepted: 10.08.2026
Published: 12.08.2026

Abstract: The rapid deployment of fifth-generation mobile networks (5G) is transforming the optical transport from a static capacity layer into a dynamic, service-critical infrastructure that must support cloud radio access, edge computing, network slicing, industrial connectivity and latency-sensitive consumer services. Faults in this layer may degrade fronthaul, midhaul and backhaul performance before a hard alarm appears. Over-conservative engineering margins contribute to cost, energy consumption and wasted spectrum. This paper discusses the potential of artificial intelligence to enable fault prediction and performance optimization in 5G optical transport networks through the integration of optical performance monitoring, telemetry analytics, digital twins, machine learning, software-defined control and closed-loop assurance. We adopt a structured narrative review approach to synthesise the literature published from 2020 to 2025 on optical failure management, quality-of-transmission prediction, loss-of-signal forecasting, soft-failure localisation, traffic forecasting, transport automation, and 5G optical fronthaul design. This paper proposes a practical AI-enabled operating framework to convert streaming measurements to failure probability, time-to-impact, root-cause ranking, optimization recommendations and governed automation actions. The review suggests that the greatest value of AI is to embed models into operational processes, rather than to use them as standalone prediction tools. For telecom operators, the key benefits are reduced mean time to repair, fewer preventable outages, improved spectrum and power efficiency, better service-level assurance and more disciplined capacity expansion. The study concludes with a phased implementation roadmap for operators seeking to move away from reactive maintenance and towards predictive, explainable and policy-controlled optical transport operations.

Keywords: AI-Enabled Optical Networks, 5G Transport, Fault Prediction, Soft Failure Detection, QoT, Performance Optimization, Predictive Maintenance.

1. INTRODUCTION

The quality of 5G service depends on having a transport network that can provide very high capacity together with predictable latency, synchronisation and availability. Heavy traffic generated by dense radio sites, cloud radio access networks, enterprise private networks, edge data centres and core aggregation is carried by optical transport. Radio innovation is often visible to users but the optical transport is the unseen continuity layer that binds together radio units, distributed units, centralised units, aggregation routers and cloud platforms. If this layer suffers from fibre degradation, amplifier drift, transponder instability, connector contamination, excessive span loss or routing congestion, the result may be perceived as reduced throughput, rising latency, deteriorated error performance or complete service loss. Another hurdle is that 5G traffic patterns are more dynamic, service classes are more varied, and operational margins are more expensive to maintain.

Traditional optical network operations are mostly reactive. Operators configure lightpaths, assign spectrum, check thresholds and respond to alarms once degradation is apparent. This model is effective for stable networks but less suitable for a 5G environment where operators have to cater for bandwidth growth, strict service level agreements and multi-layer interdependence. Machine learning has been shown to assist intelligent optical networks by learning from data, such as monitoring data, alarms, topology, modulation formats and historical incidents [1]. Failure management reviews classify the relevant AI functions into alarm analysis, fault prediction, detection, localisation and identification [2]. This classification is useful because it clarifies that prediction alone is not enough. Operators need a chain of functions that spans from early warning through to operational response.

The biggest opportunity is the detection of soft failures. A hard failure produces a clear outage. A soft failure gradually degrades the quality of transmission prior to a service-affecting event. Examples include laser aging, amplifier gain variation, filter narrowing, fiber bending, optical signal-to-noise ratio drift, polarization effects, and rising bit errors. If the operator only responds to threshold alarms, valuable time for intervention is lost. The results of studies on loss-of-signal prediction show that supervised learning can detect risk days before the event, using performance monitoring data from operational optical networks [3]. Other research explores machine-learning-assisted optical performance monitoring and quality of transmission estimation to increase planning accuracy, decrease design margins and allow for autonomous management [4, 5].

This review is based on AI-enabled fault prediction and performance optimization in 5G optical transport network. It is not just a mathematical model, but a socio-technical operating capability. The question is how telecom operators can integrate telemetry, model governance, optimization logic, software defined networking, maintenance workflows and human approval to enhance reliability without introducing unacceptable cyber, safety or operational risk. The review uses a transparent structure comprising a clear aim, objectives, methodology, thematic synthesis, conceptual framework, implementation roadmap and a 2020–2025 reference base.

2. Aim, Objectives and Contribution of the Review

This review aims to evaluate the capability of artificial intelligence to improve fault prediction and performance optimization in 5G optical transport networks. The first objective identifies the main operational problems that drive the need for AI, such as delayed fault discovery, hidden soft failures, fragmented alarm data, conservative optical margins, capacity pressure and manual restoration procedures. The second goal is to incorporate AI techniques for optical transport assurance including supervised learning, unsupervised anomaly detection, deep learning, time-series forecasting, graph-based learning, reinforcement learning and digital-twin-assisted decision support. The third objective is to connect these techniques with operational metrics that can be measured, such as mean time to detect, mean time to repair, service availability, quality of transmission, spectrum efficiency, energy efficiency, and capacity planning accuracy.

Another goal is to develop a practical framework that telecom operators can use to deploy predictive optical operations. Existing literature tends to present algorithms on controlled datasets, simulations or laboratory settings. But operators must integrate models with inventory systems, fault ticketing, field maintenance, service inventory, IP-over-WDM controllers, radio service priorities and change approval procedures. The value of this review therefore lies in three contributions. It first categorises recent research into an operational taxonomy that divides functions into prediction, diagnosis, optimization, and governance. Secondly, it describes the role of AI in improving 5G transport reliability for the fronthaul, midhaul, backhaul and metro-core layers. Third, it hints at a staged deployment path that balances automation ambition with data quality, explainability, cybersecurity and workforce readiness.

3. REVIEW METHODOLOGY

The topic brings together optical engineering, 5G transport architecture, artificial intelligence, software-defined networking and telecom operations, which leads us to use a structured narrative review methodology for this paper. The methodology consists of five stages: scope definition, source identification, thematic screening, synthesis and framework development. The scope includes research and standards-oriented literature from 2020 to 2025 only. Work prioritised optical failure management, soft-failure detection, loss-of-signal prediction, quality-of-transmission estimation, optical performance monitoring, 5G optical fronthaul, traffic forecasting, AI-based network optimization and transport automation. No reference has been made to sources outside the period, even if historically important. The literature search covered Scopus, IEEE Xplore, Web of Science, and ScienceDirect. The search identified 162 records; 118 remained after duplicate removal and were screened by title and abstract. 72 full-text sources were assessed for eligibility, and 30 sources were included in the qualitative synthesis. Eligibility required direct relevance, publication within 2020–2025, sufficient methodological detail, and an identifiable scholarly or institutional source. The selection process is summarized in the PRISMA-style flow diagram below.

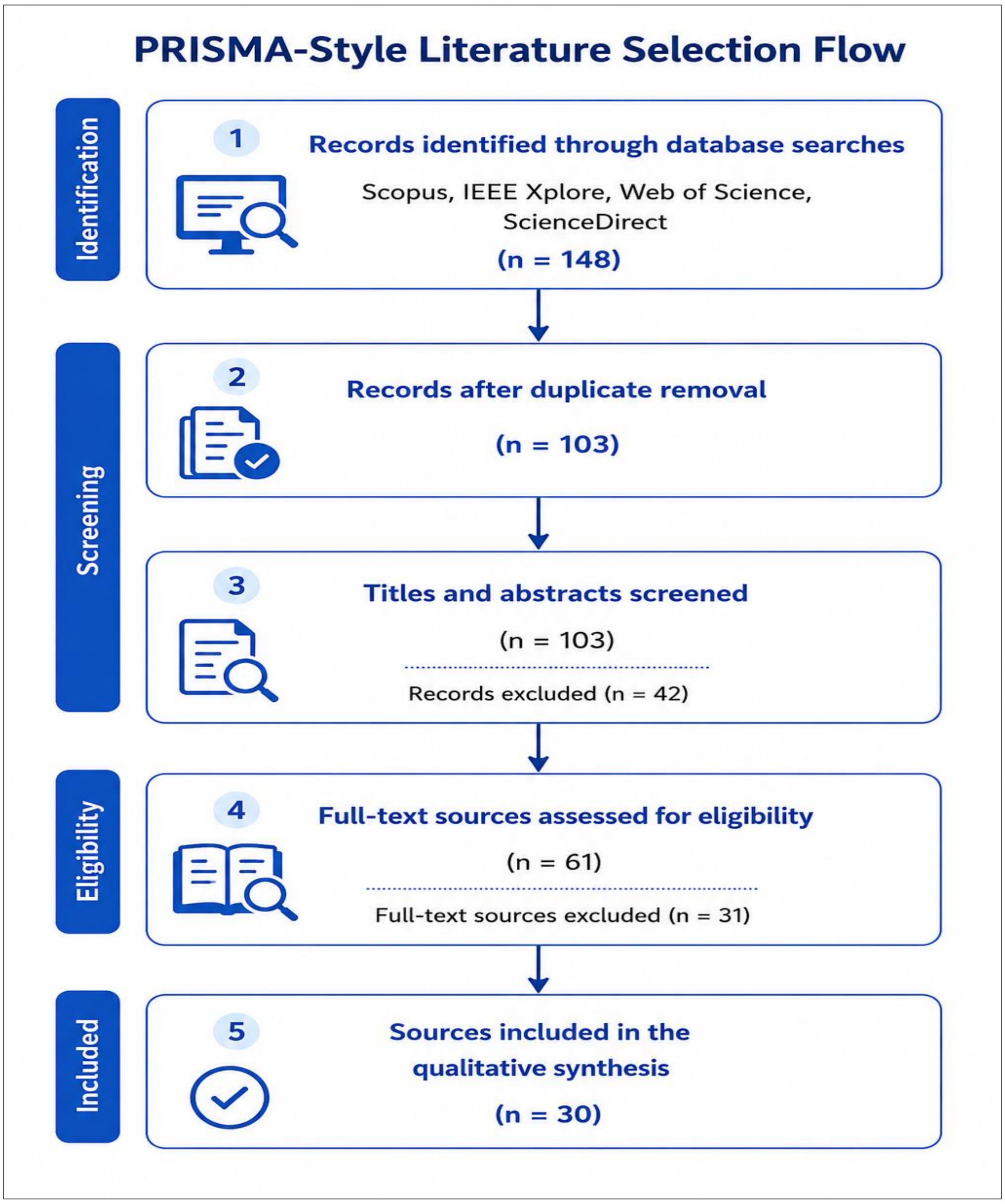

Figure 1: PRISMA-style flow of identification, screening, eligibility assessment, and inclusion

The search logic included combinations of keywords such as machine learning optical networks, AI optical transport, soft failure detection, optical performance monitoring, quality of transmission prediction, loss of signal forecasting, 5G optical fronthaul, transport automation, network fault prediction, digital twin optical network and autonomous optical networking. The studies were filtered based on four criteria: direct relevance to optical transport or 5G transport, discussion of AI or data-driven methods, link to reliability or performance optimization and publication within the specified date range. Thematic coding categorised the literature into seven themes: monitoring data and telemetry, fault prediction and early warning, detection and localisation, quality-of-transmission estimation, traffic and capacity forecasting, closed-loop optimization, and implementation barriers.

This review does not claim to offer new field measurements, proprietary operator data or a numerical benchmark. It aims at synthesising the state of knowledge and translating it into a practical framework faced by operators. The approach is timely, as AI adoption in optical transport is still uneven across commercial networks. Some functions like optical performance monitoring and anomaly detection are mature enough for field deployment, and others like fully autonomous restoration or agentic AI need stricter governance and validation. Thus the synthesis differentiates practical near-term applications from more sophisticated capabilities requiring prudent experimentation.

4.5G Optical Transport Context

5G optical transport networks are organised into fronthaul, midhaul, backhaul and metro or core aggregation domains generally. Fronthaul links radio units with distributed units and is sensitive to latency, timing and high bandwidth. Midhaul connects distributed units to centralised units, and backhaul connects aggregation nodes to the mobile core and service platforms. Optical technologies used in these areas include fibre access, passive optical networks, WDM, OTN, coherent optics, IP-over-WDM and disaggregated packet-optical systems. Cost-efficient optical fronthaul for 5G and beyond has been studied, which highlights the challenge in supporting gigantic data volume with low latency while controlling the deployment cost [6]. This trade-off between cost and performance is core to AI adoption, as predictive optimization lets operators get more efficiency out of existing assets before there's a need to invest in costly upgrades.

The optical layer confronts several failure modes. Hard failures (fibre cuts, equipment breakdowns) tend to generate alarms immediately. Soft failures are harder because they degrade transmission quality gradually. Examples include amplifier gain tilt, wavelength drift, ageing transceivers, connector contamination, excessive insertion loss, thermal instability, and partial equipment malfunction. Research on soft failures has shown that such failures can deteriorate the quality of transmission without generating explicit alarms immediately [7]. In 5G transport, the impact of operations can be severe since small degradations can impact radio synchronisation, packet delay variation, service slicing performance or availability of mission critical applications.

Adding to the complexity of handling faults is the move towards open, cloudified, disaggregated network architecture. Optical transport is increasingly interfacing with IP routing, SDN controllers, cloud RAN, edge compute and O-RAN service orchestration. Machine learning can support traffic management, resource allocation and network slicing as shown by AI in O-RAN and network optimization literature, but also raises questions around data interfaces, model lifecycle management and security [8, 9]. For optical operators this means that performance optimization cannot be focused on optical signal metrics alone. It must take into account the service context, e.g. which 5G slices, enterprise customers or critical sites rely on a given lightpath.

5. AI-Enabled Fault Prediction

Fault prediction turns raw monitoring signals into estimates of future service risk. The basic idea is to learn patterns that lead to failure and use them to identify assets, wavelengths, spans or paths that need attention. Relevant data sources include optical power, OSNR, Q-factor, BER, pre-FEC and post-FEC errors, chromatic dispersion estimates, polarisation metrics, temperature, amplifier gain, component logs, alarms, trouble tickets, and topology data. Log-based approaches are attractive as they can be deployed in existing networks without major hardware changes [10]. Performance-monitoring approaches are more accurate but rely on high-quality telemetry and consistent sampling.

Supervised learning can be useful if the historical failures are labelled. Models that can determine if a condition is likely to lead to an event include random forests, gradient boosting, support vector machines, recurrent neural networks and temporal convolutional networks. Time-series models are important, because degradation is a process evolving over time. Research on predicting loss of signal has demonstrated that models trained on large operational datasets can detect heightened risk prior to an outage, but recall can still be constrained due to the challenges of learning from rare failure events [3]. This finding is of operational importance. A model that produces few, but accurate warnings can still be useful if the warnings are related to high-impact circuits, but it should be coupled with prioritisation rules to avoid alert fatigue.

Unsupervised and semi-supervised learning can be useful where labelled failure data is scarce. They learn what normal behaviour is, and then flag anything that isn't. They can help spot unknown conditions early, but their alarms need to be interpreted carefully, since not every anomaly is a failure. Research on soft-failure localisation based on SDN telemetry shows that network-wide context is useful to identify probable root causes, since one degrading component can lead to abnormal metrics in several lightpaths [11]. Graph based learning is promising in this area as optical networks are naturally represented as nodes, links, amplifiers, transponders and services. Instead of processing metrics one by one, a graph-aware model can consider spatial propagation and path dependencies.

Digital twins provide a model-based representation of the network, thus improving fault prediction. Digital twin can simulate the effect on service quality of amplifier gain, fibre span loss, channel loading or component performance changes. The twin, along with machine learning, can validate candidate explanations and provide synthetic data for rare failure scenarios. Recent work on machine-learning agents and digital twins for optical networks suggests predictive maintenance environments where models predict risk and assess intervention options [12]. Operators benefit from digital twins, not only in terms of accuracy, but also in terms of safety, as validation can be done before any automated change is executed.

6. Performance Optimization in Optical Transport

Performance optimization uses AI to improve the planning, configuration and operation of optical resources. Routing, spectrum allocation, launch power, modulation format, coding, regeneration, protection paths, transceiver configuration, wavelength continuity, and packet-optical interaction all affect performance in optical transport. Predicting the quality of transmission is a basic task because operators must know if a lightpath will meet performance requirements before provisioning it. Surveys on ML-based QoT suggest that learning methods can complement or replace complex analytical models given sufficient data [5-13]. More accurate QoT prediction enables operators to reduce unnecessary engineering margins, thus improving spectrum utilisation.

Capacity optimization is particularly relevant for 5G, as demand is dependent on location, event, season and service type. Traffic forecasting allows operators to prepare for congestion and plan upgrades. Studies on the prediction of 5G data traffic demonstrate the growing use of current machine learning and deep learning techniques in resource management [14]. In an optical transport scenario, forecasts can tell you when to add wavelengths, increase transceiver capacity, re-optimize spectrum, change aggregation routing, or move from passive fronthaul solutions to active WDM or coherent optics. A predictive approach is more disciplined than reactive capacity expansion as it links investment timing to demand evidence. Artificial intelligence can also help to optimise energy performance. Optical transport energy consumption is contributed by transponders, amplifiers, packet switches, routers and cooling. Over-provisioning is a hedge against failure, but inefficient in power and capital. AI-based optimization can identify underutilised wavelengths, re-route to balance load, propose sleep modes when it is safe to do so, and select efficient modulation or transceiver options. But reliability constraints are to be given priority over energy objectives. a power saving decision for critical 5G services with an increased failure probability or reduced protection capacity is not acceptable. Hence it is necessary to perform multi-objective optimization balancing availability, latency, capacity, cost and energy.

Reinforcement learning and closed loop control show promise but require strong safeguards. A reinforcement learning agent can learn how to allocate assets or how to restore services, under varying demand, but uncontrolled exploration in a live telecom network is risky. For practical deployment, use offline training, simulation, digital twins, constrained action spaces and human approval for high impact actions. In the near-term AI is likely to play a role in decision support and bounded automation, rather than fully autonomous control. The operator has to decide which actions are to be performed automatically and which are to be approved by an engineer and which are only recommendations.

7. Proposed AI-Enabled Operating Framework

The proposed framework consists of five layers. The first layer is data governance and telemetry. It gathers data from optical performance monitors, transponders, amplifiers, ROADMs, packet devices, NMS logs, trouble tickets and customer experience systems. Data must be time-synchronized, cleansed, tagged, and related to asset inventory and topology. Without this layer, AI models learn inconsistent patterns and generate outputs that are not trusted. The second layer is feature engineering and contextual enrichment. Raw metrics are transformed into trends, slopes, deviations, rolling statistics, cross-path correlations and indicators of service criticality. For example, a small OSNR degradation may be a low priority on a protected best effort path, but urgent on a fronthaul path supporting a critical industrial site. The third layer is predictive intelligence. It comprises models for anomaly detection, failure probability, time-to-impact, root-cause ranking and QoT prediction. Fault prediction is not a single problem, so multiple models are preferred. A time-series model can find degradation, a graph model can find the suspected component, and an explainability module can find the metrics that led to the warning. The 4th layer is Optimization and Orchestration. It translates predictions into actions, such as rerouting, pre-positioning spare capacity, adjusting launch power, scheduling maintenance, changing protection state, issuing field work orders or recommending capacity augmentation. Governance is the fifth layer. It defines model validation, cyber controls, approval authority, rollback procedures, audit logs, and performance monitoring. Figure 1 shows this architecture. The critical thing is that AI has to come between field telemetry and operational decision making. A prediction unrelated to maintenance, ticketing or control systems raises awareness but does not enhance reliability. But automation without model governance can create new risk. Therefore, the framework needs to be designed with a human in the loop, at least in the early adoption. Operators can start with advisory dashboards, move to automated low risk actions, and eventually implement closed loop restoration for well tested scenarios.

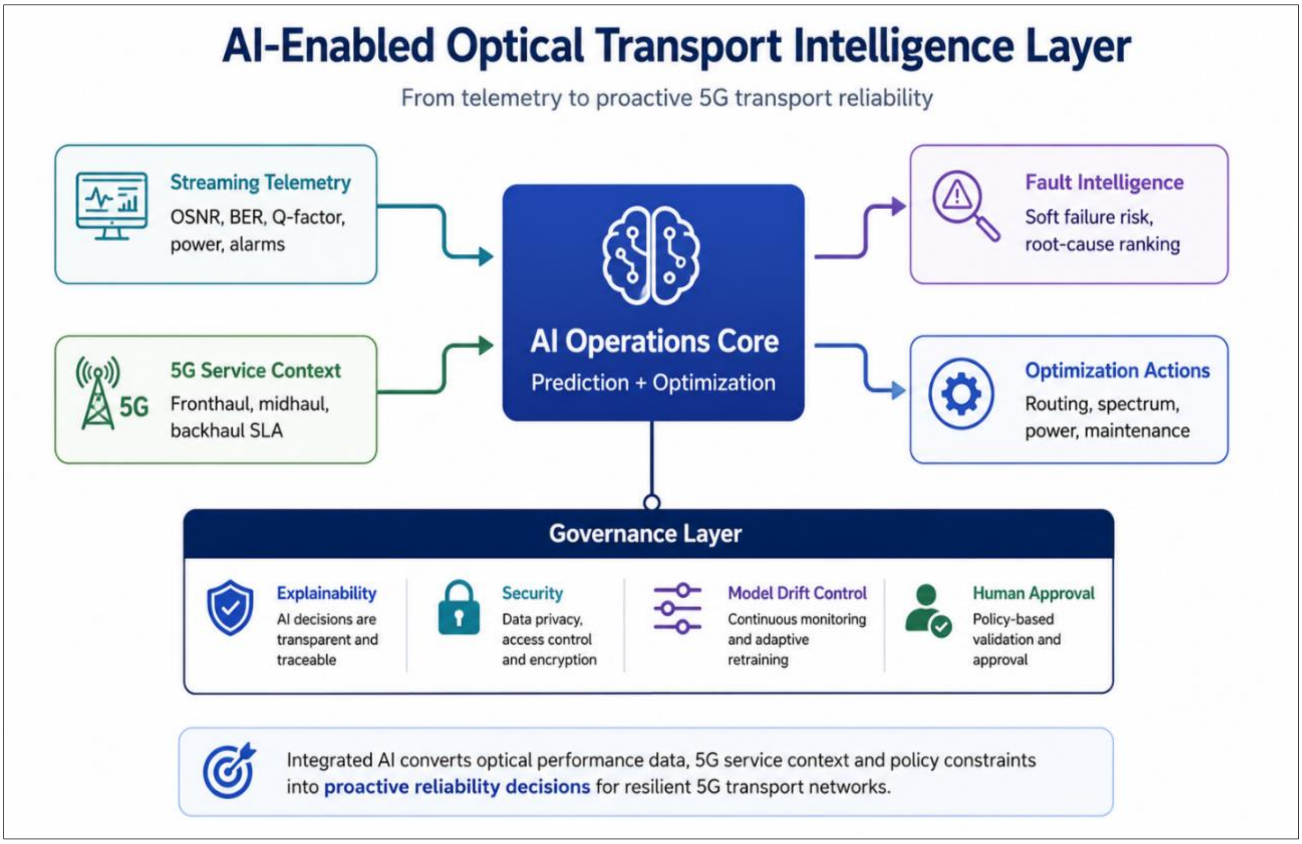

Figure 1: AI-enabled optical transport intelligence architecture linking telemetry, predictive intelligence, optimization and governed operational action

8. Tables and Thematic Synthesis

Table 1 summarises the mapping between AI functions and optical transport use cases and downtime or performance outcomes. Optical performance monitoring, QoT estimation and failure prediction and anomaly detection show the highest research maturity. These functions have measurable data and can be tested against known outcomes. Root-cause analysis and closed-loop optimization are more difficult because they require accurate topology, service dependency mapping and trust in automated decision making. The literature also warns that non-technological barriers to AI adoption include lack of operational trust, shortage of labelled data, gap in skills, organisational resistance and lack of clarity of responsibility when model recommendations go wrong [15]. Table 2 offers a practical road map. The first step in the roadmap is data readiness as most failures in AI programmes are not down to the choice of algorithm but weak data foundations. Operators need to validate topology, standardise alarms, synchronise time stamps and integrate optical metrics with service inventory first. Phase 2 will introduce predictive dashboards for high impact routes. The third phase links predictions to maintenance and restoration workflows. The fourth phase covers optimization of spectrum, routing, capacity and power. The fifth phase involves continuous improvement by model retraining, audit, drift detection, regulatory compliance and workforce training.

Table 1: Review synthesis of AI functions and downtime-reduction mechanisms in 5G optical transport networks

AI Function	Typical Data inputs	5G optical transport application	Reliability or performance value
Anomaly detection	OSNR, BER, Q-factor, power, alarms	Early detection of unusual behavior before hard alarms	Shorter detection time and reduced hidden degradation
Failure prediction	Time-series telemetry, logs, tickets	Predicts asset or path risk and expected time-to-impact	Prevents outages through planned intervention
Soft-failure localization	Topology, path metrics, SDN telemetry	Ranks likely span, amplifier, transceiver or ROADM root cause	Faster repair dispatch and fewer unnecessary truck rolls
QoT prediction	Route, modulation, spectrum, impairment features	Evaluates whether a lightpath can meet service requirements	Improves provisioning accuracy and reduces excessive margins
Traffic forecasting	Historical load, event patterns, service demand	Plans 5G fronthaul, midhaul and backhaul capacity	Supports CAPEX timing and congestion avoidance
Closed-loop optimization	Policies, predictions, digital twin simulation	Recommends rerouting, spectrum or power changes	Improves utilization while preserving service assurance

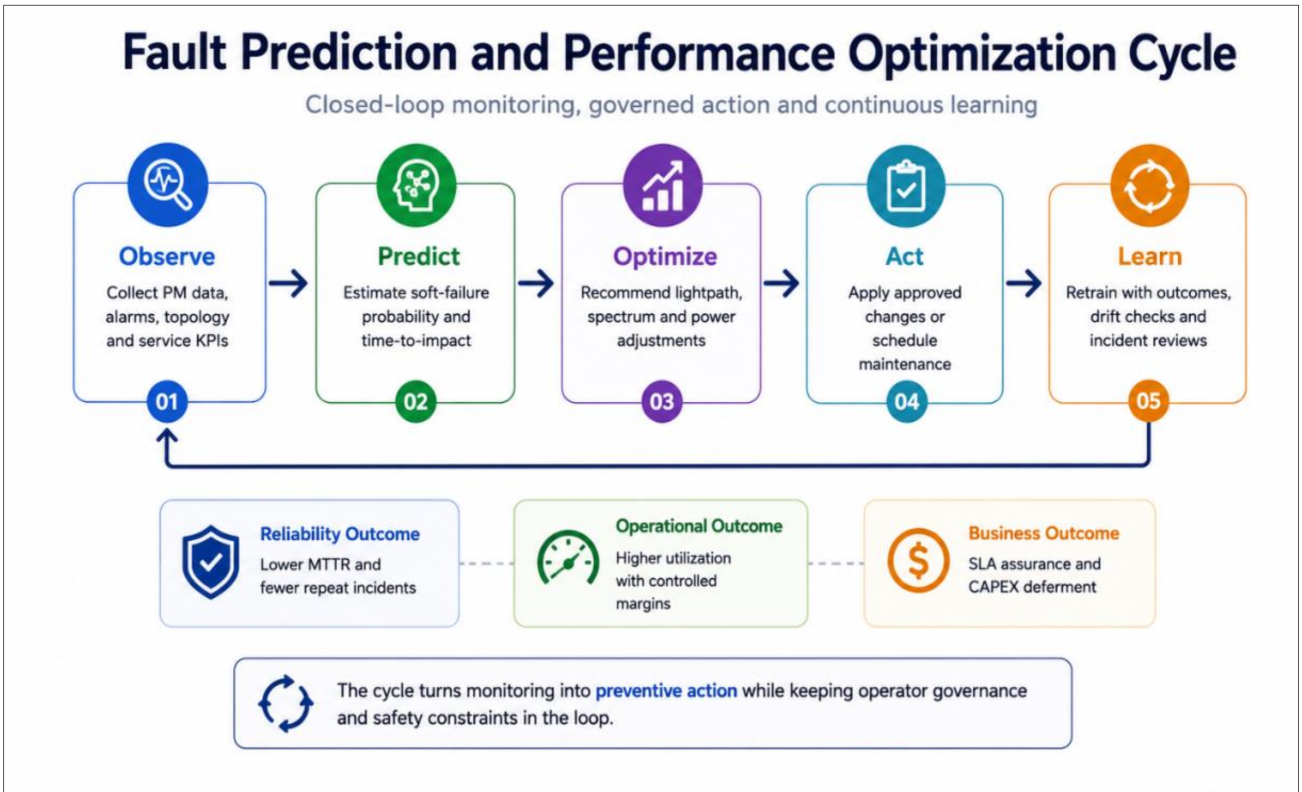

Figure 2: Closed-loop cycle for predictive monitoring, optimization action and continuous learning in 5G optical transport operations

Table 2: Phased implementation roadmap for AI-enabled fault prediction and performance optimization in telecom optical transport operations

Phase	Primary focus	Priority actions	Expected operator value
1. Data foundation	Telemetry and inventory quality	Standardize PM data, alarms, timestamps, topology and service inventory	Trusted data for prediction and post-incident analysis
2. Advisory prediction	High-impact route monitoring	Deploy anomaly and risk dashboards for critical 5G transport paths	Earlier warning and improved maintenance prioritization
3. Workflow integration	Ticketing and field action	Connect predictions to work orders, spare planning and escalation rules	Lower MTTR and fewer repeated failures

Phase	Primary focus	Priority actions	Expected operator value
4. Optimization automation	Bounded closed-loop control	Use digital twins and policies for routing, spectrum, power and capacity decisions	Better utilization with controlled operational risk
5. Continuous governance	Model lifecycle and cyber resilience	Run drift checks, audits, retraining, cybersecurity reviews and workforce training	Sustainable AI maturity and safe automation

9. DISCUSSION: BENEFITS, RISKS AND SAUDI TELECOM RELEVANCE

The advantages of AI-enabled optical transport are operational, financial and strategic. From an operational standpoint, artificial intelligence can shorten the time from degradation to intervention. It can also help reduce repeat incidents by uncovering hidden patterns across alarms and tickets. An improved QoT prediction and traffic forecast can help delay unnecessary expansion and improve utilisation of installed assets financially. Predictive transport is strategically important for advanced 5G services such as smart manufacturing, digital health, smart ports, public safety, cloud gaming and industrial private networks. These services demand not just coverage but also dependable transport performance. Saudi Arabia is a relevant deployment context, as its telecom operators are supporting fast digital transformation, large industrial zones, giga-projects, cloud investments and growing demand for high-capacity connectivity. The national focus on digital infrastructure provides strong incentives for resilient transport networks. AI-enabled optical assurance can assist operators to manage long-haul routes across harsh environments, metro aggregation for dense cities, enterprise services for industrial facilities and transport links for edge data centres. The approach also supports localisation goals as local teams can develop model operations, telemetry engineering, optical planning and managed-services capabilities.

The risks are just as important. First, AI models may overfit to historical conditions and fail under new traffic patterns, vendor changes, or topology reconfigurations. The second is that rare failure events cause class imbalance which can lead to misleading accuracy scores. Third, engineers may dismiss black-box recommendations when explanations are weak. Fourth, automation brings cyber and configuration risk. Fifth, if thresholds are not well tuned, models can generate operational noise. These risks don't make the case against AI; they make the case for disciplined application. Operators should measure precision, recall, false alarms, missed events, lead time, avoided outages, maintenance efficiency and post action impact. Business cases should be based on reliability outcomes, not simply model scores. We need governance to be balanced. Critical actions must be traceable, reversible and policy driven. A model's output includes confidence, explanation, and recommended urgency. Engineers should be able to override recommendations, and each override should feed into training. Data security is also of utmost importance, as telemetry and topology can expose sensitive data on critical infrastructure. AI platforms should therefore adhere to secure architecture principles, access control, logging and model integrity protection. This is especially important when using cloud analytics or multi-vendor automation environments.

10. Evaluation Metrics and Implementation Priorities

Evaluation must distinguish statistical accuracy from operational value. Precision measures the share of warnings that correspond to genuine degradation, while recall measures the share of relevant events detected. False-alarm rate should be tracked per circuit-day to control alert fatigue, and missed-event rate should be stratified by service criticality. Prediction lead time should be reported as the interval between the first actionable warning and the service-affecting event. Mean time to detect and mean time to repair should be compared with the pre-deployment baseline. The final business measures are avoided outages, avoided customer-impact minutes, reduced emergency dispatches and improved availability. Thresholds should be validated on temporally separated data, with confidence intervals and drift monitoring. Models should not progress to bounded automation unless they achieve stable precision and recall, acceptable false-alarm and missed-event rates, sufficient lead time for intervention, and demonstrable reductions in detection and repair time [16–30].

11. CONCLUSION

The application of AI-enabled fault prediction and performance optimization can revolutionise 5G optical transport networks from reactive infrastructure to predictive and adaptive service platforms. According to the review, artificial intelligence can help in early warning, anomaly detection, soft failure localisation, QoT estimation, traffic forecasting, energy optimization and maintenance prioritisation. 5G transport networks are facing increased capacity demand, more demanding service expectations and complex multi-layer dependencies, making such functions valuable. However, the main takeaway is that the benefits of AI are dependent on integration. A model unconnected to topology, service context, maintenance workflows and governance is not able to deliver full operational value. The proposed framework is a mixture of telemetry, feature engineering, predictive intelligence, optimization and governance. It stresses gradual maturity and practical application over immediate full autonomy. Telecom operators should start with clean data, high-impact routes, advisory dashboards and validated prediction models. Next, they should embed maintenance workflows with closed-loop recommendations and bounded automation. Operators can evolve over time to digital-twin supported optimization, graph-aware root-cause analysis and automated restoration for well-defined scenarios. This path contributes to reduce downtime, increase utilisation, control CAPEX, improve SLA performance and make the 5G service delivery more resilient. Future work should focus on operator-grade datasets, benchmark methods, Explainable AI, multi-vendor interoperability, Model drift and cybersecure automation and economic evaluation. Further field studies are required to quantify the prediction lead time into avoided outages, and the impact of QoT optimization on the real spectrum utilisation. The most promising direction is not to replace optical engineers with algorithms, but to equip them with predictive intelligence that reveals emerging risks early, ranks interventions clearly and supports reliable decisions at the speed required by modern 5G networks.

Study-Level Comparison of Included Evidence

Table 3: Study-level comparison of representative evidence included in the review

Author / year	Method	Dataset / evidence	Key result	Limitation
Musumeci *et al.*, (2022)	Tutorial review	Failure-management studies	AI spans prediction, detection, localization and identification	Operational integration remains uneven
Du *et al.*, (2022)	Supervised prediction	Operational optical telemetry	Failures can be predicted before hard alarms	Recall constrained by rare failures
Mayer *et al.*, (2021)	ML localization	Partial SDN telemetry	Network context improves root-cause localization	Topology quality affects accuracy
Silva *et al.*, (2023)	Privacy-preserving ML	Soft-failure datasets	Confidentiality can be retained with useful detection	Computational overhead
Khan (2024)	Industry perspective	AI adoption evidence	Trust, skills and governance limit deployment	Primarily qualitative evidence

Quantitative Findings Reported in the Literature

Table 4: Quantitative findings and measurable implications reported or operationalized from the cited evidence

Study	Quantitative measure	Reported value / range	Planning implication
Du *et al.*, (2022)	Prediction lead time	Multi-day early-warning objective	Measure warning usefulness before outage
Mayer *et al.*, (2021)	Localization output	Component/path probability ranking	Evaluate top-k root-cause accuracy
Silva *et al.*, (2023)	Detection quality	Precision/recall under privacy controls	Balance confidentiality and missed events
Operational benchmark	Repair performance	MTTD and MTTR before/after deployment	Use avoided outages as the business outcome

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