MANTECH Publications

Journal of Converging Technologies in Intelligent
Volume 1, Issue 1, January-April 2025

Integration of 5G/6G Communication Networks and Artificial Intelligence for Intelligent Connected Systems: A Structured Review of Architectures, Enabling Techniques, and Open Challenges

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ABSTRACT

The convergence of fifth-generation (5G) and emerging sixth-generation (6G) communication networks with artificial intelligence (AI) is reshaping how connected systems sense, communicate, and act. Network densification, millimetre-wave spectrum, massive antenna arrays, and heterogeneous service demands have made manual, rule-based network management increasingly unsustainable, while AI offers data-driven adaptation across the radio, edge, and core domains. This review presents a structured synthesis of the literature on 5G/6G–AI integration, organised around an AI-native layered architecture, five families of AI techniques (deep learning, reinforcement learning, federated learning, graph and attention models, and generative or semantic AI), and six network functions. Findings are compared against International Telecommunication Union (ITU) performance targets and mapped to four application domains: healthcare, autonomous mobility, industrial automation, and agriculture. The synthesis shows that deep learning and reinforcement learning are the most mature enablers for physical-layer and resource-management tasks, that federated learning is the most credible route to privacy-preserving intelligence, and that generative and semantic AI remain largely exploratory. Persistent barriers include scarce operator data, poor model generalisation across deployments, limited explainability, the energy cost of AI itself, and the security of learning pipelines. A research agenda centred on trustworthy, energy-aware, and standards-aligned AI-native networks is proposed.

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KEYWORDS: *5G, 6G, Artificial intelligence, Machine learning, Intelligent connected systems, Open RAN, Edge intelligence, Federated learning, Network slicing, Semantic communication*

INTRODUCTION

Modern connected systems, including autonomous vehicles, tele-surgical platforms, collaborative factory robots, and precision-agriculture networks, impose requirements that no earlier generation of mobile communication could satisfy simultaneously: multi-gigabit throughput, millisecond latency, near-perfect reliability, and connectivity for millions of devices per square kilometre. The fifth generation (5G) was standardised against the International Telecommunication Union's IMT-2020 targets to address three service classes, namely enhanced mobile broadband, ultra-reliable low-latency communication, and massive machine-type communication [1], [2]. Work toward the sixth generation (6G) extends this vision under the IMT-2030 framework to include integrated sensing and communication, ubiquitous coverage, and native artificial intelligence [3], [4], [5].

The central problem addressed in this review is that the complexity of such networks has outgrown conventional, model-based engineering. A single 5G radio access network exposes thousands of configurable parameters whose optimal values change with traffic, mobility, interference, and blockage, particularly at millimetre-wave frequencies where a passing vehicle can interrupt a link in milliseconds. Closed-form optimisation depends on tractable channel and traffic models that rarely hold in dense, heterogeneous deployments. Machine learning offers an alternative by learning mappings directly from network data, and it has been proposed for tasks ranging from channel estimation to slice orchestration [6], [7]. The relationship is bidirectional: AI improves the network, and the network in turn provides the distributed compute, data pipelines, and low-latency links on which AI services for connected systems depend [8].

The topic is also strategically significant for India, where national programmes such as the Bharat 6G Vision aim to build indigenous capability in 6G technology and intelligent networking for use cases that span dense metropolitan areas and sparsely connected rural regions [9]. This paper therefore reviews how 5G and 6G networks and AI are being integrated,

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evaluates the maturity of individual techniques against network functions, and identifies the engineering barriers that must be resolved before intelligent connected systems can be deployed at scale. The remainder of the paper is organised according to the structure of a conventional review: background, research gap, objectives, method, findings, discussion, limitations, and future scope.

LITERATURE REVIEW

The literature relevant to 5G/6G–AI integration spans wireless communications, machine learning, edge computing, and network softwarisation. This section organises prior work into four themes that are later used to structure the analytical framework.

Evolution Toward Intelligent 5G and 6G Networks

Andrews et al. characterised 5G as a combination of network densification, millimetre-wave spectrum, and massive multiple-input multiple-output (MIMO) antennas [2]. Subsequent visions of 6G emphasise terahertz bands, reconfigurable intelligent surfaces (RIS), and pervasive intelligence [10], [11], [12]. Rappaport et al. showed that frequencies above 100 GHz offer very large bandwidths but suffer severe path loss and blockage, so link adaptation must be fast and predictive [12]. Huang et al. demonstrated that RIS can improve energy efficiency by shaping the propagation environment, although jointly optimising surface phases and base-station beamforming is a high-dimensional problem well suited to learning-based methods [13]. In the standards domain, 3GPP introduced the Network Data Analytics Function (NWDAF) in the 5G core to collect data and provide analytics to other functions [14], and later studied AI/ML for the new-radio air interface [15]. Table 1 summarises the indicative performance targets that motivate this evolution.

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Table 1. Indicative Performance Targets of 4G, 5G, and 6G Systems

Parameter	4G (IMT-Advanced)	5G (IMT-2020)	6G (IMT-2030 / vision)
Peak data rate	~1 Gbps	20 Gbps [1]	50–200 Gbps; ~1 Tbps in research visions [3], [4]
User-plane latency	~10 ms	1 ms (URLLC)	0.1–1 ms [3]
Connection density	~10^5 devices/km²	10^6 devices/km²	10^6–10^8 devices/km² [3]
Mobility	Up to 350 km/h	Up to 500 km/h	500–1000 km/h [3]
Spectrum	Below 6 GHz	Sub-6 GHz and mmWave	Adds sub-THz (above 100 GHz) [12]
Role of AI	Offline analytics	NWDAF, RIC add-on [14], [16]	AI-native design [8]

Artificial Intelligence for Radio and Network Optimisation

O'Shea and Hoydis proposed treating the physical layer as an end-to-end autoencoder that is trained jointly across transmitter and receiver, which opened a line of research on learned modulation, coding, and detection [17]. Alkhateeb et al. showed that deep neural networks can predict coordinated beamforming vectors for highly mobile millimetre-wave users, reducing the training overhead of beam search [18]. For resource management, Mismar et al. applied deep reinforcement learning to jointly control beamforming, transmit power, and interference coordination in 5G cells [19]. Comprehensive surveys by Mao et al. and Zhang et al. catalogue deep-learning applications across traffic classification, mobility prediction, and network control, while Shafin et al. argue that AI-enabled cellular networks are a prerequisite for beyond-5G operation [20], [7], [21]. A recurring caveat across these studies is that most results derive from simulation or limited testbeds.

Edge Intelligence and Federated Learning

Edge intelligence moves model inference, and increasingly training, close to data sources to meet latency and privacy constraints. Zhou et al. described the architecture of edge intelligence and the trade-offs between device, edge, and cloud placement [22], while Park et al. examined how wireless networks themselves must be adapted to support distributed learning [23]. Mach and Becvar surveyed computation offloading in mobile edge computing, which remains the

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enabling mechanism for latency-critical inference [24]. Federated learning, introduced by McMahan et al., trains a shared model from decentralised data without moving raw samples [25]; Niknam et al. identified its relevance to wireless networks, where operator and user data are sensitive and bandwidth is limited [26]. Letaief et al. position edge AI as a defining feature of 6G, with learning and communication co-designed [8].

Open RAN and Semantic Communication

The Open Radio Access Network (O-RAN) architecture standardises interfaces through which third-party AI applications, called xApps and rApps, control the RAN at near-real-time and non-real-time scales [16]. Bonati et al. demonstrated data-driven control loops on an open testbed, showing that learned policies can be deployed and updated without modifying vendor equipment [27]. A complementary direction is semantic communication, which transmits task-relevant meaning rather than exact bits and is expected to reduce bandwidth demand for machine-to-machine traffic [28].

RESEARCH GAP

Existing surveys generally treat one dimension of the problem in isolation: physical-layer learning, edge intelligence, or Open RAN control. Three gaps follow. First, few works compare AI techniques against the same set of network functions, so practitioners cannot readily judge which technique is mature for which task. Second, results are rarely related to the ITU performance targets that ultimately define success for 5G and 6G. Third, deployment-oriented constraints, namely data availability, explainability, energy cost, and security of the learning pipeline, are discussed separately from algorithmic performance. This review addresses these gaps through a unified technique-by-function-by-application framework and an explicit maturity assessment.

OBJECTIVES

- To synthesise the architectural principles by which AI is integrated across the device, radio, edge, core, and cloud layers of 5G and emerging 6G networks.
- To compare five AI technique families against six network functions and assess their maturity using transparent criteria.
- To relate the progression of 5G and 6G performance targets to the AI capabilities required to meet them.

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- To map integration requirements for four intelligent connected-system domains and to identify technical barriers and research priorities.

METHODOLOGY

Review Design

A structured narrative review was undertaken, guided by the systematic-review principles of Kitchenham and Charters and the transparent-reporting philosophy of the PRISMA statement [29], [30]. The review is classified as review-based and analytical: no new network experiments were conducted, and all quantitative figures are drawn from cited standards and published studies.

Sources and Selection Criteria

The corpus comprises peer-reviewed journal articles, conference proceedings, textbooks, and standards documents published between 2014 and 2023 and accessible through IEEE Xplore, ScienceDirect, and the ITU and 3GPP document repositories. A source was included if it addressed the use of machine learning or AI in 5G or 6G systems, reported an architecture, algorithm, or measured result, and was authored by a recognised research group or standards body. Studies that analysed only theoretical capacity without a learning component, and promotional vendor material, were excluded.

Analytical Framework

Each included source was coded along three axes: the AI technique family, the network function addressed, and the target application domain. Maturity of each technique–function pairing was rated on a four-level scale. Emerging denotes proof-of-concept or simulation-only evidence; Developing denotes multiple independent simulation studies or early testbed results; Established denotes repeated testbed or field validation or demonstrable standards traction; None denotes no substantive evidence. Observed network targets were normalised against the ITU frameworks to visualise the generational progression [1], [3]. The maturity ratings are the authors' qualitative judgements and should be read as an interpretive synthesis rather than a measured quantity.

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RESULTS AND FINDINGS

AI-Native Layered Architecture

Across the reviewed literature a consistent five-layer pattern emerges, shown in Figure 1. Data flow upward from devices and radio access, through edge and core analytics, to cloud-scale training, while trained models and control policies flow downward. This closed loop operates at three time scales: real-time inference at the distributed unit or device in under 10 ms, near-real-time control through xApps in roughly 10 ms to 1 s, and non-real-time optimisation through rApps in more than 1 s [16], [27]. Placing each learning task at the appropriate scale is the principal architectural decision, because latency-critical tasks such as beam selection cannot tolerate a cloud round trip, whereas slice-level forecasting benefits from the global view available at the core [22], [8].

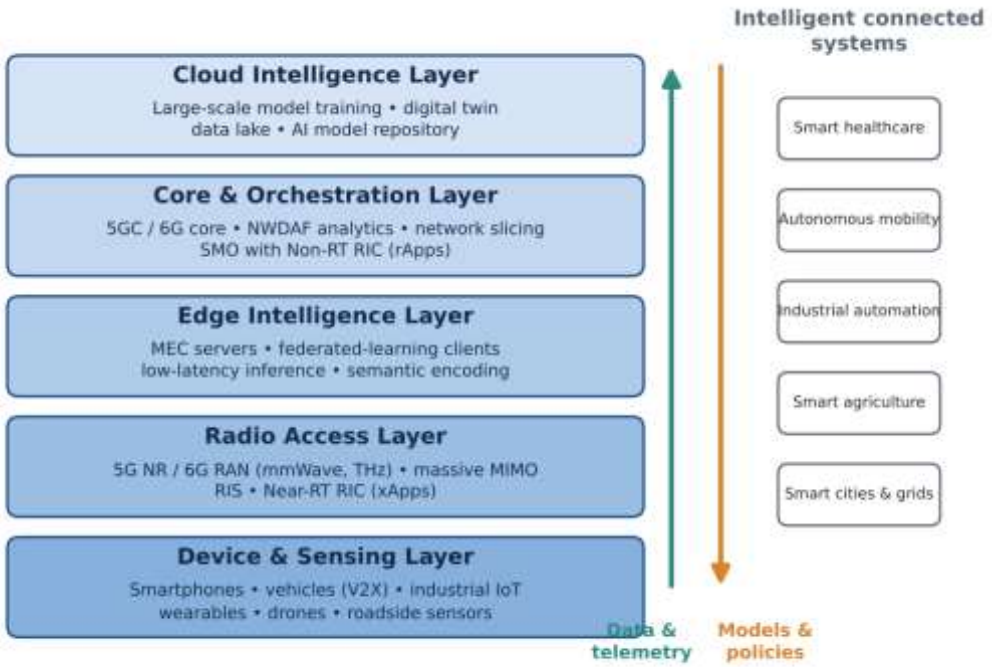


Figure 1. AI-native layered architecture for 5G/6G networks showing upward data flow, downward model and policy deployment, and supported application domains.

Progression of Performance Targets

Figure 2 compares four headline indicators across generations. Moving from IMT-2020 to the IMT-2030 framework, peak data rate rises from 20 Gbps to between 50 and 200 Gbps, user-plane latency falls from 1 ms to between 0.1 and 1 ms, and connection density grows by one

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to two orders of magnitude [1], [3]. Research visions go further, citing terabit-per-second peak rates and sub-millisecond latency [4], [5]. These targets cannot be met by static configuration, because beam management, scheduling, and mobility handling must be re-optimised within a few transmission time intervals at sub-terahertz frequencies [12].

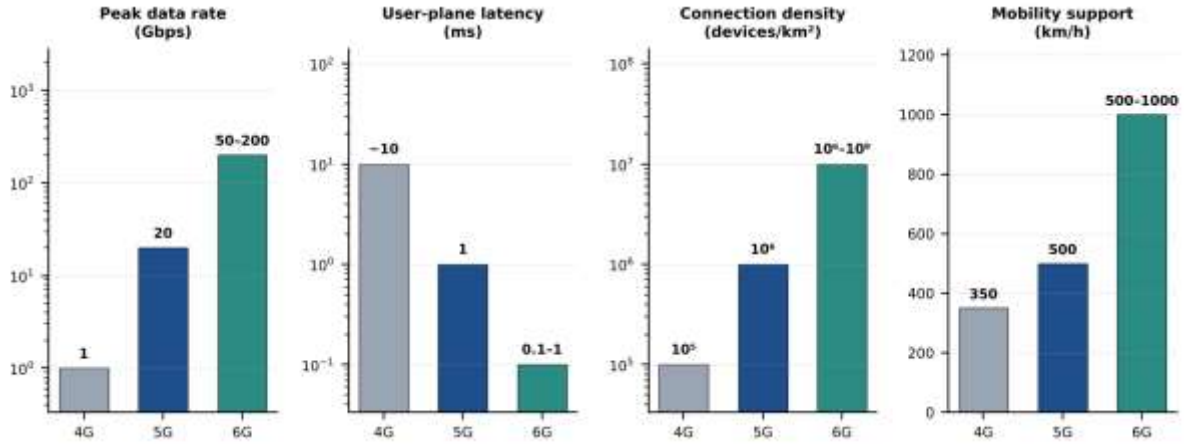


Figure 2. Progression of key performance targets from 4G to 5G and 6G (log scale where indicated); 6G values follow the IMT-2030 framework ranges.

Maturity of AI Techniques Across Network Functions

Figure 3 presents the maturity map. Deep learning is the most widely validated family, with established evidence for channel estimation and beam prediction [17], [18], supported by standards activity on the AI/ML air interface [15], and for anomaly detection and traffic classification [20], [7]. Deep reinforcement learning is established for resource allocation, slicing, and orchestration, where sequential decisions under uncertainty are natural, and has been demonstrated on open testbeds [19], [27]. Federated learning does not exceed the developing level for any function, because most studies rely on simulated clients and idealised communication [26]. Graph and attention models are developing for topology-aware tasks, and generative or semantic AI is largely emerging, with its strongest evidence in physical-layer compression [28]. Mobility and handover management is the only function with no established technique, reflecting the difficulty of obtaining labelled trajectories.

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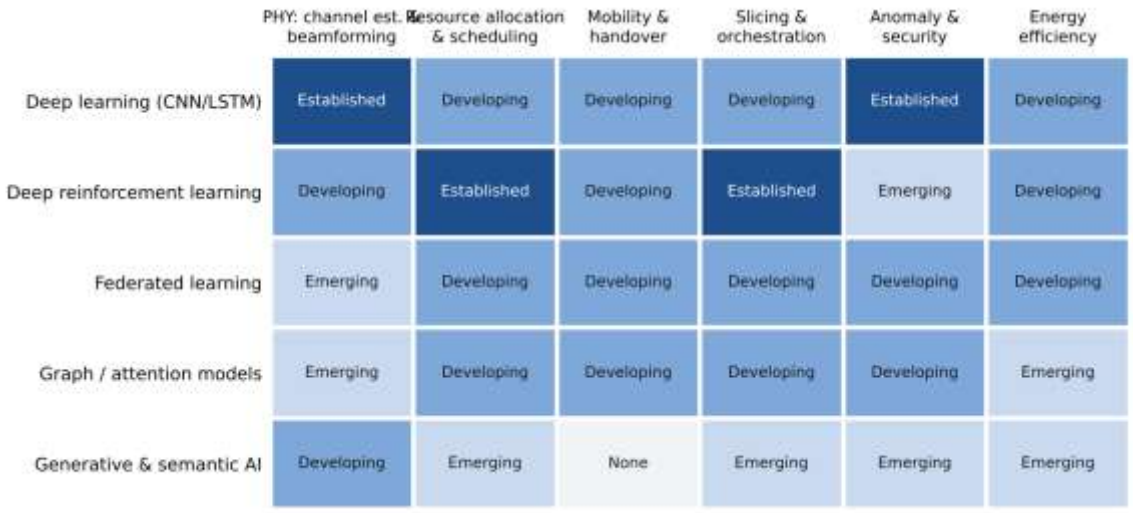


Figure 3. Qualitative maturity map of AI technique families across six network functions, based on the authors' synthesis of the reviewed literature.

Table 2 consolidates the characteristics of each technique family, including typical applications, reported benefits, and principal limitations identified in the literature.

Table 2. Characteristics of AI Technique Families in 5G/6G Networks

Technique	Typical applications	Reported benefit	Main limitation
Deep learning	Channel estimation, beam prediction, traffic classification [18], [20]	Lower pilot and beam-search overhead	Needs large labelled data
Deep reinforcement learning	Power control, scheduling, slicing [19], [27]	Adapts to dynamic states	Sim-to-real gap, unstable training
Federated learning	Privacy-preserving analytics [25], [26]	No raw-data transfer	Communication cost, poisoning
Graph and attention models	Topology-aware routing and load balancing [7]	Captures spatial structure	High compute at the edge
Generative and semantic AI	Semantic coding, data synthesis [28]	Reduced bandwidth demand	Immature, lacks standards

Application-Domain Mapping

Table 3 maps four intelligent connected-system domains to their dominant network requirement, the role of AI, and the enabling 5G/6G features. The mapping shows that no single

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technique satisfies a domain: autonomous mobility, for example, combines learned beam tracking, cooperative perception at the edge, and slice-level reliability control [10], [5].

Table 3. Application Domains and Integration Requirements for Intelligent Connected Systems

Domain	Dominant requirement	AI role	Enabling 5G/6G feature
Smart healthcare	Ultra-reliability, low latency	Anomaly detection, predictive QoS	URLLC, slicing, MEC [10]
Autonomous mobility	High mobility, millisecond latency	Beam tracking, handover prediction	V2X, mmWave, edge inference [5]
Industrial automation	Determinism, device density	Predictive maintenance, scheduling	Private 5G, URLLC [10]
Smart agriculture	Wide-area, low-power coverage	Sleep scheduling, UAV relaying	mMTC, non-terrestrial links [11]

DISCUSSION

Technical Interpretation

The maturity pattern in Figure 3 reflects the structure of the underlying problems. Supervised deep learning performs well where abundant labelled or simulator-generated data exist and where the output is a prediction, as in channel estimation and traffic classification. Reinforcement learning dominates resource control because actions alter future network state, which supervised methods cannot capture [19]. However, both families inherit a shared weakness: policies trained in simulation degrade when radio environments differ from the training distribution, so sim-to-real transfer is the main obstacle to field deployment [7]. Federated learning addresses privacy but introduces communication overhead, client heterogeneity, and vulnerability to poisoned updates, which explains its lower maturity [25], [26].

A second finding concerns the cost of intelligence. Edge training and inference consume compute and energy that must be offset by network savings; otherwise AI undermines the energy-efficiency objectives of 6G [8]. Explainability is a related concern: operators will not delegate safety-critical control, such as ultra-reliable industrial links, to opaque policies without

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bounded behaviour and audit trails. The open interfaces of O-RAN offer a pragmatic route, since xApps can be validated, rate-limited, and rolled back independently of vendor firmware [16].

Engineering and Scientific Significance

From an engineering standpoint, the review identifies where AI delivers value now (beam management, scheduling, anomaly detection) and where it remains speculative (semantic transmission, learned mobility control), which allows investment to be prioritised. Scientifically, it highlights the need for benchmark datasets and reproducible testbeds so that claims can be compared across studies, a requirement that standards bodies have begun to address [15].

Practical Applications

In healthcare, predictive quality-of-service control can protect remote-monitoring and tele-robotic sessions during congestion. In autonomous mobility, learned beam tracking and handover prediction sustain vehicle-to-everything links at high speed. In industrial automation, learning-based schedulers support deterministic wireless control of robots and predictive maintenance. In agriculture, energy-aware sleep scheduling and unmanned-aerial-vehicle relays can extend low-cost coverage to rural fields, which is directly relevant to the national connectivity goals described in the Bharat 6G Vision [9].

LIMITATIONS

- The review is restricted to English-language sources between 2014 and 2023 and may omit recent preprints and proprietary operator studies.
- Maturity ratings are qualitative judgements and may differ between reviewers; no formal inter-rater agreement was computed.
- Quantitative targets for 6G are still evolving, and values cited from research visions are indicative rather than final standardised requirements.
- Most primary studies rely on simulation, so field performance and long-term stability of learned controllers are insufficiently documented.

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FUTURE SCOPE

- Development of AI-native air interfaces in which transmitter and receiver functions are learned jointly and validated through over-the-air trials [17], [15].
- Trustworthy and explainable network AI, including formal safety envelopes, adversarial robustness, and auditable policy updates for xApps and rApps [16], [26].
- Energy-aware, green AI that jointly optimises model complexity and network power consumption in line with 6G sustainability goals [8].
- Network digital twins and RIS-assisted environments for safe pre-deployment training of reinforcement-learning agents [13], [7].
- Semantic and task-oriented communication for machine-to-machine traffic, evaluated on realistic industrial and vehicular workloads [28].

CONCLUSION

This review has synthesised the integration of 5G/6G communication networks and artificial intelligence for intelligent connected systems through an AI-native layered architecture, a comparison of five technique families across six network functions, and a mapping to four application domains. The evidence indicates that deep learning and reinforcement learning are ready to support physical-layer and resource-management tasks, supported by open interfaces and early standardisation, whereas federated, graph-based, and generative approaches require further validation before they can be relied upon in operational networks. Meeting the IMT-2030 targets will require intelligence to be placed at the correct time scale and network layer, supported by trustworthy, explainable, and energy-aware learning pipelines. Progress will depend on shared datasets, open testbeds, and field trials that move beyond simulation, an agenda to which research institutions in India can contribute through indigenous testbeds aligned with national 6G goals.

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Received Date: January 1, 2025
Accepted Date: January 14, 2025
Published Date: January 30, 2025

Citation: Ananya R. Sen, Rohit K. Das. Integration of 5G/6G Communication Networks and Artificial Intelligence for Intelligent Connected Systems: A Structured Review of Architectures, Enabling Techniques, and Open Challenges. Journal of Converging Technologies in Intelligent. 2025; 1(1): 1-15p.

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