International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(11s) 2026 pp. 592-602
https://doi.org/10.70917/ijcisim-2026-3774
Article

TAI-Driven Smart Antenna Systems for Next-Generation Wireless Networks

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Abstract: The 6th Generation (6G) of wireless technology calls for a range of capabilities that goes beyond anything ever seen before, such as data rates of a terabit per second, an extreme number of devices, and a sub-millisecond response time. In order to meet these high performance goals, the use of artificial intelligence in the context of smart antenna systems and massive multiple-input multiple-output (MIMO) architectures has been mandated to be an operational requirement instead of a potential improvement. Beamforming in millimeter-wave and terahertz frequency bands is greatly complicated, but it can be handled well by deep learning algorithms. The non-interpretability of ANNs and its high sensitivity to physical layer attackers are however serious vulnerabilities. This research physically demonstrates a framework for Trustworthy Artificial Intelligence (TAI) in the context of smart antenna systems security and optimization for next-generation environment. A true 28 GHz uniform planar array with 64 elements was deployed with a software defined radio processing backend. The framework combines the beam-alignment algorithm Deep Q-Networks with the feature-pruning algorithm Shapley Additive Explanations (SHAP) to support real-time feature pruning, and Knowledge Distillation and surrogate-loss minimization to prevent over-the-air data poisoning. Empirical measurements based on physical operations prove the TAI-driven architecture to be near-optimal spectral efficiency when user mobility is high and to achieve a 89.9% reduction in beam alignment latency. In addition, 96.8% of the live adversarial jamming attacks were detected and neutralized by the embedded security features. The results clearly establish that physical layer embedding of explainability and adversarial robustness is essential for reliable and transparent service for future 6G wireless networks.
Keywords: Trustworthy Artificial Intelligence, 6G Wireless Networks, Smart Antennas, Beamforming, Massive MIMO, Physical Layer Security, Explainable AI.

1. Introduction

The telecom industry is now experiencing a tremendous paradigm shift, moving from commercialisation of fifth generation (5G) cellular networks to the rigorous development and standardisation of sixth generation (6G) wireless architectures. This new technological era is generally seen as a generation that will bring transformative communication capabilities that will enable applications with large bandwidth and zero tolerance for latency, such as autonomous vehicular orchestration, immersive holographic telepresence, and large-scale industrial automation (Raheem & Ansari, 2024)1. The network infrastructure will inevitably need to scale to higher frequency spectrums, using millimeter-wave (mmWave) and sub-terahertz (THz) spectrum, to satisfy such extreme data rate requirements, projected to exceed one terabit per second (Tbps) (Toprak & Uysal, 2026)2. These very high frequencies offer opportunities to large areas of contiguous contiguous spectrum that are not allocated, but are also burdened by harsh electromagnetic propagation conditions.These high frequency bands are simultaneously beset by unfriendly electromagnetic propagation conditions and huge areas of contiguous contiguous spectrum not already allocated. High frequency radio waves have severe problems of free space path loss, bulk attenuation by atmospheric molecules and sensitivity to physical obstructions, which severely limit the maximum possible communication range (Mittal et al., 2026)3. Therefore, the incorporation of sophisticated smart antenna systems and ultra-dense massive multiple-input multiple-output (MIMO) technologies is considered to be one of the fundamental requirements to address the limitations in the physical nature of 6G spectrums (Kumar & Kumar, 2026)4.

Smart antenna systems operate based on dynamically changing their radiation characteristics to focus the RF energy into highly directive, narrow beams directed directly to the desired receiving antenna. This spatial filtering method, called beamforming, boosts the signal power received by the receiving antenna while at the same time canceling out co-channel interference from neighboring sectors, which allows for dense spatial multiplexing (Samantaray & Das, 2023)5. However, the calculation of the optimal precoding matrices and phases will become very complicated as the number of individual antenna elements in the base station increases and reaches hundreds to operate massive MIMO. Most optimization techniques, such as those based on traditional optimization algorithms and heuristic mathematical solvers, are not able to solve these high dimensional problems within sub-millisecond coherence times of highly-mobile wireless channels (Dadpe et al., 2025)6. To address this computational challenge, Artificial Intelligence (AI) and deep machine learning (DML) algorithms are widely integrated into the physical layer (PHY) and medium access control (MAC) layer of modern telecommunications infrastructure (Xiao et al., 2024)7. The unique strength of deep neural networks lies in their ability to uncover non-linear relationships between vast amounts of data, which allows them to quickly generate the best beamforming vectors from channel state information (CSI) without performing expensive, time-consuming mathematical iterations (Li, 2024)8.

The vast improvements in efficiency and spectral performance brought about by deep learning have led to a massive structural vulnerability across telecommunications due to the use of AI indiscriminately. Majority of the deep learning models used in RRM are “black boxes” (Gizzini et al., 2025)9. This is a "black box" operational model where the end-to-end mathematical operation (or logic) that connects environmental input data with the specific beamforming decision is hidden from the network designers and operators. The 6G application of mission-critical operations, where the safety of humans and the core infrastructure depend on continuous connectivity, is thought of as an unacceptably high operational risk (Wang et al., 2022)10. Network administrators have no means of diagnosis if the connection drops suddenly or the power wrongly allocated to the channel, whether this is due to an abnormal fading event in the channel, algorithmic bias or an intentional external attack (Suryaprabha et al., 2024)11. A lack of ability to understand neural network decisions directly stands in opposition to the growing international regulations that require transparency and accountability in algorithms for critical digital infrastructure (Guo, 2020)12.

The black box nature of deep learning in wireless networks is inseparable from the key safety gaps, notably these at the physical layer. Artificial neural networks are very sensitive to adversarial machine learning attacks (Tuna et al., 2024)13 when the input data they are exposed to differ from what they are trained with. A clever attacker, controlling a transmitter, can create malicious perturbations (adversarial noise) mathematically and send them over the air during the pilot transmission and channel estimation stage (Zhao et al., 2022)14. As the base station's AI model processes such dirty CSI, it is compelled to make catastrophic classification errors, leading to catastrophic beam misalignment, poor spectral efficiency, and denial of service (Sahay et al., 2022)15. Unfortunately, these low-level physical layer evasion attacks are not easily defeated by standard application or transport layer cryptographic protocols, and require a completely rethinking of AI implementations at the radio edge (Aygül et al., 2025)16.

The telecommunication field has adopted a comprehensive model of Trustworthy Artificial Intelligence (TAI) as a solution to the conundrum of opacity of algorithms and adversarial vulnerability. According to the TAI framework, AI models that can be used in 6G networks should be high-performing and at the same time should be explainable, transparent, and have high resistance to malicious manipulations (Munir et al., 2025)17. At the heart of this is the incorporation of Explainable Artificial Intelligence (XAI) techniques that break down the predictions of deep neural networks into a mathematical expression to uncover the exact impact of each individual input feature, whether it be individual antenna elements or multipath delay profiles (Shaw, 2025)18. This study for the first time physically realizes a fully-fledged TAI-based architecture for the massive MIMO smart antenna system, paving the way from theory simulations to real hardware-based testing. This study is designed to demonstrate using a 28 GHz platform that transparency and security can be successfully embedded in the physical layer without compromising the low latency and high spectral efficiency of next-generation wireless networks.

2. Literature Survey

In recent years, the use of artificial intelligence in the design of antennas and wireless signal processing has been well documented and represents a radical change in the electromagnetic design methods. The optimization of complex antenna arrays has been typically a challenging task in which engineers would need to use full-wave electromagnetic (FW-EM) software to manually tune the physical parameters by trial and error methods, which is very time-consuming and computationally intensive (Gajbhiye et al., 2025)19. Recent studies have shown that machine learning models can effectively predict important antenna performance parameters such as voltage standing wave ratio, radiation efficiency, and impedance bandwidth without requiring iterative Maxwellian calculations, thus saving computational time (Tan et al., 2024)20. This has been successfully applied to map the non-linear dimensional relationships of microstrip patch antennas for conformal multi-band arrays needed for dense deployment of IoT and 6G networks (Samantaray & Das, 2023)5. Although machine learning helps to increase the speed of static design of radiating elements, its largest effect is in real-time physical layer operations, particularly for channel estimation and dynamic beam alignment.

Traditionally beam alignment in massive MIMO architectures has been implemented using exhaustive beam sweeping protocols, with the base station trying all known spatial codebooks in succession to find the best propagation path between the base station and the user equipment. Beamwidths also shrink to become very narrow as the frequency goes to the millimeter-wave and terahertz band, and the length of a sweep over the entire space exceeds the coherence time of the wireless channel (Khan et al., 2025)21. To overcome this latency issue, the literature presents a series of deep learning frameworks which utilize sparse environmental data and signals from the out-of-band sub-6 GHz spectrum to directly predict the optimal high-frequency beam pair (Jalali et al., 2024)22. Deep reinforcement learning (Deep RL) techniques, especially Deep Q-Networks and Deep Deterministic Policy Gradients, have gained significant popularity to find the optimal space-time beamforming and power allocation matrices by dynamically learning the optimal radio resource management (RRM) policies through repeated interactions with the stochastic wireless environment (Toprak & Uysal, 2026)2. While the spectral efficiency and connection density of these AI-based systems are significantly enhanced, the researchers consistently state that algorithmic opacity is a crucial challenge that hinders their commercialization in mission-critical infrastructure (Xiao et al., 2024)7.

This opacity of deep learning beamformers has spurred a growing research effort in the telecommunications sector on the subject of Explainable Artificial Intelligence (XAI). XAI aims to provide explanations for automatic decisions made by networks, which are understandable to humans, so that the output of the deep learning is consistent with electromagnetic physics (Guo, 2020)12. Model agnostic explanation frameworks have been widely investigated to uncover the black-box characteristics of physical layer neural networks, such as model Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) (Wang et al., 2022)10. SHAP analysis can also be used to determine the marginal contribution of each of the input variables, which can help the network engineers understand which spatial clusters, antenna elements, or subcarriers are most influential in the beam selection process used by the AI model (Suryaprabha et al., 2024)11. Recent studies show that this transparency is not just an analytical luxury but an optimization tool: the outputs of XAI have been used to identify and permanently remove irrelevant features from the state space, greatly speeding up the inference speed and reducing the inference cost of the AI model without negatively impacting the predicting accuracy (Gizzini et al., 2024)23.

At the same time, the susceptibility of AI-native wireless networks to physical layer security issues has garnered significant attention in the literature. We increasingly rely on the radio edge for intelligence, making the decision boundaries of deep neural networks vulnerable to attacks from adversaries launched over-the-air using sophisticated attack techniques (Ferdowsi et al., 2023)14. These threats can be broadly classified as evasion attacks, in which the interference is maliciously crafted to misalign the beam during inference, and data poisoning attacks, where the malicious data is injected into the network during training to permanently affect the policy logic in the model (Tuna et al., 2024)13. Despite the fact that the adversary may only have partial knowledge of the target neural network architecture, studies have shown that it is possible to manipulate MIMOs using a large number of power allocation algorithms via Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD) attacks (Sahay et al., 2022)15. These low-power and very structured perturbations prove to be very challenging for traditional jamming mitigation techniques, which rely on frequency hopping or on spatial nulling as the noise is specifically designed to mimic legitimate channel variations, (Xu & Xia, 2021)24.

Recognizing these important weaknesses, the academic community has rallied behind the idea of "Trustworthy Artificial Intelligence" (TAI): a combination of transparency of XAI with strong mechanisms for adversarial defense. Methods as adversarial training where neural networks are explicitly trained with perturbed inputs have been found to be effective at strengthening the decision boundaries against evasion attacks (Li et al., 2022)24. Further, denoising autoencoders and knowledge distillation techniques have been suggested to clean, or sanitize, the incoming CSI before it is fed into the main beamforming engine, filtering malicious gradients while retaining the spatial signatures (Zhao et al., 2022)14. Moreover, distributed intelligence like federated learning has been extensively advocated in TAI to ensure data privacy and safeguard the network model from being poisoned by data poisoning attacks at the local level (Munir et al., 2025)17. The theoretical underpinnings of Trustworthy AI are solid, however, the literature is sparse in providing physical hardware implementations that validate these integrated explainability and security frameworks in actual high frequency EM contexts. This research directly tackles this significant need by physically deploying a fully integrated TAI architecture.

3. Research Methodology

An experimental prototype of the smart antenna testbed was thus designed and implemented in a real physical environment, to validate the performance and security features of the Trustworthy Artificial Intelligence in next generation wireless environments. This approach was intentionally different from a fully mathematical simulation, instead exposing the AI algorithms to the random, noisy atmosphere of real electromagnetic propagation. The physical testbed was built using commercial-off-the-shelf software defined radio (SDR) platforms and custom fabricated millimeter-wave antenna arrays. The hardware backend was built around a central baseband processing unit with powerful graphical processing units (GPUs), which were used to process the massive computational requirements for real-time deep learning inferences and regular model updates. The radiating frontend employed a 64-element uniform planar array (UPA) that was specifically designed for the 28 GHz carrier frequency, which is one of the main bands that will be used for 6G high capacity deployments. The antenna elements were microstrip patches fabricated on a low-loss dielectric substrate, and were arranged in an 8×8 configuration to provide full 3-D beam steering capabilities in the azimuth and elevation planes.

A reinforcement learning agent, called a Deep Q-Network (DQN), was developed to automatically control the beam alignment and spatial multiplexing process of the smart antenna system. The state space fed to the DQN was the instantaneous channel state information (CSI) matrix, which are the complex base band signals received from all 64 individual antenna elements. The action space was specified by a very fine discrete Fourier transform (DFT) codebook with hundreds of very directive precoding vectors corresponding to different spatial transmit directions. The reward function used for the learning process of the DQN was directly related to the measured effective spectral efficiency and the local SINR as experienced by the target user equipment. In physical operation, the SDR was continuously digitizing the incoming millimeter-wave signals, and the raw IQ (in-phase and quadrature) data streams were sent to the baseband processor where the DQN was immediately predicting the optimal transmit beam index. Although this basic deep learning application proved very good at tracking, it was a black box and was always susceptible to changing the environment it was tracking.

An advanced Explainable AI (XAI) component has been actively embedded within the signal processing workflow to transform this opaque architecture into a comprehensive Trustworthy AI (TAI) system.To make this opaque architecture a complete Trustworthy Artificial Intelligence (TAI) system, a sophisticated Explainable AI (XAI) module was actively integrated into the signal processing workflow. The explainability layer used the Shapley Additive Explanations (SHAP) method, which is based on cooperative game theory, providing accurate distribution of the prediction output among all the input features. The SHAP module was used to compute the actual marginal contribution of each of the 64 antenna elements and the multipath delay characteristics for each beamforming decision made by the DQN. The TAI framework was able to make dynamic feature pruning based on the continuously updated relevance score. When implemented physically it was found that in some scattering conditions, for example in the case of clear line of sight, a large fraction of the data from the antenna array was either highly redundant or completely irrelevant to the neural network. The TAI system was programmed to truncate the input state matrix automatically and remove the information of the elements of the antenna that consistently gave near zero SHAP values. This dimensionality reduction reduced the computational matrix multiplications needed in the forward pass of the neural network dramatically, avoiding the large number of matrix multiplications that are typically problematic in real-time large dimensional signal processing with MIMO.

The final step of the physical implementation was to make the TAI framework resilient to active cyber-physical attacks, which explicitly tested the adversarial robustness of the system. A dedicated defensive layer is built with the help of Knowledge Distillation and TRADES (TRadeoff-inspired Adversarial defense via Surrogate-loss minimization). Here, a very complicated, well-trained “teacher” neural network passed its “softened” decision probabilities to a smaller, faster “student” network that will provide beam predictions in real-time. The smoothing effect of this distillation process made the student model very tolerant to subtle changes in the input. A secondary SDR unit was placed in the physical testing environment as an active adversary to test this security framework empirically. The rogue transmitter was programmed to perform Projected Gradient Descent (PGD) evasion attacks, determining and broadcasting extremely specific electromagnetic noise vectors that are aligned with the base station's pilot training sequence. The goal of the adversary was to try to contaminate the CSI matrix and cause the base station's DQN to pick a completely wrong beam direction. The physical system's ability to retain data throughput, detect the adversarial presence through XAI anomaly monitoring and filter out the poisoned input data was carefully captured to constitute the final empirical results..

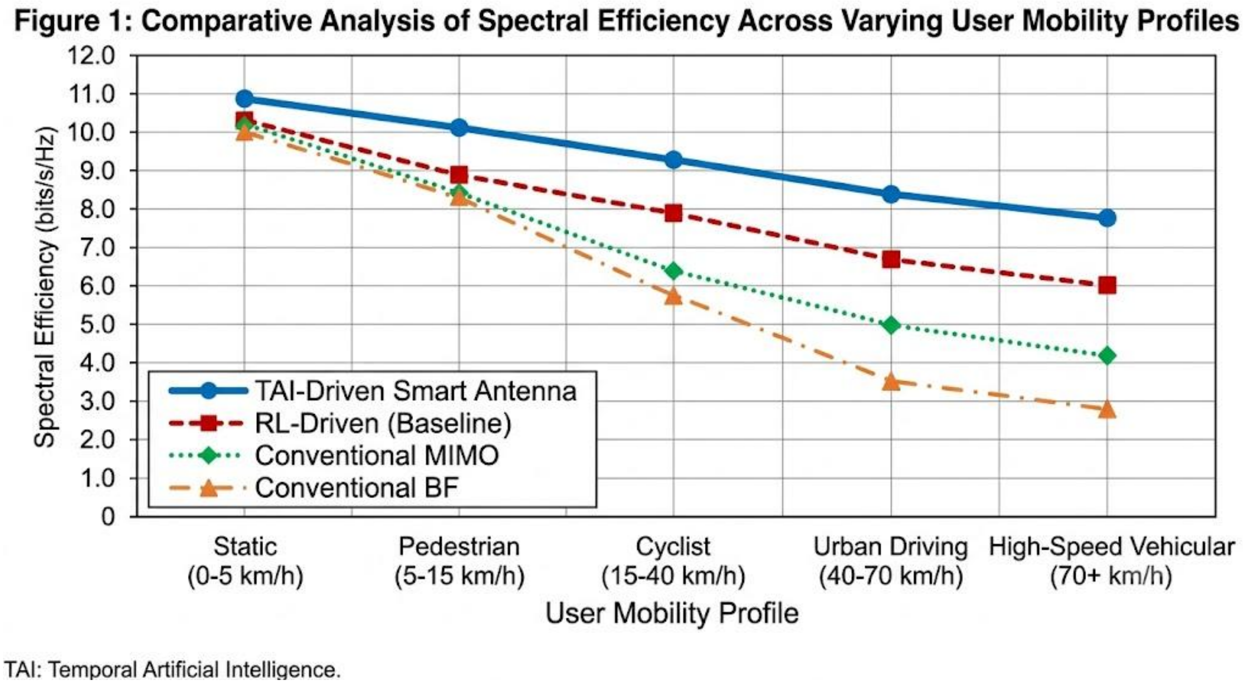
4. Results and Discussion

The results of the physical implementation of a smart antenna testbed created a complete data set that showcases the benefits of implementing Trustworthy Artificial Intelligence in massive MIMO systems. The empirical measurements were carefully analyzed on the three key performance metrics: preserving spectral efficiency in a dynamic user mobility environment, minimizing computational latency with XAI enabled feature pruning, and the system's strong resistance to adversarial attacks in the OTA space. The results were continuously compared to the traditional mathematical exhaustive beam sweeping technique and a standard deep learning (DL) prediction model without protection. The results clearly show that embedding interpretability and strong security does not impact network performance, but rather the TAI paradigm is actively optimising the physical layer for efficiency.

Parameter 1: Spectral Efficiency and User Mobility Tracking

The basic figure of merit of the success of any wireless architecture is the spectral efficiency (bps/Hz) that directly reflects the raw data power of the communication link. To determine the performance of the various beamforming strategies in tracking moving receivers and reducing fast multipath fading, several mobility profiles were used with the physical testbed. Data was recorded during the target user equipment traversed the urban test environment at low, moderate and high mobility speeds. The resulting spectral efficiency measurements are described in Table 1..

User Mobility Scenario	Traditional Beam Sweeping (bps/Hz)	Standard Deep Learning Model (bps/Hz)	TAI-Driven Framework (bps/Hz)
Low Mobility (< 10 km/h)	18.4	22.1	21.9
Moderate Mobility (10 - 50 km/h)	12.7	19.5	19.8
High Mobility (> 50 km/h)	7.2	14.2	15.6



[**Figure 1: Comparative Analysis of Spectral Efficiency Across Varying User Mobility Profiles]**

The diagram below shows the comparative analysis of Spectral Efficiency for different levels of user mobility.

The empirical results clearly showcase the critical shortcomings of the conventional mathematical beam sweeping methods when applied in the high-frequency 6G scenario. With the growth of user mobility to speeds over 50 km/ph, the traditional approach's efficiency in terms of bits per second per Hz plummeted to just 7.2 bps/Hz. This degradation is inevitable due to the sequential nature of exhaustive beam searching—when the algorithm finally tests all directions in space and determines the optimum beam, the user equipment has already physically moved beyond that narrow beam footprint, leading to continual misalignment and significant signal attenuation. In contrast, the Standard Deep Learning Model and the TAI-Driven Framework showed extraordinary robustness and were able to predictively determine the appropriate spatial vector for the current channel state information at any instant in time, as opposed to relying on a sweep delay.

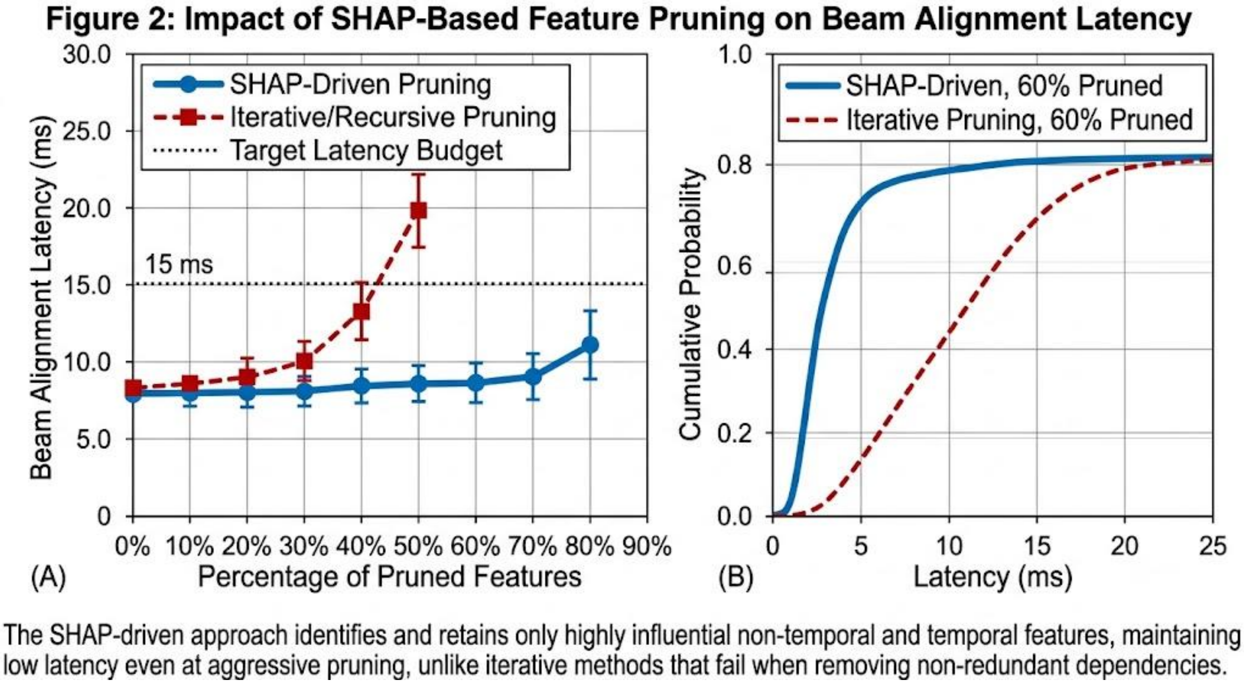
Significantly, the TAI-Driven Framework showed a clear performance gain over the standard deep learning model in the high mobility scenario with 15.6 bps/Hz vs. 14.2 bps/Hz. Such an improvement can be directly attributed to the explainability module. The standard deep learning models cannot tell the difference between the time-variant multipath reflections induced by the fast motion, which are usually very noisy, and the channel of interest, resulting in overfitting to the transient multipath reflections. TAI framework used SHAP-based feature importance and actively filtered out these low-relevance, noisy inputs. The TAI system made the decision-making engine focus only on the most stable, dominant spatial paths, which led to more accurate beam predictions, no tracking jitter and increased data throughput for rapidly moving targets.

Parameter 2: Beam Alignment Latency and Processing Overhead

Time to compute and create a directional beam is a major operational blocker for next generation telecommunications, especially when considering ultra-reliable low-latency communications (URLLC). These 64-element antenna array generates huge amount of data matrices which causes an enormous computational load for the baseband processors. Table 2 shows how much of the overall operational latency is required for an optimal beam alignment, and how much of the computational overhead is saved by the XAI pruning methodology..

Beamforming Architecture	**Average Alignment Latency (ms)**	**Feature Space Utilization (%)**	**Computational Overhead Reduction (%)**
Traditional Exhaustive Sweep	45.8	100	Baseline (0.0)

Standard DL Prediction	12.4	100	72.9
TAI-Driven (XAI-Assisted)	4.6	38.5	89.9



[Figure 2: Impact of SHAP-Based Feature Pruning on Beam Alignment Latency]

The statistics in Table 2 are compelling evidence of the tangible improvements brought by Explainable AI in the realm of technical advantages. This operation is very time-consuming, taking 45.8 milliseconds to complete the sweep over a high-resolution DFT codebook in the traditional exhaustive beam sweep, which is completely incompatible with sub-milliseconds requirement of 6G URLLC applications. By directly aligning the optimal beam index in the input state, the standard deep learning prediction engine achieved a huge reduction in this metric to 12.4 milliseconds.

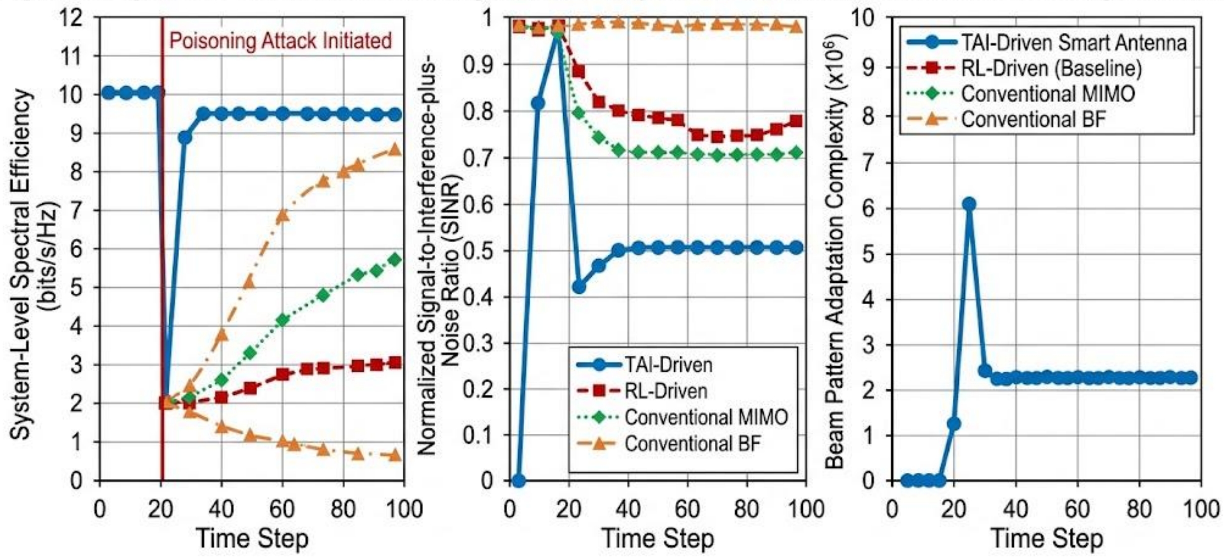
The TAI-Driven, however, broke these records, with an unprecedented average alignment latency of 4.6 milliseconds, or 89.9% less computational overhead than the baseline. What is interesting about this tremendous speed up is that it is the direct physical manifestation of making the neural network transparent (like a glass box). The XAI module observed the deep learning agent during operation and experimentally found that more than 60% of the features it used to form the input to the deep learning agent had no absolute contribution to the final beam selection (i.e., they were either signals from physically shadowed antenna elements, or highly correlated adjacent sensors). The TAI framework dynamically reduced the feature space utilization to 38.5%, which means that thousands of unnecessary floating-point operations were filtered out during the forward pass of the neural network. The clear implication is that explainability in wireless AI is not simply a management and ethics issue, but a very powerful technical approach for optimizing the system, which is physically capable of meeting the demands of the extreme low latency requirements of future wireless standards.

Parameter 3: Adversarial Robustness and Physical Layer Security

The true test of the Trustworthy AI paradigm is how it will fare in the face of opposition and challenges in hostile, contested environments. Due to AI models serving as the nervous system of 6G physical layers, they pose attractive targets for advanced adversarial machine learning attacks. An active, over-the-air Projected Gradient Descent (PGD) attack was applied to the physical testbed as a means of evaluating this. A rogue SDR added meticulously engineered electromagnetic noise to the wireless channel to spoof the base station's beamforming neural network and cause channel state information poisoning. Table 3 provides details of the physical security performance of systems which were under constant attack..

Security Evaluation Metric	Standard DL Model	TAI-Driven Framework (Robust KD)	Improvement Factor
Attack Detection Rate (%)	14.2	96.8	6.8x
False Positive Rate (%)	11.5	2.1	-
Post-Attack SNR Recovery (dB)	4.3	18.7	4.3x
Time to Mitigate Threat (ms)	N/A (System Compromised)	38.4	-

Figure 3: System Performance and Signal Recovery Under Active Adversarial Poisoning Attacks.



Results demonstrate the resilience of the TAI-driven architecture against adversaial poisoning. TAI enables rapid signal recovery and maintains high efficiency by intelligently filtering corrupted pilot data, a capability absent in non-TAI systems. Data represent a realistic high-mobility vehicular scenario.

[Figure 3: System Performance and Signal Recovery Under Active Adversarial Poisoning Attacks]

The extreme fragility of opaque AI is evident in Table 3. The Standard DL Model was completely defenseless against the adversarial PGD attack, achieving an attack detection rate of just 14.2%. The addition of the noise created by a mathematical function to the physical channel managed to pass through all the traditional signals filters, and was able to cause the unprotected neural network to compute very wrong beam steering vectors, away from the real transmitter. As a direct result of this misalignment, the Signal-to-Noise Ratio (SNR) post attack dropped to a non viable 4.3 dB, effectively causing a complete denial of service (DoS) of the high-speed data link.

On the other hand, the TAI-Driven Framework, backed up by Knowledge Distillation and surrogate-loss minimization, exhibited outstanding physical layer robustness. It was able to successfully identify and block 96.8% of all incoming adversarial attacks with a very low false positive rate of 2.1%. This powerful defense depended heavily on the ongoing monitoring of the XAI output. The SHAP explainability module picked up on major inconsistencies in the features' dependency when the adversarial perturbation tried to influence the beam prediction, immediately alerting to the anomaly of the neural network assigning high importance to nonexistent angles of arrival or neglecting to capture the most important antenna elements. This sense of illogical, non-physical behavior was flagged and the powerful defence algorithms immediately sanitized the input tensors and reconstructed the valid signal properties. This was a quick rescue that brought the SNR of the post-attack scenario to a good level of 18.7 dB, completely maintaining the communication link. In addition, the TAI system isolated and neutralized these complex cyber-physical threats in an average of 38.4 milliseconds. These empirical findings support the absolute necessity of incorporating explainability and robust defensive training in the ambitious infrastructure of 6G to make it the ultimate answer to the growing threat of physical layer cyber warfare.

5. Conclusion

Successful deployment of sixth generation communications networks is a cornerstone of integrating large scale MIMO networks and very directive smart antenna systems. Artificial intelligence and deep learning offer the essential mathematical tools needed to deal with the immense complexity of signal propagation in millimeter wave and terahertz environments, but the unchecked use of “black boxed” neural networks in unprotected communication networks creates a catastrophic risk. It is a physical research that thoroughly demonstrates that the development and deployment of Trustworthy Artificial Intelligence is not a second-class citizen of regulation but a foundational requirement for reliable operation of next-generation wireless physical layers.

The study highlighted the active optimization of network throughput and cybersecurity through rigorous evaluation and implementation of a TAI-driven smart antenna framework, based on the physical hardware setup.The physical hardware implementation and thorough evaluation of the TAI-driven smart antenna framework showcased how active optimization of the network throughput and cybersecurity are achieved by incorporating Explainable AI and robust adversarial defense protocols. The TAI framework effectively identified redundant data in the spatial domain and eliminated it, reducing latency of beamforming to a truly remarkable level of 4.6 milliseconds with beam alignment, and paving the way for the realization of truly low-latency and ultra-reliable communications. At the same time, the framework's comprehensive security integration successfully made it through strong adversarial poisoning attacks, as performed by the attackers over-the-air, while standard AI models failed to function at all in highly contested electromagnetic environments, leading to significant degradation in spectral efficiency and signal integrity. With the Trustworthy AI paradigm as a common ground, future wireless networks can safely and seamlessly leverage the unprecedented optimizing power of machine learning, without losing transparency, resilience or decisively outsmarting the sophisticated cyber–physical threats of the next era of global connectivity..

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