future internet

Review

AI-Driven Network Optimization for the 5G-to-6G Transition: A Taxonomy-Based Survey and Reference Framework

Rexhep Mustafovski [1], Galia Marinova [2,*], Besnik Qehaja [2], Edmond Hajrizi [2], Shejnaze Gagica [3] and Vassil Guliashki [4]

1 Military Academy "General Mihailo Apostolski", 'Goce Delcev University' Stip, 1000 Skopje, North Macedonia; redzep.mustafovski@ugd.edu.mk
2 Department "Technologies and Management of Communication Systems", Technical University of Sofia, 1756 Sofia, Bulgaria; besnik.qehaja@ubt-uni.net (B.Q.); ehajrizi@ubt-uni.net (E.H.)
3 Faculty of Economics, University "Kadri Zeka", 60000 Gjilan, Kosovo; shejnaze.gagica@uni-gjilan.net
4 Institute of Information and Communication Technologies, Bulgarian Academy of Sciences, 1113 Sofia, Bulgaria; vassil.guliashki@iict.bas.bg
* Correspondence: gim@tu-sofia.bg

Abstract

This paper presents a taxonomy-based survey of AI-driven network optimization mechanisms relevant to the transition from fifth generation (5G) to sixth generation (6G) mobile communication systems. In contrast to earlier generational shifts that are often described as technology replacement cycles, the 5G-to-6G evolution is increasingly characterized in the literature as a prolonged period of coexistence, hybrid operation, and progressive integration of new capabilities across radio, edge, core, and service layers. To structure this transition, the paper organizes prior work into a transition-oriented taxonomy covering migration strategies, AI-enabled closed-loop control, RAN disaggregation and edge intelligence, core virtualization and slice orchestration, spectrum-aware coexistence, service-driven requirements, and security-aware governance. Rather than introducing a new optimization algorithm or an experimentally validated architecture, the contribution of this survey is analytical and integrative. Specifically, it consolidates fragmented research directions into a reference view of how AI-driven control mechanisms are distributed across spectrum, RAN, edge, and core domains during hybrid 5G–6G operation. In addition, the paper includes a structured evidence synthesis of performance trends, deployment maturity signals, and recurring methodological limitations reported across the literature. The review indicates that meeting anticipated 6G objectives, including ultra-low latency, high reliability, scalability, and improved energy efficiency, depends less on isolated enhancements at individual protocol layers and more on coordinated cross-layer optimization supported by AI-native control loops. At the same time, the surveyed literature reveals persistent gaps in service-to-control mapping, security-aware orchestration, interoperability across heterogeneous domains, and reproducible evaluation methodologies for hybrid 5G–6G environments. The survey is intended to provide researchers, network operators, and standardization stakeholders with a structured analytical basis for assessing how AI-driven optimization can support the staged evolution from 5G systems toward 6G-ready infrastructures.

Keywords: active 5G–6G transition; network optimization framework; artificial intelligence; intelligent radio access networks; edge computing

Academic Editor: Paolo Bellavista

Received: 14 February 2026
Revised: 12 March 2026
Accepted: 13 March 2026
Published: 17 March 2026

1. Introduction

The evolution of mobile communication systems has repeatedly required not only higher transmission capabilities, but also new forms of network control, service orchestration, and infrastructure integration. While fifth-generation (5G) systems significantly extended the operational range of wireless networks through enhanced mobile broadband, ultra-reliable low-latency communications, and massive machine-type communications, current research increasingly recognizes that the requirements associated with future digital services exceed the optimization scope of conventional 5G-centric management approaches [1–10]. These requirements include tighter latency and reliability constraints, broader integration of heterogeneous access domains, higher automation levels, and stronger alignment between service intent and network control.

The emerging 6G vision is therefore not defined solely by higher data rates or wider spectrum utilization. Rather, it is commonly associated with AI-native network operation, integrated sensing and communication, distributed edge intelligence, tighter coupling between terrestrial and non-terrestrial systems, and support for immersive and mission-critical services under highly dynamic conditions [2–8]. From this perspective, the transition from 5G to 6G is not simply a future deployment milestone, but a multi-stage systems evolution problem involving technological coexistence, gradual function redistribution, and increasing dependence on intelligent closed-loop control.

A central challenge in this transition is that 6G capabilities are unlikely to emerge through abrupt infrastructure replacement. Instead, the literature points toward a prolonged period of hybrid 5G–6G operation in which legacy 5G assets, virtualized core functions, disaggregated radio access components, edge intelligence platforms, and new spectrum technologies must interoperate under shared performance and operational constraints [4–7,11–18]. This coexistence-oriented perspective shifts the research question from how to design isolated 6G mechanisms to how to coordinate migration, optimization, and service continuity across heterogeneous domains and deployment phases.

Artificial intelligence and machine learning have consequently become central themes in the 5G/6G literature. Existing studies examine AI-assisted resource allocation, mobility and handover optimization, traffic prediction, slice orchestration, anomaly detection, energy-aware control, and adaptive radio optimization under increasingly dynamic conditions [4,6,7,11–23]. However, these contributions are often organized around specific technical enablers or application areas rather than around the transitional logic of hybrid 5G–6G operation. As a result, the literature remains fragmented across spectrum management, RAN intelligence, edge control, core orchestration, and security governance, with limited analytical synthesis of how these layers interact during phased migration.

This fragmentation is also reflected in the current survey landscape. Recent review papers have examined AI applications in 5G and 6G networks from broad taxonomic perspectives, while others have focused more narrowly on handover and load balancing, slice security, reconfigurable intelligent surfaces, or AI-native physical-layer intelligence [19–23]. These works provide valuable domain-specific insights, yet they do not fully address the transition problem as a coexistence-aware, cross-layer optimization challenge. In particular, the literature still lacks a structured survey that jointly examines migration phases, AI-enabled control loops, cross-domain orchestration, and evidence synthesis within a unified 5G-to-6G transition perspective.

Recent surveys have examined AI applications in 5G/6G networks from broad, application-centric, or technology-specific perspectives, including handover optimization, slice security, RIS-enabled learning, and AI-native PHY design [19–23]. However, a transition-centred synthesis focused on coexistence, phased migration, and cross-layer control integration remains limited.

Motivated by this gap, this paper presents a taxonomy-based survey of AI-driven network optimization mechanisms supporting the transition from 5G to 6G. The aim is not to introduce a new standalone algorithm, protocol, or experimentally validated architecture. Instead, the paper synthesizes the literature into a transition-oriented analytical structure that helps explain how optimization responsibilities evolve across spectrum, RAN, edge, core, and service layers during hybrid and progressively 6G-dominant operation.

The main contributions of the paper are as follows:

1. Transition-oriented taxonomy. The paper classifies AI-driven optimization mechanisms according to their role in coexistence management, phased migration, and cross-domain adaptation during the 5G-to-6G evolution.
2. Cross-layer reference synthesis. It derives a structured reference view of how AI-enabled control loops are distributed across spectrum intelligence, RAN disaggregation, edge processing, core virtualization, and service orchestration layers.
3. Evidence-based literature consolidation. It summarizes reported performance tendencies, deployment readiness indicators, and recurring methodological limitations across heterogeneous studies, thereby moving beyond descriptive listing toward comparative synthesis.
4. Gap analysis and research directions. It identifies unresolved issues related to service-to-control mapping, interoperability, security-aware closed-loop operation, and reproducible evaluation practices for hybrid 5G–6G systems.

The remainder of this paper is organized as follows. Section 2 introduces the proposed taxonomy and positions the surveyed literature within the main transition dimensions. Section 3 analyzes the principal research gaps emerging from this body of work. Section 4 outlines the review methodology and derives the cross-layer reference synthesis. Section 5 presents the structured evidence synthesis and discussion. Section 6 concludes the paper and outlines directions for future research.

2. Literature Review

2.1. Scope and Taxonomy of the 5G–6G Transition

The transition from 5G to 6G is increasingly discussed in the literature as a prolonged coexistence and capability-integration process rather than a discrete generational replacement event [1,4,6–10]. In contrast to earlier mobile network upgrades, this transition is expected to involve concurrent operation across heterogeneous radio technologies, multi-band spectrum resources, disaggregated network functions, and diverse service classes with different performance constraints [4,6,11–18,24].

Recent studies describe the 5G–6G evolution as a multi-domain transformation involving radio access disaggregation, cloud-native core evolution, spectrum expansion, service-aware orchestration, and increasing reliance on AI-enabled control [4,7,11–18]. At the same time, recent taxonomy-oriented surveys confirm the broad applicability of AI across 5G/6G domains, while also indicating that the transitional logic of coexistence, phased migration, and cross-layer coordination remains comparatively under-synthesized [19–23].

To organize this fragmented body of work, the present survey groups the literature into seven analytical domains:

(i) Migration and coexistence strategies;
(ii) AI-native closed-loop control;
(iii) RAN evolution and edge intelligence;
(iv) Core network orchestration and slicing;
(v) Spectrum intelligence and multi-band coordination;
(vi) Service-driven requirements;

(vii) Security, trust, and governance.

This taxonomy is intended as a survey-oriented synthesis tool for structuring the literature and identifying recurring transition-related gaps, rather than as a new architectural standard or implementation model.

2.2. Migration and Coexistence Frameworks (5G → 6G)

Standardization efforts increasingly point toward staged migration rather than abrupt generational substitution. 3GPP Releases 17–19 emphasize lifecycle management, slicing evolution, and cloud-native deployment mechanisms that support gradual architectural transformation [11,12]. In parallel, ITU IMT-2030 documents define capability objectives and high-level performance targets for future 6G systems [8–10].

Academic and industrial sources further describe 5G-Advanced as a transitional platform supporting multi-RAT coordination, spectrum refarming, and progressive virtualization [3,7,25]. These developments suggest that hybrid deployment conditions will likely persist over extended periods, requiring interoperability between legacy and emerging infrastructure components.

However, much of the literature treats migration either as a roadmap issue or as a set of isolated performance improvements. Comparatively fewer studies analyze coexistence as a cross-domain optimization problem involving service continuity, backward compatibility, phased infrastructure upgrade constraints, and dynamic allocation of control responsibilities. This limitation reduces the analytical clarity with which the transition itself is currently understood.

2.3. AI-Native and Closed-Loop Network Control

AI-driven networking has evolved from parameter-level tuning toward intent-driven, adaptive, and increasingly automated control paradigms [4,15,16]. Existing studies report applications in radio resource management, mobility support, anomaly detection, traffic prediction, slice orchestration, and energy-aware adaptation across different parts of the network stack [4,11–23].

Recent surveys identify reinforcement learning, federated learning, and graph-based approaches as particularly relevant for distributed network intelligence in 5G/6G environments [4,20,22,23]. These methods are attractive because they support adaptation under heterogeneity, partial decentralization, and large-scale telemetry-driven decision making.

Nevertheless, the literature remains fragmented. Many AI-enabled solutions are developed for isolated control domains such as RAN scheduling, handover, or slicing, with limited treatment of cross-layer interaction under hybrid 5G–6G conditions. Recurring open issues include control-loop coupling, learning stability under non-stationary traffic, explainability of automated decisions, and lifecycle management of deployed models across multi-vendor operational environments.

2.4. RAN Evolution: O-RAN, Cloud-RAN, and Edge Intelligence

RAN architectures are progressively moving toward disaggregation, openness, and programmability through O-RAN and cloud-native design principles [17,18]. The introduction of near-real-time and non-real-time RAN Intelligent Controller (RIC) functions, together with xApps and rApps, enables optimization at multiple timescales and supports increasing algorithmic control over radio operations.

Recent work on AI-driven handover and load balancing in ultra-dense 5G/6G settings illustrates the practical value of learning-based RAN optimization but also shows that most current approaches remain function-specific rather than transition-aware [19]. Cloud-RAN and edge computing further improve deployment flexibility by enabling dynamic placement of processing functions and by supporting latency-sensitive services through closer proximity to users and applications [5,18,26].

At the same time, the literature consistently reports interoperability constraints, fronthaul limitations, synchronization challenges, and difficulties in coordinating distributed intelligence across heterogeneous RAN deployments [6,17,18]. These factors become even more important under coexistence conditions, where RAN decisions cannot be treated independently from core orchestration, service requirements, or spectrum policies.

2.5. Core Network Evolution: SBA, Slicing Orchestration, and Virtualization Overheads

Service-based architectures (SBA) and Network function virtualization (NFV)-enabled microservice design are central to the evolution of the mobile core toward greater flexibility and automation [4,11,12]. 3GPP orchestration and slicing specifications define lifecycle control, isolation mechanisms, and management interfaces that are increasingly relevant for multi-service and hybrid deployment scenarios [11,12].

Existing studies show that virtualization and containerization improve adaptability, but may also introduce latency overhead, orchestration complexity, and reliability trade-offs, especially in mission-critical contexts. Much of the literature evaluates slicing, orchestration, and virtualization efficiency as separate topics. Fewer studies examine how these mechanisms interact under phased 5G–6G evolution, where backward compatibility, resource contention, and dynamic reallocation of network functions must be considered jointly.

This suggests that core evolution should not be assessed only through architectural flexibility, but also through its role in cross-domain control integration during coexistence.

2.6. Spectrum Evolution: Sub-6 GHz, mmWave, THz, and Dynamic Sharing

Spectrum expansion toward mmWave, sub-THz, and THz bands remains one of the most visible technical dimensions of 6G research [2,3,6,27]. A large body of work addresses propagation modelling, beamforming, channel characterization, transceiver design, reconfigurable intelligent surfaces, and high-frequency communication constraints [26–58].

Recent AI-enabled RIS and spectrum-aware learning approaches further suggest that physical-layer adaptation is becoming increasingly data-driven and distributed [22,23]. Dynamic spectrum sharing and multi-band coordination are also widely discussed as enablers of coexistence between legacy and emerging systems.

Despite this richness, the surveyed literature often treats spectrum intelligence as a largely self-contained optimization problem. In many cases, physical-layer adaptation is not explicitly linked to service-level requirements, orchestration logic, or slice-level guarantees. This disconnect remains one of the clearest examples of fragmentation across the current 5G/6G research landscape.

2.7. Service-Driven Requirements: XR, Digital Twins, and Mission-Critical Applications

Emerging services such as immersive XR, digital twins, industrial automation, and autonomous systems impose heterogeneous requirements in latency, reliability, synchronization, and availability [6–8]. The literature increasingly quantifies these demands, but their translation into coordinated control actions across spectrum, RAN, edge, and core layers remains limited.

This problem becomes more acute during coexistence phases, where infrastructure capabilities are unevenly distributed and not all network segments can simultaneously satisfy the most demanding service constraints. As a result, service-aware optimization remains an important but underdeveloped link between high-level 6G use-case visions and operationally feasible migration strategies.

2.8. Security, Trust, and Governance in AI-Native Networks

Open, virtualized, and AI-driven network architectures expand the attack surface of future communication systems and introduce additional risks related to automation, data integrity, and distributed decision making [21,38,43]. Existing studies examine intrusion detection, anomaly detection, policy enforcement, and cross-layer slice protection using SDN/NFV and AI-assisted mechanisms [21,50,56].

However, security is still frequently treated as a parallel function rather than as an explicit dimension of the optimization process itself. The surveyed literature indicates persistent gaps related to AI model integrity, adversarial robustness, data poisoning in distributed learning, cross-slice isolation, and governance accountability in increasingly autonomous environments.

These issues are particularly relevant during transitional coexistence periods, where heterogeneous infrastructure and uneven trust capabilities complicate consistent policy enforcement across network domains.

2.9. Gap Synthesis and Motivation

Across the surveyed literature [1–18,24–66], five recurring gaps emerge:

1. Limited treatment of coexistence as a cross-domain optimization problem;
2. Insufficient cross-layer integration of AI-enabled control mechanisms;
3. Persistent separation of spectrum, RAN, core, and service-level optimization studies;
4. Weak integration of security and trust constraints into adaptive control logic;
5. Limited explicit linkage between migration stages and control responsibilities.

Taken together, these observations motivate the need for a transition-oriented synthesis that organizes the literature around coexistence, phased evolution, and cross-layer coordination, rather than around isolated technical enablers alone.

Table 1 presents a critical analysis of related work papers.

Table 1. Critical Analysis of Related Work on 5G-to-6G Transition.

Block	Domain	Representative Works	Key Limitations
1	Migration and coexistence	[8–12,25]	Lack of end-to-end optimization during coexistence
2	AI-native control	[4,16,38,57]	Fragmented control loops, stability issues
3	RAN evolution	[5,6,17,26]	Coordination of distributed intelligence
4	Core and slicing	[13,14,36,45]	Orchestration latency, reliability trade-offs
5	Spectrum and THz	[2,26–28,30–58]	Spectrum intelligence isolated from services
6	Services	[5,7,62,64]	No service-aware network control
7	Security and governance	[16,43,50]	Security not integrated in control loops

To anchor the survey in measurable indicators, Table 2 summarizes representative quantitative performance characteristics and architectural attributes of 5G, 5G-Advanced, and 6G targets based on reported literature and standardization documents. The values reflect commonly reported ranges rather than strict standard-mandated thresholds and are included to support structured comparison and transition analysis.

Table 2 highlights that while 6G ambitions significantly exceed current 5G capabilities in terms of peak throughput, latency, reliability, and spectrum expansion, the maturity gap remains substantial. AI-native control, integrated sensing, sub-THz communication, and autonomous slice orchestration are predominantly in early research or pre-standardization stages. This comparison indicates that the gap between currently deployed 5G capabilities and reported 6G ambitions is not only a matter of performance scale, but also of deployment maturity and cross-domain integration. The literature therefore supports analyzing the transition as a phased coexistence problem rather than as an abrupt architectural replacement scenario.

Table 2. Quantitative and Architectural Comparison of 5G, 5G-Advanced, and 6G Targets Based on Reported Literature and Standardization Documents.

Parameter/Capability	5G (Commercial Deployment)	5G-Advanced (Release 18/19 Trends)	6G (Reported Targets/Research Vision)	Representative Sources
Peak Data Rate	Up to 20 Gbps	20–40 Gbps (enhanced mmWave, aggregation)	100 Gbps–1 Tbps (THz bands)	[2,3,6,7]
User-Experienced Data Rate	~100 Mbps	100–1000 Mbps	>1 Gbps	[6,7]
End-to-End Latency	~1 ms (URLLC target)	Sub-ms in optimized edge deployments	0.1–0.5 ms (extreme URLLC scenarios)	[6–8]
Reliability	10^{-5} BLER (URLLC)	Improved deterministic reliability	10^{-7} or higher reliability targets	[6,7]
Mobility Support	Up to 500 km/h	Enhanced high-speed optimization	High-speed + integrated NTN mobility	[24,33]
Spectrum Bands	Sub-6 GHz, mmWave	Improved multi-band aggregation	Sub-THz/THz + integrated sensing bands	[27,28,34]
AI Integration	AI-assisted optimization (optional)	Increased AI orchestration	AI-native control plane and automation	[4,7,38]
Network Slicing	Static/dynamic slicing	Enhanced slice automation	Fully autonomous slice lifecycle management	[14,36]
Edge Intelligence	MEC-based	Deep edge–cloud coordination	Distributed AI across edge–device–cloud	[26,47]
Integrated Sensing	Limited/experimental	Emerging support	Native communication + sensing integration	[6,30]
Security Architecture	SDN/NFV-based protection	Enhanced slicing isolation	AI-driven, zero-trust, cross-layer security	[38,43]
Energy Efficiency	Incremental optimization	Improved energy-aware scheduling	Order-of-magnitude energy-per-bit reduction target	[5,55]
Technology Readiness	Technology Readiness Level (TRL) 8–9	TRL 7–8	TRL 3–5 (early research stage)	[8–10]

Moreover, the comparison confirms that many 6G targets require coordinated improvements across multiple layers rather than isolated physical-layer enhancements. For example, achieving sub-millisecond latency depends not only on radio interface advancements but also on edge placement strategies, slicing automation, and closed-loop AI orchestration issues that are fragmented across existing studies and motivate the transition-oriented synthesis developed in Section 4.

3. Critical Analysis and Research Gaps

Although extensive research addresses AI-native networking, RAN disaggregation, spectrum expansion, and service-driven requirements, the surveyed literature reveals structural gaps that become particularly critical during the prolonged coexistence phase between 5G and 6G systems. Rather than isolated technical limitations, these gaps reflect systemic integration challenges across architectural, operational, and governance domains.

The following subsections synthesize recurring deficiencies identified across Sections 2.2–2.8 and structure them into four interrelated categories.

3.1. Cross-Layer Integration Gaps

A central limitation of the surveyed literature lies in the fragmented treatment of optimization domains. Numerous works address spectrum efficiency [27,28], RAN intelligence [17], slicing orchestration [36], or AI-native control [38] independently. However, the 5G–6G transition requires coordinated optimization across physical, access, edge, and core layers under coexistence constraints.

First, spectrum intelligence is frequently optimized at the physical layer without explicit linkage to service-level constraints or slice orchestration policies. For example, dynamic spectrum allocation and beamforming strategies [26,27,30–58] improve spectral efficiency but rarely incorporate end-to-end QoS or SLA objectives.

Second, RAN disaggregation through O-RAN and Cloud-RAN enables programmable control via RIC architectures [17], yet the coordination between RAN-level decisions and core-level slicing remains underdeveloped. Most works treat RAN optimization and core orchestration as separate control problems.

Third, AI-driven solutions are typically implemented within isolated control loops (e.g., scheduling, handover, energy management), lacking unified cross-layer feedback integration [4,38,56]. This becomes particularly problematic during hybrid 5G–6G operation, where backward compatibility constraints limit feasible control actions.

Consequently, achieving 6G targets (Table 2) cannot rely on improvements within a single domain. Sub-millisecond latency, for instance, depends simultaneously on edge placement, slicing automation, fronthaul optimization, and spectrum decisions. The absence of cross-layer coordination frameworks remains a primary structural gap in current research.

3.2. Data, Control, and Evaluation Gaps

A second category of limitations concerns control-loop stability, data dependency, and evaluation methodologies.

AI-native networking approaches rely heavily on high-quality telemetry and training data [34,47]. However, during migration phases, heterogeneous infrastructure, partial deployment, and multi-vendor environments may produce inconsistent data quality and observability constraints. The literature rarely models such partial visibility conditions explicitly.

Moreover, learning stability under non-stationary traffic patterns, mobility shifts, and spectrum variability remains insufficiently addressed [57]. Many reinforcement learning and federated learning approaches assume stationary or semi-stationary environments, which may not hold in hybrid 5G–6G deployments.

Evaluation practices also vary significantly. Performance results are often derived from simulation-based RAN scenarios, isolated slicing experiments, or analytical PHY-layer models [26,27,30–58], without unified benchmarking across coexistence configurations. As a result, cross-study comparability is limited.

In addition, few studies explicitly model migration-phase transitions as decision variables. For example, the proportion of 6G-capable nodes, traffic share evolution, and phased infrastructure upgrades are rarely incorporated into optimization formulations.

This gap in deployment-aware evaluation limits the practical interpretability of many AI-native proposals and motivates structured evidence synthesis and migration-aware modelling approaches.

3.3. Security, Trust, and Governance Gaps

The shift toward open, virtualized, and AI-driven architectures significantly expands the attack surface of future networks [38,43]. Multi-vendor O-RAN deployments, software-defined infrastructure, and distributed AI agents introduce new vulnerabilities.

Although AI-based intrusion detection and anomaly detection mechanisms are widely proposed [50,56], security is frequently treated as a parallel subsystem rather than as an integrated optimization dimension embedded within control loops [13,14].

Several specific gaps emerge:

- AI model integrity and robustness against adversarial manipulation are rarely integrated into network-level optimization frameworks.
- Data poisoning risks in federated learning-based RAN intelligence remain underexplored.
- Cross-slice isolation and zero-trust policies are not consistently incorporated into dynamic slicing orchestration models.
- Governance, accountability, and explainability of automated decisions receive limited quantitative treatment.

During coexistence phases, legacy infrastructure may lack native support for advanced trust mechanisms, further complicating security integration. Embedding security constraints directly into cross-layer optimization models remains an open research challenge.

3.4. Sustainability and Economic Gaps

Sustainability and economic feasibility are increasingly recognized as critical pillars of 6G development [5,55]. While energy-efficient scheduling, sleep modes, and AI-driven resource optimization demonstrate potential improvements, these metrics are often evaluated independently from latency, reliability, and deployment cost.

Few works provide multi-objective optimization formulations balancing the following:

- Energy efficiency;
- Capital expenditure (CAPEX);
- Operational expenditure (OPEX);
- Performance targets.

Furthermore, migration-phase investment planning such as staged hardware upgrades, spectrum refarming, and edge deployment expansion is rarely formalized as an optimization problem.

The maturity gap highlighted in Table 2 indicates that many 6G technologies remain in early readiness stages. Therefore, economic risk and incremental deployment feasibility must be considered alongside technical performance targets.

Without integrating sustainability and economic dimensions into cross-layer control strategies, architectural proposals risk remaining conceptually attractive but operationally impractical.

3.5. Transition-Oriented Synthesis Derived from the Review

Building on the integration, evaluation, security, and sustainability gaps identified in Sections 3.1–3.4, the surveyed literature can be organized into a transition-oriented synthesis of the main control domains involved in 5G–6G evolution. This synthesis is not intended as a finalized architectural blueprint or normative design proposal. Rather, it provides an analytical structure for comparing how existing studies address spectrum intelligence, RAN and edge coordination, core slicing and orchestration, service-aware adaptation, and embedded security considerations across different stages of migration.

A central observation emerging from the review is that the coexistence period should be treated as a staged operational condition rather than as a temporary implementation detail. Different phases of transition place different demands on observability, control-loop coupling, resource allocation, and backward compatibility. Organizing the literature around these phases helps reveal where current proposals remain domain-specific and where they begin to address cross-layer interaction more explicitly.

From this perspective, the survey-derived synthesis supports the following:

- Identification of missing interfaces between optimization domains;
- Analysis of fragmentation across control loops;
- Assessment of the extent to which security is embedded into adaptive decision processes;
- Comparison of how explicitly migration constraints are represented in current studies.

To make this positioning more transparent, Table 3 compares recent representative surveys and framework-oriented studies with respect to coexistence awareness, cross-layer AI integration, security embedding, migration-phase treatment, and evaluation style.

Table 3. Comparison of Representative AI-Native 5G/6G Frameworks and Surveys.

Work	Coexistence Modelling (5G–6G)	Cross-Layer AI Integration	Security Embedded in Control Loop	Migration Phases Explicitly Modelled	Evaluation Approach	Distinction from This Survey
Omheni et al. (2025)—AI for 5G/6G Survey [20]	Limited (focus on AI taxonomy)	Yes (AI applications classified)	Partially discussed	No	Survey-based	Broad AI taxonomy; does not focus on transition-aware coexistence modelling
Chabira et al. (2025)—AI-driven Handover [19]	No	RAN-level optimization	No	No	Simulation-based	Focused on ultra-dense RAN optimization; not migration-oriented
Allaw et al. (2025)—Cross-layer Slice Security [21]	No	Cross-layer slicing	Yes (security-centric)	No	Framework + analysis	Security-focused slice framework; does not model 5G–6G coexistence
Zaoutis et al. (2025)—AI-controlled RIS [22]	No	PHY-layer AI	No	No	Analytical + experimental	Focus on RIS control; limited architectural scope
Mutescu et al. (2025)—AI-Native PHY [23]	No	PHY-layer spectrum-aware AI	Limited	No	Technical modelling	PHY-layer AI-native spectrum approach
This Survey (2026)	**Yes**	**Cross-layer literature mapping**	**Discussed as an optimization dimension**	**Yes**	**Structured evidence synthesis**	**Transition-oriented taxonomy and coexistence-aware literature synthesis**

As illustrated in Table 3, while recent works extensively address AI-driven optimization, RAN disaggregation, slice security, or physical-layer intelligence, explicit modelling of the 5G–6G coexistence period as a phased, cross-layer optimization problem remains limited. Most surveyed frameworks focus either on specific architectural layers or on broad AI taxonomies without incorporating deployment constraints, backward compatibility requirements, and migration-aware decision processes.

The distinguishing contribution of this survey therefore lies not in introducing a new algorithmic solution, but in organizing AI-native networking research into a transition-aware analytical structure that integrates coexistence modelling, cross-layer coordination, and phased evolution. This synthesis provides the analytical basis for the transition-oriented structuring developed in Section 4.

4. Review Methodology and Synthesis Procedure

This section describes the methodological approach used to synthesize the surveyed literature and to organize the main transition-related themes identified across prior work. Unlike simulation-based or experimentally validated design studies, the present paper follows a structured review and analytical synthesis methodology intended to consolidate fragmented research directions into a coherent coexistence-aware perspective.

4.1. Literature Selection and Classification Criteria

This survey focuses on peer-reviewed journal articles, major conference papers, and selected standardization documents addressing the following:

- AI-native networking and automation;
- RAN disaggregation and O-RAN architectures;
- Network slicing and cloud-native core evolution;
- Spectrum expansion toward mmWave and THz;
- Migration strategies from 5G toward 6G.

The review literature was classified according to the seven thematic domains introduced in Section 2:

(1) Migration and coexistence strategies;
(2) AI-native closed-loop control;
(3) RAN evolution and edge intelligence;
(4) Core orchestration and slicing;
(5) Spectrum intelligence;
(6) Service-driven requirements;
(7) Security, trust, and governance.

Inclusion required explicit relevance to network-level optimization, migration-aware architectural constraints, cross-layer interaction, or AI-enabled operational control. Standardization documents from 3GPP, ITU, ETSI, and O-RAN were included when they directly informed deployment constraints, orchestration logic, or reported capability targets relevant to coexistence analysis.

To ensure that the synthesized evidence reflects representative trends rather than isolated results, studies included in the evidence synthesis were selected based on three criteria: (i) explicit relevance to AI-driven optimization mechanisms or architectural evolution in 5G/6G systems, (ii) availability of reported performance indicators or maturity signals, and (iii) methodological transparency sufficient to interpret the baseline comparison context.

When multiple studies addressed similar mechanisms (e.g., AI-assisted scheduling, dynamic slicing, or spectrum coordination), representative values were extracted from works reporting clearly defined baseline comparisons. Reported improvements were normalized by expressing them as relative percentage changes with respect to the baseline configuration described in each study. This normalization approach allows heterogeneous results obtained under different deployment assumptions to be interpreted as indicative performance ranges rather than directly comparable measurements.

4.2. Evidence Extraction and KPI Normalization

To improve transparency, the survey extracts quantitative Key Performance Indicators (KPIs) from the literature only where they are explicitly reported. The main performance dimensions considered include the following:

- End-to-end latency;
- Throughput;
- Reliability;
- Energy efficiency;
- Deployment maturity or technology readiness indicators.

Because assumptions differ substantially across studies, reported values were interpreted relative to their baseline context rather than treated as directly comparable measurements. Where possible, improvements were grouped by baseline type and expressed in relative rather than absolute terms. Reported ranges were preserved to avoid overgeneralization.

No new simulations, experiments, or proprietary datasets were generated for this study. Accordingly, all quantitative statements in Section 5 should be interpreted as evidence synthesized from published sources rather than as independently validated results.

4.3. Reference Framework Derivation and Architectural Mapping

Based on recurring themes in the surveyed literature, the paper develops a transition-oriented synthesis that maps the main domains in which AI-driven optimization is discussed during the evolution from 5G to 6G. This synthesis is intended as an organizational aid for comparing prior work, not as a proprietary architecture or implementation-ready system design.

The mapping highlights recurring interaction points among the following:

- Spectrum management;
- RAN and edge coordination;
- Core slicing and orchestration;
- AI-enabled control;
- Service-driven requirements;
- Security and governance constraints.

It also makes explicit that the literature increasingly treats the transition as phased and heterogeneous, rather than as a single-step generational replacement process.

Because the reviewed studies employ heterogeneous experimental settings, datasets, and network configurations, absolute performance values were not aggregated directly. Instead, relative improvement ranges reported by the original authors were preserved and grouped by optimization domain. This approach enables comparative interpretation of performance tendencies while avoiding misleading cross-study equivalence.

4.3.1. Layered Synthesis of Transition Domains

Figure 1 provides a survey-derived layered summary of the main optimization domains repeatedly identified in the literature, spanning spectrum resources, RAN and edge control, core orchestration, AI-enabled adaptation, and service-level requirements.

Figure 1 summarizes the surveyed literature along two analytical dimensions: migration phase and control domain. Rows represent the main optimization domains identified in the review, while columns represent the staged evolution from coexistence to hybrid optimization and more 6G-dominant operation. The figure is intended as a taxonomy-based synthesis of literature rather than as prescriptive architecture.

Control Domain	**Coexistence Phase**	**Hybrid Optimization Phase ●**	**6G-Dominant Phase ◐**
Spectrum Intelligence	Dynamic spectrum sharing, spectrum refarming, multi-band coordination	AI-assisted band selection, joint mmWave/sub-THz allocation	THz-native allocation, sensing-assisted spectrum control
RAN and edge control	Non-Standalone/Standalone (NSA/SA) interoperability, mobility and handover continuity	O-RAN control, edge-assisted scheduling	Distributed AI-native RAN coordination
Core and slice orchestration	Legacy compatibility, continuity of network slices	Adaptive slicing, cloud-native orchestration	Autonomous end-to-end slice lifecycle
Service-aware adaptation	KPI translation under constrained infrastructure	Service-driven resource coordination	Intent-driven orchestration for XR, digital twins, and immersive services
Security and governance	Legacy trust gaps, policy inconsistency across domains	Cross-domain policy enforcement	embedded zero-trust AI governance

Figure 1. Transition-oriented taxonomy of AI-driven optimization domains in the 5G-to-6G. evolution. Legend: ●—widely studied; ◐—partially studied.

This figure presents a transition-oriented taxonomy synthesis of the surveyed literature. Instead of depicting a new architectural framework, the figure organizes prior work according to two analytical dimensions: the main network control domains involved in AI-driven optimization and the migration phases across which these mechanisms are discussed. This representation is intended to make the coexistence logic of the 5G-to-6G transition more explicit and to support the gap analysis developed in Sections 2 and 3.

4.3.2. Deployment Evolution Context

Figure 2 provides historical and deployment-level context for coexistence analysis by summarizing standardized Long-Term Evolution (LTE)–5G evolution options adapted from prior industry documentation [25]. The figure illustrates that previous generational transitions already relied on staged anchoring strategies, including standalone and non-standalone modes with different dependencies between radio access and core components.

This figure provides historical context for staged deployment logic. In the context of this survey, Figure 2 is not used as evidence for a specific 5G–6G architecture. Rather, it serves to illustrate why phased migration and interoperability constraints are analytically relevant when discussing future 5G–6G coexistence scenarios.

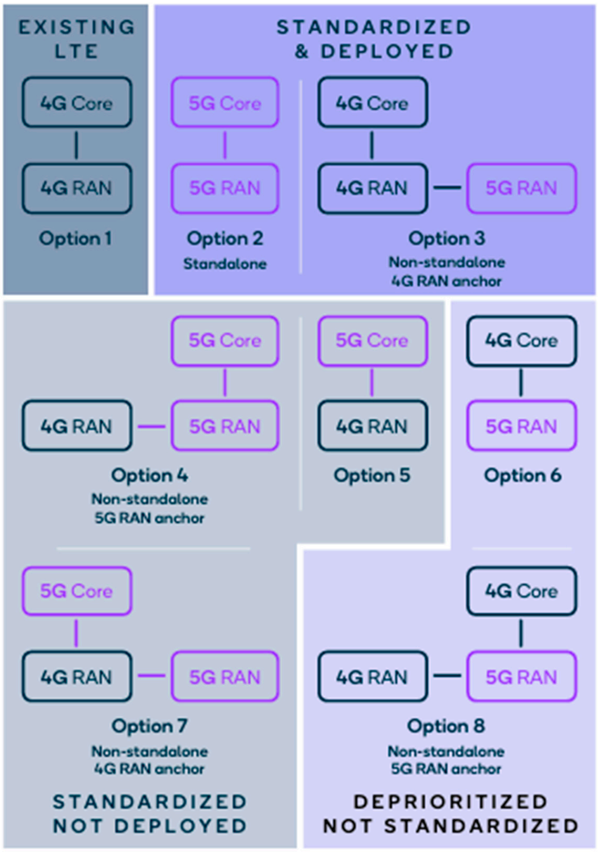

Figure 2. Deployment options and migration paths from LTE to 5G architectures. Adapted from Qualcomm Technologies [25].

4.3.3. Functional Evolution of Open RAN

Figure 3 summarizes the functional evolution of Open RAN concepts from 5G toward more cloud-native and programmable future architectures [25]. The literature commonly uses such decomposition to illustrate increasing flexibility in the allocation of processing functions across centralized, distributed, and edge environments.

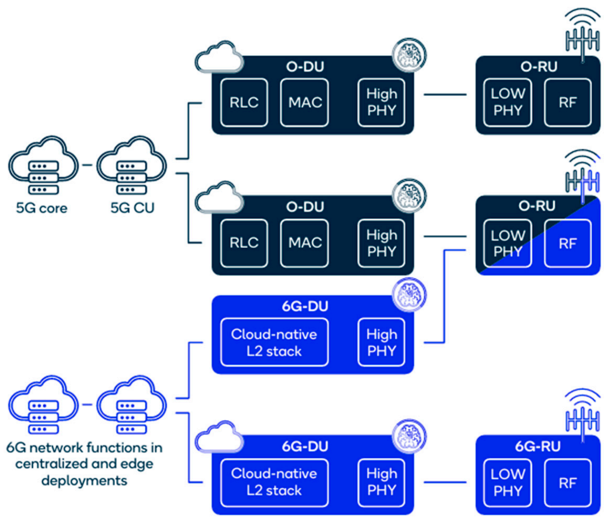

Figure 3. Functional evolution of Open RAN Architecture from 5G to 6G [25].

Within the present survey, this evolution is relevant because it shows how intelligence and control become more distributed across the RAN stack. This, in turn, reinforces one of the core findings of the review: that future optimization problems cannot be adequately understood within a single architectural layer, but require closer analytical linkage between RAN adaptation, orchestration logic, service constraints, and broader coexistence conditions.

4.4. Survey-Derived Abstraction of Transition-Aware Control Dimensions

This subsection does not introduce a new optimization algorithm or a validated system model. Instead, it provides a compact analytical abstraction of the main control dimensions that repeatedly appear across the surveyed literature on hybrid 5G–6G operation. The purpose of this abstraction is to clarify how the review findings can be organized in terms of optimization objectives, control domains, transition states, and representative operational constraints.

Rather than serving as a prescriptive formulation, this abstraction functions as a synthesis tool that connects the taxonomy and gap analysis in Sections 2 and 3 with the evidence-oriented discussion in Section 5.

4.4.1. Main Optimization Dimensions Reported in the Literature

Across the reviewed studies, AI-driven network optimization is typically associated with a recurring set of performance dimensions, even though individual works emphasize different subsets of them. The most frequently recurring dimensions include the following:

- End-to-end latency;
- Energy efficiency;
- Reliability;
- Operational efficiency or deployment cost;
- Service continuity under heterogeneous deployment conditions.

These dimensions are rarely optimized jointly across spectrum, RAN, edge, and core domains. Instead, the literature often addresses them separately within narrower technical contexts. From a transition-aware perspective, this fragmentation is itself an important analytical finding, because hybrid 5G–6G operation requires simultaneous trade-offs across multiple layers and deployment constraints.

A generic way to express this observation is to consider an aggregate optimization objective that combines latency, energy, reliability, and cost-related terms over time. In the context of this survey, such an expression should be interpreted only as a compact representation of recurring trade-offs in the literature, not as a standalone validated model:

$$\mathbf{min}\ \boldsymbol{J} = \sum_{t=1}^{T} (\alpha_1 L(t) + \alpha_2 E(t) - \alpha_3 R(t) + \alpha_4 C(t))$$

where $L(t)$ denotes latency-related cost, $E(t)$ energy-related cost, $R(t)$ a reliability-related utility term, and $C(t)$ an operational or deployment-related cost proxy. The coefficients α_i indicate that the relative importance of these dimensions depends on the service context and migration stage.

4.4.2. Cross-Layer Control Domains

The surveyed literature suggests that transition-aware control must span several interacting decision domains rather than a single network layer. For analytical clarity, these domains can be summarized through the following abstract control vector:

$$\mathbf{x}(t) = \left\{ s_f(t), r_u(t), b_k(t), e_m(t), \pi_p(t) \right\},$$

where $s_f(t)$ represents spectrum allocation decisions, $r_u(t)$ RAN-level scheduling and radio resource control, $b_k(t)$ slice-level bandwidth or isolation configuration, and $e_m(t)$ edge or function placement decisions.

The term $\pi_p(t)$ is best interpreted not as a conventional control action, but as a transition-state indicator reflecting the migration condition under which the other decisions are made. Including it in the abstraction makes explicit that control choices in hybrid 5G–6G environments depend not only on traffic or radio conditions, but also on the current stage of infrastructure evolution.

4.4.3. Representative Constraint Categories

Another recurring observation from the review is that optimization in hybrid 5G–6G environments is constrained by heterogeneous technical and operational conditions. Across the literature, these constraints can be grouped into several representative categories:

- Capacity constraints, reflecting limited radio, transport, or processing resources;
- Spectrum constraints, reflecting the availability of legacy and emerging bands;
- Latency and reliability constraints, reflecting service-level requirements;
- Backward compatibility constraints, reflecting coexistence with legacy infrastructure;
- Security and isolation constraints, reflecting slice protection, trust, and governance requirements.

A compact analytical representation of these categories may be written as

$$\begin{gathered} \sum r_u(t) \leq R_{\max} \\ s_f(t) \in \mathcal{S}_{5G} \cup \mathcal{S}_{6G} \\ L(t) \leq L_{\mathrm{SLA}} \\ R(t) \geq R_{\min} \end{gathered}$$

In this survey, these expressions are not intended as a complete optimization problem. Their role is instead to illustrate that the literature repeatedly points to coexistence-aware constraints extending beyond classical single-layer resource optimization.

Backward compatibility and security conditions are especially important because they are often discussed qualitatively in existing studies, but less frequently incorporated into unified formal treatment. This mismatch further supports the reviewer's concern that the field still lacks sufficiently integrated evaluation methodologies.

4.4.4. Transition-State Representation

A central argument of this survey is that the 5G-to-6G evolution should be interpreted as a staged process. For that reason, the literature can be usefully organized around a simple transition-state abstraction:

$$\pi_p(t) \in \{P_1, P_2, P_3\},$$

where P_1 denotes a coexistence phase, P_2 a hybrid optimization phase, and P_3 a more 6G-dominant operational phase.

This representation is not intended to imply that real deployments evolve according to a universal three-state rule. Rather, it provides an analytical shorthand for distinguishing different control conditions reported across the literature. For example, early coexistence stages emphasize backward compatibility and interoperability, whereas later stages place greater emphasis on tighter AI-driven coordination across cloud-native and disaggregated infrastructure.

One simple indicator discussed in migration-oriented studies is the increasing share of traffic, functionality, or infrastructure attributed to 6G-capable components. In abstract form, such a tendency may be represented as:

$$\gamma(t) = \frac{\text{6G traffic share}}{\text{Total traffic}}$$

where increasing values of $\gamma(t)$ indicate progressive transition toward more 6G-oriented operation. Within the present survey, this term is used only as an interpretive migration indicator, not as a validated switching rule.

4.4.5. Interpretive Role of the Abstraction

The analytical abstraction presented above has a limited but useful role in the manuscript. It does not constitute a new optimization framework, an algorithmic contribution, or an experimentally supported control strategy. Its purpose is narrower: to make explicit the main categories of objectives, control domains, constraints, and migration states that recur across the surveyed literature.

Seen in this way, the abstraction helps explain why current studies remain difficult to compare directly. Different works optimize different variables, assume different deployment conditions, and evaluate different subsets of constraints. Making these dimensions explicit supports the evidence synthesis in Section 5 and reinforces one of the main conclusions of this review: the field still lacks sufficiently standardized, cross-layer, coexistence-aware evaluation practices for hybrid 5G–6G systems.

This abstraction connects the taxonomy and gap analysis with a compact analytical summary of recurring control dimensions.

5. Evidence Synthesis and Discussion

This section synthesizes performance trends and maturity signals extracted from the reviewed literature. The discussion does not present new simulation results or empirical validation but consolidates reported findings across heterogeneous studies to interpret recurring patterns relevant to the 5G–6G transition.

The purpose of this section is to contextualize the taxonomy synthesis presented in Sections 3 and 4 using structured evidence extracted from published sources. To support transparency, the evidence mapping in Figures 4 and 5 was constructed by extracting and normalizing performance and maturity indicators reported in the surveyed sources, then grouping them by domain and transition phase. A consolidated evidence table (source-to-figure mapping) is provided in the revised manuscript to ensure traceability.

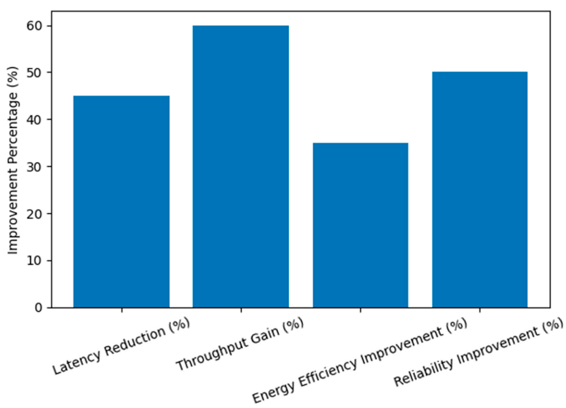

Figure 4. Synthesized relative performance tendencies associated with AI-enabled cross-layer optimization in 5G–6G transition scenarios. Bars represent indicative improvement ranges extracted from representative studies listed in Table 4.

Table 4. Evidence Sources Supporting Synthesized Performance and Maturity Trends.

Domain	Performance Indicator	Representative Sources	Baseline Comparison Context	Figure Reference
RAN/Edge Intelligence	Latency reduction, scheduling efficiency	[4,6,17,26,38]	Static scheduling vs. AI-assisted RIC control	Figure 4
Network Slicing	Throughput stability, resource utilization	[14,36,45]	Static slicing vs. dynamic slice orchestration	Figure 4
Spectrum Coordination	Spectral efficiency, multi-band optimization	[26–28,30–39]	Fixed allocation vs. sensing-assisted dynamic allocation	Figure 4
Energy Optimization	Energy per bit reduction	[5,55]	Fixed power vs. AI-based adaptive power control	Figure 4
Integrated Sensing	Communication–sensing integration	[6,30]	Communication-only baseline	Figure 4
Technology Readiness	TRL maturity positioning	[8–10]	Standardization milestones and deployment signals	Figure 5

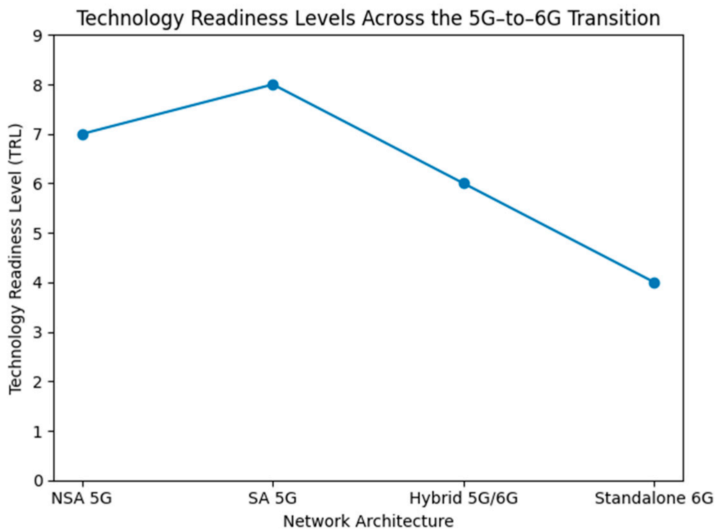

Figure 5. Literature-informed qualitative positioning of technology readiness levels across 5G–6G evolution stages.

5.1. *Reported Performance Trends Across Domains*

Across the reviewed studies, AI-enabled slicing, edge intelligence, and dynamic spectrum coordination are frequently associated with reported improvements in latency reduction, throughput enhancement, and energy efficiency when compared to static or non-AI baselines. However, the magnitude of improvement varies depending on deployment assumptions, traffic models, spectrum configuration, and architectural constraints.

In the RAN and edge domain, AI-assisted scheduling and predictive resource allocation are frequently linked to reduced queuing delays and improved mobility robustness, particularly in URLLC scenarios. Several studies addressing O-RAN architectures and near-real-time RIC control loops report latency improvements under high-load conditions when compared to conventional rule-based schedulers. Nevertheless, these gains depend strongly on fronthaul capacity and model training quality.

In the core and slicing domain, dynamic slice adaptation and intent-driven orchestration are associated with improved resource utilization and service isolation compared to static slicing configurations. The literature indicates that slice elasticity and predictive scaling can reduce over-provisioning and improve throughput stability, especially under heterogeneous traffic conditions.

In the spectrum domain, multi-band coordination and sensing-assisted allocation mechanisms are reported in several studies to enhance spectral efficiency relative to fixed spectrum assignment. Contributions addressing mmWave and THz coordination emphasize that intelligent beam management and adaptive band switching can mitigate propagation variability, although performance depends on mobility patterns and environmental conditions.

Energy efficiency improvements are most frequently attributed to AI-driven sleep modes, adaptive transmission power control, and workload-aware edge placement strategies. However, reported energy gains are sensitive to baseline assumptions, including network density and traffic intensity.

The graphical summaries in Figures 4 and 5 were designed as evidence-oriented visualizations to improve readability of the synthesized trends across heterogeneous studies.

Figure 4 synthesizes representative relative performance ranges reported across the literature and maps them to the cross-layer control domains discussed in Section 4. These values represent consolidated trends rather than experimentally verified measurements within a single unified testbed. The ranges illustrated in Figure 4 were derived by extracting representative improvement values reported in the surveyed studies and normalizing them relative to their baseline assumptions.

The figure summarizes representative improvement ranges reported across the surveyed literature for latency reduction, throughput gain, energy efficiency, and reliability enhancement. Values reflect normalized trends derived from heterogeneous studies and should be interpreted as indicative patterns rather than results obtained under a unified experimental framework.

Overall, the evidence suggests that performance improvements attributed to AI-native networking are not solely driven by radio-layer advancements but by coordinated cross-layer optimization. However, variability across study assumptions underscores the need for standardized benchmarking methodologies for hybrid 5G–6G environments.

5.2. Technology Readiness Interpretation

Beyond performance indicators, migration feasibility depends on technology maturity. To support structured discussion of phased deployment, Technology Readiness Levels (TRLs) were interpreted based on maturity signals reported in standardization documents (e.g., 3GPP, ITU) and recent peer-reviewed literature.

The TRL mapping presented in this study does not represent formal certification or official evaluation. Instead, it provides a qualitative maturity positioning intended to contextualize the coexistence, hybrid optimization, and 6G-dominant phases.

Commercial standalone 5G systems are widely regarded as high-maturity deployments (TRL 8–9), supported by operational infrastructure and standardized procedures. 5G-Advanced developments exhibit intermediate readiness (TRL 7–8), reflecting near-commercial enhancements.

In contrast, many 6G technologies—including THz communication, integrated sensing and communication, and fully AI-native control planes remain in early research or prototype stages (TRL 3–5). This maturity gap reinforces the importance of migration-aware frameworks that enable incremental integration of emerging capabilities without requiring abrupt generational replacement.

Figure 5 visualizes this qualitative positioning across deployment stages.

The visualization summarizes literature-informed maturity signals across deployment stages rather than formal TRL certification values. The depicted TRLs represent literature-informed maturity signals rather than formal certification values. They are included to support discussion of phased migration feasibility.

The combined interpretation of performance trends and readiness signals supports a phased transition model. Early coexistence phases rely primarily on mature 5G infrastructure augmented by selective AI-enabled optimization. Hybrid phases progressively incorporate emerging 6G components as maturity increases. Full 6G-dominant deployment becomes feasible only when enabling technologies to reach higher readiness levels.

5.3. Implications for Migration-Aware AI-Native Networking

Synthesizing the evidence across performance and maturity dimensions leads to three observations:

(1) Cross-layer AI coordination appears consistently associated with improved performance compared to static configurations, but gains are context-dependent.
(2) Migration feasibility is constrained not only by technical performance but by readiness maturity and deployment economics.
(3) Standardized benchmarking frameworks for hybrid 5G–6G systems remain underdeveloped, limiting comparability across studies.

These observations reinforce the relevance of a transition-aware analytical framework that integrates performance optimization with phased deployment considerations.

6. Conclusions

This paper presented a survey-driven analysis of the technological, architectural, and operational challenges associated with the transition from 5G to 6G mobile networks. By organizing recent research and standardization efforts into a transition-oriented taxonomy and synthesizing recurring gaps across the literature, the study emphasized that the 5G-to-6G evolution is best understood as a prolonged coexistence process requiring coordinated adaptation across multiple network domains rather than abrupt infrastructure replacement.

Across the reviewed literature, several enabling directions consistently emerge. These include spectrum-aware coexistence across heterogeneous frequency bands, disaggregated and cloud-native RAN architectures with embedded edge intelligence, virtualized core networks supporting automated slice lifecycle management, and AI-enabled control mechanisms capable of coordinating optimization across RAN, edge, and core domains while incorporating security and governance considerations.

A central insight of the survey is that the performance objectives commonly associated with 6G-oriented services such as extended reality, digital twins, and mission-critical connectivity cannot be achieved through isolated physical-layer improvements alone. Instead, the literature consistently highlights the need for coordinated cross-layer optimization combining spectrum allocation, RAN scheduling, edge function placement, core orchestration, and service-aware control policies.

At the same time, persistent limitations remain visible across existing studies. These include fragmented cross-layer control strategies, virtualization and orchestration overheads, incomplete mapping between service requirements and network-level KPIs, security and trust challenges in open AI-driven ecosystems, and the absence of standardized benchmarking methodologies for hybrid 5G–6G environments.

The quantitative figures included in this survey represent structured evidence mapping of commonly reported performance tendencies and technology readiness signals across heterogeneous sources rather than independent experimental validation. Consequently, future research should prioritize reproducible evaluation methodologies for transition-aware architectures, including standardized KPI normalization, security-aware benchmarking under coexistence conditions, and systematic modelling of migration phases.

Overall, this survey contributes a structured taxonomy of AI-driven optimization domains, a synthesis of recurring cross-domain gaps, and a transition-oriented analytical perspective intended to support comparative research, system design discussions, and deployment planning toward robust and AI-native 6G ecosystems.

Author Contributions: Conceptualization: all authors; methodology: G.M. and V.G.; validation: G.M. and V.G.; formal analysis: G.M. and V.G., writing—original draft preparation: R.M., G.M., B.Q., E.H., S.G., and V.G.; writing—review and editing: G.M. and V.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research work was funded by the European Regional Development Fund within the Operational Program "Bulgarian national recovery and resilience plan" and the procedure for direct provision of grants "Establishing of a network of research higher education institutions in Bulgaria", under the Project BG-RRP-2.004-0005 "Improving the research capacity and quality to achieve international recognition and resilience of TU-Sofia". The APC was funded by the Project BG-RRP-2.004-0005.

Data Availability Statement: No special datasets were used in this review article.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CAPEX	Capital Expenditure
GHz	Gigahertz
IMT	International Mobile Communications
ITU	International Telecommunication Union
KPIs	Key Performance Indicators
LTE	Long-Term Evolution
mMTC	Massive Machine-Type Communications
NFV	Network Function Virtualization
NSA	Non-Standalone
OPEX	Operational Expenditure
O-RAN	Open Radio Access Network
QoE	Quality of Experience
QoS	Quality of Service
RAN	Radio Access Networks
RAT	Radio Access Technology
RIC	RAN Intelligent Controller
SA	Standalone
SBA	Service-Based Architectures
SDN	Software-Defined Networking
THz	Terahertz
TRL	Technology Readiness Level
URLLC	Ultra-Reliable Low-Latency Communications
XR	Extended Reality
3GPP	3rd Generation Partnership Project

References

1. Rajatheva, N.; Atzeni, I.; Bjornson, E.; Bourdoux, A.; Buzzi, S.; Dore, J.B.; Erkucuk, S.; Fuentes, M.; Guan, K.; Hu, Y.; et al. White paper on broadband connectivity in 6G. *arXiv* **2020**, arXiv:2004.14247. [CrossRef]
2. Rappaport, T.S.; Xing, Y.; Kanhere, O.; Ju, S.; Madanayake, A.; Mandal, S.; Alkhateeb, A.; Trichopoulos, G.C. Wireless communications and applications above 100 GHz: Opportunities and challenges for 6G and beyond. *IEEE Access* **2019**, *7*, 78729–78757. [CrossRef]
3. Yang, P.; Xiao, Y.; Xiao, M.; Li, S. 6G wireless communications: Vision and potential techniques. *IEEE Netw.* **2019**, *33*, 70–75. [CrossRef]
4. Letaief, K.B.; Chen, W.; Shi, Y.; Zhang, J.; Zhang, Y.-J.A. The roadmap to 6G: AI empowered wireless networks. *IEEE Commun. Mag.* **2019**, *57*, 84–90. [CrossRef]
5. Strinati, E.C.; Barbarossa, S.; Gonzalez-Jimenez, J.L.; Ktenas, D.; Cassiau, N.; Maret, L.; Dehos, C. 6G: The next frontier: From holographic messaging to artificial intelligence using sub-terahertz and visible light communication. *IEEE Veh. Technol. Mag.* **2019**, *14*, 42–50. [CrossRef]
6. Giordani, M.; Polese, M.; Mezzavilla, M.; Rangan, S.; Zorzi, M. Toward 6G networks: Use cases and technologies. *IEEE Commun. Mag.* **2020**, *58*, 55–61. [CrossRef]
7. Saad, W.; Bennis, M.; Chen, M. A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. *IEEE Netw.* **2020**, *34*, 134–142. [CrossRef]
8. ITU-R Recommendation M.2160-0. Framework and Overall Objectives of the Future Development of IMT for 2030 and Beyond. (11/2023). Available online: https://www.itu.int/dms_pubrec/itu-r/rec/m/R-REC-M.2160-0-202311-I!!PDF-E.pdf (accessed on 15 January 2026).
9. ITU. ITU Advances the Development of IMT-2030 for 6G Mobile Technologies. Available online: https://www.itu.int/en/mediacentre/Pages/PR-2023-12-01-IMT-2030-for-6G-mobile-technologies.aspx (accessed on 15 January 2026).
10. ITU-R. IMT Towards 2030 and Beyond (IMT-2030). Available online: https://www.itu.int/en/ITU-R/study-groups/rsg5/rwp5d/imt-2030/pages/default.aspx (accessed on 15 January 2026).
11. 3GPP TS 28.530. 5G Management and Orchestration: Concepts, Use Cases and Requirements (Release 18). Available online: https://www.etsi.org/deliver/etsi_ts/128500_128599/128530/18.00.00_60/ts_128530v180000p.pdf (accessed on 15 January 2026).
12. 3GPP TS 28.533. 5G Management and Orchestration: Architecture Framework (Release 18). Available online: https://www.etsi.org/deliver/etsi_ts/128500_128599/128533/18.01.00_60/ts_128533v180100p.pdf (accessed on 15 January 2026).
13. 3GPP Specification Series TS 28. Available online: https://www.3gpp.org/dynareport?code=28-series.htm (accessed on 15 January 2026).
14. 3GPP. Management, Orchestration and Charging for 5G Networks. Available online: https://www.3gpp.org (accessed on 15 January 2026).
15. ETSI GS ZSM 002. Zero-Touch Network and Service Management (ZSM): Reference Architecture. 2019. Available online: https://www.etsi.org/deliver/etsi_gs/ZSM/001_099/002/01.01.01_60/gs_ZSM002v010101p.pdf (accessed on 15 January 2026).
16. ETSI. Zero-Touch Network and Service Management Overview. Available online: https://www.etsi.org/technologies/zero-touch-network-service-management (accessed on 15 January 2026).
17. O-RAN Alliance. O-RAN Specifications. Available online: https://www.o-ran.org/specifications (accessed on 15 January 2026).
18. ETSI TS 104 226. Non-RT RIC & A1/R1 Interface: Use Cases and Requirements. 2025. Available online: https://www.etsi.org/deliver/etsi_ts/104200_104299/104226/10.01.00_60/ts_104226v100100p.pdf (accessed on 15 January 2026).
19. Chabira, C.; Shayea, I.; Nurzhaubayeva, G.; Aldasheva, L.; Yedilkhan, D.; Amanzholova, S. AI-Driven Handover Management and Load Balancing Optimization in Ultra-Dense 5G/6G Cellular Networks. *Technologies* **2025**, *13*, 276. [CrossRef]
20. Omheni, N.; Koubaa, H.; Zarai, F. Artificial Intelligence for 5G and 6G Networks: A Taxonomy-Based Survey of Applications, Trends, and Challenges. *Technologies* **2025**, *13*, 559. [CrossRef]
21. Allaw, Z.; Zein, O.; Ahmad, A.-M. Cross-Layer Security for 5G/6G Network Slices: An SDN, NFV, and AI-Based Hybrid Framework. *Sensors* **2025**, *25*, 3335. [CrossRef]
22. Zaoutis, E.A.; Liodakis, G.S.; Baklezos, A.T.; Nikolopoulos, C.D.; Ioannidou, M.P.; Vardiambasis, I.O. 6G Wireless Communications and Artificial Intelligence-Controlled Reconfigurable Intelligent Surfaces: From Supervised to Federated Learning. *Appl. Sci.* **2025**, *15*, 3252. [CrossRef]
23. Mutescu, P.-M.; Petrariu, A.-I.; Coca, E.; Patachia-Sultanoiu, C.; Mihai, R.M.; Lavric, A. AI-Native PHY-Layer in 6G Orchestrated Spectrum-Aware Networks. *Sensors* **2025**, *25*, 7206. [CrossRef] [PubMed]
24. Fan, P.; Zhao, J.; I, C.-L. 5G high mobility wireless communications: Challenges and solutions. *China Commun.* **2016**, *13*, 1–13. [CrossRef]
25. Qualcomm Technologies. Make the Migration from 5G to 6G a Rewarding Experience. Available online: https://www.qualcomm.com (accessed on 15 January 2026).

26. Ishibashi, T.; Muramoto, Y.; Yoshimatsu, T.; Ito, H. Uni-traveling-carrier photodiodes for terahertz applications. *IEEE J. Sel. Top. Quantum Electron.* **2014**, *20*, 79–88. [CrossRef]
27. Akyildiz, I.F.; Jornet, J.M.; Han, C. Terahertz band: Next frontier for wireless communications. *Phys. Commun.* **2014**, *12*, 16–32. [CrossRef]
28. Akyildiz, I.F.; Jornet, J.M.; Han, C. TeraNets: Ultra-broadband communication networks in the terahertz band. *IEEE Wirel. Commun.* **2014**, *21*, 130–135. [CrossRef]
29. Federal Communications Commission (FCC). FCC Takes Steps to Open Spectrum Horizons for New Services and Technologies. Available online: https://docs.fcc.gov/public/attachments/doc-356588a1.pdf (accessed on 15 January 2026).
30. Abadal, S.; Han, C.; Jornet, J.M. Wave propagation and channel modeling in chip-scale wireless communications. *IEEE Access* **2019**, *8*, 278–293. [CrossRef]
31. Nagatsuma, T.; Ducournau, G.; Renaud, C.C. Advances in terahertz communications accelerated by photonics. *Nat. Photonics* **2016**, *10*, 371–379. [CrossRef]
32. Nagatsuma, T.; Carpintero, G. Recent progress and future prospect of photonics-enabled terahertz communications research. *IEICE Trans. Electron.* **2015**, *98*, 1060–1070. [CrossRef]
33. Ito, H.; Ishibashi, T. Photonic terahertz-wave generation using slot antenna-integrated uni-traveling-carrier photodiodes. *IEEE J. Sel. Top. Quantum Electron.* **2017**, *23*, 1–7. [CrossRef]
34. Kloosterman, J.L.; Hayton, D.J.; Ren, Y.; Kao, T.-Y.; Hovenier, J.; Gao, J.R.; Klapwijk, T.M.; Hu, Q.; Walker, C.K.; Reno, J.L. Hot electron bolometer heterodyne receiver with a 4.7-THz quantum cascade laser as a local oscillator. *Appl. Phys. Lett.* **2013**, *102*, 011123. [CrossRef]
35. Burford, N.M.; El-Shenawee, M.O. Review of terahertz photoconductive antenna technology. *Opt. Eng.* **2017**, *56*, 010901. [CrossRef]
36. Yachmenev, A.E.; Lavrukhin, D.V.; Glinskiy, I.A.; Zenchenko, N.V.; Goncharov, Y.G.; Spektor, I.E.; Khabibullin, R.A.; Otsuji, T.; Ponomarev, D.S. Metallic and dielectric metasurfaces in photoconductive terahertz devices: A review. *Opt. Eng.* **2019**, *59*, 061608. [CrossRef]
37. Momeni, O.; Afshari, E. A broadband mm-wave and terahertz traveling-wave frequency multiplier on CMOS. *IEEE J. Solid-State Circuits* **2011**, *46*, 2966–2976. [CrossRef]
38. Gamzina, D.; Li, X.; Hurd, C.; Tang, Y.; Huang, X.; Zheng, Y.; Himes, L.; Gonzalez, M.; Li, H.; Pan, P.; et al. Backward wave oscillator for high-power generation at THz frequencies. In *Terahertz Emitters, Receivers, and Applications VIII*; SPIE: Bellingham, WA, USA, 2017.
39. Vazquez, P.; Grzyb, J.; Sarmah, N.; Pfeiffer, U.R.; Heinemann, B. Towards THz high data-rate communication: A 50-Gbps all-electronic wireless link at 240 GHz. In Proceedings of the 4th ACM International Conference on Nanoscale Computing and Communication, Washington, DC, USA, 27–29 September 2017.
40. Zak, A.; Andersson, M.A.; Bauer, M.; Matukas, J.; Lisauskas, A.; Roskos, H.G.; Stake, J. Antenna-integrated 0.6-THz FET direct detectors based on CVD graphene. *Nano Lett.* **2014**, *14*, 5834–5838. [CrossRef]
41. Andersson, M.A.; Zhang, Y.; Stake, J. A 185–215-GHz subharmonic resistive graphene FET integrated mixer on silicon. *IEEE Trans. Microw. Theory Tech.* **2017**, *65*, 165–172. [CrossRef]
42. Akyildiz, I.F.; Jornet, J.M. Graphene-Based Plasmonic Nano-Antenna for Terahertz Band Communication. U.S. Patent 14/253,539, 9 May 2017.
43. Akyildiz, I.F.; Jornet, J.M. Graphene-Based Plasmonic Nano-Transceiver Employing HEMT for Terahertz Band Communication. U.S. Patent 14/560,213, 19 July 2016.
44. Jornet, J.M.; Akyildiz, I.F. Channel modeling and capacity analysis for electromagnetic wireless nanonetworks in the terahertz band. *IEEE Trans. Wirel. Commun.* **2011**, *10*, 3211–3221. [CrossRef]
45. Jornet, J.M.; Akyildiz, I.F. Graphene-based plasmonic nano-transceiver for terahertz band communication. In Proceedings of the 8th European Conference on Antennas and Propagation (EuCAP), The Hague, The Netherlands, 6–11 April 2014.
46. Han, C.; Jornet, J.M.; Akyildiz, I.F. Ultra-massive MIMO channel modeling for graphene-enabled terahertz-band communications. In Proceedings of the IEEE Vehicular Technology Conference (VTC Spring), Porto, Portugal, 3–6 June 2018.
47. Priebe, S.; Kürner, T. Stochastic modeling of THz indoor radio channels. *IEEE Trans. Wirel. Commun.* **2013**, *12*, 4445–4455. [CrossRef]
48. He, D.; Guan, K.; Fricke, A.; Ai, B.; He, R.; Zhong, Z.; Kasamatsu, A.; Hosako, I.; Kürner, T. Stochastic channel modeling for kiosk applications in the terahertz band. *IEEE Trans. Terahertz Sci. Technol.* **2017**, *7*, 502–513. [CrossRef]
49. Cid-Fuentes, R.G.; Jornet, J.M.; Akyildiz, I.F.; Alarcón, E. A receiver architecture for pulse-based electromagnetic nanonetworks in the terahertz band. In Proceedings of the IEEE International Conference on Communications (ICC), Ottawa, ON, Canada, 10–15 June 2012.
50. Han, C.; Akyildiz, I.F.; Gerstacker, W.H. Timing acquisition and error analysis for pulse-based terahertz band wireless systems. *IEEE Trans. Veh. Technol.* **2017**, *66*, 10102–10113. [CrossRef]

51. Xia, Q.; Hossain, Z.; Medley, M.J.; Jornet, J.M. A link-layer synchronization and medium access control protocol for terahertz-band communication networks. *IEEE Trans. Mob. Comput.* **2019**, *20*, 2–18. [CrossRef]
52. Kürner, T.; Priebe, S. Towards THz communications—Status in research, standardization and regulation. *J. Infrared Millim. Terahertz Waves* **2014**, *35*, 53–62. [CrossRef]
53. Gharouni-Chamansabz, A.; Moldovan, A.; Gerstacker, W.H. Performance comparison of equalization techniques for indoor THz communications. In Proceedings of the ACM International Conference on Nanoscale Computing and Communication, Washington, DC, USA, 27–29 September 2017.
54. Han, C.; Zhang, X.; Wang, X. On medium access control schemes for wireless networks in the millimeter-wave and terahertz bands. *Nano Commun. Netw.* **2019**, *19*, 67–80. [CrossRef]
55. Choudhury, R.R.; Vaidya, N.H. Deafness: A MAC problem in ad hoc networks when using directional antennas. In Proceedings of the IEEE International Conference on Network Protocols, Berlin, Germany, 8 October 2004.
56. *IEEE 802.15.3c*; Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specification for High-Rate Wireless Personal Area Networks. IEEE: New York, NY, USA, 2009.
57. Han, C.; Tong, W.; Yao, X.-W. MA-ADM: A memory-assisted angular-division-multiplexing MAC protocol in terahertz communication networks. *Nano Commun. Netw.* **2017**, *13*, 51–59. [CrossRef]
58. Gao, X.; Dai, L.; Zhang, Y.; Xie, T.; Dai, X.; Wang, Z. Fast channel tracking for terahertz beamspace massive MIMO systems. *IEEE Trans. Veh. Technol.* **2016**, *66*, 5689–5696. [CrossRef]
59. Zhang, M.; Zhang, S.; Cao, J. Fusing received signal strength from multiple access points for WLAN user location estimation. In Proceedings of the International Conference on Internet Computing in Science and Engineering, Harbin, China, 28–29 January 2008; pp. 173–180.
60. Li, R. Towards a new internet for the year 2030 and beyond. In Proceedings of the Third Annual ITU IMT-2020/5G Workshop and Demo Day, Geneva, Switzerland, 18 July 2018.
61. Mohapatra, S.; Mohanty, S.; Mohanty, S. Smart healthcare: An approach for ubiquitous healthcare management using IoT. In *Big Data Analytics for Intelligent Healthcare Management*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 175–196.
62. Bresson, G.; Alsayed, Z.; Yu, L.; Glaser, S. Simultaneous localization and mapping: A survey of current trends in autonomous driving. *IEEE Trans. Intell. Veh.* **2017**, *2*, 194–220. [CrossRef]
63. Shakeri, R.; Al-Garadi, M.A.; Badawy, A.; Mohamed, A.; Khattab, T.; Al-Ali, A.K.; Harras, K.A.; Guizani, M. Design challenges of multi-UAV systems in cyber-physical applications: A comprehensive survey and future directions. *IEEE Commun. Surv. Tutor.* **2019**, *21*, 3340–3385. [CrossRef]
64. Lasi, H.; Fettke, P.; Kemper, H.-G.; Feld, T.; Hoffmann, M. Industry 4.0. *Bus. Inf. Syst. Eng.* **2014**, *6*, 239–242. [CrossRef]
65. Abood, D.; Quilligan, A.; Narsalay, R. *Industry X.0: Combine and Conquer*; Technical Report; Accenture PLC: Dublin, Ireland, 2017.
66. Liaskos, C.; Nie, S.; Tsioliaridou, A.; Pitsillides, A.; Ioannidis, S.; Akyildiz, I.F. A novel communication paradigm for high capacity and security via programmable indoor wireless environments in next-generation wireless systems. *Ad Hoc Netw.* **2019**, *87*, 1–16. [CrossRef]