

AI-driven approaches in electromagnetic metamaterials design and application: a review

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Abstract. At present, the increasingly sophisticated functional demands for electromagnetic metamaterials pose significant challenges to conventional design approaches reliant on numerical simulation and empirical knowledge, particularly in terms of computational efficiency and design capability. The integration of artificial intelligence has revitalized metamaterials research, enabling rapid forward performance prediction from structural parameters, inverse design from target properties to structural configurations, as well as adaptive functional enhancement and physical mechanism interpretation. This review examines two dominant pathways in AI-assisted electromagnetic metamaterial design and application: forward prediction coupled with inverse design, and adaptive control integrated with physical insight. We summarize recent advances in deep learning and generative models that enhance design efficiency, generalization capability, and interpretability of AI-driven metamaterial models. Furthermore, we explore emerging trends and persistent challenges in developing intelligent, self-adaptive, and multiphysics-coupled metamaterial systems powered by artificial intelligence.

Keywords: Electromagnetic metamaterials / artificial intelligence-driven / forward prediction and inverse design / mechanism analysis / intelligent design

1 Introduction

Electromagnetic metamaterials, which are architected from subwavelength artificial unit cells, have garnered significant research interest in recent years due to their capacity to transcend the limitations of natural materials and enable sophisticated manipulation of electromagnetic wave propagation [1–4]. Their applications span a wide spectrum, ranging from negative refraction [5,6] and cloaking technologies [7–9], to metalenses [10,11] and programmable meta surfaces [12], continuously redefining the frontiers of electromagnetic wave control. However, as functional requirements grow increasingly complex and application scenarios diversify, conventional design approaches are revealing their constraints. The geometric dimensionality and parameter space of metamaterials are expanding exponentially, rendering traditional optimization methods reliant on numerical simulations—such as the finite element method [13] and finite-difference time-

domain method [14]—increasingly inadequate in terms of computational complexity and efficiency. Concurrently, analytical approaches for capturing intricate coupled physical laws often depend on simplified models or empirical assumptions, thereby restricting the depth and scope of metamaterial design.

In this context, the integration of artificial intelligence (AI) has infused new vitality into the study of electromagnetic metamaterials. Leveraging AI, researchers are now equipped not only to accurately forecast material performance by utilizing extensive datasets [15,16], but also to inversely deduce structural configurations from desired properties and interpret underlying complex physical mechanisms [17], thereby facilitating the elucidation of sophisticated electromagnetic phenomena. It is noteworthy that contemporary research on artificial intelligence models predominantly centers on electromagnetic responses, whereas the modeling and integration of multiphysics coupling phenomena remain in their infancy [18–20]. This underscores both the pioneering nature and the inherent complexity of incorporating electromagnetic, thermal, and mechanical properties into a unified intelligent design framework. Such a paradigm shift in research

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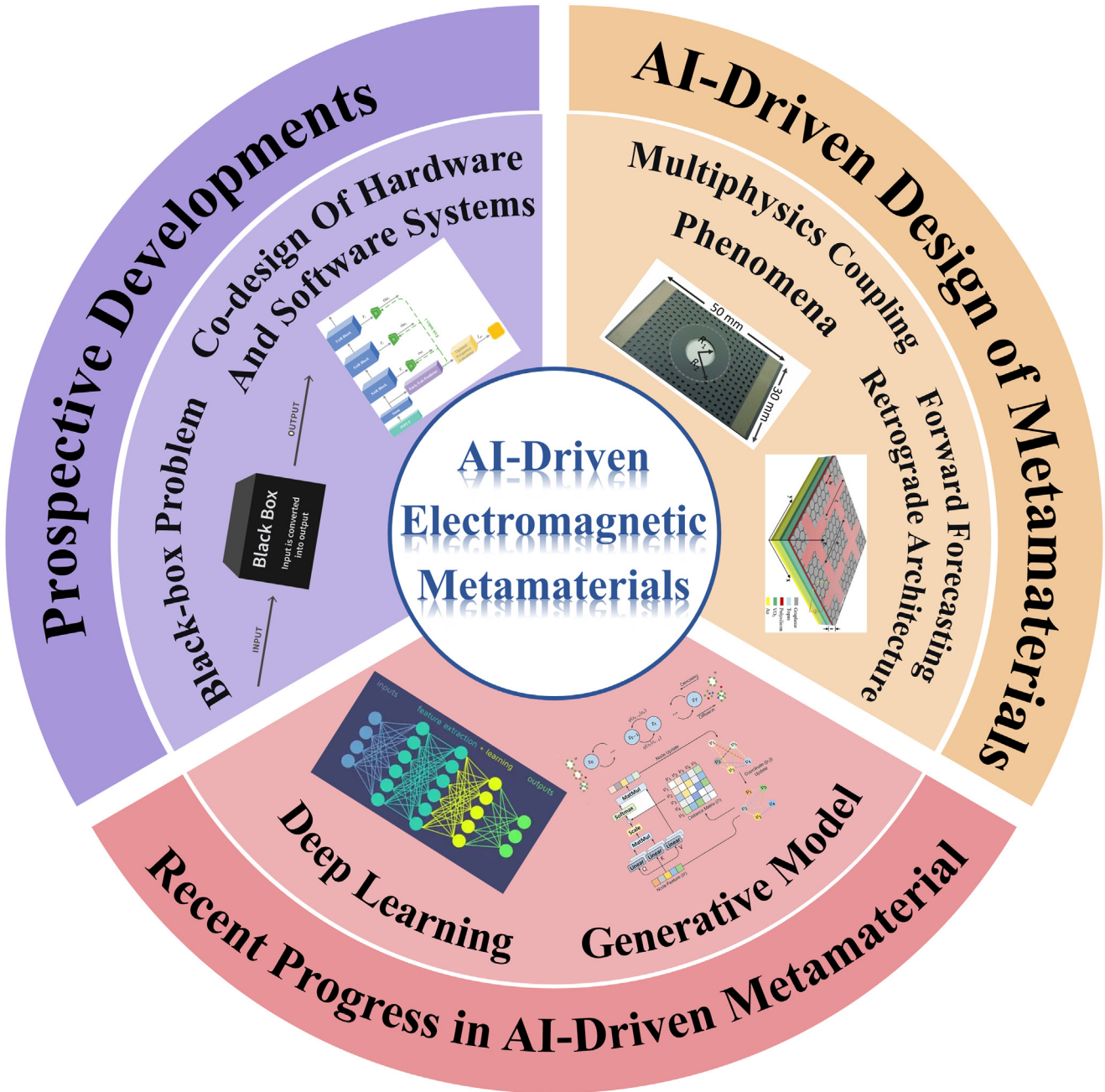


Fig. 1. The current state of integration between AI and electromagnetic metamaterials.

methodology is progressively liberating metamaterial studies from reliance on empirical knowledge and simulation-based approaches, steering the field toward an AI-facilitated adaptive optimization era.

In recent years, AI has gradually evolved two dominant approaches in metamaterial design. The first involves forward prediction coupled with inverse design [21], employing efficient predictive models for rapid structural screening while leveraging generative algorithms to automatically derive novel configurations with targeted functionalities. The second focuses on adaptive enhancement and mechanistic interpretation [22,23], endowing metamaterials with dynamic tunability and the capacity

for discovering underlying physical principles. These developments not only broaden the methodological spectrum for metamaterial design but also foreshadow the extensive application prospects of intelligent metamaterials across multiple domains such as information technology [12,24–26], energy systems [27–29], telecommunications [30–32], and national defense [33–35].

Accordingly, this review centers on AI-driven structurally and functionally integrated electromagnetic metamaterials, with a focused examination of the roles played by AI in forward and inverse design, adaptive control and elucidation of physical mechanisms (Fig. 1). It systematically synthesizes current research developments and

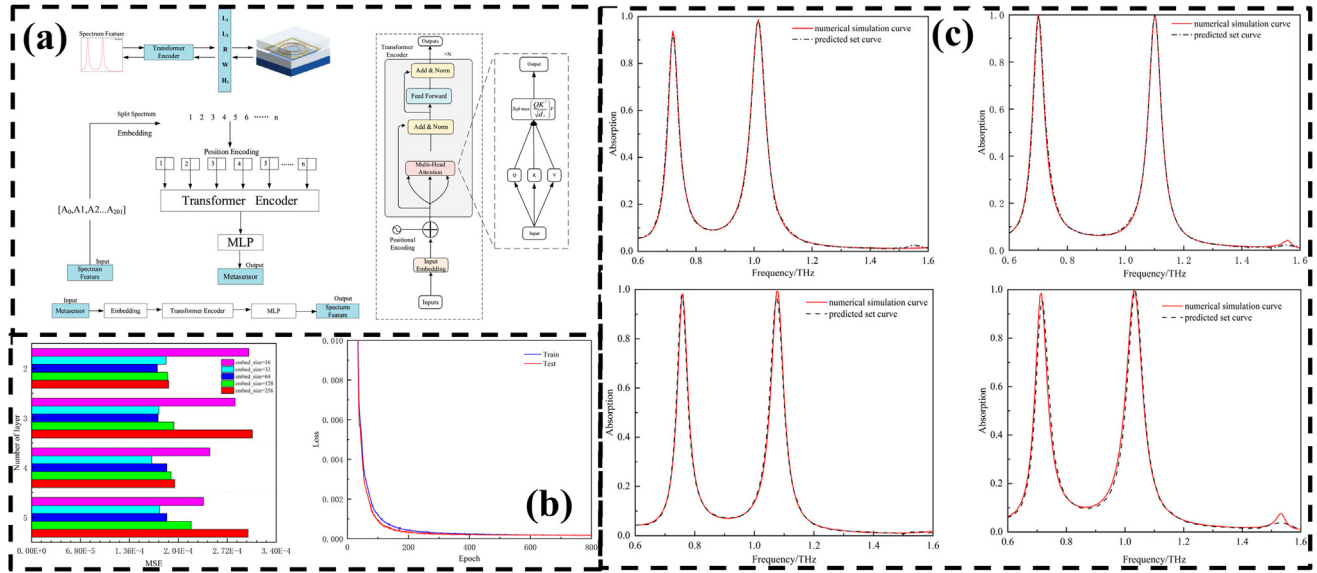


Fig. 2. (a) Schematic diagram of the network model architecture, workflow of forward prediction and inverse design, and transformer encoder model [51]. (b) Comparison of MSE under different numbers of encoder layers and embedding dimensions in forward prediction and loss function curve of the forward prediction model [51]. (c) Comparison of the predicted absorption curves from the forward prediction model and numerical simulation results [51].

practical implementations, building upon this foundation to project future directions. Through this comprehensive analysis, we aim to furnish novel conceptual frameworks and research insights to advance the intelligent design and application of electromagnetic metamaterials.

2 AI-driven design and optimization of metamaterials

2.1 Forward performance prediction and inverse design frameworks

In the realm of electromagnetic metamaterial design and optimization, AI contributes primarily through two central pathways: forward prediction and inverse design [36–42]. Conventional approaches rely on physical modeling [43,44] and numerical simulations [45,46] to explore structure–property relationships. However, the rapid expansion of geometric degrees of freedom [47] and growing complexity [48] in functional requirements have rendered traditional trial-and-error methods increasingly inadequate for contemporary metamaterial development. The integration of AI techniques has effectively addressed these challenges.

Forward prediction focuses on estimating the electromagnetic response of a given structural configuration under specific conditions such as frequency, polarization, or angle of incidence [36,37,49,50]. The objective here is to establish high-fidelity digital replicas that serve as streamlined computational surrogates for laborious numerical analyses. In addressing the critical need for ultra-sensitive detection in terahertz (0.6–1.6 THz) microfluidic sensors, Zhang et al. [51] introduced a deep learning model based on the Transformer encoder for forward prediction. As illustrated in Figure 2a, the core components of this model comprise multi-head self-attention layers, feedforward neural

networks, as well as embedding and positional encoding modules. This approach transcends the constraints of conventional convolutional neural networks (CNNs) in extracting local features, enabling the dynamic capture of holistic interdependencies among structural parameters. Moreover, by leveraging the self-attention mechanism, it effectively addresses the modeling of multi-resonance peak coupling phenomena.

A model was developed to correlate key structural parameters of metamaterials—specifically, the side lengths of metallic rings (L_1 and L_2), ring radius (R), line width (W), and microchannel height (H_3)—with their corresponding electromagnetic absorption spectra. Based on 3,000 data samples subjected to standardization, the architecture integrated a four-tier encoder with a 32-dimensional embedding. Residual linkages and layer normalization were implemented to counteract gradient dissipation. Optimization of the parameter-to-absorption-spectrum relationship was conducted using mean squared error (MSE) as the loss function. The training process spanned 800 epochs in just 185 s, attaining an MSE of 0.000167 (Fig. 2b). Subsequent validation in Figure 2c revealed close alignment between CST simulation results and the model’s predicted curves. Moreover, predicting a single absorption spectrum required less than 10 milliseconds, achieving an efficiency gain of 72,000 times relative to conventional CST simulations, which typically consume around 2 h per analysis.

Inverse design follows an opposing trajectory: researchers begin with desired functional requirements—such as specific transmittance, reflectance, or absorption spectral profiles—and allow algorithms to autonomously generate structural parameters that fulfill these criteria [51–53]. Conventionally, this process demanded immense computational resources. However, with the

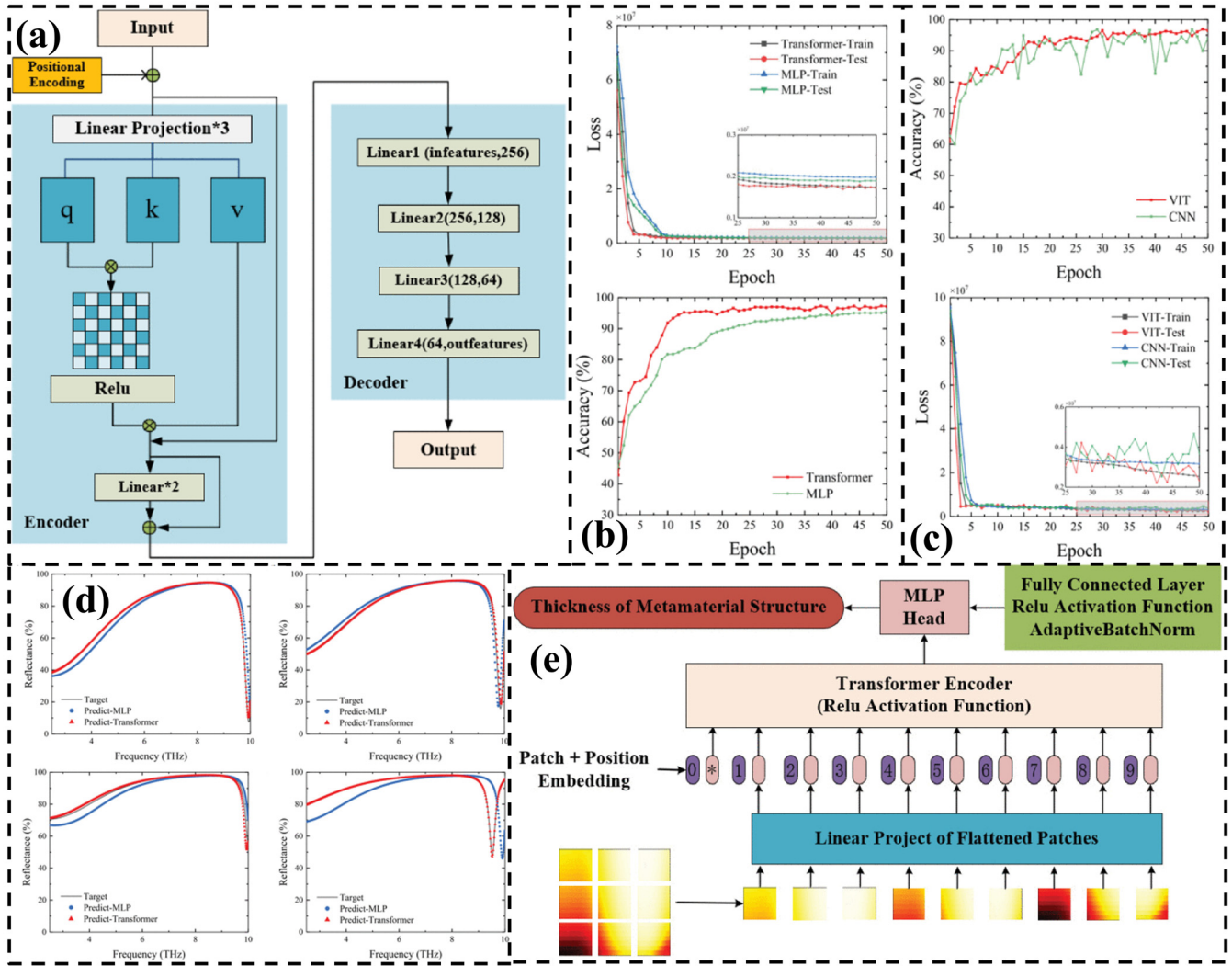


Fig. 3. (a)Architecture of the improved transformer [53]. (b) Training and validation loss curves of transformer and MLP for spectrum-based prediction. Prediction accuracy of transformer and MLP [53]. (c) Prediction accuracy of VIT and CNN. Training and validation loss curves of VIT versus CNN for 2-D heat map prediction [53]. (d) Reflectance spectra of target and predicted thicknesses based on MLP and improved transformer algorithms [53]. (e) Architecture of the improved VIT [53].

integration of AI, inverse design is progressively transitioning from impracticality to high efficiency. In a study by Cai et al. [53], an enhanced Transformer-based framework was employed for inverse design, leveraging self-attention mechanisms to establish a high-fidelity mapping from target reflection spectra to the geometric parameters of graphene metamaterials. As illustrated in Figure 3a, the network adopts an encoder-decoder architecture. The encoder utilizes positional encoding and self-attention to capture global characteristics of the input spectrum, while the decoder consists of four fully connected layers that transform the encoded representations into structural parameters. By embedding a forward physical model within the inverse design workflow, this approach effectively mitigates the generalization limitations commonly observed in conventional neural networks when applied to tunable metamaterial design.

Figure 3b presents a comparative analysis of the Transformer and Multilayer Perceptron (MLP) models in spectral inverse design tasks. The results indicate that the Transformer architecture achieves convergence in merely five epochs, attaining a test accuracy of 96.85%, which markedly surpasses the MLP's performance of 94.98%. Furthermore, Figure 3d demonstrates that the reflection spectra corresponding to the structural parameters predicted by the Transformer align closely with the target profiles. This confirms the model's ability to accurately represent the intricate nonlinear relationships between spectral responses and structural configurations, thereby enabling effective on-demand design. This inherent superiority of the Transformer architecture in capturing intricate spectral interactions—such as coupled multi-resonance phenomena—explains its tendency to achieve accelerated convergence and enhanced predictive accuracy

compared to CNNs and MLPs. Different artificial intelligence architectures exhibit varying emphases when addressing electromagnetic challenges in metamaterials. Therefore, the selection of the architectural solution must fundamentally be based on the nature of the target problem: CNNs leverage their local connectivity and parameter sharing mechanisms, demonstrating significant capabilities in handling spatially correlated configurations (such as the geometric patterns of supercells), and can efficiently capture local features such as edges and vertices. However, for spectral data presented in a one-dimensional sequence form, the remote coupling effects between resonant peaks become particularly important. The Self-Attention mechanism is the core of the Transformer architecture, which can dynamically calculate the relationship weights between any positions in the sequence, thus having a natural advantage in modeling such global interdependencies.

It is important to note that forward prediction and inverse design do not exist in isolation; rather, they form a complementary closed-loop system [36,54,55]. Forward prediction delivers rapid and accurate physical modeling, supplying discriminators and training data for inverse design. In turn, inverse design continuously challenges forward prediction models with novel structural configurations and functional targets, driving iterative refinement of predictive capabilities [36,56–58]. This cyclical interaction manifests in metamaterials research as a convergent “design–validate–redesign” process, substantially shortening the development cycle from conceptual design to experimental verification.

Hou et al. [59] adopted a strategy that leverages forward models as intermediaries to train inverse models, introducing a goal-driven deep learning framework. By employing spectral responses as a bridging mechanism, their method enables inverse design of metamaterial absorber structural parameters based on customized performance metrics. The framework integrates three core neural networks: a Feature Transformation Neural Network (FTNN) that converts performance specifications into target absorption spectra; a Generative Neural Network (GNN) that produces structural parameters corresponding to the target spectra; and a Prediction Neural Network (PNN) that replaces conventional electromagnetic simulations to rapidly evaluate the absorption performance of generated structures (Fig. 4a). Implemented as a 9-layer deep neural network, the PNN allows real-time performance assessment during GNN training. Through backpropagation guided by a loss function, the GNN parameters are iteratively optimized, establishing a closed-loop “design–verify–optimize” workflow.

The proposed framework attains an average accuracy of 93.5% on the test set. In contrast to conventional approaches, it directly translates performance metrics critical to designers into manufacturable structural parameters. This methodology not only eliminates the randomness inherent in traditional optimization algorithms but also addresses the limited practical applicability often associated with purely spectral inverse design strategies, as illustrated in Figure 4b.

Furthermore, our comprehension of the comparative strengths among various AI architectures—such as Transformer networks, CNNs, Variational Autoencoders

(VAE), and Generative Adversarial Networks (GAN)—remains insufficiently delineated with respect to their demands for training datasets, computational expenditures, and generalization capacities. This analysis aims to assist practitioners in selecting appropriate frameworks based on specific operational constraints, including available data volume, computational resources, and requisite generalization performance (Tab. 1).

2.2 Adaptive functionality augmentation and interpretation of physical mechanisms

A pivotal advancement in electromagnetic metamaterials lies in their adaptive capability [60–62], enabling autonomous modulation of electromagnetic responses according to varying external conditions—such as frequency [7,63], polarization [64], angle of incidence [65,66], external electric fields [67,68], external magnetic fields [69,70] and temperature [71,72]. This adaptability serves as the cornerstone for intelligent communications [73,74], stealth protection [75,76], and programmable electromagnetic platforms [77], marking a critical transition from static configurations to dynamic, intelligent systems. The integration of AI overcomes the limitations of conventional approaches that rely on fixed geometric parameters or limited tunable dielectric components, offering a novel pathway for both constructing adaptive metamaterials and deciphering their underlying physical mechanisms.

In their work, Cai et al. [53] enhanced neural network architectures to advance the adaptability of electromagnetic metamaterials, optimizing the inverse design process through the integration of diverse data representations. Specifically, the team employed a modified Transformer network to analyze one-dimensional reflection spectrum data (illustrated in Fig. 3a), alongside an adapted Vision Transformer (ViT) for interpreting two-dimensional heatmap data (depicted in Fig. 3e). Leveraging self-attention mechanisms, these networks effectively capture long-range dependencies within the input data, enabling precise prediction of structural parameters in metamaterial design.

Figures 3b and 3c present comparative evaluations of an enhanced Transformer architecture and a conventional MLP model under varying input data conditions, illustrating differences in training loss and prediction accuracy. The Transformer achieves convergence significantly faster (e.g., at epoch = 5) while attaining superior accuracy (96.85% versus 94.98%). These results underscore the efficacy of the self-attention mechanism in effectively capturing discriminative spectral features.

AI has not only enhanced the adaptive capabilities of electromagnetic metamaterials but also facilitated the interpretation of underlying physical mechanisms. It is evident that beyond merely assisting in material design, the greater significance of AI lies in its potential to uncover intricate physical principles. The intrinsic nature of metamaterials often involves multi-scale and multi-physical coupling phenomena. For instance, conventional approaches struggle to quantitatively analyze the synergistic interactions among electric dipole, magnetic dipole, and toroidal dipole resonances (Figs. 5a and 5b). In their study, Zhang et al. [78]

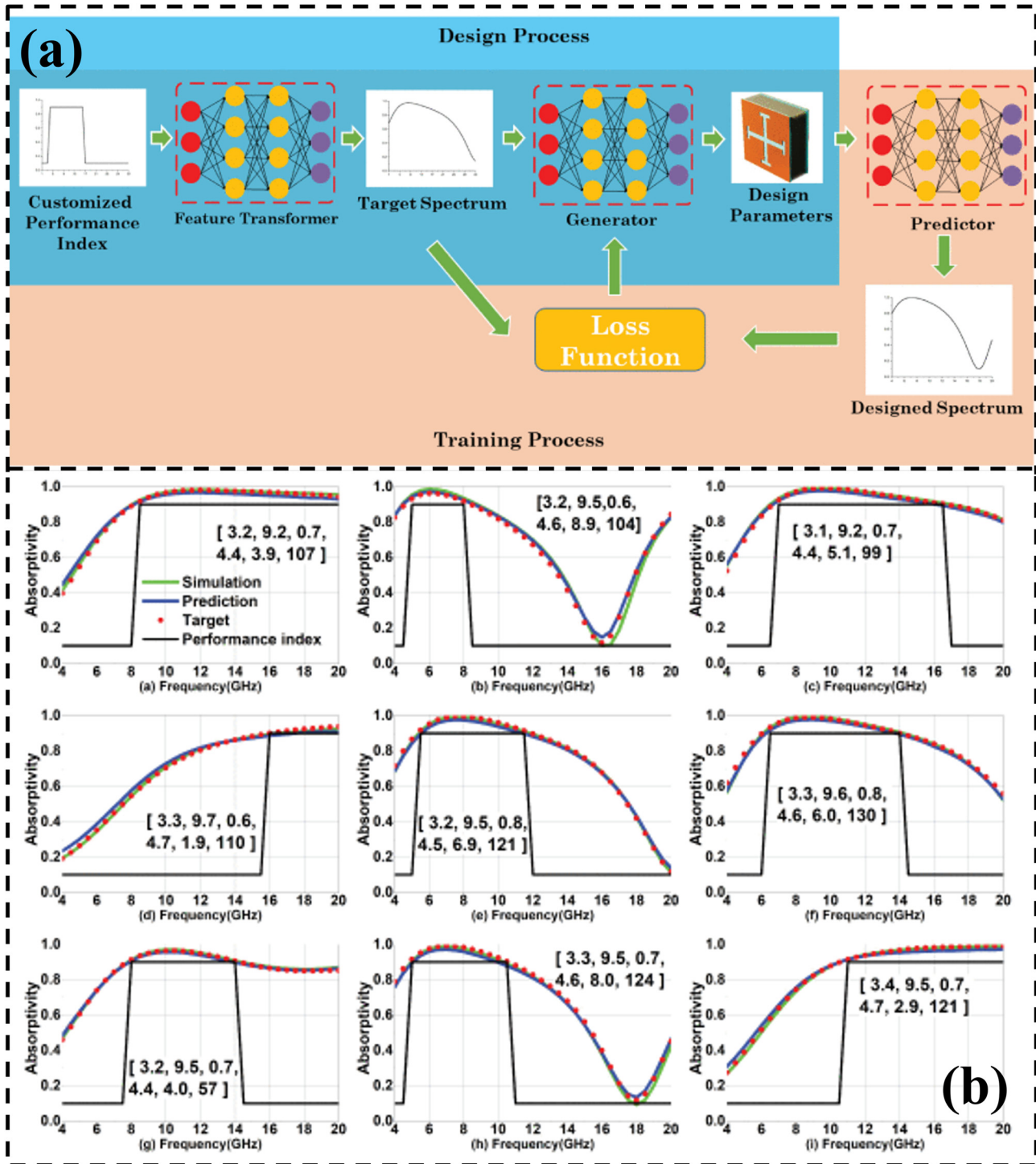


Fig. 4. (a) Deep learning framework [59]. (b) Absorption spectrum, expected performance spectrum, expected performance result, performance indicator [59].

employed CNNs to analyze structural parameters and surface current distribution data of metallic strips, rings, and closed rectangular split-ring resonators illustrated in Figure 5a. This approach enabled automated identification of dominant resonance modes excited by different configurations. The AI-driven

analysis revealed that anisotropic surface currents in strip structures correspond to ED resonances (Fig. 5b), whereas circulating currents in closed-loop configurations are associated with MD resonances. Such analytical capability establishes an intrinsic model connecting “structural parameters – resonance modes – electro-

Table 1. The comparative advantages of different AI models in terms of training data requirements, computational costs, and generalization capabilities.

Model type	Training Data Requirement	Computational Cost	Generalization Capability	Primary Application Scenarios
Transformer	High	High	Strong	Sequential/spectral data, long-range dependency modeling
CNN	Medium	Medium	Medium	Image/structural data, local feature extraction
VAE	Medium-High	Medium-High	Strong	Latent space modeling, generating diverse structures
GAN	High	High	Medium	High-fidelity image/structure generation

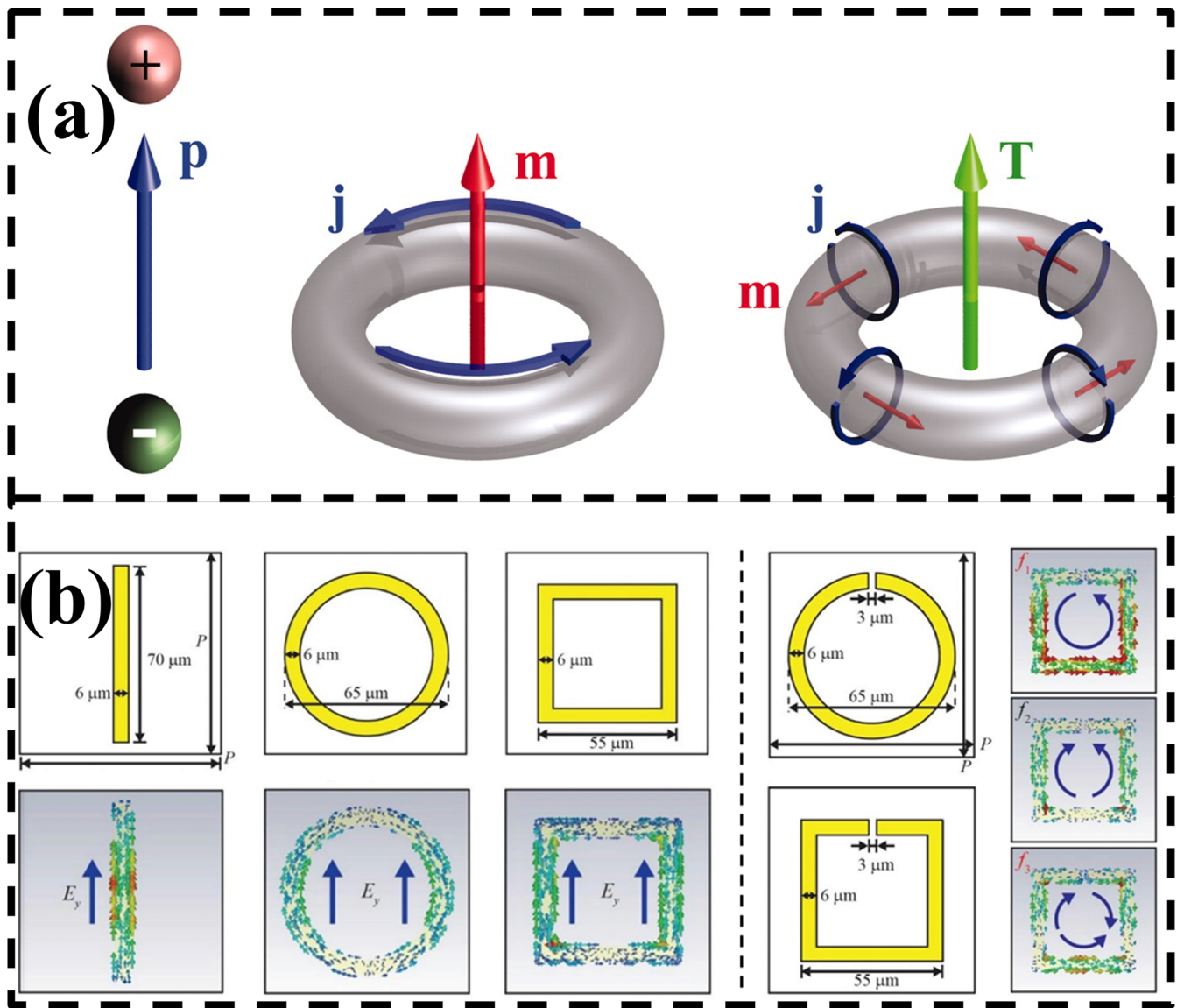


Fig. 5. (a) ED: one positive and one negative charge forming an electric dipole p ; MD: the current j flowing through the closed loop exciting the magnetic dipole m ; TD: the current flowing along the radial direction of the torus forming a circular dipole T . [79] (b) THz transmission spectra and resonance surface currents of ED and MD metamaterials [78].

magnetic responses” in metamaterials, thereby circumventing oversimplified assumptions inherent in manual analysis and achieving quantitative interpretation of complex resonance physics.

3 Recent progress in AI-driven metamaterial investigations

In prior discussions, we examined the current integration approaches and performance enhancement pathways of AI and metamaterials. Evidently, this interdisciplinary synergy is facilitating a paradigm shift in metamaterials—from static configurations toward dynamic, intelligent systems. Specifically, it progressively enables the creation of metamaterials with self-adaptive capabilities and interpretability for intricate physical mechanisms. Such advancement critically relies on AI technologies to drive the design, optimization, and control processes. This chapter will subsequently delve into representative studies in the field.

3.1 Deep learning

As one of the earliest and most extensively explored approaches in integrating AI with electromagnetic metamaterials, deep learning fundamentally employs architectures such as CNN, fully connected networks (FNN), or GNN to capture the nonlinear relationship between geometric parameters of metamaterials and their electromagnetic responses. By learning underlying patterns from extensive existing datasets, this methodology enables both rapid forward prediction of performance from structural configurations and inverse design of geometric parameters based on desired electromagnetic characteristics.

To address two major challenges in deep learning applications—the “black-box” dilemma and limited generalization capability—Yiming et al.¹ proposed a circuit-theory-informed neural network (CTINN) for designing plasmonic stacked metamaterials. This framework incorporates equivalent Resistor-Inductor-Capacitor (RLC) circuit theory, representing metamaterial unit cells as RLC circuits. By introducing electromagnetic parameters as physical constraints, the model provides interpretable insights into electromagnetic response mechanisms, thereby overcoming the limitations of conventional black-box modeling.

The architecture of CTINN (Fig. 6a) incorporates normalization layers, hidden layers, circuit parameter layers, and physics-operation layers, which collectively transform structural parameters into circuit parameters. These parameters subsequently generate spectral responses through circuit-based functions. This design leverages electromagnetic principles to convert high-dimensional spectral predictions into a lower-dimensional circuit parameter optimization task, thereby reducing model complexity and data dependency. Experimental results (Figs. 6b and 6c) demonstrate that CTINN achieves over 50% lower test error with only 10% of the training samples required by conventional approaches. It also surpasses standard multilayer perceptron models in both

structural and wavelength extrapolation tasks. Addressing the challenge of poor generalization, CTINN exhibits not only high predictive accuracy within the training domain but also robust performance in predicting spectra for structural dimensions beyond the training range and across extended wavelength regimes, as illustrated in Figure 6d.

To address the issue of poor generalizability, Hua et al. [80] adopted a distinct strategy by developing a hybrid CNN-Long Short-Term Memory (LSTM) framework. This architecture integrates the capability of CNNs in capturing localized patterns with the strength of long short-term memory networks in modeling sequential dependencies, enabling multi-level analysis of frequency band response data (Fig. 6e). Comparative experiments illustrated in Figure 6f demonstrate that data augmentation techniques achieve high-precision design of metamaterial structural parameters even with limited samples. Specifically, the median prediction error in Figure 6f drops to 1.09×10^{-5} , whereas the error in Figure 6f without data augmentation is nearly an order of magnitude higher (1.39×10^{-4}). These findings validate that constructing a well-defined feature space significantly enhances the model’s generalization performance.

The close alignment between the anticipated and predicted performance curves in Figures 6f and 6d visually underscores the precision of inverse design. Leveraging this experimental methodology and AI framework, Hua et al. successfully fabricated a reflective linear polarization converter exhibiting broadband polarization conversion across the 2.2–18 GHz spectrum. The strong correlation between simulated and experimental outcomes confirms that the AI-optimized metamaterial architecture maintains robust functional performance despite manufacturing imperfections, thereby validating the viability and reliability of AI-driven design approaches.

The above case demonstrates that addressing the challenges of data scarcity and generalization in metamaterial design is crucial for the practical application of deep learning. The current research strategies mainly focus on two aspects: one is to introduce physical prior knowledge to reduce data dependence, such as CTINN which integrates equivalent circuit theory to convert high-dimensional spectral prediction into low-dimensional physical parameter optimization; the other is to utilize advanced network architectures and data augmentation techniques, such as the hybrid CNN-LSTM model which captures the local and sequential dependencies of frequency response data and combines data augmentation to achieve high-precision design with a small number of samples. These methods are essentially in line with concepts such as physical information neural networks and small sample learning, providing an effective path for constructing efficient and reliable AI-driven design models under limited data conditions.

3.2 Generative modeling frameworks

Unlike deep learning approaches, the emergence of generative models signifies a pivotal shift in AI-driven metamaterial design—transitioning from “predictive learning” to “autonomous innovation”. Models such as VAE (a),

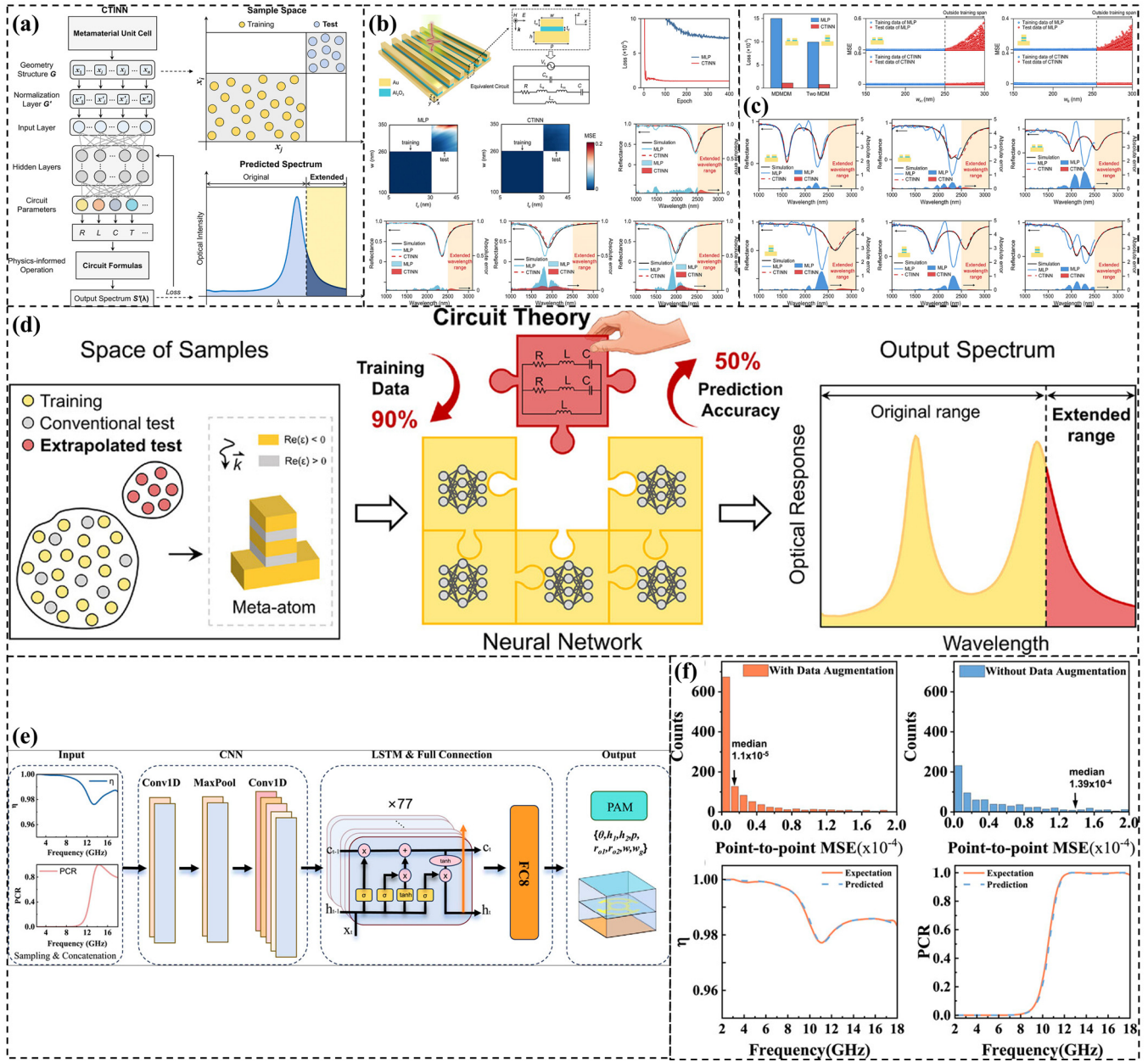


Fig. 6. (a) Schematic drawing of CTINN with the circuit-theory-derived capability of generalization for metamaterial design [81]. (b) Design generalization of sample space and wavelength range for PSM with meta-atoms of single MDM stack [81]. (c) Design generalization of sample space and wavelength range for PSMs with meta-atoms of double MDM stacks [81]. (d) Conceptual diagram of highly intelligent metamaterial design empowered by circuit-physics-driven deep learning [81]. (e) Schematic illustration of the CNN-LSTM neural network structure [80]. (f) Comparison of the point-to-point mean square error with the expected value and predicted value of η , PCR, using or not using data augmentation methods [80].

GAN, and diffusion models are capable of independently exploring high-dimensional design spaces, generating novel structural configurations, and even uncovering electromagnetic topologies that surpass human empirical knowledge.

Kim et al. [82] introduced a framework combining discrete latent representations with graph neural networks to embed mechanical principles into AI systems. This approach enables efficient mapping between metamaterial topologies and their mechanical properties. As shown in Figure 7a, a dataset comprising 16,383 structures

constructed from 14 fundamental unit types was utilized. A variational autoencoder coupled with a latent diffusion model learned a compact representation of the structure-property relationship. The method maintains high predictive accuracy even under extremely limited data conditions, highlighting its exceptional generalization capability.

The proposed framework is applicable not only to forward prediction but also to inverse design. Figure 7b illustrates how conditional generation using denoising diffusion implicit models and latent space perturbation-based optimization

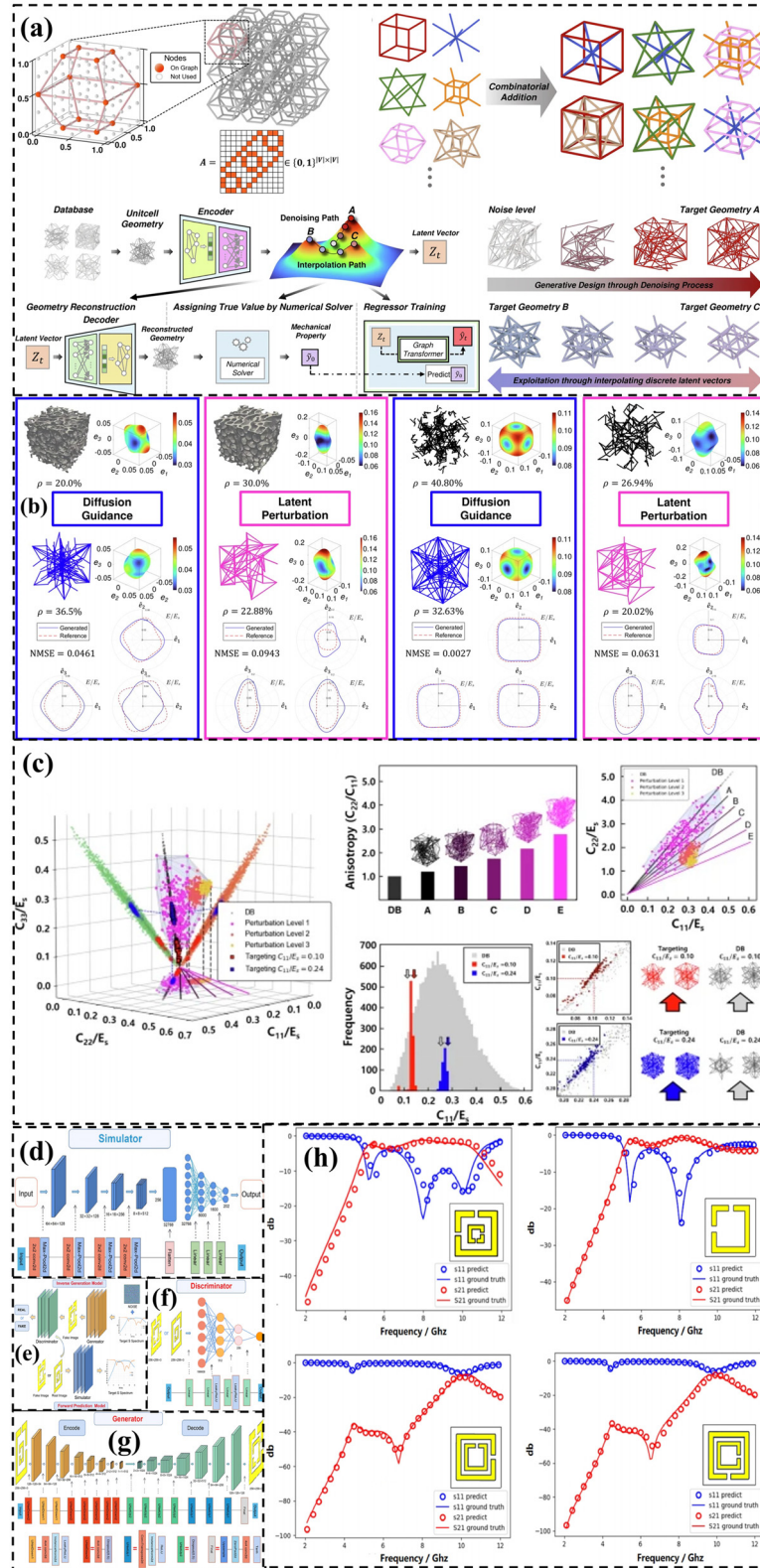


Fig. 7. (a) An overview of database construction from fundamental unit cells and their subsequent training process over the latent space [82]. (b) This diagram displays a selection of inverse design candidates and their elastic property visualizations generated through DDIM with guidance and latent space perturbation methods [82]. (c) Exploration and exploitation on the mechanical property space [82]. (d) The Schematic diagram of the simulator architecture [83]. (e) The whole architecture of CPC metasurface based on depth generation model [83]. (f) The architecture schematic of the discriminator [83]. (g) The architecture schematic of the generator [83]. (h) The S-spectrum comparison between the numerical simulation results and the forward prediction model results [83].

enables the inverse design of complex target structures. When designing with anisotropic materials, the model generates asymmetric configurations exhibiting extreme elastic modulus ratios (Fig. 7c), surpassing the symmetry constraints of the training dataset and demonstrating its potential for multifunctional material design.

Li et al. [83] developed a dual-component framework integrating CNNs with Wasserstein GNN, establishing a forward S-parameter prediction model coupled with an inverse Cross Polarization Converter(CPC) meta surface generator. This system enables on-demand design by first rapidly predicting electromagnetic responses from structural patterns and then reconstructing geometric configurations from target spectral responses.

The forward prediction module, constructed via CNNs, adopts the architecture illustrated in Figure 7d. It processes $128 \times 128 \times 3$ CPC meta surface patterns through four convolutional layers, four pooling layers, and three fully-connected layers, ultimately outputting 202 S-parameter data points. For the inverse modeling component, a Wasserstein generative adversarial network is employed. As depicted in Figure 7e, the generator utilizes a U-Net architecture (Fig. 7g) where encoder-decoder blocks with skip connections produce high-resolution, structurally coherent CPC patterns. The discriminator (Fig. 7f) employs a fully-connected network to compute Wasserstein distance between generated and authentic samples, replacing the conventional Jensen–Shannon divergence to mitigate training instability and vanishing gradients that commonly plague standard GANs.

As illustrated in Figure 7h, the predicted S-parameter curves generated by the model demonstrate remarkable consistency with results obtained from CST simulations. This validates the capability of the proposed forward model to precisely forecast electromagnetic responses within milliseconds, thereby substantially reducing the time expenditure associated with conventional full-wave simulation processes. The model establishes a mapping relationship between structural patterns and electromagnetic behavior through learning from extensive CST simulation datasets.

4 Concluding remarks and prospective developments

In previous discussions, the integration of artificial intelligence has shifted metamaterial design from traditional approaches reliant on empirical knowledge and limited simulations toward adaptive optimization governed by physical constraints. Represented by deep learning and generative models, forward prediction and inverse design have substantially accelerated the design process while enhancing efficiency [36–42]. These methodologies also assist researchers in uncovering intricate physical principles, thereby strengthening the adaptability, robustness, and generalization capabilities of metamaterials [84,85]. This evolution propels their development into an intelligent phase centered on data and algorithmic innovation.

The integration of AI into metamaterial design transcends mere instrumental substitution, extending into a cognitive expansion at the conceptual level. By leveraging

its nonlinear learning capabilities within multidimensional feature spaces [86,87], AI assists researchers in uncovering and elucidating patterns related to geometric parameters [88,89], electromagnetic resonances [90,91], and multiphysical coupling effects [90,92]. This shifts the paradigm of material design from being experience-driven to knowledge-oriented, establishing a novel pathway for comprehending physical mechanisms and constructing theoretical frameworks. Such progress offers theoretical guidance for developing advanced topological meta surfaces [93,94], broadband absorbers [95,96], and adaptive wave-transparent devices [97–99].

Although AI has driven innovative designs for electromagnetic metamaterials, their transition to practical application confronts several critical hurdles: predictive models must achieve high efficiency while ensuring interpretability and adherence to physical laws, thereby mitigating the “black box” dilemma [100,101]. Modeling capabilities should advance beyond sole electromagnetic properties to incorporate multiphysics coupling, such as thermal and mechanical interactions [102–105]. Furthermore, effective integration of intelligent algorithms with programmable hardware is essential to maintain device stability and robustness under complex operational conditions [103,106–109].

Looking ahead, the deep integration of artificial intelligence and electromagnetic metamaterials is shifting the design paradigm from traditional approaches reliant on physical intuition and trial-and-error toward an intelligent, closed-loop framework of “algorithm-physics-experimentation”. Leveraging its robust capabilities in nonlinear fitting [21] and inverse design [110,111], AI is pushing the boundaries of electromagnetic manipulation, enabling metamaterials to achieve multifunctional coupling in areas such as negative parameters, broadband absorption, and intelligent wave transmission. As a result, metamaterials are evolving into “intelligent matter” endowed with environmental awareness, autonomous learning, and dynamic responsiveness, capable of functional integration across domains including communications, stealth, energy harvesting, and spatial information processing.

AI-driven integrated smart metamaterials represent not only a breakthrough in materials science but also a critical infrastructure for the future intelligent society. This evolution fosters a conceptual transition from “designing materials” to “materials as design”, where the design process becomes an intrinsic attribute of the material itself. Such progress signifies a profound methodological shift in how humanity controls the material world. Metamaterials are set to develop into active systems capable of perception, judgment, and decision-making, supporting applications like reconfigurable communications, neuromorphic computing, and adaptive sensing. This marks the dawn of a new era in which materials and intelligence are deeply intertwined.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

Data will be made available on request.

Author contribution statement

Haoyang Yu: Writing – Literature research, literature analysis, writing, revision. Zixuan Liu: Writing – review & editing. Rui Hou: Writing – review & editing. Zidong Zhang: Writing – review & editing, Project administration, Conceptualization.

References

1. X. Zhao, G. Duan, A. Li, C. Chen, X. Zhang, Integrating microsystems with metamaterials towards metadevices, *Microsyst. Nanoeng.* **5**, 5 (2019)
2. Z.L. Wang, X. Wang, J.L. Wang, Research advance on the sensing characteristics of refractive index sensors based on electromagnetic metamaterials, *Adv. Condens. Matter Phys.* **2021**, 27 (2021)
3. B. Wood, Structure and properties of electromagnetic metamaterials, *Laser Photonics Rev.* **1**, 249 (2007)
4. X.J. Liu, F. Xia, M. Wang, J. Liang, M.J. Yun, Working mechanism and progress of electromagnetic metamaterial perfect absorber, *Photonics* **10**, 205 (2023)
5. H. Ammari, W. Wu, S. Yu, Double-negative electromagnetic metamaterials due to chirality, *Quart. Appl. Math.* **77**, 105 (2018)
6. M.R.C. Mahdy, A. Al Sayem, A. Shahriar, J. Shawon, G.D. Al-Quaderi, I. Jahangir, M.A. Matin, Electromagnetic metamaterial-inspired band gap and perfect transmission in semiconductor and graphene-based electronic and photonic structures, *Eur. Phys. J. Plus* **131**, 92 (2016)
7. Y.S. Feng, M.S. Liang, X.G. Zhao, R. You, Fabrication and modulation of flexible electromagnetic metamaterials, *Microsyst. Nanoeng.* **11**, 14 (2025)
8. F. Yenilmez, I. Mutlu, Production of metamaterial-based radar absorbing material for stealth technology, *Braz. J. Phys.* **54**, 60 (2024)
9. J.P. Peng, S.M. Wang, B.Y. Liang, Q.Y. Wen, C.L. Sun, K. Li, X.S. Zhang, Y. Zhang, Review of micro and nano scale 3D printing of electromagnetic metamaterial absorbers: mechanism, fabrication, and functionality, *Virtual Phys. Protot.* **19**, 39 (2024)
10. D.H. Han, W.K. Li, M. Liu, T. Sun, Y.S. Hou, X.M. Chen, H. Y. Shi, Z.J. Fan, X.Q. Wang, F.Q. Meng, L.Y. Zhang, X.F. Chen, Kirigami-inspired planar deformable metamaterials for multiple dynamic electromagnetic manipulations, *Laser Photonics Rev.* **17**, 2300374 (2023)
11. T.R. Howarth, Hot topics in engineering acoustics: acoustic metamaterials, *J. Acoust. Soc. Am.* **128**, 2390 (2010)
12. G.X. Li, X.A. Luo, T.J. Cui, Optical metamaterials and information metamaterials, *Adv. Opt. Mater.* **12**, 2303101 (2024)
13. H.L. An, J. Yuan, J. Li, L.Q. Cao, Long-distance and anti-disturbance wireless power transfer based on concentric three-coil resonator and inhomogeneous electromagnetic metamaterials, *Int. J. Circuit Theory Appl.* **51**, 2030 (2023)
14. J.L. Wang, Z.X. Yang, X.C. Dong, L. Yin, H.D. Wan, H.M. Chen, K. Zhong, VO₂ based terahertz anisotropic coding metasurface, *Acta Physica Sinica* **72**, 124204 (2023)
15. Y.X. Wang, Y. Li, Z.C. Tang, H. Li, Z.L. Yuan, H.G. Tao, N. L. Zou, T. Bao, X.H. Liang, Z.Z. Chen, S.H. Xu, C. Bian, Z. M. Xu, C. Wang, C. Si, W.H. Duan, Y. Xu, Universal materials model of deep-learning density functional theory Hamiltonian, *Sci. Bull.* **69**, 2514 (2024)
16. X. Jiang, H.D. Fu, Y. Bai, L. Jiang, H.T. Zhang, W.R. Wang, P.W. Yun, J.J. He, D.Z. Xue, T. Lookman, Y.J. Su, J. X. Xie, Interpretable machine learning applications: a promising prospect of AI for materials, *Adv. Funct. Mater.* **35**, 2507734 (2025)
17. A.M. Mroz, A.R. Basford, F. Hastedt, I.S. Jayasekera, I. Mosquera-Lois, R. Sedgwick, P.J. Ballester, J.D. Bocarsly, E.A.D. Chanona, M.L. Evans, J.M. Frost, A.M. Ganose, R. L. Greenaway, K.K. Hii, Y.Z. Li, R. Misener, A. Walsh, D.D. Zhang, K.E. Jelfs, Cross-disciplinary perspectives on the potential for artificial intelligence across chemistry, *Chem. Soc. Rev.* **54**, 5433 (2025)
18. G. Yang, Q. Xiao, Z. Zhang, Z. Yu, X. Wang, Q. Lu, Exploring AI in metasurface structures with forward and inverse design, *iScience* **28**, 111995 (2025)
19. Y. Shan, C. Wang, B. Wen, W. Tang, J. Wang, H. Chen, K. Jiang, X. Zhang, W. Xia, Perspective on low-dimensional carbon materials: synergistic advancement of electromagnetic wave attenuation and AI-driven functionalization, *Carbon* **245**, 120783 (2025)
20. Y. Hu, J. Huang, J. Li, Y. Sui, J. Zhang, T. Zheng, W. Wang, C. Zhu, Q. Guo, L. Li, X. Zhang, N. Chen, J. Chen, Y. Chen, X. Zheng, Z. Yang, J. Chen, Artificial intelligence in nanophotonics: from design to optical computing, *Chin. Phys. Lett.* **42**, 8 (2025)
21. C. Qian, I. Kaminer, H.S. Chen, A guidance to intelligent metamaterials and metamaterials intelligence, *Nat. Commun.* **16**, 1154 (2025)
22. W.P. Huang, W. Tang, Z.W. Chen, L.H. Tang, C. Chen, L. F. Hou, Reinforcement-learning empowered adaptive piezoelectric metamaterial for variable-frequency vibration attenuation, *Eng. Struct.* **332**, 120013 (2025)
23. J. Song, J. Lee, N. Kim, K. Min, Artificial intelligence in the design of innovative metamaterials: a comprehensive review, *Int. J. Precis. Eng. Manuf.* **25**, 225 (2024)
24. X.Y. Ma, Z.R. Wang, W.P. Zhang, P. Yan, Programmable metamaterials with perforated shell group supporting versatile information processing, *Adv. Sci.* **12**, 2417784 (2025)

25. K.K. Chen, X.J. Dong, P.L. Gao, Q. Chen, Z.K. Peng, G. Meng, Physics-informed neural networks for topological metamaterial design and mechanical applications, *Int. J. Mech. Sci.* **301**, 110489 (2025)
26. L.L. Li, T.J. Cui, Information metamaterials – from effective media to real-time information processing systems, *Nanophotonics* **8**, 703 (2019)
27. P.C. Jiao, Mechanical energy metamaterials in interstellar travel, *Prog. Mater. Sci.* **137**, 101132 (2023)
28. W.J. Luo, S. Yan, J. Zhou, Ceramic-based dielectric metamaterials, *Interdiscip. Mater.* **1**, 11 (2022)
29. T. Tan, Z.M. Yan, H.X. Zou, K.J. Ma, F.R. Liu, L.C. Zhao, Z.K. Peng, W.M. Zhang, Renewable energy harvesting and absorbing via multi-scale metamaterial systems for Internet of things, *Appl. Energy* **254**, 113717 (2019)
30. P.K. Sharma, D. Sharma, T.J.V.S. Rao, J.R. Szymanski, M. Zurek-Mortka, M. Sathiyarayanan, Design & implementation of a meta-material based ultra-wide band microstrip patch antenna for vehicular communication, *Microsyst. Technol.* **31**, 547 (2024)
31. H.Z. Guo, Z. Sun, C. Zhou, Practical design and implementation of metamaterial-enhanced magnetic induction communication, *IEEE Access* **5**, 17213 (2017)
32. S. Abadal, C. Liaskos, A. Tsioliaridou, S. Ioannidis, A. Pitsillides, J. Solé-Pareta, E. Alarcón, A. Cabellos-Aparicio, Computing and communications for the software-defined metamaterial paradigm a context analysis, *IEEE Access* **5**, 6225 (2017)
33. F.Y. Dong, L.D. Shao, C.N. Niu, W.R. Zhu, Optically transparent microwave metamaterial absorbers, *J. Optics* **27**, 043004 (2025)
34. J.Y. Zhang, B. Hu, S.B. Wang, Review and perspective on acoustic metamaterials: from fundamentals to applications, *Appl. Phys. Lett.* **123**, 010502 (2023)
35. A.S. Dhillon, D. Mittal, R. Bargota, Triple band ultrathin polarization insensitive metamaterial absorber for defense, explosive detection and airborne radar applications, *Microw. Opt. Technol. Lett.* **61**, 89 (2018)
36. Y. Luo, K.P. Qiu, T.Q. Xu, F.L. Zhang, P. Yue, Design of a novel multiband terahertz metamaterial absorber using a deep learning framework, *Eng. Appl. Artif. Intell.* **151**, 110801 (2025)
37. S. Yin, H.T. Zhong, W. Huang, W.T. Zhang, Deep learning enabled design of terahertz high-Q metamaterials, *Opt. Laser Technol.* **181**, 111684 (2025)
38. S. Xie, L. Gu, J. Guo, Design of chiral plasmonic metamaterials based on interpretable deep learning, *J. Phys. D: Appl. Phys.* **57**, 045103 (2023)
39. L. Zhu, W. Hua, C. Lv, Y. Liu, Rapid inverse design of high degree of freedom meta-atoms based on the image-parameter diffusion model, *J. Lightwave Technol.* **42**, 5269 (2024)
40. X.Y. Zheng, J. Shiomi, T. Yamada, Optimizing metamaterial inverse design with 3D conditional diffusion model and data augmentation, *Adv. Mater. Technol.* **10**, 2500293 (2025)
41. X. Lyu, X. Ren, Variational autoencoder guided conditional diffusion generative model for material microstructure reconstruction and inverse design, *Mater. Today Commun.* **48**, 113087 (2025)
42. Z. Liu, D. Zhu, S.P. Rodrigues, K.-T. Lee, Cai, Wenshan, A generative model for inverse design of metamaterials. [arXiv:1805.10181](https://arxiv.org/abs/1805.10181) [physics.optics] (2018)
43. A.J.D. Shaikeea, Exploration of truss metamaterials with graph based generative modeling, *Nat. Commun.* **14**, 75651 (2023)
44. H.Y. Zhang, J. Paik, Kirigami design and modeling for strong, lightweight metamaterials, *Adv. Funct. Mater.* **32**, 2107401 (2022)
45. J. Sim, S. Wu, S. Hwang, L. Lu, R.R. Zhao, Selective actuation enabled multifunctional magneto-mechanical metamaterial for programming elastic wave propagation, *Adv. Funct. Mater.* **35**, 2422325 (2025)
46. A. Li, X. Zhao, G. Duan, S. Anderson, X. Zhang, Metamaterials: diatom frustule-inspired metamaterial absorbers: the effect of hierarchical pattern arrays, *Adv. Funct. Mater.* **29**, 1809029 (2019)
47. C. Xiao, M. Liu, K. Yao, Y. Zhang, M. Zhang, M. Yan, Y. Sun, X. Liu, X. Cui, T. Fan, C. Zhao, W. Hua, Y. Ying, Y. Zheng, D. Zhang, C.-W. Qiu, H. Zhou, Ultrabroadband and band-selective thermal meta-emitters by machine learning, *Nature* **643**, 80 (2025)
48. J.T. Orasugh, A. Mohanty, A. Malakar, S. Bose, S.S. Ray, Design and applications of multi-frequency programmable metamaterials for adaptive stealth, *Adv. Funct. Mater.* **12**, e13726 (2025)
49. L.M. Si, R. Niu, C.Y. Dang, X.E. Bao, Y.Q. Zhuang, W.R. Zhu, Advances in artificial intelligence for artificial metamaterials, *Apl Mater.* **12**, 120602 (2024)
50. S. Yin, H. Zhong, W. Huang, W. Zhang, J. Han, Deep learning enabled design of terahertz high-Q metamaterials. [arXiv:2312.13986](https://arxiv.org/abs/2312.13986) [physics.optics] (2023)
51. Y. Zhang, Z. Chen, H. Ge, K. Jia, Y. Jiang, Y. Bu, S. Wei, Intelligent design of terahertz metamaterial sensors based on a transformer encoder model, *AIP Adv.* **15**, 085302 (2025)
52. Y.H. Wang, C. Pang, Y.Z. Wang, J.R. Qi, Electromagnetic manipulation evolution from stacked meta-atoms to spatially cascaded metasurfaces, *Annalen Der Physik* **537**, 2400158 (2025)
53. Y. Cai, Y. Huang, N. Feng, Z. Huang, Improved transformer-based target matching of terahertz broadband reflective metamaterials with monolayer graphene, *IEEE Trans. Microw. Theory Tech.* **71**, 3284 (2023)
54. T.V. Tran, S.S. Nanthakumar, T. Rabczuk, X.Y. Zhuang, On-demand inverse design of metamaterials using deep neural networks with bayesian optimization, *Intell. Comput.* **4**, 0139 (2025)
55. Z.Y. Zhao, J. You, J. Zhang, S.Y. Du, Z.L. Tao, Y.H. Tang, T. Jiang, Data enhanced iterative few-sample learning algorithm-based inverse design of 2D programmable chiral metamaterials, *Nanophotonics* **11**, 4465 (2022)
56. K.F. Ding, Y. Yang, Reverse design of load-bearing broadband metamaterial absorber assisted by deep learning, *Smart Mater. Struct.* **33**, 125029 (2024)
57. G.Q. Lan, Y. Wang, J.Y. Ou, Optimization of metamaterials and metamaterial-microcavity based on deep neural networks, *Nanoscale Adv.* **4**, 5137 (2022)
58. N.B. Roberts, M.K. Hedayati, A deep learning approach to the forward prediction and inverse design of plasmonic metasurface structural color, *Appl. Phys. Lett.* **119**, 061101 (2021)

59. J.J. Hou, H. Lin, W.L. Xu, Y.Z. Tian, Y. Wang, X.T. Shi, F. Deng, L.J. Chen, Customized inverse design of metamaterial absorber based on target-driven deep learning method, *IEEE Access* **8**, 211849 (2020)
60. H.Y. Yang, H.B. Lu, D.W. Shu, Y.Q. Fu, Multimodal origami shape memory metamaterials undergoing compression-twist coupling, *Smart Mater. Struct.* **32**, 075013 (2023)
61. P. Dorin, K.W. Wang, Broadband frequency and spatial on-demand tailoring of topological wave propagation harnessing piezoelectric metamaterials, *Front. Mater.* **7**, 602996 (2021)
62. M.A. Bessa, P. Glowacki, M. Houlder, Bayesian machine learning in metamaterial design: fragile becomes super-compressible, *Adv. Mater.* **31**, 1904845 (2019)
63. S.C. He, X.C. Yao, J. Tao, K. Wang, H.S. Tang, C.J. Wang, F. Gao, Z.J. Wang, J.Z. Song, Multifunctional reconfigurable electromagnetic metamaterials based on compression-torsion coupling structures for transmission modulations and holographic displays, *Adv. Funct. Mater.* **35**, 2421065 (2025)
64. L.D. Shao, W.R. Zhu, Recent advances in electromagnetic metamaterials and metasurfaces for polarization manipulation, *J. Phys. D-Appl. Phys.* **57**, 343001 (2024)
65. J.W. Liu, G.J. Lian, W.B. You, R.X. Zhang, Y.F. Cheng, C. Zhang, R.C. Che, Bayesian active learning for accelerated design of broadband polarization-insensitive metasurfaces, *Intell. Comput.* **4**, 0135 (2025)
66. M.A. Ardeshtana, F.N. Thakkar, S.G. Domadia, S-band application: ultra-slim metamaterial absorber unit cell with dual-negative characteristics and polarization neutrality, *J. Magn. Magn. Mater.* **593**, 171866 (2024)
67. R. Fang, X. Zhang, B. Song, Z. Zhang, L. Zhang, J. Song, Y. Yao, M. Gao, K. Zhou, P. Wang, J. Lu, Y. Shi, 3D and 4D printing of electromagnetic metamaterials, *Engineering* **51**, 171 (2025)
68. D. Shin, J. Kim, I. Seo, K. Kim, Quasi-conformal transformation optics with elasto-electromagnetic metamaterials: design algorithm, *Appl. Phys. Lett.* **107**, 021908 (2015)
69. J.T. Hu, C. Zhang, X.K. Liu, H.D. Liu, G.Q. Liu, Design of a new open-type active electromagnetic metamaterial for magnetic field control based on numerical method, *J. Appl. Phys.* **137**, 083101 (2025)
70. X.C. Xing, X.Y. Tian, X.Y. Jia, D.C. Li, Reconfigurable liquid electromagnetic metamaterials driven by magnetic fields, *Appl. Phys. Express* **14**, 041002 (2021)
71. H.T. Chen, Compact fano-type liquid metamaterial resonator for high-precision temperature sensing, *Front. Mater.* **9**, 941395 (2022)
72. L. Ma, D.X. Chen, W.X. Zheng, J. Li, S.R. Zahra, Y.F. Liu, Y.D. Zhou, Y.J. Huang, G.J. Wen, Advanced electromagnetic metamaterials for temperature sensing applications, *Front. Phys.* **9**, 657790 (2021)
73. G.H. Feng, L.X. Guo, H.Y. Yu, Y. Li, B. Ren, B. Liu, L. Wan, J. Sun, X. He, Q.G. Fu, H.J. Li, J. Lu, Uniting superior electromagnetic wave absorption with high thermal stability in bioinspired metamaterial by direct ink writing, *Adv. Funct. Mater.* **35**, 2424499 (2025)
74. B.Y. Shan, Y. Shen, X.R. Yi, X.Q. Chi, K.J. Chen, Agile inverse design of polarization-independent multi-functional reconfiguration metamaterials based on doped VO₂, *Materials* **17**, 3534 (2024)
75. C.C. Wang, X.Y. Lin, C.S. Hu, Y. Ding, Z.Q. Wang, Y.H. Zhou, X. Lin, J.T. Xu, Bio-based derived carbon materials for permittivity metamaterials: dual efficacy of electromagnetic wave protection and Joule heating, *Mater. Horizons* **12**, 6349 (2025)
76. C. Quan, S. Gu, J.L. Zou, C.C. Guo, W. Xu, Z.H. Zhu, J.F. Zhang, Phase change metamaterial for tunable infrared stealth and camouflage, *Optics Express* **30**, 43741 (2022)
77. Z.Y. Zheng, Q.W. Zhang, S.L. Ren, M. Lei, F.H. Zhang, P. Zhang, Y. Yu, H.Q. Wei, Stretchable conductive shape-memory nanocomposites for programmable electronics via photo-mediated multiscale structural design, *Chem. Eng. J.* **497**, 154656 (2024)
78. N. Zhang, M.M. Zhang, Q. Ouyang, L. Chen, Application of terahertz technology for chiral molecular sensing, *Trac-Trends Anal. Chem.* **191**, 118360 (2025)
79. T. Kaelberer, V.A. Fedotov, N. Papasimakis, D.P. Tsai, N.I. Zheludev, Toroidal dipolar response in a metamaterial, *Science* **330**, 1510 (2010)
80. J.Y. Hua, X.D. He, Broadband metamaterial linear polarization converter designed by a hybrid neural network with data augmentation, *Aip Adv.* **14**, 095013 (2024)
81. Y.M. Yan, F.J. Li, J.Q. Shen, M.Y. Zhuang, Y. Gao, W. Chen, Y.Y. Li, Z.L. Wu, Z.G. Dong, J.F. Zhu, Highly intelligent forward design of metamaterials empowered by circuit-physics-driven deep learning, *Laser Photonics Rev.* **19**, 2400724 (2025)
82. N. Kim, D. Lee, C. Kim, D.S. Lee, Y. Hong, Simple arithmetic operation in latent space can generate a novel three-dimensional graph metamaterials, *Npj Comput. Mater.* **10**, 236 (2024)
83. J.W. Li, A. Qinhuo, Q.S. Lan, J.T. Yang, L.J. Yun, Y.L. Xia, C.F. Yang, Research on a demand design method of a cross polarization converter metasurface based on a depth generation model, *Opt. Mater. Express* **13**, 2497 (2023)
84. S.J. Niu, X.M. Liu, C.C. Wang, W.Z. Mu, W. Xu, Q. Wang, Breaking the trade-off between complexity and absorbing performance in metamaterials through intelligent design, *Small* **21**, 202502828 (2025)
85. S. Arulkumar, S. Gopinath, U.A. Kumar, H. Kraiem, Ultra-broadband metamaterial solar absorber based on S-shaped resonator design for enhanced industrial thermal energy harvesting with AI for behaviour prediction, *Case Stud. Thermal Eng.* **75**, 107052 (2025)
86. S. Saeed, M. Müftüoğlu, G.R. Cheeran, T. Bocklitz, B. Fischer, M. Chemnitz, Nonlinear inference capacity of fiber-optical extreme learning machines, *Nanophotonics* **14**, 2749 (2025)
87. P. Figge, E. Anderson, K. Lewis, EXPRESS: AI-Human learning systems: investigating the strategic role of AI for organizational learning, *Strateg. Organ.* (2025). <https://doi.org/10.1177/14761270251385860>
88. W. Qu, Y. Wang, G. Li, Z. Xie, Z. Li, H. Deng, L. Shang, An adaptive assisted method based on MOPSO for THz MMA effective designing, *J. Phys. D: Appl. Phys.* **58**, 035103 (2024)

89. M. Kalogeropoulou, A. Kracher, P. Fucile, S.M. Mihaila, L. Moroni, Blueprints of architected materials: a guide to metamaterial design for tissue engineering, *Adv. Mater.* **36**, 202408082 (2024)
90. J. Gao, Y.M. Zhang, Q. Wu, All dielectric terahertz left-handed metamaterial based on Mie resonance coupling effects, *IEEE Access* **7**, 94882 (2019)
91. H. Zhang, L. Kang, S.D. Campbell, J.T. Young, D.H. Werner, Data driven approaches in nanophotonics: a review of AI-enabled metadevices, *Nanoscale*, **17**, 23788 (2025)
92. Z.D. Li, X.X. Wang, Z.G. Wang, X.W. Li, X. Yu, S. Ramakrishna, Y. Lu, L. Cheng, Emerging acousto-mechanical metamaterials: from physics-guided design to coupling-driven performance, *Mater. Today* **89**, 151 (2025)
93. A. Vakulenko, S. Kiriushchikina, M. Wang, M. Li, D. Zhirihin, X. Ni, S. Guddala, D. Korobkin, A. Alù, A.B. Khanikaev, Near-field characterization of higher-order topological photonic states at optical frequencies, *Adv. Mater.* **33**, 202004376 (2021)
94. A. Karnieli, Y. Li, A. Arie, The geometric phase in nonlinear frequency conversion, *Front. Phys.* **17**, 12301 (2021)
95. L.L. Yan, Y.S. Wang, W.C. Li, S. Yin, W. Huang, Z. Yin, D. M. Jia, Y.Q. Li, A bilayer array metamaterial based on silicon carbon foam/FeSiAl for broadband electromagnetic absorption, *J. Alloys Compd.* **954**, 170129 (2023)
96. J.J. Bai, M.L. Ge, J.N. Li, C.X. Tang, X.D. Sun, H.Y. Xing, S.J. Chang, Numerical investigation of broadband THz metamaterial absorber with double composite structure layer, *Opt. Commun.* **423**, 63 (2018)
97. Y.M. Wang, Z.K. Lei, X.C. Wang, Z.L. Chen, M.H. Lu, R.X. Bai, C. Yan, Mechano-electromagnetic coupling in negative Poisson's ratio metamaterials: dynamic deformation-driven multimodal wave absorption and integrated theoretical framework, *Appl. Mater. Today* **47**, 102942 (2025)
98. Y.Z. Ye, B. He, R. Liu, B. Sima, Z.W. Sun, Adaptive multimodes absorption with enhanced electromagnetic environment compatibility, *J. Appl. Phys.* **134**, 113103 (2023)
99. W.W. Li, M.J. Chen, Z.H. Zeng, H. Jin, Y.M. Pei, Z. Zhang, Broadband composite radar absorbing structures with resistive frequency selective surface: optimal design, manufacturing and characterization, *Compos. Sci. Technol.* **145**, 10 (2017)
100. S. Mehdi, P. Tiwary, Thermodynamics-inspired explanations of artificial intelligence, *Nat. Commun.* **15**, 7859 (2024)
101. C. Zednik, Solving the black box problem: a normative framework for explainable artificial intelligence, *Philos. Technol.* **34**, 265 (2019)
102. J.B. Hopkins, Mechanical neural networks: an overview of self-learning metamaterials, *J. Intell. Mater. Syst. Struct.* **36**, 1266 (2025)
103. A.P. Garland, B.C. White, S.C. Jensen, B.L. Boyce, Pragmatic generative optimization of novel structural lattice metamaterials with machine learning, *Mater. Des.* **203**, 109632 (2021)
104. Y.J. Zheng, H.J. Dai, J.Y. Wu, C.P. Zhou, Z.W. Wang, R.G. Zhou, W.X. Li, Research progress and development trend of smart metamaterials, *Front. Phys.* **10**, 1069722 (2022)
105. M. Lei, J. Wang, G.L. Dai, P. Tan, J.P. Huang, Temperature-dependent transformation multiphysics and ambient-adaptive multiphysical metamaterials, *EPL* **135**, 54003 (2021)
106. Q. Ma, X.X. Gao, Z. Gu, C. Liu, L.L. Li, J.W. You, T.J. Cui, Intelligent neuromorphic computing based on nanophotonics and metamaterials, *MRS Commun.* **14**, 1235 (2024)
107. P. Sinha, T. Mukhopadhyay, Programmable multi-physical mechanics of mechanical metamaterials, *Mater. Sci. Eng. R-Rep.* **155**, 100745 (2023)
108. L. Huangchen, J.L. Peng, X. Yang, Z.P. Zhang, J. Zhou, Y. D. Hou, Classification principle enabled optimal frames for high-performance and intelligent polarimeters, *Opt. Express* **33**, 12111 (2025)
109. J. Chen, S. Hu, S. Zhu, T. Li, Metamaterials: from fundamental physics to intelligent design, *Interdiscip. Mater.* **2**, 5 (2022)
110. Z.X. Fu, H.N. Mao, B.L. Yin, Inverse design of lattice metamaterials for fully anisotropic elastic constants: a data-driven and gradient-based method, *Compos. Struct.* **359**, 118975 (2025)
111. B. Liu, L.J. Xu, Y.X. Wang, J.P. Huang, Diffusion model-based inverse design for thermal transparency, *J. Appl. Phys.* **135**, 125101 (2024)

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