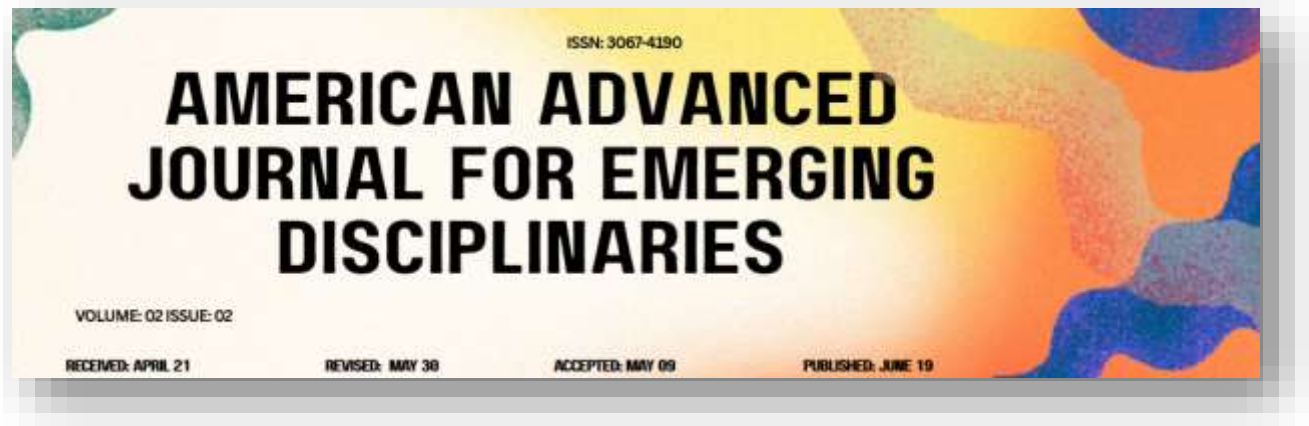




## Machine Learning Approaches for Next-Generation Wireless Networks

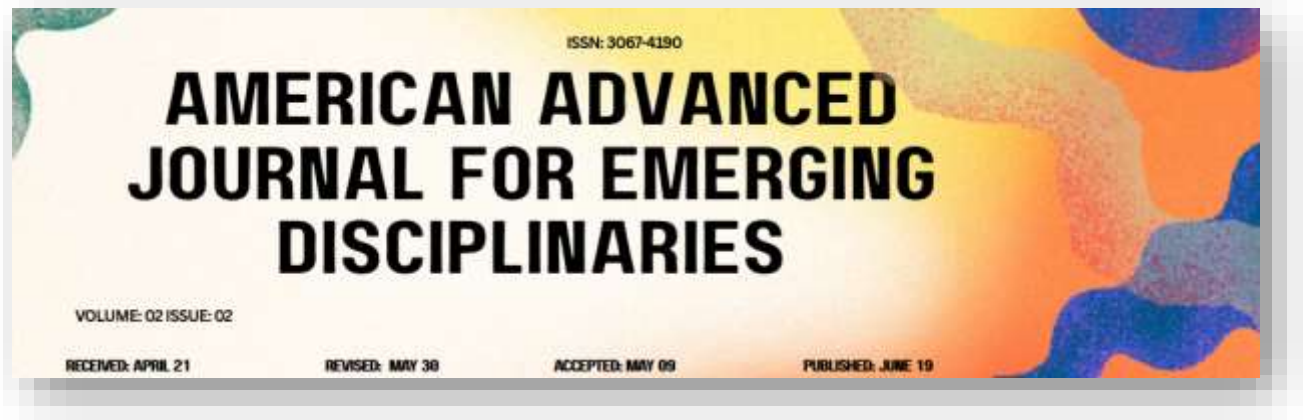
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### Abstract

Over the last few decades, the world has witnessed a tremendous growth in wireless communication. Wireless devices used to connect people around the globe are increasing in number, requiring faster data transfer with better tolerance to fading and interference. Simultaneously, the data generated by these devices is becoming larger and more complex. Learning from prior observations, decisions, and actions has been widely recognized as an effective way of tackling complex problems. For instance, human learning is often accomplished using visual information, and the fact that trained humans can classify tens of thousands of objects makes it natural to use deep neural networks, which take advantage of large labeled datasets, for computer vision problems.

Inspired by the capability of humans to learn from experiences or by leveraging the experiences of others, machine learning finds its place within Artificial Intelligence (AI). AI resides at the higher levels of the communication chain, bringing together advanced optimization and machine learning algorithms to tackle increasingly complex problems, and proposes entirely new designs. Control Theory has been dismissed due to the complexities introduced by the massive data sets and high-dimensional or coupled nature of the problems it has been addressing in practice. High-dimensional and coupled problems are tackled using AI tools that learn lower dimensional descriptions or policies of the original problems. The physical layer, offering advantages of reduced latency, overhead, processing, and predictive gain, has been applying Machine Learning (ML) to specific problems with promising results.

**Keywords:** Wireless Communication Evolution, High-Speed Data Transfer, Fading And Interference Mitigation, Large-Scale Wireless Data, Machine Learning In Communications, Artificial Intelligence Integration, Deep Neural Networks, Computer Vision Inspiration, Experience-Based Learning, Data-Driven Decision Making, High-Dimensional Optimization, Coupled System Modeling, AI-Driven Communication Design, Limitations Of Control Theory, Low-Dimensional Policy Learning, Physical Layer Intelligence, Machine Learning At Physical Layer, Latency And Overhead Reduction, Predictive Gain In Wireless Systems, Intelligent Communication Architectures.



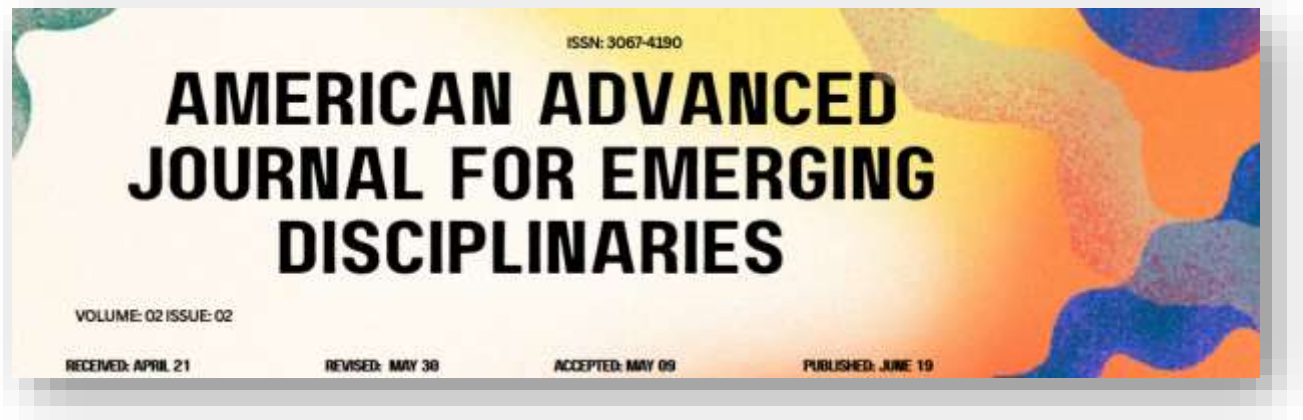
## **1. Introduction**

Seamless integration of artificial intelligence (AI) with wireless and mobile communications can enhance the performance of wireless systems and services. AI is well suited for the configuration, optimization, adaptation, and resourceful utilization of wireless networks and devices, particularly in challenging applications characterized by high complexity, dynamics, and/or uncertainty.

Moving towards the integration of AI and wireless communication systems, this review is focused on the utilization and contribution of AI techniques and models for wireless-related communication problems as well as the specific impacts of wireless and mobile communications systems on AI. Machine learning paradigms conceived for communication are discussed, along with the specific roles of deep learning architectures in wireless systems. Solutions with embedded physical-layer AI are examined in the context of overheadless channel estimation and sensing, as well as for intelligent symbol modulation, coding, and resource allocation. AI-related advances addressing higher layers in the functional architecture of wireless systems are reported for network optimization and scheduling. The implications of adversarial attacks and robustness, trustworthy AI, and privacy in the context of wireless communications based on AI techniques are highlighted. Finally, open data sources, benchmark datasets, and performance metrics for robust and efficient AI-enabled wireless systems are surveyed.

### **1.1. Overview of Wireless Communication and AI Integration**

From the first-ever communication model developed in 1948, research in wireless communications has experienced an exceptional growth. The foundation of the first generation mobile services introduced the concept of wireless communication to the general public. The second generation brought a reliable infrastructure with voice encoding and reduced maintenance costs. The third generation addressed the ever-increasing demand with a broader range of services. The attractiveness of fourth generation communication networks lies in their high speed, quality, and increased capacity. The next generation hops on the newest wave of information processing advances—namely transmissions containing video content. The introduction of support for multimedia in recent generations has resulted in a dramatic rise in resource consumption. But with that increased traffic, security and privacy in wireless communication systems also become an issue. Many researchers focus on developing new designs with the aid of artificial intelligence (AI) techniques in order to ensure these issues are



properly addressed. Consequently, research on communication systems has been increasingly oriented toward intelligent wireless communication networks. Intelligent wireless networks promise extraordinary gains in speed, performance, throughput, and the overall quality of service experienced by end users.

Machine learning (ML) and deep learning (DL) have recently emerged as promising techniques that can automatically learn from data and extract inherent patterns in an unsupervised or near-unsupervised manner. These data-driven AI technologies can complement classical communication designs in various aspects, enabling novel solutions to some of the most demanding challenges (e.g., channel estimation, demodulation, and resource allocation). Successful implementations of these techniques offer models that support a broad range of future wireless communication problems, including resource allocation, quality of service or quality of experience attainability, security and privacy concerns, and development of trustworthy AI solutions.

## **2. Foundations of Artificial Intelligence for Wireless Systems**

Two paradigms of Machine Learning (ML) and a class of Deep Learning (DL) architectures popular for wireless applications and systems are presented. Classical Supervised Learning is widely used for many wireless applications. Its use is highly successful for conventional channel reactive problems such as channel estimation, modulation classification, and resource allocation. Often Convolutional Neural Networks (CNNs) crop up as the best model.

Reinforcement Learning (RL) is a family of ML techniques capable of solving problems with exploration and exploitation goals and are ideally suited for communications in the presence of dynamics or uncertainties. While other topologies such as Generative Adversarial Networks (GANs) and Graph Neural Networks (GNNs) also find application in wireless, here their exposition is omitted due to space limitations. The main focus is still on traditional communications problems, often yielded better results than their CNN-based counterparts.

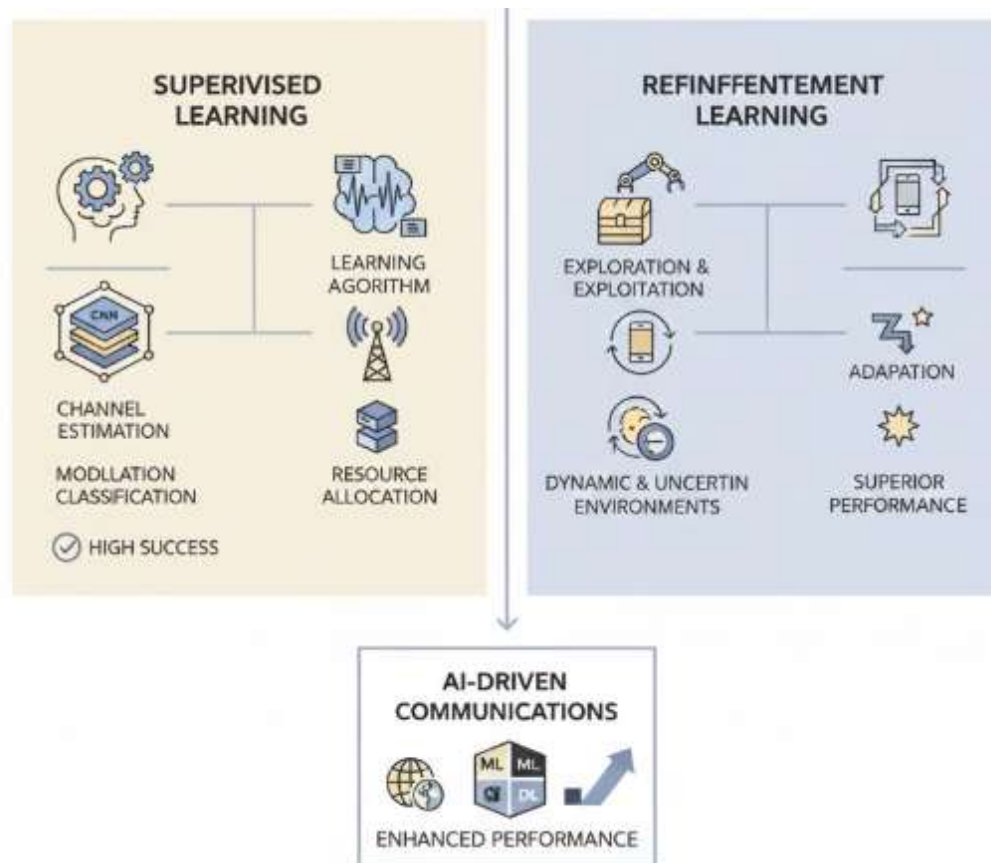
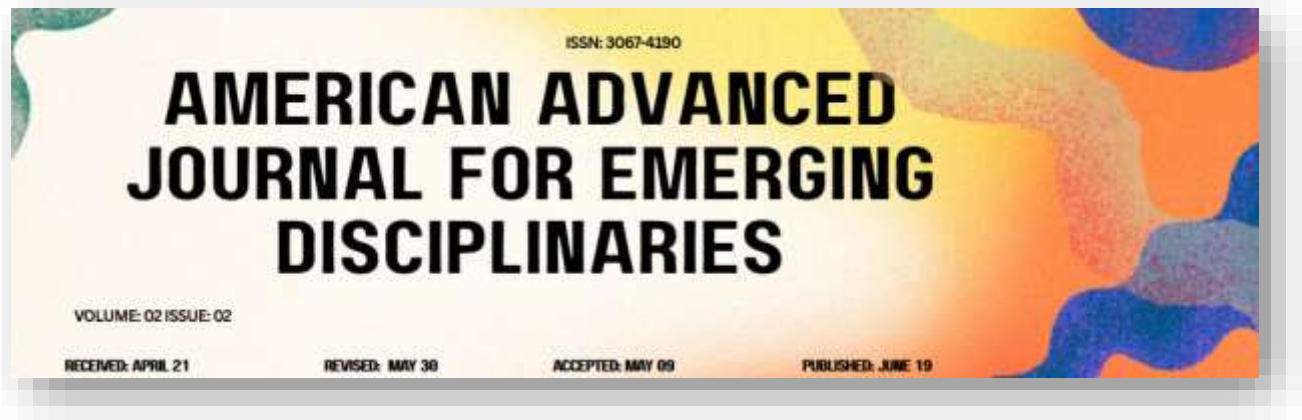
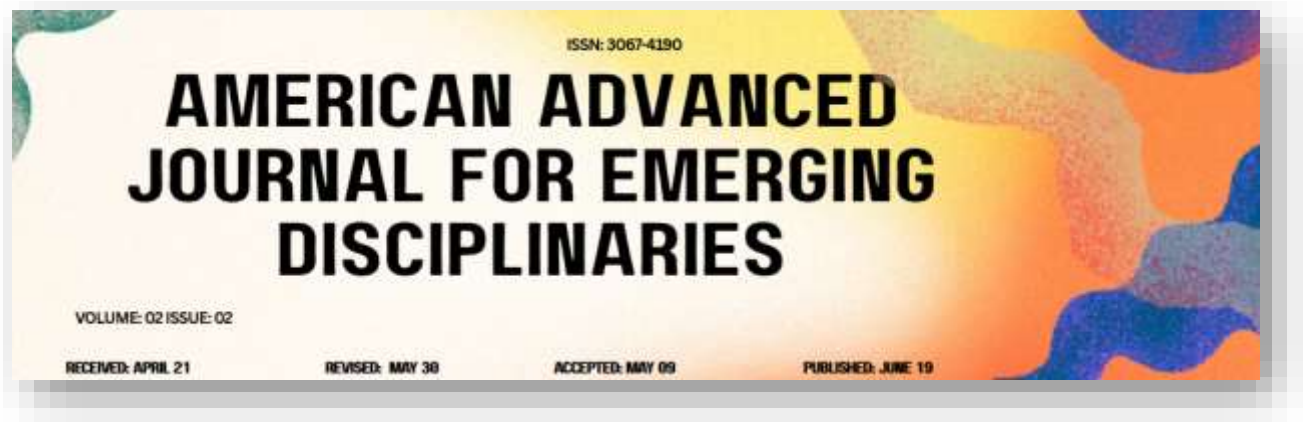


**Fig 1: Machine Learning Paradigms for Intelligent Wireless Systems: Comparative Architectures in Supervised Channel Estimation and Reinforcement-Based Dynamic Optimization**

### 2.1. Machine Learning Paradigms for Communication

Machine learning (ML) encompasses various paradigms and algorithms that are used to extract models or knowledge from data. They are generally categorized into supervised and unsupervised learning, with reinforcement learning as a distinct third branch. In wireless communications, network optimization and various other important tasks can be formulated as either classification (or regression) problems or detection problems, where the objective is to



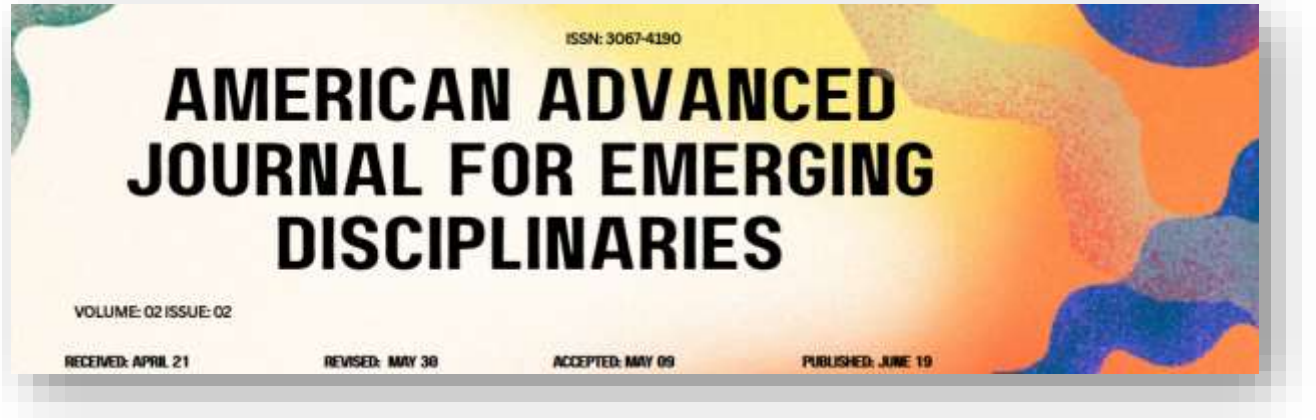
construct a mapping between the input and the output. Learning-based algorithms can also be designed for multi-agent systems, enabling distributed wireless communication design, such as network scheduling or resource allocation.

For classification problems where the received observables can be correctly labeled with the corresponding decision variables, supervised learning can be employed. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have shown state-of-the-art performance in image, video, and voice data processing, respectively. Graph neural networks (GNNs) are also gaining ground as a novel architecture and have been used in scheduling problems in wireless communication. Supervised learning can also be utilized in automatic modulation classification of received signals. Another important task in wireless communication is the detection of users, which may be designed as a classification problem. In cases where labeled data are not available, unsupervised learning—especially generative methods like adversarial networks—may still be used for effective feature extraction.

## **2.2. Deep Learning Architectures in Wireless**

Deep neural networks have been employed in wireless applications requiring the representation of complex, high-dimensional data such as images, video, and audio. These networks consist of several layers, where each layer applies a non-linear transformation to its input, allowing multiple stages of abstraction for the data representation. For instance, in the case of deep convolutional networks, every two subsequent layers work in the spatial domain and the corresponding outputs are transmit images that feed the next layer in the frequency domain; deconvolutional networks have also been used to generate visual content.

Recurrent architectures incorporate a cyclic mechanism to introduce information from previous time steps into the current internal state for tasks where input and/or output sequences appear, such as natural language and speech processing. The time relationships observed in these tasks are also taken into account in the training process through BackPropagation Through Time (BPTT), an extension of the back-propagation algorithm that back-propagates the global error through the entire sequence of time steps rather than through a single time step as in standard feedforward networks. The use of BPTT makes recurrent networks computationally demanding, although simpler architectures with constraints on the internal states have allowed for more efficient learning.



## Equation 1: Pilot-based channel estimation → LS and MMSE

### System model (pilot observation)

1. Transmit known pilot vector  $x$  over channel  $h$ , receive:

$$y = xh + n, \quad n \sim CN(0, \sigma^2 I)$$

### A) Least Squares (LS)

**Goal:** minimize squared error:

$$\hat{h}_{LS} = \underset{\hat{h}}{\operatorname{argmin}} \|y - x\hat{h}\|^2$$

1. Expand objective:  $(y - x\hat{h})^H (y - x\hat{h})$
2. Differentiate w.r.t.  $\hat{h}^*$  and set to zero:

$$-x^H y + x^H x \hat{h} = 0$$

3. Solve:

$$\boxed{\hat{h}_{LS} = (x^H x)^{-1} x^H y}$$

If pilot energy  $x^H x = LP$ , then:

$$MSE_{LS} = \frac{\sigma^2}{LP} = \frac{1}{L \cdot SNR}$$

### B) Bayesian MMSE

Assume prior  $h \sim CN(0, \sigma_h^2)$ .

1. Posterior variance:

$$\operatorname{Var}(h|y) = \left( \frac{1}{\sigma_h^2} + \frac{x^H x}{\sigma^2} \right)^{-1}$$



2. Posterior mean (MMSE estimator):

$$\hat{h}_{MMSE} = Var(h|y) \cdot \frac{x^H y}{\sigma^2}$$

Scalar simplification:

$$\hat{h}_{MMSE} = \frac{\sigma_h^2 x^H}{\sigma_h^2 x^H x + \sigma^2} y$$

And MMSE error:

$$MSE_{MMSE} = Var(h|y) = \frac{\sigma_h^2 \sigma^2}{\sigma_h^2 x^H x + \sigma^2}$$

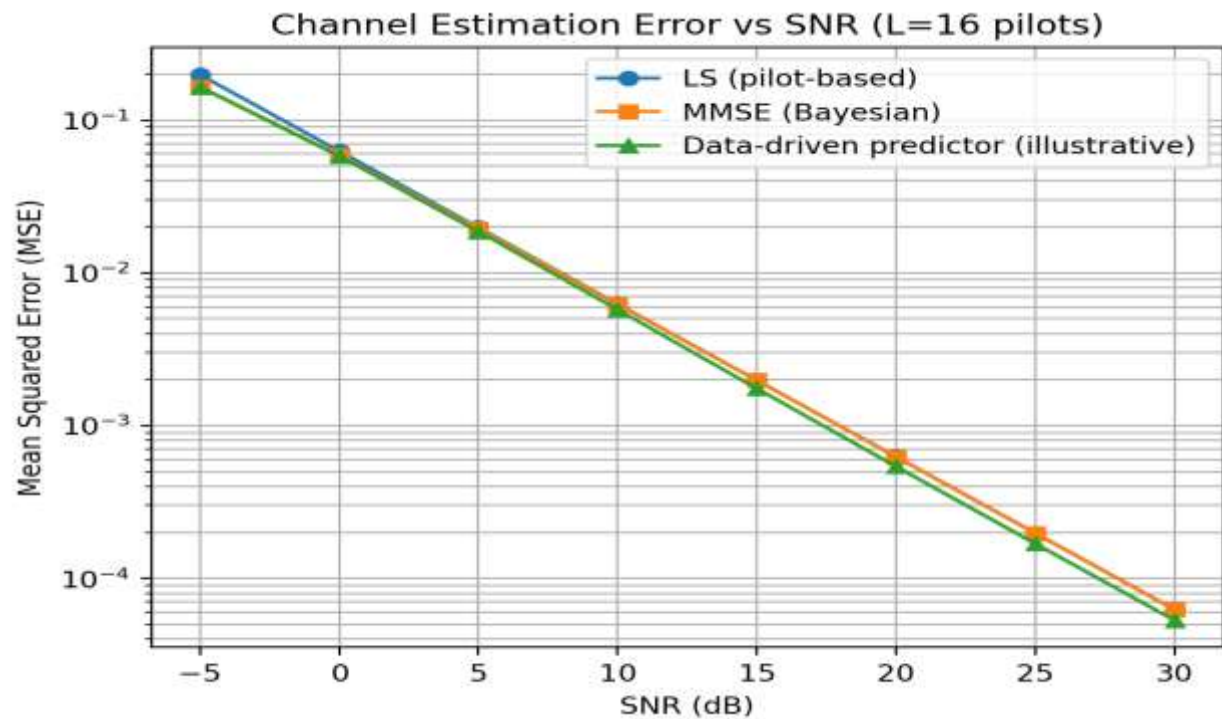
### 3. AI-Driven Physical Layer Techniques

Important physical-layer tasks—channel estimation, modulation classification, error-correcting code detection, and resource allocation—become learning problems with smart data acquisition, appropriate hardware, and a wealth of transceiver data. Physical-layer security, meanwhile, benefits from intelligent learning strategies.

Wireless channels exhibit rapid temporal and spatial variations, rendering frequent channel quality estimation impractical. Instead of relying on expensive parabolic reflectors, expensive array antennas, or complicated design procedures, joint estimation of radio and surroundings utilising camera input has recently gained traction. Furthermore, instead of estimating the channel to select a transmitter-receiver pair, reliable sensing and learning of the channel can facilitate high-quality wireless communications by predicting the best paths over a large-scale environment. The ability of generative models to learn distributions and subsequently generate values for non-available inputs can be exploited for efficient long-range communication design.

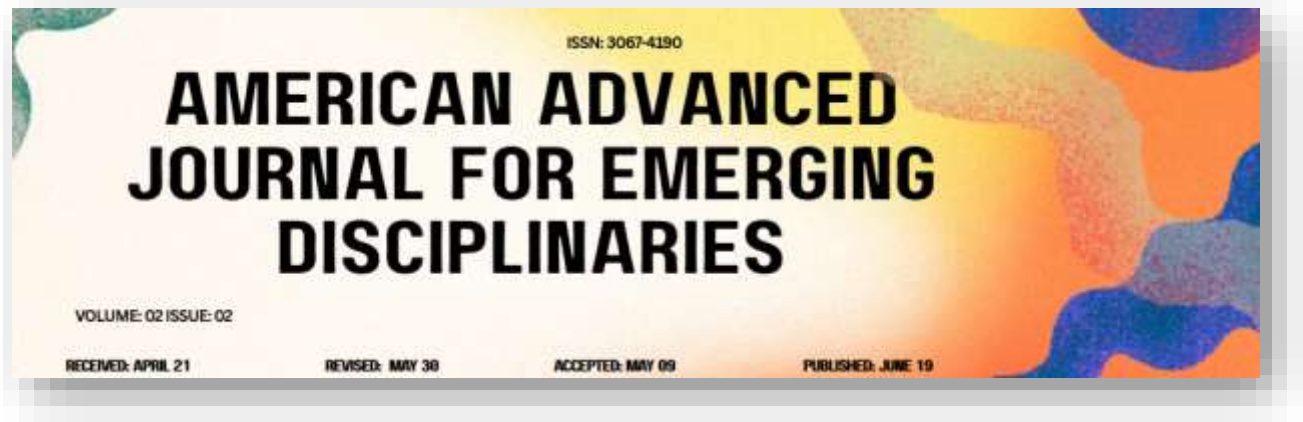
Deep learning has been explored to predict the modulation format of received radio signals, identify applied error control codes, and provide resource-allocation solutions to communication systems. The goal of intelligent communication would be to consider the entire data-transmission process—from source to destination—as a single end-to-end learning problem.

Such endeavours exploit the diverse data captured by transceivers for the purpose of learning and automate the optimal design process.



### 3.1. Channel Estimation and Sensing with Learning

Machine learning models can be trained to predict channels rather than estimate channels, and a generative neural network can be developed that generates channel realizations directly from the statistics. Generative adversarial networks (GANs) have been used for communication problems including phase retrieval and non-line-of-sight communication. GANs model the distribution of the channel state information and enable the generation of arbitrary channel realizations. A GAN can exploit channels with specific characteristics; for example, when the pilot training patterns of additively white Gaussian noise channels can overlap. In some scenarios where a limited amount of channel training data is available or there is a high noise level in the

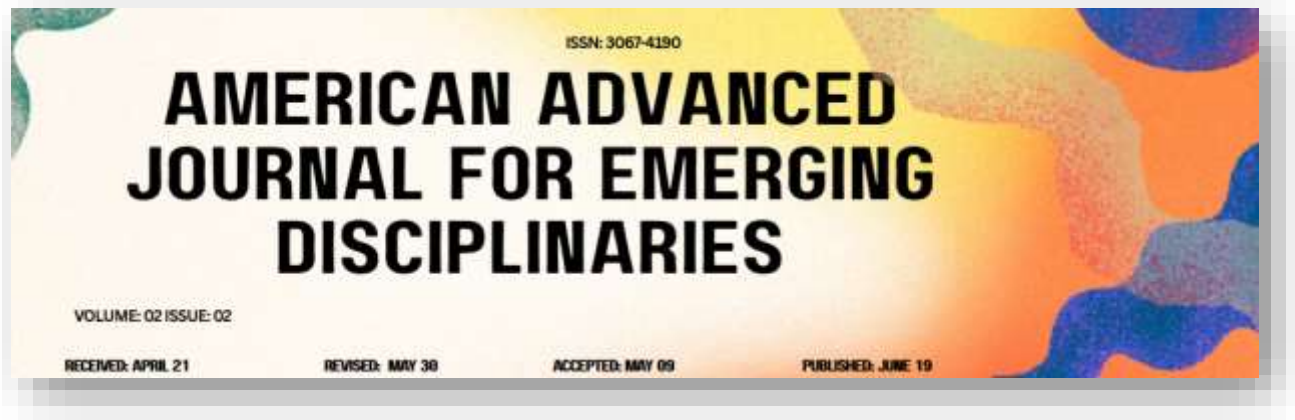


data, the detection performance using a GAN can outperform the optimal minimum mean square error estimator.

Deep learning algorithms and neural networks have been proposed for approximating the channel and data demodulating modules of a communication receiver. The proposed generative model assumed sufficient labeled data were available for both the target channels and current channels to make the receiver learn available data pairs from the channel training dataset as well. The basic concept of GANs has been adopted in the design of the artificial-intelligence-aided communication receiver and has been modified to compensate for the limitation of the GAN architecture. GANs can be used to approximate the pilots of a multiple-input–multiple-output channel that minimize the mean-square error of the channel estimates, reconstruct a channel-reading matrix in a smart city supported by coexisting wireless wide-area and local area networks, estimate indoor wireless channels with 2D and 3D channel image data, and learn an adaptive pilot arrangement for a millimeter-wave massive MIMO system.

### **3.2. Modulation, Coding, and Resource Allocation with AI**

In the area of the physical layer, the intelligent modulation and coding design problem is receiving increasing attention. Besides, semi-blind approaches have shown great promise, especially for low pilot overhead, leading to novel adaptive or even data-aided receiver



structures.

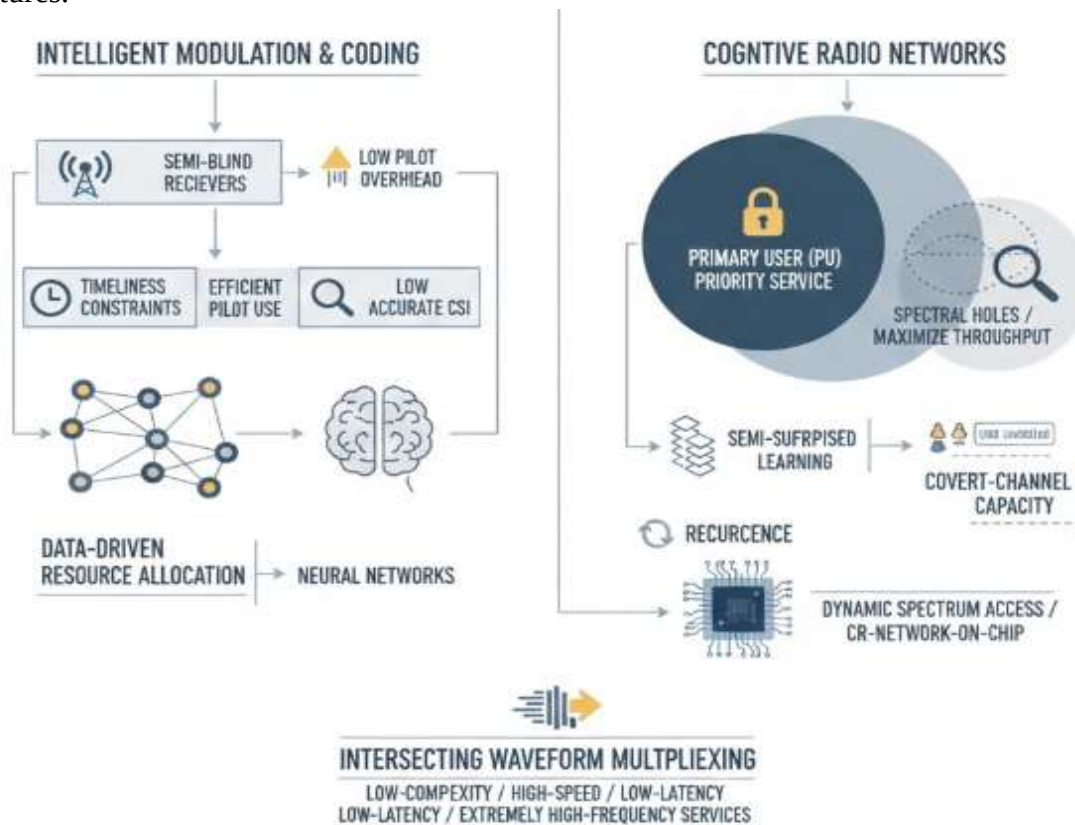
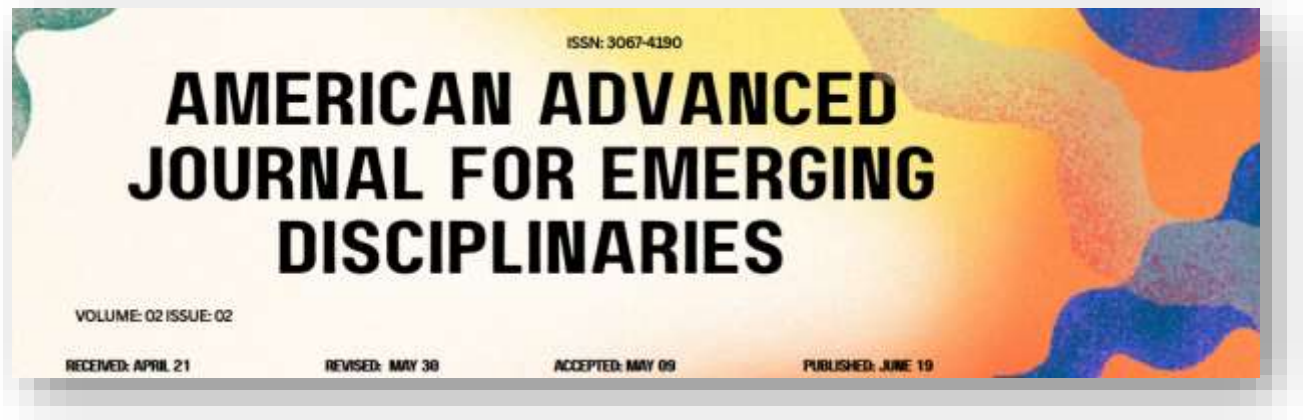


**Fig 2: AI-Driven Physical Layer Intelligence: Semi-Supervised Learning Frameworks for Cognitive Radio Resource Allocation and Dynamic Spectrum Access**

Various radio services impose different data traffic and Quality-of-Service requirements on the network and thereby on the corresponding radio channel state information (CSI) at the transmitter. Packets with low timeliness requirements can permit a more accurate channel estimate, while packet transmission with stringent timeliness constraints can allocate pilot symbols judiciously for efficient use of channel resources. Apart from CSI, the long-term average capacity of the wireless channel can be utilized in an intelligent traffic scheduler for resource-allocation decisions. However, in practical situations, accurate statistical knowledge of the channel is difficult to obtain, which has motivated data-driven approaches with neural



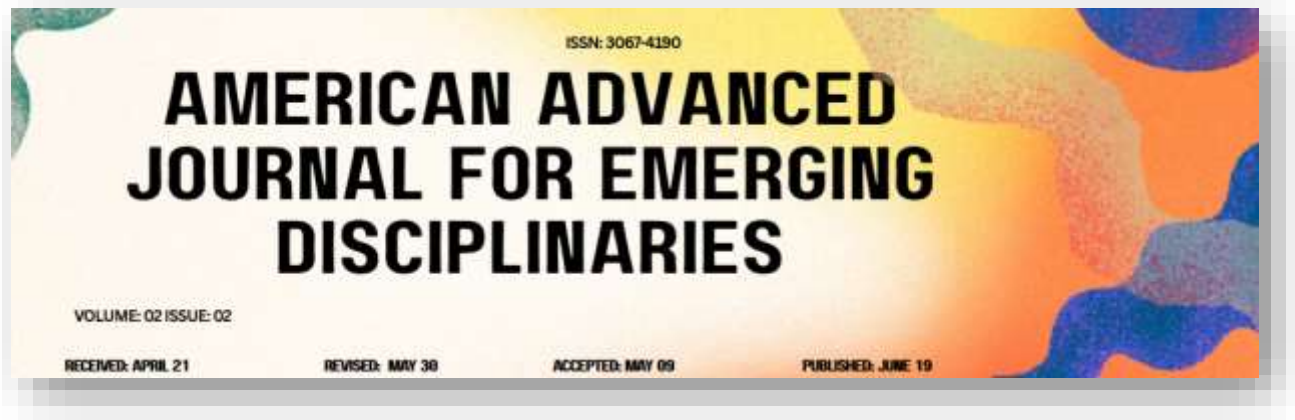
networks (NNs) that learn the connection between the statistics of the fading channel and the allocation in such multiparty systems.

AI can also be employed in cognitive radio (CR) networks, where the primary user (PU) service is of utmost priority, while the secondary user (SU) network exploits the spectral holes to maximize its own throughput. Resource allocation in this hybrid system can thus be cast as a semi-supervised learning problem with a small amount of labeled data for the PU and abundant unlabeled data for both the PU and SU, which offers additional Covert-channel capacity. These developments can be further advanced by recurrence for dynamic spectrum access in template-driven CR-Network-on-Chip design with a customizable template. Small-scale AI-enabled intersecting waveform multiplexing provides low-complexity support for simultaneous high-speed low-latency extremely high-frequency services.

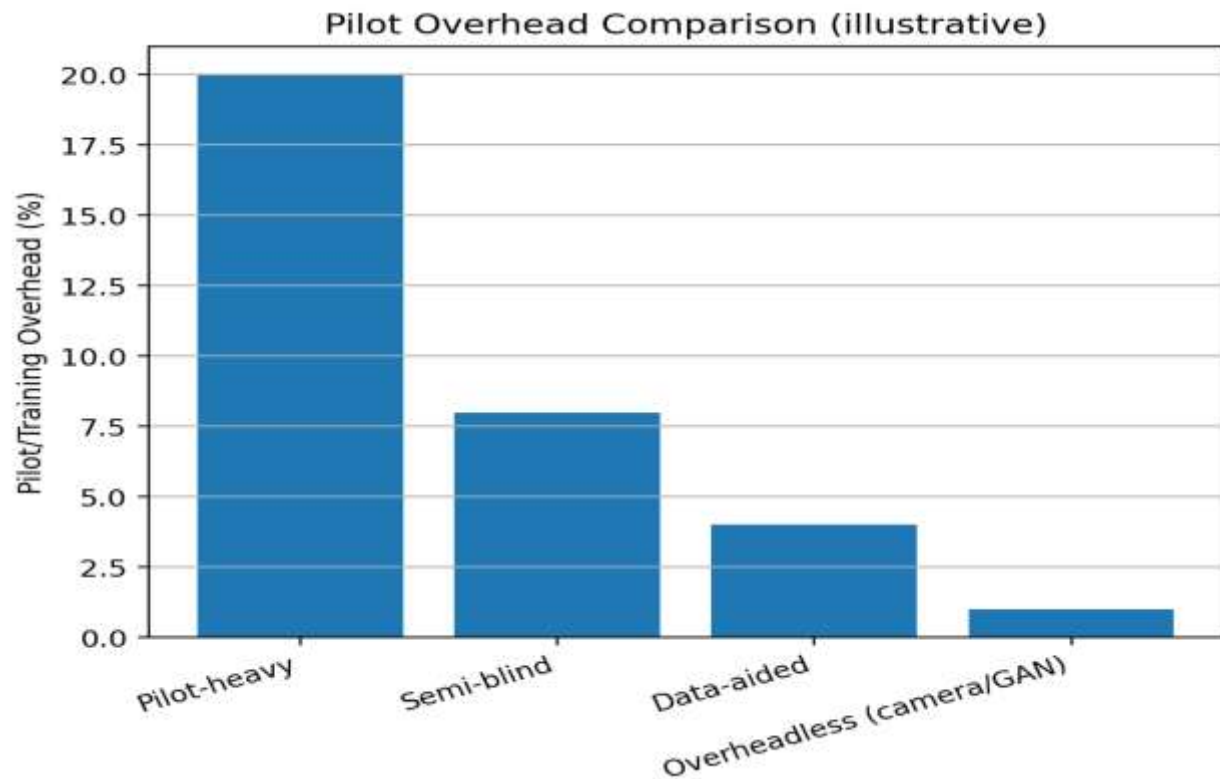
#### **4. AI in Network Layer and Architecture**

The applications of AI expand across the entire protocol stack, with focus on optimising the network layer and higher-layer protocols—and even the architecture of the network itself—these methods cover all aspects of AI for wireless communication except security. Some implement fully fledged AI model for scheduling across base stations and users; others tune parameters of heuristics from classical network theory. For the latter class, as well as in cases where AI-based solutions are incorporated at busier times, hand-optimised performance remains superior to the AI alternative, thus providing an interesting perspective on the applicability of AI in that area. Among the former methods, the AI-assisted approaches introduce new improvements over the original heuristics.

AI is also employed in controlling new 6G architecture in a learning-free way. Conventionally, 6G relies on centralised infrastructure orchestrated by a single entity. As users travel or hash load changes, the system may absorb new base stations or exit the architecture. A machine-in-the-loop architecture has recently been shown to improve QoS while handling new devices at minimal cost. A reservation-based scheme add further gains. With increasing traffic and bandwidth demand, the evolution of the network becomes an open-scheduling problem. Every operator is free to allocate its resources based on self-interested and possibly untruthful information, but the master entity minimises the overall service lag. Such systems maintain stability even when the number of connections grows faster than the number of facilities, with minimal constraints over the service rates of the different resources.



While these methods are directly related to the network layer and aim to solve problems that fall into its domain, the influence of AI in the network is much broader. From advanced applications such as self-organised networking, where the concept is directly applied, to the transparent for the user behaviours and models—such as the detection of the social network of the users and the impact of their interconnections over the communications processes—AI provide insights into the historical and actual network structure and behaviour. Such knowledge allows the network to make informed predictions that guide its work.



#### Equation 2: GAN objective for channel modeling

1. Real channel samples:  $h \sim p_{data}(h)$
2. Noise input:  $z \sim p(z)$ , generator outputs  $\tilde{h} = G(z)$



3. Discriminator predicts “realness”:  $D(\cdot)$

Minimax objective:

$$\min_G \max_D \mathbb{E}_{h \sim p_{data}} [\log D(h)] + \mathbb{E}_{z \sim p(z)} [\log (1 - D(G(z)))]$$

Key result (why it works): for fixed  $G$ , optimal discriminator is:

$$D^*(h) = \frac{p_{data}(h)}{p_{data}(h) + p_G(h)}$$

which drives  $p_G \rightarrow p_{data}$  during training.

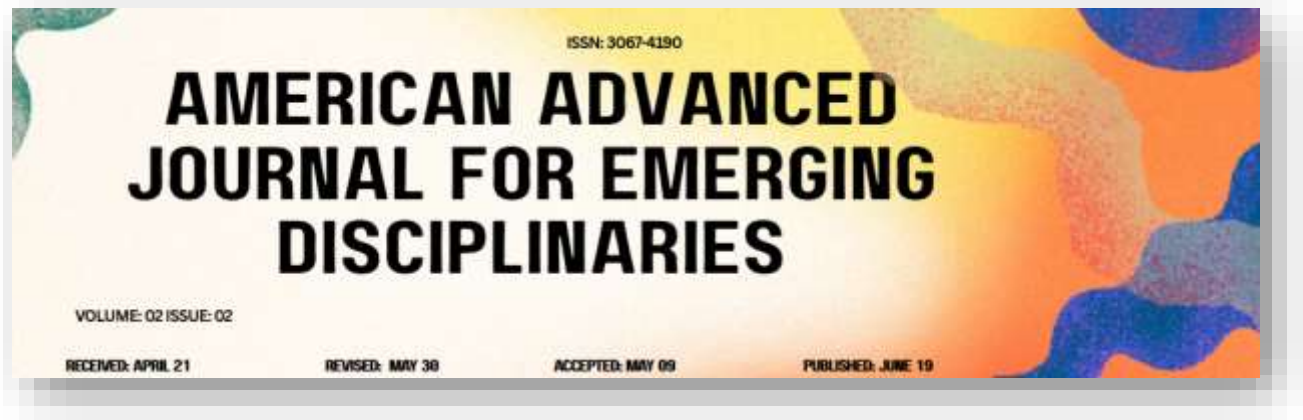
#### 4.1. Network Optimization and Scheduling

Deep reinforcement learning (DRL) provides a compelling framework for optimizing wireless networks. DRL algorithms can learn communication network models, either from simulated environments or directly from real-world network data, without requiring explicit modeling or knowledge of the network dynamics. Efficient exploration is crucial for allowing the agent to learn the optimal policy, and safer exploration schemes can decrease the risk of catastrophic failures. Using stateful deep Q-learning networks, DRL solutions can also be designed for resource allocation in multi-user systems, albeit at the expense of an increased action space.

Conventional into account model-driven approaches can be exploited by combining a model of the network dynamics with a learning approach and as a training ground for reinforcement learning-based solutions, learning of approximating these models can be conducted in a use-and-forget mode, allowing them to be applied only to predetermined use cases. An important class of solutions consist of estimator-based DRL agents with low persistent exploration probabilities, that learn based on temporally correlated network state sequences and thus resemble supervised learning procedures.

### 5. Security, Privacy, and Reliability in AI-Enabled Wireless Networks

Within AI-based wireless systems, security against adversarial attacks and methods for data privacy preservation remain largely underexplored. Considerable attention is being directed



toward trustworthy AI. The robustness of AI-enabled systems has been evaluated against adversarial samples, with the goal of learning such samples automatically. Additionally, methods based on generative adversarial networks (GANs) have shown promise for data generation and transfer learning.

The privacy-preserving capabilities of federated learning have been studied in wireless networks with multiple unauthenticated users. In a federated learning scenario, the learning model is executed in a fully-decentralized manner without requiring a central server; only the model updates from participants are sent to the parameter server, which sends the updated model to the recipients but does not have access to users' private data. Updates from model holders are not given equal weight during federated aggregation; instead, an arbitrary weight is assigned to each holder based on the contribution level in the last round, thus improving the convergence performance of the federated learning framework. Further exploits of federated learning in cooperative relaying have been demonstrated.

### **5.1. Adversarial Robustness and Trustworthy AI**

Despite rapid advances in AI for wireless applications, many techniques remain susceptible to adversarial cues in both training and evaluation stages, such as physical-layer structured attacks on neural network predictions. Moreover, most AI-enabled communication systems rely on an implicit trust assumption, which contradicts the secrecy and trustworthiness principles of secure transactions. To address these two issues, research endeavors have made strides toward enhancing the adversarial robustness of AI systems and reducing their inherent vulnerability. An example of the former includes the introduction of latent domain transformation networks that automatically encode adversarial noise. Adversarial training with such domains has been shown to reduce the target attack rate in two-way relaying scenarios. Trustworthy AI has also emerged as an area of great interest, offering practical methodologies and architectures for compromising attacks based on encryption and watermarking.

Consequently, the design of AI-within-AI systems using secure channels or watermarking-based authentication is now an area of active research. Furthermore, it is essential to specify auditing and monitoring systems that aim to detect and mitigate anomalous AI behavior. A novel measure of trustworthiness for neural networks based on their prediction confidence, coined as the trust rate, and associated methodologies for enforcing a minimum trust rate level have been proposed and established through testing in attack scenarios.

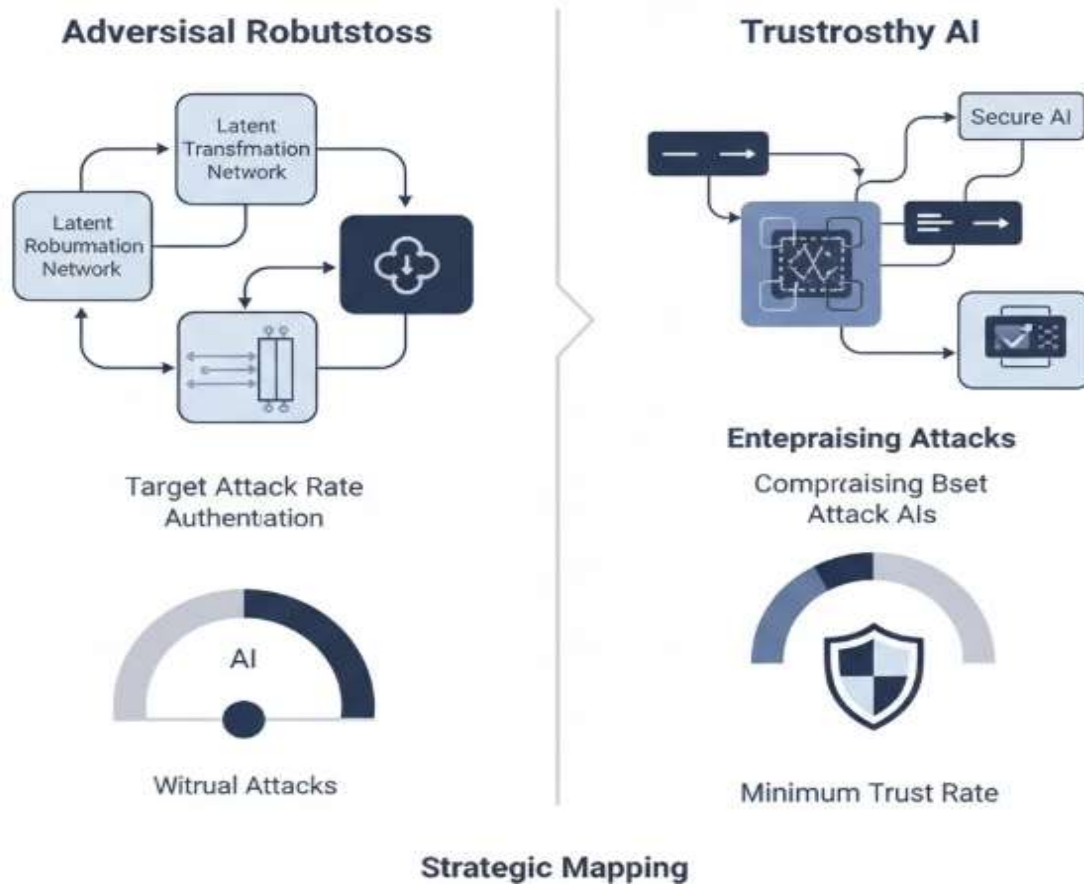
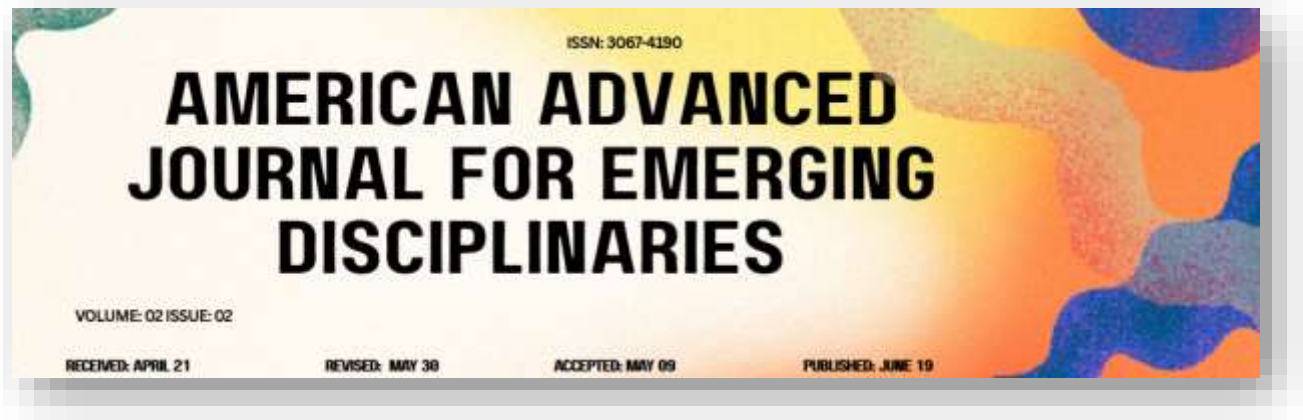


**Fig 3: Securing Secure & Wireless and AI Trustworthiness**

## 5.2. Privacy-Preserving Learning in Wireless Environments

Focusing on preventing data leakage and protecting users' privacy throughout the learning process, approaches for privacy-preserving learning span several paradigms. Recent work in federated learning enables decentralized data storage greatly mitigating the risks of traditional central training. Users' data remains at their locations, and only locally computed gradients for the global model are shared, hence limiting exposure. Nonetheless, leakage could



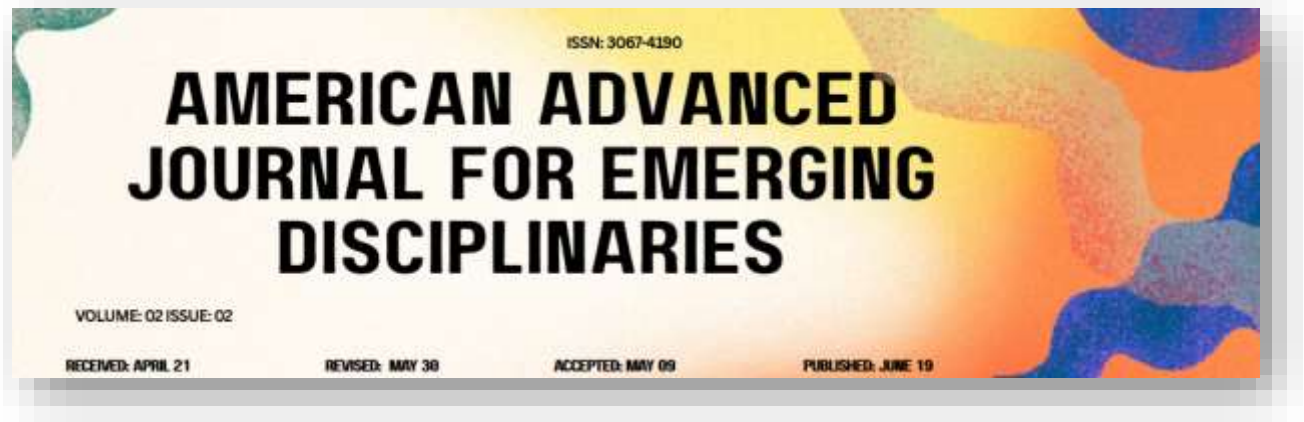
still occur through these gradients. Utilizing techniques such as secure multiparty computation, differential privacy, or homomorphic encryption protects user data further.

Research in the federated-learning context has explored several wireless-network facets, including AI-based channel prediction, scheduling, and resource allocation in IoT networks. Seminal work developed a learning-aided task-classification architecture leveraging user-device heterogeneity while raising privacy concerns among user environments with sensitive content. An approach based on the consensus of users' gradients, appropriate for Internet-of-Things systems with a large number of devices, was proposed to enhance communication efficiency. Extension to the multihead attention architecture improved overall accuracy in wireless systems with Federated Learning framework. A multilabel-encryption system is built on the uplink of federated learning, with preliminary results indicating reduced computation complexity that addresses energy constraints of smart-devices greatly.

## **6. Data, Evaluation, and Experimental Methodologies**

The integration of artificial intelligence (AI) methods into wireless communications relies heavily on the availability of high-quality datasets. In particular, the evaluation of algorithms is vital for determining their capability, robustness, and efficiency, and the creation of benchmarks can assist researchers and practitioners. Supervised learning methods depend on historical data, which may result in poor generalization if the test data contains samples that are not represented in the training data. Consequently, variations in the parameters of the communication and network model should be considered, for example, with respect to signal-to-noise ratio, fading distributions, modulation types, user locations, and channel gain values. The complexity of intelligent methods may also necessitate the generation of synthetic data. Data augmentation strategies should, therefore, be considered in order to improve generalization for visual- and metric-centric applications.

Appropriate performance metrics are critical for the evaluation of intelligent algorithms or models in wireless environments. Training, testing, and deployment are distinct aspects that need careful attention in order to achieve reliable results. Common performance metrics have been established for supervised or unsupervised training and testing phases, such as mean squared error, accuracy, and training time. Nonetheless, performance also needs to be considered from a different angle, as the use of intelligent solutions may entail additional overheads compared with traditional techniques. Therefore, for realistic examination, scaling factors such



as computational complexity, training phase time, training set size, and resource consumption should be included in the evaluation process.

**Equation 3: Modulation classification → softmax + cross-entropy**

2. Network outputs logits  $a \in \mathbb{R}^C$
3. Softmax:

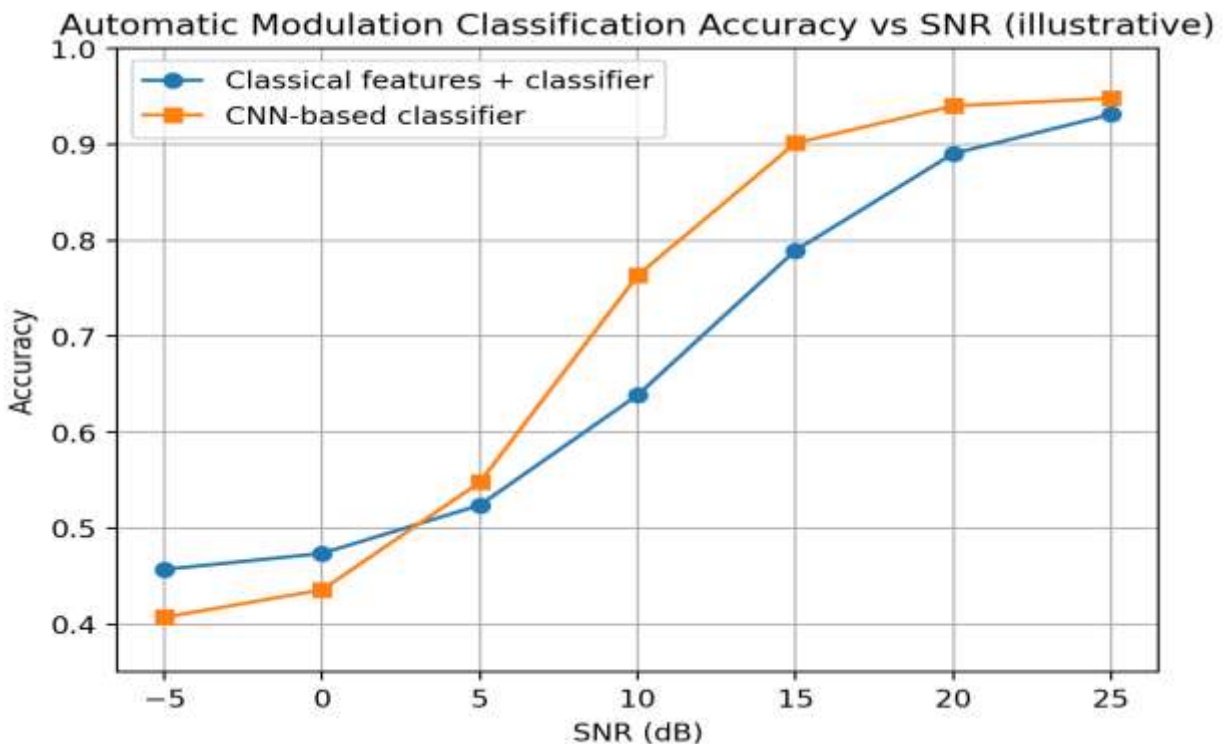
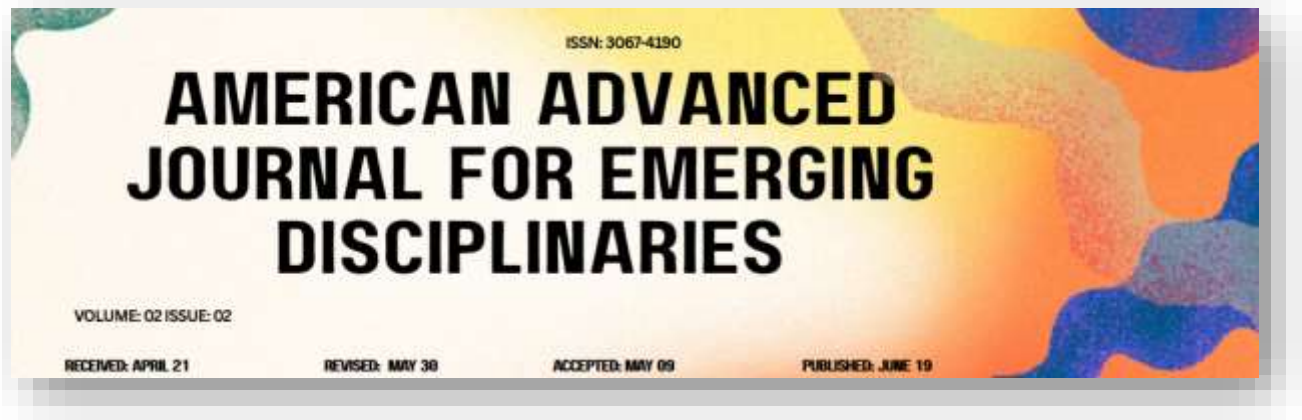
$$p_c = \frac{e^{a_c}}{\sum_j e^{a_j}}$$

4. Cross-entropy loss:

$$L = - \sum_{c=1}^C y_c \log(p_c)$$

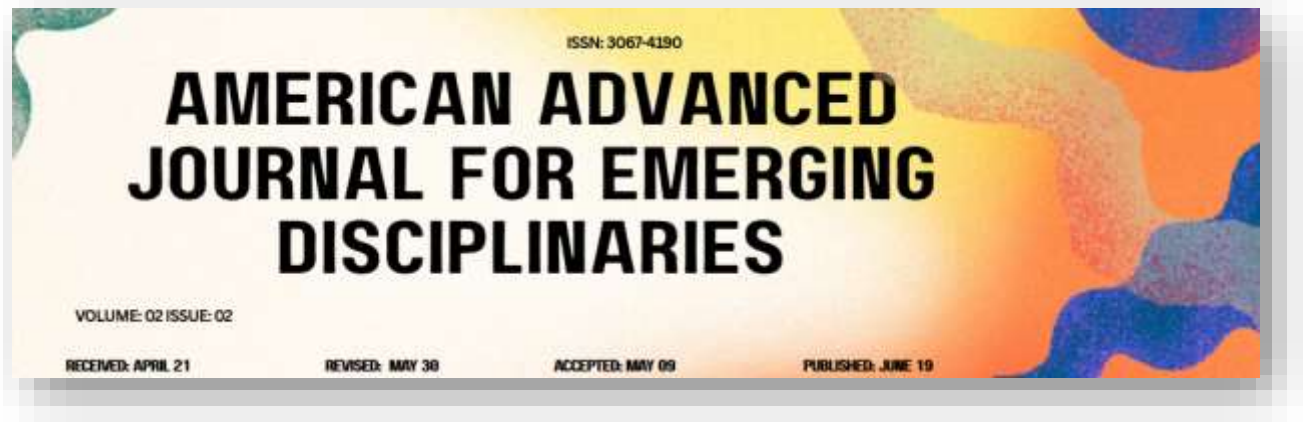
4. Useful gradient (what backprop uses):

$$\frac{\partial L}{\partial a_c} = p_c - y_c$$



### 6.1. Data Collection, Benchmarks, and Open Datasets

In wireless communication, the most common approach to performance evaluation traditionally involves simulating the wireless system according to the scenario considered and subsequently comparing different methods according to the obtained results. However, this methodology has several disadvantages, including its limited generalization capability, long simulation times, and the difficulty of testing robustness and computational efficiency. Indeed, recently proposed ML techniques generated hype in the field, leading to practically zero-cost solutions. They were shown to achieve superior performance without being too demanding in terms of computational load. Markedly, these claims were often solely demonstrated via simulation. An adversarial evaluation of these methods is therefore important to avoid this hurdle. A data-driven approach that blends experimentation, simulation, and empirically generated data instead of relying exclusively on one of the techniques has hence gained traction.



Two general solutions are currently being explored: establishing a large open data repository to improve the evaluation of ML-based techniques and proposing benchmarking organisations to manage and facilitate the performance comparison of existing ML techniques against each other as well as methods developed without ML. The two systems are naturally complementary—open datasets enable the reproduction of existing experiments, thereby facilitating their verification and improvement, while benchmarks assist in the initial effort of creating the data, which will eventually evolve into an open dataset.

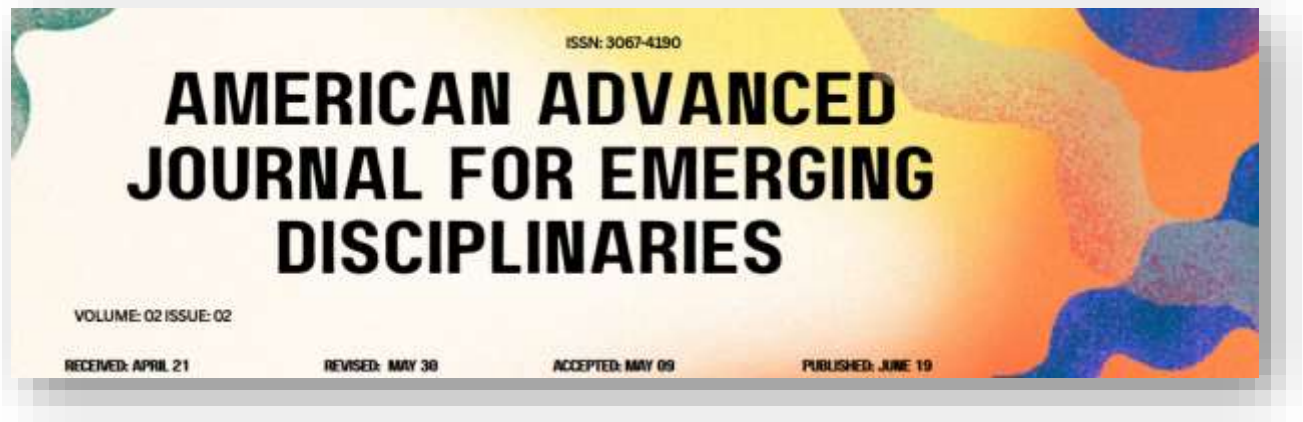
## **6.2. Metrics for Performance, Robustness, and Efficiency**

Quantifying the advantages and principles of AI designs is a crucial aspect for their integration into wireless systems. These contributions can generally be categorized into three main areas: performance enhancement over classical methods; robustness and reliability when exposed to adversarial or unexpected conditions; and resource efficiency in terms of computational, memory, or energy demands.

For classification tasks, metrics such as accuracy and balanced accuracy are commonly employed, while regression tasks often use root mean square error or mean absolute error. Additional metrics such as cause-accuracy, AUC, or F1 score are applicable depending on the context-related impact of misclassification. The detection of adversarial samples can be assessed against existing metrics (robustness) or through field testing in the specific scenario. Efficiency evaluations can focus on latency, model size, or energy consumption, with mnemonic or hardware-efficient designs sought for classification or object detection on small systems.

## **7. Conclusion**

In addition to collecting data to facilitate model training and validation, developing benchmarks and open datasets is vital to assess methods involving AI for wireless systems. Benchmarks define representative scenarios, specify the main metric(s) required for comparisons, and list alternative models/artifacts that can be used. Open datasets help both the research community and practitioners in several aspects including comparative evaluation, study of adversarial behavior, and validation of models before deployment. These initiatives play a pivotal role in



enhancing the reliability and credibility of the proposed AI solutions.

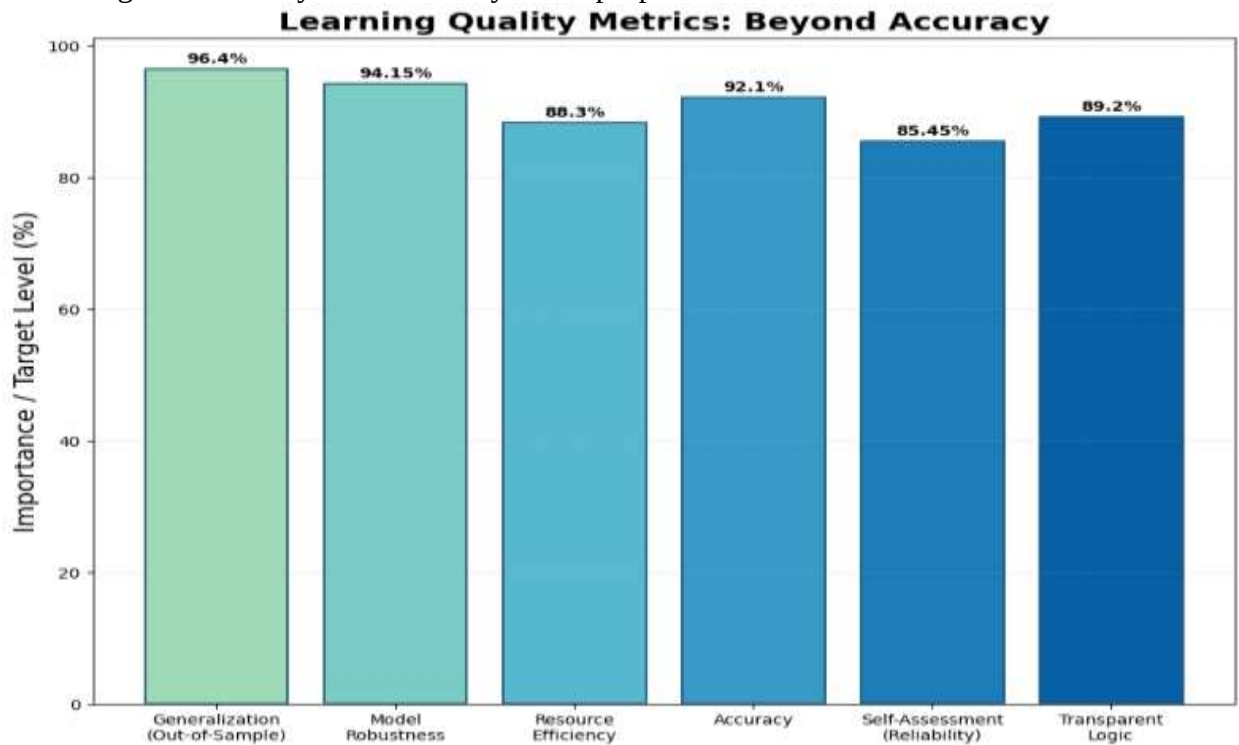
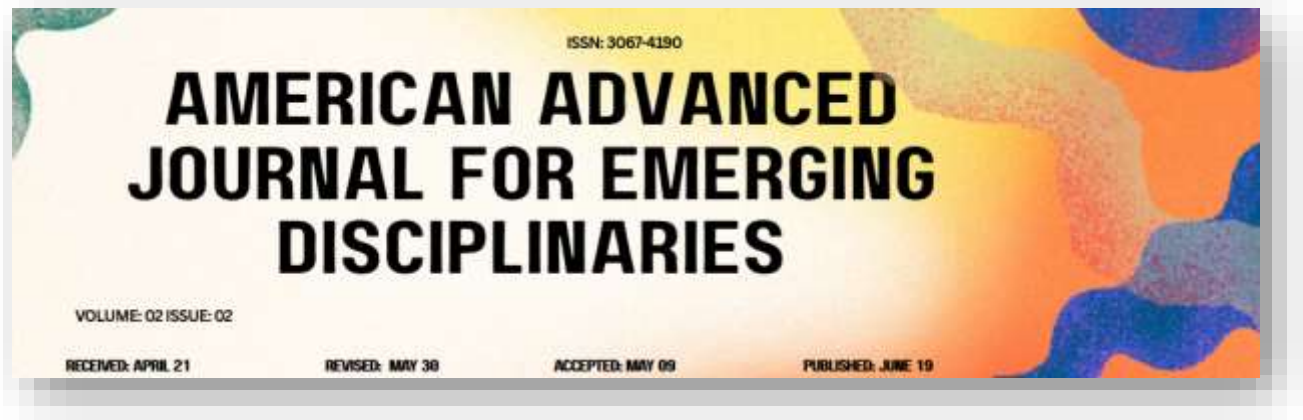


**Fig 4: Learning Quality Metrics: Beyond Accuracy**

Furthermore, the wireless domain presents specific challenges, make the generalization of AI-driven methods difficult. Therefore, it is important that the definitions of the learning quality metrics and the validation of the results focus not only on accuracy but also on robustness and resource efficiency. Generalization – low out-of-sample error for unseen time-space scenarios, with or without data from the test region during training – is one of the high-level goals of AI-based methods in wireless networks. A transparent logic behind the learning should also enable the identification of the main sources of failures, and it is essential that the models are qualified to assess their own reliability. All such considerations contribute to a trustworthy development and offer reliable AI solutions.

### 7.1. Data Acquisition, Benchmarking Standards, and Accessible Datasets

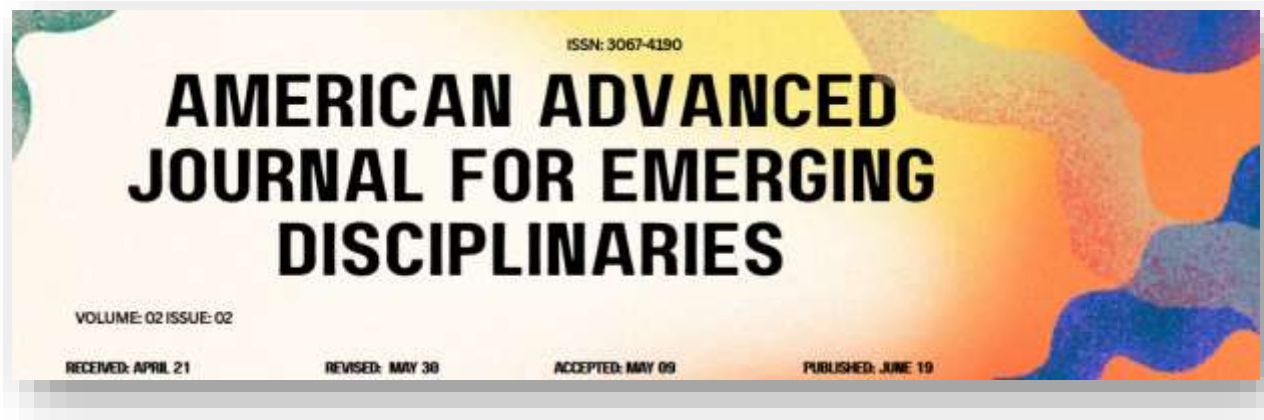


Recent years have witnessed the emergence of numerous AI-based approaches for addressing problems in wireless communication. Nevertheless, few corresponding datasets for benchmarking have yet become available. This solicits a call for the sharing of the input-output pairs required for supervised learning and the generation of challenge datasets for future AI-enabled wireless networks.

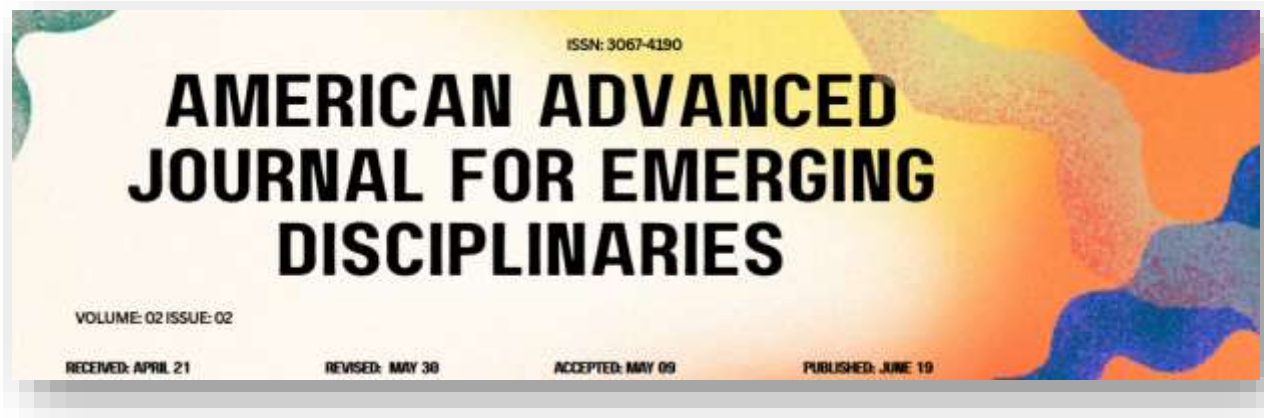
Wireless devices generate an incredible amount of data collected by network operators and devices with a large variety of characteristics including spectrum, signal-to-noise ratio, mobility and clustering. These data sets can be ingested as input for machine learning and graphical model-based methods within an unsupervised or semi-supervised framework to learn high-level abstractions and decision rules including jointly optimizing multiple parameters. Heterogeneity is acknowledged by the development of Federated Learning, an emerging collaborative ML paradigm designed to learn models over multiple distributed servers vertically split by privacy but horizontally aligned with the same data distribution. Using all available data to train models typically gives better performance than local models. By bridging multiple server/user disconnections and supported by B5G and 6G communications, Dataset Sharing enables the aggregation of users progressively switching server location to jointly improve aging models in dynamic environments.

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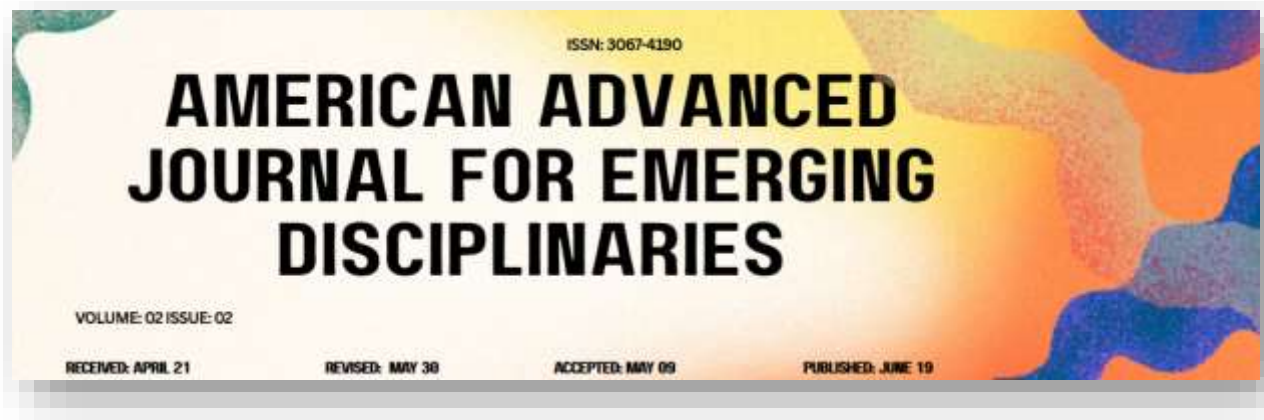
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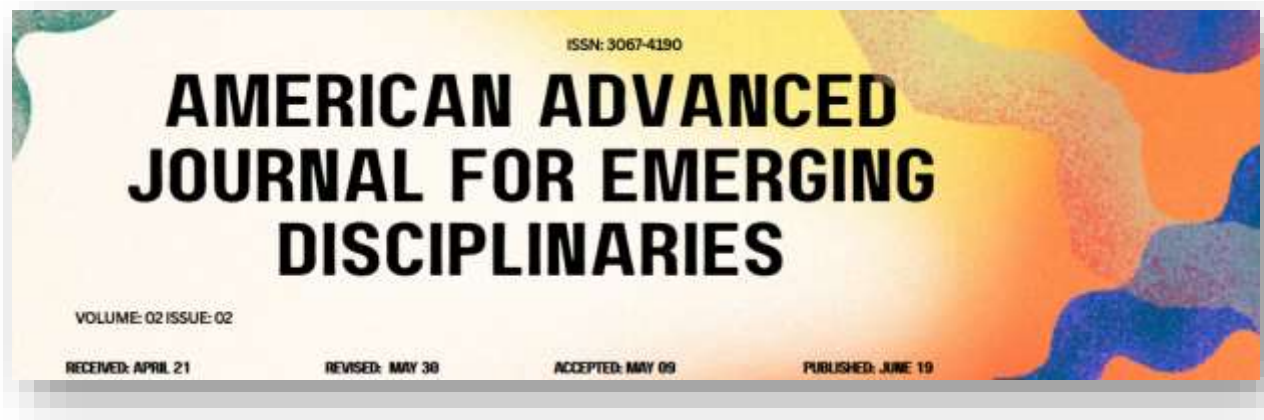
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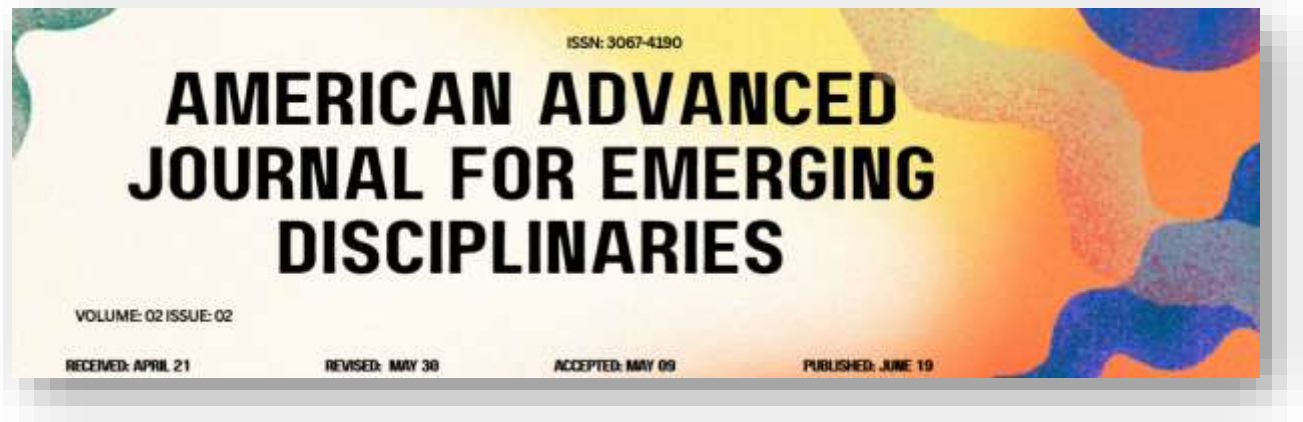
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