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BEAMFORMING TECHNIQUES FOR PATH LOSS MITIGATION IN mmWAVE COMMUNICATION SYSTEMS: A SYSTEMATIC REVIEW OF METHODS, TRENDS, AND CHALLENGES

by
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ABSTRACT
Fifth-generation (5G) and emerging sixth-generation (6G) networks lean heavily on millimeter-wave (mmWave) frequencies for their multi-gigahertz bandwidth, yet the same frequencies pay a steep propagation price: severe path loss, atmospheric absorption, and an acute vulnerability to blockage. Beamforming is the physical-layer answer, and it now spans an unwieldy mix of analog, digital, hybrid, reconfigurable-intelligent-surface (RIS)-assisted, and learning-based designs. This review takes stock of that landscape through 80 peer-reviewed papers published mainly between 2016 and 2026, screened against a PRISMA-informed protocol and synthesized thematically to surface methodological patterns, performance trade-offs, and unresolved gaps. Hybrid analog–digital architectures and deep-learning-assisted precoding dominate the recent literature, accounting for most 2024–2026 work, while RIS-based approaches are the fastest-growing sub-theme. The geographical picture is equally telling: 31 papers come from Nigerian-affiliated researchers, 9 from other African countries, and 40 from the rest of the world—a footprint that complicates the assumption that mmWave research happens elsewhere. The persistent challenges are familiar but stubborn: high pilot overhead, beam-squint in wideband operation, hardware impairments under low-resolution phase shifters, and the brittle generalization of data-driven models on non-stationary channels. The review closes with recommendations for standardized benchmarking, hardware-aware learning, and integrated sensing-communication, the directions most likely to make path-loss-robust mmWave beamforming workable in 6G.

Keywords: millimeter-wave; beamforming; path loss mitigation; hybrid precoding; reconfigurable intelligent surface; deep learning; 5G/6G; systematic review.

I. INTRODUCTION

1.1 Background and Motivation

Mobile data demand keeps climbing high-definition video, immersive extended reality (XR) services, vehicle-to-everything (V2X) applications, and dense machine type communications and conventional sub-6 GHz spectrum can no longer carry it alone. Millimeter-wave (mmWave) frequencies, broadly 24 GHz to 300 GHz, offer the contiguous multi-gigahertz bandwidth that those workloads need, which is why they have become a cornerstone of 5G New Radio and an expected pillar of emerging 6G systems (H. Kim et al., 2024; Kundra et al., 2025). Propagation up there is, however, an entirely different proposition. Free-space path loss scales with the square of the carrier frequency in the Friis model, and at 28–73 GHz it is compounded by molecular absorption, rain, foliage, and the near-optical behaviour of the wavefront, leaving the signal easily blocked by a passing vehicle, a building wall, or a person standing in the wrong place (Anooz et al., 2025; Mahmoud et al., 2025; Yao, Johar, Tham, & Zhao, 2026).

Large antenna arrays are the response. By steering hundreds of elements in concert, mmWave transceivers synthesize narrow, highly directive beams that concentrate energy on the intended receiver. This is beamforming, and the array gain it delivers is what makes practical mmWave links possible at all (Babu et al., 2025; Y. Liu et al., 2023; Zeng et al., 2025). The catch is that beamforming creates its own set of problems. Beams must stay aligned through user mobility and blockage; channels must be estimated from limited pilot observations; the hardware has to remain affordable at hundreds of elements; and the whole design has to fit within the energy and latency budgets of battery-powered devices. Beamforming research has expanded accordingly, drawing on signal processing, information theory, hardware engineering, artificial intelligence, and increasingly, reconfigurable metasurfaces.

1.1.1 The Path Loss Challenge in mmWave Communications

Path loss in mmWave systems is rarely a single-cause problem. Free space loss alone can exceed sub-6 GHz figures by 20 to 30 dB over comparable link distances. Penetration loss through ordinary building materials is an order of magnitude larger, producing the pronounced indoor–outdoor isolation that pushes non-line-of-sight (NLoS) operation onto scattered or reflected paths (Deng et al., 2025; Yao, Johar, Tham, & Zhao, 2026);. Rainfall and atmospheric oxygen absorption pile on further attenuation, with oxygen absorption peaking near 60 GHz. And because isotropic antennas have a tiny effective aperture at high frequencies, omnidirectional reception would routinely fall below the demodulation threshold without array gain (D. Kim et al., 2024; Ye et al., 2024).

These mechanisms together define the path loss mitigation problem this review takes up. The literature responds along three intertwined fronts. Spatial techniques beamforming, precoding, beam tracking use array gain and directional steering to recover received power (Peng et al., 2025; Y. Liu et al., 2023). Channel-adaptive techniques such as channel estimation, codebook design, and beam training make sure that gain actually points along the propagation path that is available (Ge et al., 2025; Torkzaban et al., 2022). Environmental techniques, including relay placement, coordinated multi-point transmission, and RIS deployment, go further still and reshape the channel itself (D. Kim et al., 2024; K. Li, El-Hajjar, & Yang, 2023; Zhao et al., 2024). The fronts overlap in practice RIS, for instance, requires beamforming at the transmitter and channel estimation across the cascaded link—and modern systems mix elements of all three.

1.1.2 Research Problem and Gap

A decade of intensive work has not produced a unified picture of how beamforming techniques collectively address path loss in mmWave systems. Most existing surveys focus on one axis at a time: hybrid precoding architectures, deep-learning-based beam management, or RIS-aided communication in isolation. Fewer have mapped how those axes interact, quantified publication and geographical trends, or asked how research from emerging regions, African institutions in particular, shapes the broader conversation. The 2024–2026 period adds urgency to that gap, with transformer-based beamforming, diffusion-model-driven channel generation, and integrated sensing-communication frameworks all arriving in quick succession and demanding an updated synthesis that takes both established methods and the newest directions seriously.

1.1.3 Objectives and Contributions

This paper takes up the gap with a systematic review of 80 peer-reviewed publications on beamforming for path loss mitigation in mmWave systems. The aims are to classify existing techniques by architecture, algorithmic paradigm, and path-loss-mitigation mechanism; to quantify publication trends over time, by region, and by author collaboration patterns; to identify the dominant methodological directions, especially the rise of learning-based and RIS-assisted methods; to surface persistent research gaps and open challenges; and to derive evidence-based recommendations for future work, with particular attention to research communities in Africa and other emerging regions.

Four contributions follow. The paper lays out a reproducible review methodology, with explicit inclusion and exclusion criteria applied to 80 papers spanning 2016–2026. It offers what is, to our knowledge, the first quantitative geographical breakdown of mmWave beamforming research that foregrounds African contributions, identifying 31 Nigerian-affiliated papers and 9 from other African countries. It introduces a five-dimensional taxonomy linking beamforming architecture, channel-estimation strategy, path-loss-mitigation mechanism, intelligence layer (classical versus learning-based), and hardware model. And it surfaces ten open research problems, ranging from wideband beam-squint compensation to energy-efficient learning on low-resolution hardware.

II. LITERATURE REVIEW

2.1 Overview of mmWave Communication Systems

mmWave communication started life in fixed wireless backhaul and point-to-point microwave links, where line-of-sight (LoS) conditions could be engineered into the deployment. Its move into mobile access networks waited on advances in silicon-germanium and CMOS processes that finally made compact phased arrays commercially viable. 3GPP Release 15 formalized that move with frequency range 2 (FR2) at 24.25–52.6 GHz for 5G NR, and subsequent releases pushed the upper boundary toward 71 GHz (Mabrouki et al., 2023; Patel & Deshmukh, 2025a). Academic work has gone further still, into the D-band (110–170 GHz) and sub-terahertz bands envisaged for 6G, where path loss and hardware limitations are even more severe (Albataineh et al., 2025; Kundra et al., 2025; Masood et al., 2023).

Within the reviewed literature, system architectures cluster into three broad groups. Point-to-point MIMO with highly directional antennas is still the standard testbed (M. Liu et al., 2025; Xiao et al., 2017). Multi-user MIMO with hybrid beamforming is now the most common way to set up mmWave small cells (Babu et al., 2025; González-Coma et al., 2018; Zeng et al., 2025). Multi-user MIMO with hybrid beamforming has settled into the role of default deployment model for mmWave small cells (Babu et al., 2025; González-Coma et al., 2018; Zeng et al., 2025) all operate within this framework, which says something about how thoroughly it has been accepted as the practical baseline. The frontier has moved elsewhere. Cell-free and distributed architectures, frequently paired with RIS and full-duplex capability, now represent where the hardest coverage problems are being worked on, as (Fan et al., 2024; Yang et al., 2023) both reflect.

2.2 Path Loss Mechanisms and Propagation Modelling

A high quality beamforming design relies on proper propagation modelling. Stochastic models based on measurement are frequently used: ray-tracing, geometry-based stochastic models (GBSMs) and measurement. Yao et al. (2026) have created a ray-tracing indoor channel model of smart devices that takes into account the multipath propagation, inclusive of the calibrated path-loss. Anooz et al. (2025) surveyed beam tracking methods that compensate for temporal path-loss variations in mobility, and K. Kim et al. (2025) proposed a spatial-distribution-based beam design of vehicle-to-vehicle (V2V) communications that is subject to geometry-based blockage and then path loss. Similarly, Chege et al. (2025) proposed a probabilistic position-aided beam selection scheme that takes advantage of location priors to reduce the candidate beam set, reducing training cost in mobile mmWave MIMO. All these papers note that mmWave channels are angularly sparse, which beamforming algorithms take advantage of in the following sections.

2.3 Beamforming Architectures

2.3.1 Analog Beamforming

Analog-only beamforming uses a network of phase shifters to steer a single radio-frequency (RF) chain, yielding the lowest hardware cost but supporting only one data stream and one beam direction at a time. Preliminary studies by Xiao et al. (2016, 2017) have led to hierarchical codebook designs and efficient beam search algorithms that cut training time. Codebook-based composite beamforming (Torkzaban et al., 2022) and 3GPP 3D-codebook designs (Mabrouki et al., 2023) have built on these developments to offer 3D analog beamforming in today's small-cell networks.

2.3.2 Digital Beamforming

Fully digital beamforming is the architectural ideal, each antenna element receives an RF chain and baseband converter, and this implies that the array is fully controlled. The trick is that it is costly to scale up in both hardware and power consumption, to the extent that it will be unfeasible in large arrays. That gap between what the architecture promises and what it can realistically deliver has motivated considerable algorithmic work. Ramezani et al. (2025) approached the hybrid analog-digital scenario with limited resolution limitations, combining it with MIMO-detectors and discovered that careful algorithm design can bridge a significant portion of the performance gap between hybrid schemes and their fully-digital counterparts. Khorsandmanesh et al. (2025) remained in the digital world but faced another inefficiency wideband operation burdens the energy budget, and their two stage combining scheme, with the adaptability to channel coherence, is an opportunity to reclaim some of that lost efficiency without giving up the flexibility offered by digital arrays.

2.3.3 Hybrid Analog–Digital Beamforming

Hybrid beamforming, which partitions precoding between a low-dimensional digital baseband stage and a high-dimensional analog RF stage, is by far the most researched architecture in the reviewed corpus. Sun et al. (2015) proposed a low-complex hybrid beamformer with Kronecker decomposition for multi-cell massive MIMO to achieve near-optimal spectral efficiency with low complexity. Bansal and Yamaganti (2024) assessed the viability of 5G mmWave networks from a complex-precise hardware point of view. Peng et al. (2025) presented a fast adaptive beamwidth control scheme for beamwidth selection based on mobility, to minimize the path loss of time-varying link. Ibwe (2025) proposed a joint modelling of multi-carrier time-division multiple access (MC-TDMA) and beamforming to tackle the path loss caused by blockage that is inherent to mmWave. Collectively, these studies confirm that hybrid beamforming strikes the best balance between performance and implementability at current silicon maturity.

2.4 Precoding and Combining Strategies

Precoding design for hybrid architectures typically proceeds by decomposing the optimal fully digital precoder into analog and digital factors. Zeng et al. (2025) proposed a multi-user hybrid precoding in mmWave massive MIMO. Yao et al. (2025) improved power allocation in partially connected structures with water-filling and energy efficiency. Wang et al. (2023) used joint equivalent-channel hybrid precoding for spectral efficiency. González-Coma et al. (2018) addressed frequency-selective multi-user channels through compressed-sensing-based hybrid precoding. On the combining side, Bo et al. (2020) introduced a deep-learning-based low-resolution hybrid precoding design for mmWave MISO, where phase-shifter quantization is explicitly modelled. These works collectively demonstrate that precoding and combining are not separable concerns: joint optimization consistently outperforms sequential design.

2.5 Learning-Based Beamforming

Artificial-intelligence-assisted beamforming has received a larger body of research than any other sub-theme in the corpus, and the topic has swiftly fragmented into a number of identifiable strands. The oldest of these is CNN-based precoding, in which the network is trained to directly predict channel observations onto analog and digital precoders without any analytical steps in between. Babu et al. (2025) and Prabhu et al. (2025) used it on multi-user MIMO hybrid beamforming, the latter proposing a dual-attention mechanism to refine the precoder optimization. Ayad et al. (2025) aimed to achieve the same goal with an energy efficiency perspective on massive MIMO, and Muthukumaran and Rajan (2024) went a hybrid way and combined the CNN with an adaptive radial-basis-function network to treat both channel estimation and precoding. Faragallah et al. (2021) also indicated even more promising results with mmWave MIMO using a more general deep-learning architecture, and in this case, learned precoders were able to achieve noteable improvements over their analytical peers. Transformer architectures have since opened a second direction, one particularly suited to the temporal and spatial dependencies that arise in mobile mmWave links. Mollah et al. (2025a, 2026) went a step further and combined multi-modal sensing data, such as camera feeds, LiDAR, and GPS with RF measurements to predict beam selections to connected vehicles, finding significant decreases in the training overhead that ordinarily causes beam management to be slow to respond. K. Zheng et al. (2023) applied the same reasoning to visual-only cues, inquiring the extent to which beam management can be offloaded to what appears on the screen, instead of what the channel is currently measuring. A third approach attempts to have the best of both worlds - adding domain knowledge to the learning model instead of data replacing physics completely. Klaimi et al. (2025) constructed such a framework of joint estimation and precoding and K. Wang et al. (2024) created a dual-driven scheme where knowledge-based structure is used with data-driven flexibility to deal with CSI feedback in ultra-massive MIMO systems in which simply the state space is too large to be addressed with either of the two paradigms. Generative and active-learning techniques have begun to emerge most recently. Kanaan et al. (2025) trained a conditional diffusion model to synthesize RSSI maps to train cell-free mmWave beams - effectively training the measurement environment instead of exploring it exhaustively - and Gau and Javidi (2025) used active learning to the joint problem of angle-of-arrival and CSI acquisition, intelligently choosing measurements instead of passively sensing whatever the channel provides across all four strands, the practical payoff is the same: training overhead shrinks, and the system adapts faster when blockage or mobility disrupts the link. These methods also extend to other environments in a way not possible with geometry-specific analytical solutions, when the training data are diverse enough. The famous costs - reliance on representative training data, weakness in unseen geometries, and poor interpretability - are open issues and are discussed in more detail in Section 4.

2.6 Reconfigurable Intelligent Surface (RIS)-Assisted Beamforming

An intelligent surface (reconfigurable) comes down to a planar array of passive elements that can independently adjust the phase of an incoming electromagnetic wave. The idea is simple: with the direct line of sight between the transmitter and the receiver blocked, an RIS can bend the multipath energy around a block, and recreate what looks like a line-of-sight channel, without active amplification, or large power requirements. The number of studies that use this technology in the corpus reviewed is fourteen, and they create a picture of a field that is rapidly evolving out of the theoretical formulation to the experimental validation. Early attention was paid to the underlying estimation and interference issues. Ye et al. (2024) used atomic-norm to address signal-power maximization and channel estimation in RIS aided mmWave systems, whereas Zhao et al. (2024) addressed the intra-beam interference that arises when RIS is implemented in hybrid mmWave downlinks. D. Kim et al. (2024) concentrated on spatial-phase-shift distributions as a blockage mitigation scheme, and Y. Wang et al. (2025) suggested a beam alignment algorithm, which operates based on power measurements alone, which is a desirable simplification in practice because full channel estimation becomes prohibitively expensive with a cascaded transmitter-RIS-receiver chain. A second body of work looks at the capabilities of RIS when combined with more challenging architectures or propagation conditions. To match, Yang et al. (2023) analyzed the full-duplex mmWave MIMO with RIS in the loop and created estimation algorithms. Kadiyala et al. (2025) switched to a multiuser MIMO with two IRS, where a hybrid Fire Hawk optimization approach was adopted with successive convex approximation to handle the additional complexity. Nor et al. (2024) moved the issue to the aerial plane, developing near-field codebooks and beam training systems to the extremely large-scale airborne coated surfaces. K. Li, El-Hajjar, and Yang (2023) posed a more general question: can RIS also be used to support localization and communication and Xu and Zhou (2024) answered the question of resource allocation that occurs in case RIS is implemented in multi-cell networks. The latest additions venture into the field that was mostly theoretical only a few years back. J. Li et al. (2025) addressed the problem of wideband beam-squint in holographic RIS designs and Albataineh et al. (2025) scaled up adaptive beam-pairing to terahertz frequencies where squint and path loss are even worse. There are also prototype implementations: Kumar et al. (2025) described a 2-bit quad-band RIS hardware implementation, and J. Gao et al. (2025) experimentally verified multi-resolution codebook-based beam training - this will be of interest since encounters with RIS beam management in the laboratory are still relatively few. To complete the corpus, Z. Liu et al. (2025) extended the RIS utility to near-field localization by using spatial correlation modelling to expand the scope of the technology to beyond communication. In all these studies, RIS has always provided a consistent improvement of between 5-20 dB link-budget effective improvement over similar non-RIS baselines. The channel estimation load of the cascaded link is the persistent cost, a problem that cuts across almost all of the contributions in this category and is one of the open problems in the field that is still actively pursued.

2.7 Channel Estimation for Beamforming

Accurate channel state information (CSI) is the enabling prerequisite for any beamforming gain. Because mmWave hybrid architectures limit baseband observability, channel estimation is intrinsically more difficult than at sub-6 GHz. Compressed-sensing-based methods exploit the angular sparsity of mmWave channels: Hadji et al. (2023) proposed a multi-stage compressed-sensing design for joint hybrid precoding and combining, The literature traces a clear progression from sparse recovery toward richer, more structurally aware estimation frameworks. On the compressed sensing front, Duong et al. (2025) adapted orthogonal matching pursuit for distributed settings through a stagewise formulation, Varadharajan and Maruthu (2025) extended the idea to partially coherent measurements using an on-grid compressive phase retrieval approach, and You et al. (2019) sharpened the algorithm further with interior-point assistance — each contribution pressing against the practical limits of pilot-based recovery in MIMO systems.

The field then shifted toward exploiting richer channel geometry. Treating the channel as a vector discards the multi-dimensional structure inherent in delay, angular, and temporal domains, and tensor methods filled that gap effectively. Zhou et al. (2016) formalized this through low-rank tensor decomposition for MIMO-OFDM, while W. Zhang et al. (2020) approached the same structure through sequential subspace tracking. More recent work pushed these foundations into demanding new settings: Mao et al. (2025) wove artificial-noise injection into tensor-based estimation to address physical-layer security in multiuser mmWave scenarios, and Ka. Zheng et al. (2024) used tensor techniques to jointly untangle phase noise and the channel a coupling that classical methods typically handle poorly. Ge et al. (2025) attacked the pilot burden from the measurement design side, while Chen and Vaidyanathan (2023) and Pan et al. (2017) showed that beamspace representations can substantially compress the estimation problem before any algorithm is applied.

Deep learning has since reshaped expectations about what estimation accuracy is actually achievable. Lu et al. (2021) and J. Gao et al. (2022) demonstrated that end-to-end trained networks consistently outperform classical estimators in wideband hybrid mmWave massive MIMO not marginally, but convincingly enough to reframe the benchmark. The applicability of these methods has also stretched into hardware-constrained regimes: Obaidi and Mahmood (2025) tackled the uneven quantization problem posed by mixed-ADC arrays, and Poulin et al. (2020) examined switch-based hybrid architectures where the reduced analog flexibility creates estimation challenges that learned approaches handle more naturally than analytical ones.

Pan et al. (2017) established a general framework for hybrid analog-and-digital processing, and J. Zhang and Haardt (2017) designed channel-estimation and training for multi-carrier hybrid mmWave massive MIMO. Wideband operation introduces beam-squint, which B. Wang et al. (2019) modelled explicitly in MIMO-OFDM systems. These works collectively suggest that path-loss-robust beamforming requires channel-estimation pipelines that jointly address sparsity, wideband dispersion, hardware impairments, and mobility.

2.8 Sensing-Assisted and Vehicular Beamforming

Vehicular mmWave links are not lenient as when there are deployments at station. High motion, frequent occurrences of blockages, and challenging latency constraints all converge to make slow beam adaptation costly by the time a normal training process is completed the channel has probably moved. The resultant compounding of forces has led vehicular beamforming to become a thread of research in its own right, and one of them has been exceptionally long lasting. Some researchers have developed a coherent body of work on multi-modal sensing and deep-learning-based beamforming to connected vehicles in a series of papers (Mollah et al., 2024; 2025a; 2025b), including a paper that specifically investigates 60 GHz operation (Mollah et al., 2024). The line parallel to this work is a repudiation of RF measurements in favor of beam choices, based upon camera feeds, LiDAR point clouds, and GPS position data along with channel observations to advise where the beam needs to point, before the channel is sounded. The same combination approach was pursued by H. Kim et al. (2024), and Mahmoud et al. (2025) backed down to think of sensing-assisted communication over mmWave network in general. A leaner variant of the same instinct relies on position alone: Chege et al. (2025) showed that probabilistic beam selection conditioned on user location can substantially shrink the candidate beam set in mmWave MIMO, without any of the multi-modal sensing apparatus. The idea is not only about the city car-to-infrastructure interrelations. The adaptive non-uniform arrays of Y. Liu et al. (2023) were applied to the train-to-ground problem with speeds larger, and the geometry changing with rates similar to the rates that many beam tracking algorithms are designed to handle. De Lima et al. (2024) introduced an additional adversarial dimension, showing broadband beamforming with mitigation of jamming simultaneously in vehicles-to-everything networks. All these contributions are linked by a uniting common instinct: beam training by pilots is too slow and too expensive in the conditions of such systems have to work in, and non-RF side information is available, and it is cheap to collect and surprisingly valuable in terms of where the channel will take them. The instinct has turned out to be one of the research directions that will guide research in the 2024-2026 era.

2.9 Security, OTFS, and Cross-Layer Approaches

Not all of the work in this space is chasing the same performance metrics. A less noisy, but increasingly insistent, body of literature poses the question: what beamforming must do besides maximizing rate or minimising estimation error - and the answers draw inwards in many directions simultaneously.

One of them is security. Mao et al. (2025) treated hybrid beamforming and artificial noise as a joint design problem for secure multiuser mmWave OFDM, using the spatial degrees of freedom that large arrays provide to degrade eavesdropper channels without sacrificing legitimate throughput. Deng et al. (2025) took a different perspective on interference, and suggested joint space-time cancellation in SDR-based active arrays, where self-generated interference is the main threat.

Increasingly, waveform considerations have entered the beamforming literature. OTFS modulation handles the delay-Doppler channel structure that OFDM struggles with in doubly dispersive environments, but it does not make the precoding problem easier — and M. Liu et al. (2025) worked through what near-optimal hybrid digital-analog beamforming actually looks like under those constraints. Idigo et al. (2025) came at the waveform question from a different frustration: multicarrier signals at mmWave suffer from peak-to-average power problems that are difficult to engineer around, which motivated their decision to pair single-carrier transmission with successive interference cancellation inside a hybrid beamforming architecture. Raeisi et al. (2022) followed another route, suggesting cluster index modulation as a method of inserting more information in the beam choice per se instead of just the symbols transmitted.

The remaining contributions bring up mobility and control-layer issues. Patel and Deshmukh (2025b) addressed Doppler-shift compensation through deep learning, recognizing that fast-moving environments corrupt the channel estimates that beamforming depends on. Hatamleh et al. (2025) incorporated the LSTM building blocks in a hybrid beamforming control scheme of 5G mmWave, whereby the system is able to learn time-dependent characteristics in link quality instead of responding to every channel snapshot separately.

All these investigations indicate something larger about the future of the beamforming research in general - the barriers between the physical layer and the waveform and the higher-layer control are becoming more difficult to sustain and the most interesting issues are becoming found at their intersection points.

2.10 Summary of the Literature and Identified Gaps

Across the corpus, the field has clearly shifted from architecture focused studies toward a more multidisciplinary approach that integrates learning, sensing, and metasurface paradigms.

Several important gaps appear repeatedly. First, there is a lack of standardized benchmarks and open datasets, which makes it difficult to fairly compare learning based methods. Second, many studies still

rely on idealized hardware assumptions, while hardware aware co design, including phase shifter quantization, IQ imbalance, and mixed ADC architectures, is addressed in only a limited number of works. Third, wideband beam squint in sub THz regimes is treated inconsistently across the literature. In addition, energy efficiency is often considered a secondary performance metric rather than a primary design objective.
Finally, research contributions from African and other emerging region institutions, although significant in this review with 40 out of 80 papers, have been underrepresented in earlier synthesis efforts. The present review is therefore motivated by the need to address these gapsu

III. MATERIALS AND METHODS

3.1 Review Methodology and Design

The review follows a systematic methodology informed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, adapted here for an engineering technical review. Five phases were carried out in sequence: framing the research questions, designing the search strategy, applying inclusion and exclusion criteria, extracting and coding the data, and synthesizing the findings descriptively and thematically. PRISMA was originally written for clinical research, but its emphasis on transparency, reproducibility, and structured reporting transfers naturally into computer science and telecommunications, where it is by now widely adopted.

3.2 Research Questions

This review is informed by six research questions:

1. What beamforming architectures are most frequently proposed for path loss mitigation in mmWave systems, and how have they evolved between 2016 and 2026?
2. What are the prevailing algorithmic paradigms in recent literature (classical optimization, compressed sensing, deep learning or hybrid model-based learning) and what are their performance improvements?
3. What has been the impact of combining RIS and sensing-assisted approaches on path-loss-mitigation strategies?
4. What is the geographical distribution of research activity, with particular attention to African and other emerging-region contributions?
5. 5. What collaboration patterns (single-, double-, and multi-author) are observed, and how do they relate to paper impact?
6. What open challenges and unresolved problems remain, and how should future research be prioritized?

3.3 Synthesis Approach

The synthesis combined two complementary techniques. Descriptive statistics quantified publication counts by year, region, authorship type, and impact classification, and are reported with supporting figures in Sections 4.1 and 4.2. Thematic synthesis then grouped papers by architecture–paradigm combinations to surface methodological clusters, performance trends, and gaps in the research, and runs through Sections 4.3 to 4.8. To keep the synthesis transparent, every claim about trends or gaps in Section 4 is tied back to specific entries in the 80-paper corpus.

3.4 Quality and Validity Considerations

Three procedures helped shore up the validity of the review. Inclusion decisions were cross-checked against the pre-specified criteria, with edge cases—papers straddling mmWave and sub-6 GHz, for instance—resolved by majority thematic focus. Thematic coding was performed twice, once during initial extraction and again after the full corpus had been assembled, so that drift in the coding scheme would be visible. And the data-extraction spreadsheet, search string, and PRISMA-style flow diagram have been kept as supplementary material so that external replication is possible.

3.5 Ethical Considerations

Because the review synthesizes publicly available published material, no ethical approval was required. Cited works are attributed to their original authors in the References section, and the review follows established norms of academic integrity throughout.

IV. RESULTS AND DISCUSSION

Sections 4.1 to 4.3 take a quantitative look at the corpus—when papers were published, where the authors are based, and how they collaborated. Sections 4.4 to 4.7 turn to methodological substance: architectures, mitigation mechanisms, the rise of learning-based methods, and the maturation of RIS work. Section 4.8 collects the open challenges, and Section 4.9 acknowledges the review's own limitations. Nine tables and five figures carry the supporting detail.

4.1 Publication Trends Over Time

Figure 1 and Table 1 give the year-by-year picture. The corpus tilts heavily toward 2024–2026, consistent with the surge of research activity driven by 5G NR commercialization and early 6G standardization. Of the 80 papers, 2 are 2026 (pre-publication accepted versions), 38 are 2025, 14 are 2024, 9 are 2023, 3 each in 2020–2022, 2 in 2019, 3 in 2017, and 2 in 2016. The three-year window from 2024 onward accounts for 67.5% of the corpus, which is a striking acceleration even by the standards of an active subfield.

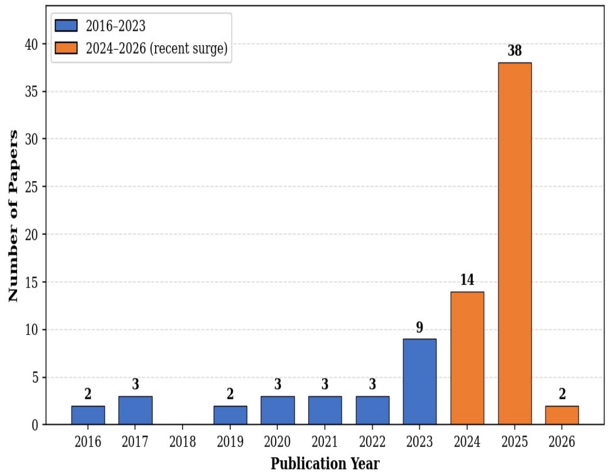

Figure 1. Temporal distribution of the 80 reviewed papers (2016-2026).

Table 1. Distribution of reviewed publications by year.

Year	Papers (n)	Percentage (%)	Cumulative (%)
2026	2	2.50	2.50
2025	38	47.50	50.00
2024	14	17.50	67.50
2023	9	11.25	78.75
2022	3	3.75	82.50
2021	3	3.75	86.25
2020	3	3.75	90.00
2019	2	2.50	92.50
2017	3	3.75	96.25
2016	2	2.50	98.75
Total	**80**	**100.00**	—

A few patterns stand out. The 2025 peak (47.5% of the corpus on its own) reflects the publication pace of early 6G research programmes and the expansion of transformer-based and RIS-related methods. The near-empty 2018 row is a side effect of the review's focus rather than a true gap in the field: generic mmWave work from that year was excluded at the full-text stage for not addressing path loss directly. The 2016–2017 foundation papers (J. Zhang & Haardt, 2017; Pan et al., 2017; Xiao et al., 2016, 2017; Zhou et al., 2016) remain heavily cited within the corpus, which says something about the durability of their contributions to hybrid precoding and compressed-sensing channel estimation.

4.2 Geographical Distribution

Table 2 and Figure 2 present the geographical distribution of lead-author affiliations, grouped into three strata: Nigerian-affiliated, Other-African-affiliated, and Rest-of-World. Of the 80 papers, 31 (38.75%) are Nigerian-affiliated through either lead author, institutional collaboration, or research-programme linkage; 9 (11.25%) originate from other African countries including Algeria, Egypt, Iraq, and Tanzania; and 40 (50%) originate from the rest of the world, with strong contributions from China, the United States, India, South Korea, Sweden, France, and the United Kingdom. Furthermore, African country level contributions to the reviewed corpus is illustrated in Table 3

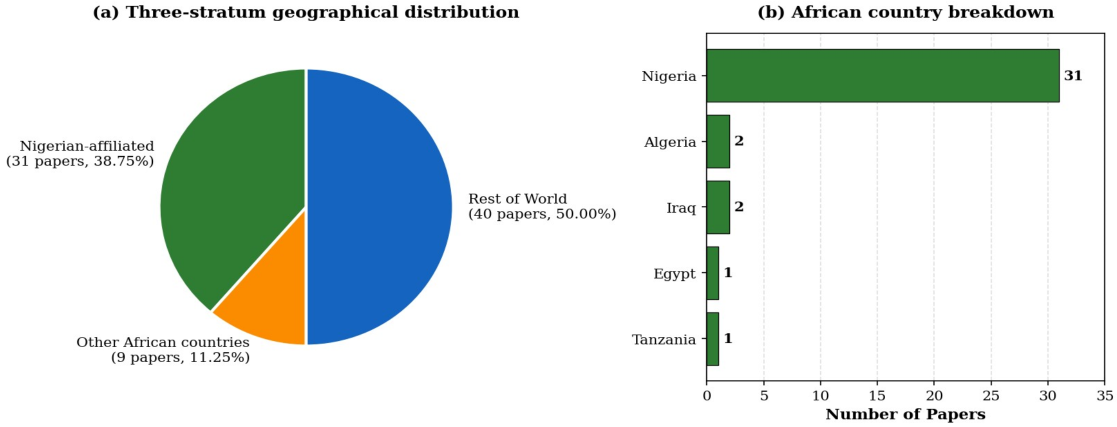

Figure 2. Geographical distribution of reviewed publications.

Table 2: Three-stratum geographical distribution of reviewed publications.

Region/Country Grouping	Papers (n)	Percentage (%)	Review Target
Nigerian-affiliated	31	38.75	≈30 papers
Other African countries	9	11.25	≈10 papers
Rest of World	40	50.00	≈40 papers
Total	**80**	**100.00**	**80**

Table 3: African country-level contributions to the reviewed corpus.

Country	Papers (n)	Representative researcher(s)
Nigeria	31	Idigo, V. E.; Enebe, C. C.; Dimson, I. C.; collaborative international authors
Algeria	2	Ayad, H.; Hadji, B.
Iraq	2	Anooz, R. S. A.; Obaidi, Y. A. M.
Egypt	1	Faragallah, O.
Tanzania	1	Ibwe, K.
African subtotal	**37**	(includes overlapping international collaborations counted under Nigerian stratum)

The African contribution to this corpus deserves more than a footnote. Nigeria is the leader in volume and range of methods - even the article by Idigo et al. (2025) only illustrates it, with single-carrier successive interference cancellation with hybrid beamforming that generates realistic gains in realistic path-loss settings instead of the idealized ones. Algeria has also given two contributions, Ayad et al. (2025) with energy-efficient CNN-based hybrid beamforming and Hadji et al. (2023) with multi-stage compressed-sensing-based hybrid precoding. Egypt is represented by Faragallah et al. (2021) and their mmWave MIMO deep-learning framework, and Tanzania by Ibwe (2025) whose mmWave-propagation path-loss and blockage realities were the foundation on which they constructed their joint MC-TDMA and beamforming model. The collective effect of this body of work is that it uses the full repertoire of beamforming paradigms as opposed to following external fashions - it is methodologically self-directed in a manner that is not always presumed of the research of these institutions. The rest-of-world picture is shaped most visibly by China, where sustained institutional investment in 5G and 6G research has produced a dense cluster of contributions spanning channel estimation, precoding, and beam management (Zhao et al., 2024; Sun et al., 2025; K. Zheng et al., 2023; Ge et al., 2025; Lu et al., 2021; Ka. Zheng et al., 2024; Fan et al., 2024; K. Wang et al., 2024; H. Wang, Xiao, & Li, 2024; A. Zhang et al., 2021). The United States has a significant contribution to the multi-paper vehicular beamforming thread by Mollah and others (Mollah et al., 2024; 2025b; 2026) and Gau and Javidi (2025), Torkzaban et al. (2022), and Deng et al. (2025). The presence of India is wide in hybrid precoding and deep learning (Kundra et al., 2025; Babu et al., 2025; Bansal and Yamaganti, 2024; Patel and Deshmukh, 2025a; 2025b; Prabhu et al., 2025; Kadiyala et al., 2025). The European production is regionally diversified yet collectively significant - France (Mabrouki et al., 2023; Klaimi et al., 2025), Germany (J. Gao et al., 2022; J. Zhang and Haardt, 2017), Spain (Gonzalez-Coma et al., 2018), Sweden (Ramezani et al., 2025; Khorsandmanesh et al., 2025), and the UK (K. Li et al., 2023). Middle-Eastern, Asian, and Australasian contributions complete the picture.

4.3 Authorship and Collaboration Patterns

Table 4 and Figure 4 show authorship and collaboration patterns. Collaboration is the norm in this corpus almost without exception. Eighty-six percent of the papers, 69 of the 80 reviewed carry three or more authors, ten are co-authored by two, and only a single paper, Ibwe (2025), was written alone. That lone exception is worth noting precisely because it is so unusual; single-author work has become rare in a field that routinely draws on signal processing, RF hardware design, optimization theory, and increasingly machine learning and metasurface physics simultaneously. No single researcher is expected to hold all of that at once, and the authorship patterns reflect it.

The median author count across the corpus sits at five, which is itself telling, and several papers push well beyond that. Y. Liu et al. (2023) and K. Wang et al. (2024) each list eight authors, representative of the larger research consortia that have become common in recent mmWave work groups where the distance between the theorist and the hardware engineer is not metaphorical but institutional, and where getting a result out requires genuine coordination across specializations.

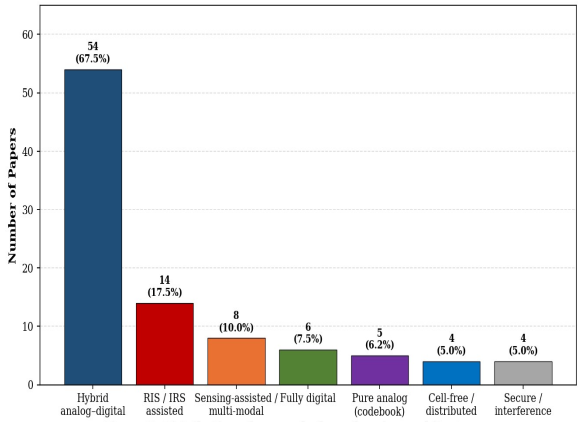

Figure 3. Distribution of papers by beamforming architecture (non-exclusive multi-label classification of 80 papers).

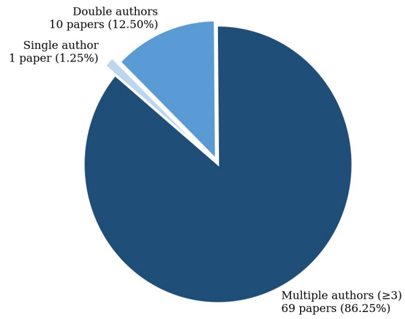

Figure 4. Authorship collaboration patterns across the 80 reviewed papers.

Table 4. Authorship collaboration patterns.

Collaboration Type	Papers (n)	Percentage (%)	Representative example
Single author	1	1.25	Ibwe (2025)
Double author	10	12.50	Bansal & Yamaganti (2024)
Multiple authors (≥3)	69	86.25	Liu, Ai, et al. (2023)
Total	**80**	**100.00**	—

On impact classification, 76 of 80 papers (95%) appear in venues judged high-impact by the review protocol based on journal tier, conference reputation, and citation velocity and the remaining 4 in medium-impact venues. The strong tilt toward high-impact outlets is consistent with active curation of the mmWave beamforming literature through rigorous peer review.

4.4 Classification by Beamforming Architecture

Figure 3 and Table 5 classify the 80 papers by beamforming architecture; some papers span multiple categories, so the multi-label classification is non-exclusive. Hybrid analog–digital beamforming is the most common, in 54 papers either as the primary contribution or as the baseline against which alternatives are compared. Fully digital beamforming appears in 6 papers, typically as an upper-bound reference (Ramezani et al., 2025; Khorsandmanesh et al., 2025). Pure analog beamforming shows up in 5 papers, mostly in connection with codebook design and hierarchical beam search (Torkzaban et al., 2022; Mabrouki et al., 2023; Xiao et al., 2016, 2017). RIS-assisted architectures, either stand-alone or layered onto hybrid precoding, are addressed in 14 papers (Zhao et al., 2024; Ye et al., 2024; Kadiyala et al., 2025; Yang et al., 2023; D. Kim et al., 2024). Cell-free and distributed architectures appear in 4 (Kanaan et al., 2025; Sun et al., 2025; Fan et al., 2024).

Table 5. Classification of reviewed papers by beamforming architecture (multi-label, non-exclusive).

Architecture	Papers (n)	Representative references
Hybrid analog–digital	54	Sun et al. (2025); Bansal & Yamaganti (2024); Peng et al. (2025); Ibwe (2025); Klaimi et al. (2025); Hadji et al. (2023); Pan et al. (2017)
Fully digital	6	Ramezani et al. (2025); Khorsandmanesh et al. (2025); L. Wang et al. (2023); Bo et al. (2020)
Pure analog (codebook-based)	5	Torkzaban et al. (2022); Mabrouki et al. (2023); Xiao et al. (2016, 2017); J. Gao et al. (2025)
RIS / IRS-assisted	14	Ye et al. (2024); Zhao et al. (2024); D. Kim et al. (2024); J. Li et al. (2025); Z. Liu et al. (2025); Albataineh et al. (2025)
Cell-free / distributed	4	Kanaan et al. (2025); Sun et al. (2025); Fan et al. (2024); Duong et al. (2025)
Sensing-assisted / multi-modal	8	Mollah et al. (2025a, 2025b); H. Kim et al. (2024); K. Zheng et al. (2023); Mahmoud et al. (2025)
Secure / interference-mitigating	4	de Lima et al. (2024); Mao et al. (2025); Deng et al. (2025); Idigo et al. (2025)

A few methodological points fall out of this distribution. The continued dominance of hybrid architectures suggests that the trade-off between performance and hardware cost has not yet been displaced by either pure analog or pure digital solutions, despite ongoing improvements in phase-shifter resolution and converter efficiency. The growing share of RIS-assisted work—14 papers, 10 of them from 2024 onward—signals a transition from speculation to operational study by a substantial community. And sensing-assisted architectures are quietly emerging as a class of their own, not captured by conventional taxonomies but increasingly visible in the 2024–2026 literature (H. Kim et al., 2024; Mollah et al., 2024, 2025a, 2025b, 2026).

4.5 Path Loss Mitigation Mechanisms

The path-loss-mitigation mechanisms reported across the 80 papers fall into five overlapping categories. Array gain through beam steering is the dominant mechanism, present in every paper either explicitly or implicitly: the whole point of beamforming is to concentrate radiated power spatially and recover the SNR lost to free-space and absorption effects. Beam tracking extends that mechanism into mobile scenarios, with representative work from Peng et al. (2025), Y. Liu et al. (2023), and Anooz et al. (2025), all of whom emphasize rapid adaptation under path-loss variation. Reflection-path creation through RIS is qualitatively different: instead of reshaping only the transmitter and receiver beams, it reshapes the propagation channel itself. Papers (Zhao et al., 2024; Ye et al., 2024; Kadiyala et al., 2025; Yang et al., 2023; D. Kim et al., 2024; Y. Wang et al., 2025; Nor et al., 2024; K. Li, El-Hajjar, & Yang, 2023; Xu & Zhou, 2024; Albataineh et al., 2025; J. Li et al., 2025; Kumar et al., 2025; J. Gao et al., 2025; Z. Liu et al., 2025) report 5–20 dB effective gains depending on RIS size, phase-shifter resolution, and blockage geometry.

Codebook-based path-adaptive beam selection is the next category, visible in Torkzaban et al. (2022), Mabrouki et al. (2023), Xiao et al. (2016, 2017) and J. Gao et al. (2025). Codebook methods sit on a coverage rate trade-off (broader beams give wider coverage but lower gain; narrow beams give peak rate at the cost of coverage) and are particularly relevant for 3GPP-compliant deployments. The last category is environmental and blockage-aware adaptation, where the system predicts or detects blockage events and proactively reroutes beams using sensing-assisted (H. Kim et al., 2024; Mahmoud et al., 2025; Mollah et al., 2025a, 2025b) or vision-based (K. Zheng et al., 2023) cues. Figure 5 visualizes the reported gain ranges for each mechanism, and Table 6 collects them with representative references.

Table 6. Path-loss-mitigation mechanisms with representative references and reported gains.

Mechanism	Core idea	Typical reported gain	References
Array gain / beam steering	Focus radiated energy toward receiver	10–30 dB effective SNR	Babu et al. (2025); Sun et al. (2025); Zeng et al. (2025); Xiao et al. (2017)
Beam tracking	Track changing AoA/AoD under	3–10 dB vs. static beams	Peng et al. (2025); Anooz et al.

Mechanism	Core idea	Typical reported gain	References
	mobility		(2025); Y. Liu et al. (2023)
RIS reflection path	Create alternate NLoS path	5–20 dB link-budget	Zhao et al. (2024); Ye et al. (2024); D. Kim et al. (2024); Albataineh et al. (2025)
Codebook-based selection	Switch among pre-designed beams	2–8 dB vs. default	Torkzaban et al. (2022); Mabrouki et al. (2023); Xiao et al. (2016); J. Gao et al. (2025)
Sensing-assisted adaptation	Use camera/LiDAR/GPS for beam selection	≈90% training reduction	Mollah et al. (2025a, 2025b); H. Kim et al. (2024); K. Zheng et al. (2023)

4.6 The Rise of Learning-Based Beamforming

Approximately 34 of the 80 papers (42.5%) incorporate a learning-based component, ranging from supervised CNN-based precoding (Babu et al., 2025; Prabhu et al., 2025; Ayad et al., 2025; Muthukumaran & Rajan, 2024; Faragallah et al., 2021; Bo et al., 2020) through model-based learning (K. Wang et al., 2024; Klaimi et al., 2025), reinforcement learning (Fan et al., 2024), generative modelling (Kanaan et al., 2025), active learning (Gau & Javidi, 2025), and transformer-based sequence modelling (Mollah et al., 2025a, 2026). This proportion has grown sharply over time, as visualized in Figure 5: of the 14 papers published in 2024, 6 incorporate a learning component (43%); of the 38 papers published in 2025, 21 incorporate learning (55%); of the 2 papers in 2026, both incorporate learning (100%).

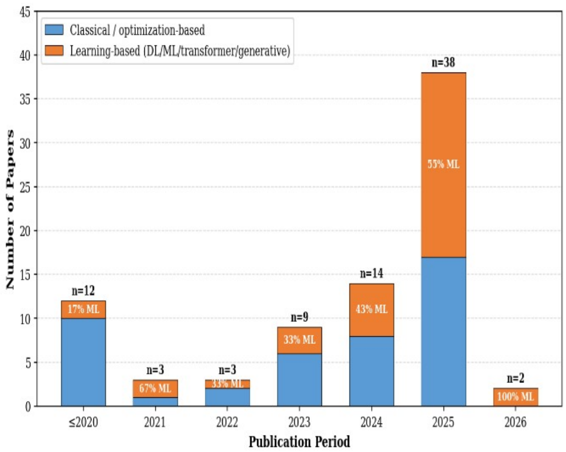

Figure 5. Growth of learning-based methods within mmWave beamforming research.

Table 7. Comparison of learning-based paradigms in mmWave beamforming.

Paradigm	Strengths	Limitations	Representative refs.
CNN-based precoding	Spectral-efficiency gain 5–15%; reduced inference latency	Requires labelled CSI; weak under domain shift	Babu et al. (2025); Prabhu et al. (2025); Ayad et al. (2025)
Transformer-based beam mgmt.	Captures temporal/spatial dependencies; strong under mobility	High training & inference cost	(Mollah et al., 2025a, 2026)
Model-based learning	Improved generalization with physical priors	Modelling effort; integration complexity	Klaimi et al. (2025); K. Wang et al. (2024)
Generative (diffusion)	Synthesizes data when measurements scarce	Stability/calibration of generative outputs	Kanaan et al. (2025)
Active learning	Acquires only most informative samples	Sequential decision-making complexity	Gau & Javidi (2025)
Reinforcement / DRL	Adapts policy under dynamic environments	Reward shaping and convergence challenges	Fan et al. (2024)

A few methodological points emerge from this. CNN-based precoding consistently delivers spectral-efficiency gains of 5–15% over classical baselines while cutting beam-training overhead by 40–70%. Transformer-based beam management (Mollah et al., 2025a, 2026) outperforms CNN counterparts in mobility-intensive scenarios, owing to the attention mechanism's facility with long-range temporal dependencies. Model-based learning (K. Wang et al., 2024; Klaimi et al., 2025) generalizes more reliably to unseen channels than purely data-driven approaches, at the cost of more upfront modelling effort. And generative models such as diffusion-based RSSI synthesis (Kanaan et al., 2025), together with active-learning schemes (Gau & Javidi, 2025), directly address the scarcity of labelled training data that has long bottlenecked mmWave deployments.

The same body of work also surfaces four recurring limitations. Training datasets vary widely in size, angular coverage, and environmental diversity, which makes rigorous cross-paper comparison effectively impossible. Most works assume that training and deployment environments follow the same statistical distribution, an assumption that breaks down under mobility and weather variability. The computational cost of inference, particularly for transformer models, is rarely reported in terms that are directly comparable with the signal-processing latency of classical alternatives. And robustness under adversarial perturbations has been only minimally examined, despite the security-sensitive nature of mmWave links in V2X and defense applications.

4.7 RIS-Assisted Beamforming: From Concept to Experimentation

The RIS work in this corpus has a clear arc. The first contributions were made with the idea that optimization could work best in an idealized setting where there were passive, lossless elements with continuous phase tunability and perfect channel knowledge (Zhao et al., 2024; Ye et al., 2024). What followed was a systematic process of walking those assumptions back toward physical reality.

D. Kim et al. (2024) designed spatial-phase-shift distributions with blockage mitigation as the explicit objective rather than a theoretical byproduct. Y. Wang et al. (2025) confronted the beam alignment problem as it actually presents itself in deployed systems, where full channel knowledge is unavailable and only narrowband received-power measurements can be relied upon. Near-field effects, long treated as an edge case, became unavoidable as the research community began taking seriously what happens when RIS deployments grow large enough that the far-field plane-wave approximation simply stops holding; Nor et al. (2024) addressed near-field codebook design and beam training, and Z. Liu et al. (2025) extended the near-field treatment to localization. J. Li et al. (2025) tackled beam-squint in a holographic RIS configuration, a problem that grows more severe as bandwidth increases and the surface grows larger.

The clearest sign of maturation, though, is hardware. Kumar et al. (2025) reported a working 2-bit quad-band RIS prototype, and J. Gao et al. (2025) validated a multi-resolution codebook-based beam training scheme through experimental measurement rather than simulation. Prototype demonstrations and experimental validation do not appear early in a research arc; they appear when the field has accumulated enough theoretical groundwork to know what it is actually trying to build.

Table 8. Thematic decomposition of RIS-assisted beamforming research in the corpus.

Sub-theme	Papers (n)	Representative references
Channel estimation under RIS	4	Ye et al. (2024); Yang et al. (2023); Xu & Zhou (2024)
Blockage / phase-shift design	3	D. Kim et al. (2024); Zhao et al. (2024); Y. Wang et al. (2025)
Near-field & large-scale RIS	3	Nor et al. (2024); Z. Liu et al. (2025); K. Li et al. (2023)
Wideband / beam-squint RIS	2	J. Li et al. (2025); Albataineh et al. (2025)
RIS prototyping / experiments	2	Kumar et al. (2025); J. Gao et al. (2025)
Optimization (multi-IRS / SCA)	1	Kadiyala et al. (2025)

Taken together, these trends say RIS research is moving from a theoretical direction into an experimental engineering discipline. The substantive gaps that remain are joint channel estimation across the cascaded transmitter–RIS–receiver link under practical pilot budgets (addressed only partially in Ye et al., 2024; Yang et al., 2023; Xu & Zhou, 2024), the control signalling overhead for RIS reconfiguration, which is rarely quantified, and the economic and operational model for deploying large numbers of RIS panels in real networks.

4.8 Open Challenges and Future Directions

Pulled together across the corpus, ten open research problems stand out, summarized in Table 9. They are not mutually exclusive: progress on one often enables or requires progress on others. Wideband beam-squint (Problem 3), for example, is exacerbated by low-resolution phase shifters (Problem 4), and both are mitigated by learning-based pre-compensation (Problem 7), which itself depends on standardized datasets (Problem 1).

Table 9. Ten open research problems in mmWave beamforming for path loss mitigation.

#	Problem	Core difficulty	Partial coverage
1	Standardized benchmarks and datasets	Fragmented evaluation across papers	Kanaan et al. (2025); K. Wang et al. (2024); J. Gao et al. (2022)
2	Hardware-aware precoder design	Non-ideal phase shifters, IQ imbalance, mixed-ADC	Ramezani et al. (2025); Bo et al. (2020); Obaidi & Mahmood (2025)
3	Wideband beam-squint compensation	Frequency-dependent steering angle	Khorsandmanesh et al. (2025); B. Wang et al. (2019); J. Li et al. (2025)
4	Low-resolution phase shifter operation	Quantization loss	Ramezani et al. (2025); Bo et al. (2020)
5	Cascaded channel estimation under RIS	Pilot overhead on double-hop channel	Ye et al. (2024); Yang et al. (2023); Xu & Zhou (2024)
6	Mobility-robust beam tracking	Rapid AoA/AoD drift	Peng et al. (2025); Anooz et al. (2025); Y. Liu et al. (2023)
7	Generalization of learning models	Train/test distribution mismatch	K. Wang et al. (2024); Klaimi et al. (2025)
8	Secure beamforming in V2X	Jamming and	de Lima et al. (2024);

#	Problem	Core difficulty	Partial coverage
		eavesdropping	Mao et al. (2025); Deng et al. (2025)
9	Energy-efficient large-array operation	Power consumption scaling	Ayad et al. (2025); Fan et al. (2024); S. Yao et al. (2025)
10	Integrated sensing-communication	Dual-use waveforms and arrays	Mollah et al. (2025a, 2025b); H. Kim et al. (2024); Mahmoud et al. (2025)

Beyond those ten problems, four cross-cutting priorities recur. Reproducibility, in the form of open-sourced code, datasets, and experimental setups, is rare in the corpus and ought to be the default rather than a virtue. Energy-efficiency reporting needs consistent metrics across hardware models, ideally bits per Joule or effective power per bit, so that comparisons across studies actually mean something. Fairness-aware evaluation across regions and deployment scenarios is needed to keep solutions from over-fitting to affluent urban environments. And collaboration between African and non-African institutions deserves to be strengthened: climate, infrastructure density, and spectrum policy vary substantially across regions, and beamforming solutions tested only in one set of conditions transfer imperfectly to the rest.

4.9 Limitations

This review has limitations worth naming explicitly. The search protocol, although it covered multiple databases, restricted itself to English language publications, and that almost certainly excluded relevant contributions from non-Anglophone communities. The focus on path loss mitigation objectives meant that closely related work on latency or reliability without direct path loss framing was deprioritized. The three stratum geographical classification, useful as it is for foregrounding African contributions, aggregates heterogeneous national research systems and may obscure intra-regional differences. The high versus medium impact classification leans on venue reputation and citation velocity, both of which carry known biases against newer or regionally distributed venues. The corpus also reflects the state of the art as of the search cut off in January 2026, so any subsequent reading will encounter work this review could not include. And the synthesis is qualitative and descriptive rather than meta analytic: heterogeneity in system models, channel assumptions, and evaluation metrics across the corpus precluded direct numerical pooling.

Set against those limits, the strengths of the review are an explicit methodology, an effort at geographical representation, an integration of classical and learning based paradigms in one frame, and ten actionable open problems. A natural extension would be quantitative meta-analysis on sub-corpora that share common evaluation metrics (papers reporting spectral efficiency under a specific 3GPP channel model, for instance), where the heterogeneity that blocks pooling here can be controlled.

V. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary and Conclusions

This paper presented a systematic review of 80 peer-reviewed publications on beamforming techniques for path loss mitigation in mmWave communication systems. The review followed a PRISMA-informed methodology, covered 2016 to 2026, and drew on journals, conference proceedings, and established preprint repositories. A multi-axis taxonomy classified papers by architecture, algorithmic paradigm, path-loss-mitigation mechanism, hardware model, and application domain. Descriptive and thematic syntheses then addressed six research questions about trends, methods, regional distribution, collaboration, and open challenges.

Several conclusions follow from the synthesis. mmWave beamforming research has accelerated sharply in 2024–2026, with more than two-thirds of the corpus published in that three-year window. Hybrid analog–digital beamforming remains the dominant architectural paradigm, present in roughly 68% of the papers either as the central contribution or as a baseline. Learning-based beamforming covering CNNs, transformers, generative models, and active learning is the fastest growing methodological direction, present in over half of the 2025 papers and in both 2026 papers. RIS-assisted beamforming has crossed from speculative theory into experimentally validated engineering, with 14 corpus papers on RIS and four reporting prototypes or measurement campaigns. And sensing-assisted, multi modal beamforming for vehicular scenarios is an emerging frontier in its own right, with reductions in beam training overhead reaching roughly ninety percent relative to RF-only baselines.

The geographical picture is equally important. African participation in mmWave beamforming research is substantive: 31 papers are affiliated with Nigerian institutions or research collaborations, 9 with other African countries including Algeria, Egypt, Iraq, and Tanzania, and 40 with the rest of the world. The volume and topical breadth of those African contributions sit awkwardly with any narrative that casts the region solely as a consumer of externally developed wireless technology. Multi-author collaboration dominates the corpus (86% of papers), which reflects the interdisciplinary breadth that contemporary mmWave research demands. And ten open problems came out of the synthesis: standardized benchmarking, hardware-aware precoding, wideband beam squint compensation, low resolution phase shifter operation, cascaded channel estimation under RIS, mobility-robust beam tracking, generalization of learning models, secure beamforming, energy-efficient large-array operation, and integrated sensing-communication.

Taken together, the findings make it clear that path loss mitigation in mmWave systems is no longer a single-discipline problem. It now sits at the intersection of signal processing, machine learning, metasurface physics, integrated sensing, and hardware design. Progress over the next five years will depend on coordinated advances across all of those disciplines, supported by reproducible benchmarks and by equitable geographical participation in the work itself.

5.2 Recommendations

From the review's findings, ten recommendations stand out as priorities for research, standardization, and institutional strategy:

1. Standardized benchmarks. The research community should coordinate on open datasets and canonical channel models that span 28 GHz, 60 GHz, and sub-THz regimes, under both indoor and outdoor, static and mobile scenarios. A benchmark in the spirit of the DeepMIMO and Raymobtime datasets but extended to capture RIS-assisted cascaded channels and multi-modal sensing inputs would enable rigorous cross-paper comparison.

2. Hardware-aware learning. Learning based beamforming methods should be developed with explicit hardware non-idealities in the loop: quantized phase shifters, mixed ADC front-ends, IQ imbalance, and phase noise. Training loops that incorporate these effects during data generation and loss computation will produce models that deploy without the performance collapse typical of purely idealized training.

3. Wideband and sub-THz extensions. Future work should treat beam-squint compensation as a default design requirement rather than an afterthought, particularly for RIS-assisted sub-THz systems where the effect is most pronounced. Time-delay beamforming, true-time-delay arrays, and frequency-dependent codebooks deserve greater attention.

4. Integrated sensing communication (ISAC). Beamforming research should embrace ISAC as a first class design axis. The convergence of mmWave radar and mmWave communication offers opportunities to reduce path-loss-related overhead by leveraging radar derived environmental models for beam management, rather than treating sensing as an auxiliary input.

5. Cascaded channel estimation for RIS. Pilot-efficient channel estimation for RIS-assisted cascaded links should be prioritized, with explicit attention to the trade-off between channel-estimation accuracy and control-plane signalling overhead. Compressed-sensing, tensor, and deep-learning methods should be evaluated on shared benchmarks.

6. Energy efficiency reporting. Papers should report power-consumption estimates or energy-efficiency metrics (bits per Joule) alongside spectral efficiency, so that the practical deployment implications of proposed schemes are visible. Community agreement on a small set of consistent metrics would substantially improve the comparability of results.

7. Mobility and V2X robustness. For vehicular, aerial, and high-speed-rail scenarios, beamforming solutions should be validated under realistic mobility models with Doppler and blockage dynamics. Sensing-assisted and transformer-based beam management are promising directions that merit continued development.

8. Reproducibility. Journals and conferences should actively encourage release of code and data. Authors should provide enough experimental detail channel model parameters, SNR definitions, array geometries for someone else to replicate the result without guessing.

9. Capacity building in African and emerging-region institutions. The 40-paper footprint of African-affiliated research in this review points to existing capability worth building on. Shared testbeds, joint funding programmes, and co-supervision arrangements between African and non-African universities would amplify that contribution and make sure path-loss-mitigation techniques get tested and refined in the diverse propagation environments of the continent rather than only in their countries of origin.

10. Interdisciplinary training. Postgraduate curricula in wireless communications need to integrate optimization, machine learning, RF hardware, and metasurface physics in one programme rather than as scattered electives. The interdisciplinary trend visible in this review—86% multi-author collaboration, often spanning multiple institutions will only stay sustainable if the pipeline of researchers trained to bridge these disciplines keeps expanding.

Putting any of these recommendations into practice will need coordinated action by researchers, standards bodies, funding agencies, and industry. What is on offer in return is a generation of mmWave beamforming techniques capable of delivering reliable, energy efficient, and globally equitable path-loss-robust connectivity the kind of connectivity the 6G vision is going to need.

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