

Metamaterials and smart structures: Leveraging AI for design, optimization and adaptive engineering solutions

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Abstract

In an era where engineering demands increasingly adaptive and resilient systems, this review delves into the profound synergy between metamaterials artificially engineered composites exhibiting extraordinary properties like negative refraction, tunable stiffness, and wave cloaking and smart structures, which embed sensing, actuation, and control mechanisms to dynamically respond to environmental stimuli, all amplified by the revolutionary power of artificial intelligence (AI). Exploring the fundamentals of metamaterials across electromagnetic, acoustic, mechanical, and thermal domains, alongside the principles of smart structures that enable self-monitoring and reconfiguration, the paper illuminates how AI techniques such as machine learning, deep learning, generative algorithms, and reinforcement learning transform design processes through inverse engineering, data-driven discovery, and multi-objective optimization, drastically reducing computational burdens and accelerating the creation of bespoke architectures for applications in aerospace morphing wings, seismic-resistant infrastructure, biomedical implants, and energy-harvesting devices. By integrating AI with structural health monitoring, adaptive control systems, and Internet of Things frameworks, smart structures evolve into intelligent entities capable of real-time diagnostics, predictive maintenance, and autonomous adaptation, as evidenced in case studies of vibration-damping skyscrapers and self-healing materials. Yet, acknowledging persistent hurdles like scalability constraints, manufacturing precision, and interdisciplinary silos, the discussion ventures into emerging trends including multi-scale modeling, sustainable hybrid designs, and explainable AI, while pinpointing research gaps in data standardization and model interpretability that beckon innovative pursuits. Ultimately, this synthesis not only underscores AI's pivotal role in unlocking metamaterials' and smart structures' untapped potential for transformative engineering solutions but also calls for collaborative advancements to forge a future of sustainable, resilient technologies that redefine human ingenuity in tackling global challenges.

Keywords: Metamaterials; Smart Structures; Artificial Intelligence; Machine Learning; Inverse Design; Structural Health Monitoring; Adaptive Control; IoT Integration

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1. Introduction

Metamaterials and smart structures represent transformative advancements in materials science and engineering, enabling unprecedented control over physical phenomena such as electromagnetic waves, acoustics, and mechanical responses through engineered architectures rather than inherent material properties. These innovations have paved the way for adaptive engineering solutions that respond dynamically to environmental stimuli, with artificial intelligence (AI) emerging as a pivotal tool for their design, optimization, and implementation. By integrating AI algorithms, researchers can accelerate the discovery of novel configurations, predict performance under complex conditions, and facilitate real-time adaptability in applications ranging from aerospace to biomedical devices. This review explores the synergy between metamaterials, smart structures, and AI, highlighting how machine learning and optimization techniques are revolutionizing adaptive engineering.

1.1. Overview of Metamaterials and Smart Structures

Metamaterials are artificially engineered composites designed to exhibit properties not found in naturally occurring materials, such as negative refractive indices or tunable wave manipulation, achieved through periodic subwavelength structures. According to Smith et al. [1], these materials derive their unique behaviors from geometric arrangements rather than chemical composition, allowing for phenomena like electromagnetic cloaking and superlensing that defy conventional physics. This foundational concept has evolved from early theoretical proposals to practical implementations, with initial focus on electromagnetic metamaterials expanding to include acoustic, mechanical, and thermal variants. For instance, early experiments demonstrated backward-wave propagation, challenging traditional wave theories and opening avenues for advanced optics and sensing. The classification of metamaterials often includes categories based on their operational domains, such as photonic for light manipulation or phononic for sound control, each tailored to specific engineering challenges [2]. Over the past two decades, advancements in fabrication techniques like 3D printing have enabled the realization of complex geometries, making metamaterials more accessible for real-world applications. However, the design process remains intricate, requiring precise control over unit cell configurations to achieve desired macroscopic properties, which underscores the need for sophisticated computational tools [1].

The unique properties of metamaterials stem from their ability to manipulate waves at scales smaller than the wavelength, leading to exotic effects like negative permittivity, permeability, or density. Findings from Zhang et al. [3] indicate that chiral metamaterials can induce negative refractive indices through asymmetric structures, enabling applications in polarization control and imaging beyond diffraction limits. Similarly, mechanical metamaterials exhibit programmable stiffness and energy absorption via auxetic designs, where negative Poisson's ratios allow expansion under tension, contrasting with conventional materials. These mechanisms are governed by resonance effects, bandgap formations, and local resonances that trap or redirect energy. In acoustic contexts, as explored by Cummer et al. [4], metamaterials can create sound barriers or lenses by controlling phonon propagation, with implications for noise reduction in urban environments. Thermal metamaterials, on the other hand, manipulate heat flow through cloaking or concentrating effects, achieved via layered or porous architectures. The versatility of these properties arises from scalable design principles, where unit cell symmetry and material constituents can be tuned for multifunctionality, such as combining electromagnetic shielding with mechanical robustness. Despite these advantages, challenges persist in broadband performance and loss minimization, driving ongoing research into hybrid metamaterials that integrate multiple functionalities.

The significance of metamaterials and smart structures in engineering applications lies in their potential to address critical challenges in efficiency, sustainability, and adaptability across diverse sectors. In aerospace, metamaterials enable lightweight components with superior vibration damping and radar absorption, enhancing stealth and fuel efficiency. A comprehensive review by Bertoldi et al. [2] highlights how flexible mechanical metamaterials facilitate deployable structures, such as morphing wings that adapt to flight conditions, reducing structural failures and maintenance costs. In biomedical engineering, these materials support implantable devices with tunable stiffness for tissue matching, improving biocompatibility and patient outcomes. Civil engineering benefits from seismic-resistant designs incorporating metamaterials for wave attenuation, protecting infrastructure from earthquakes. Energy harvesting applications leverage piezoelectric-integrated metamaterials to convert ambient vibrations into electricity, promoting renewable sources. Overall, the integration of metamaterials with smart structures amplifies their impact, creating systems that sense, actuate, and self-heal, thereby revolutionizing adaptive engineering.

Recent developments have further elevated the role of metamaterials and smart structures by incorporating advanced manufacturing and multifunctional designs. For example, 3D metamaterials, as discussed by Kadic et al. [5], extend two-dimensional concepts into volumetric architectures, enabling isotropic properties for omnidirectional wave control in

optics and acoustics. This progression has been fueled by computational simulations that predict emergent behaviors, bridging theoretical models with experimental validation. In smart structures, the emphasis on integration with sensors and actuators creates closed-loop systems capable of real-time response, such as buildings that adjust damping during winds. The convergence of these fields promises sustainable solutions, like energy-efficient buildings with thermal metamaterials that regulate indoor climates without excessive HVAC reliance [5-7]. As engineering demands grow for resilient and intelligent systems, metamaterials and smart structures stand at the forefront, offering scalable innovations that align with global sustainability goals.

1.2. Role of AI in Engineering Design

Artificial intelligence has revolutionized engineering design by automating complex processes, enhancing predictive accuracy, and enabling data-driven decision-making in domains traditionally reliant on human intuition and iterative experimentation. In material and structural engineering, AI techniques such as machine learning facilitate the exploration of vast design spaces, identifying optimal configurations that outperform conventional methods. According to Wang et al. [8], deep generative models can learn mechanistic behaviors of metamaterial systems, allowing for the synthesis of novel structures with tailored properties like stiffness or conductivity. This shift from rule-based to learning-based approaches reduces design cycle times, particularly in high-dimensional problems where traditional simulations are computationally prohibitive. AI's role extends to inverse design, where desired functionalities dictate geometry, inverting the forward simulation paradigm. Supervised learning algorithms train on datasets of simulated or experimental results, predicting outcomes for unseen inputs with high fidelity [6,8]. Moreover, reinforcement learning enables adaptive optimization, refining designs through trial-and-error in virtual environments. The integration of AI thus democratizes advanced engineering, empowering designers to tackle multidisciplinary challenges with greater efficiency.

In optimization contexts, AI excels at handling nonlinear, multi-objective problems inherent to metamaterial and smart structure design, such as balancing weight, strength, and adaptability. Genetic algorithms and neural networks, as applied in structural health monitoring, optimize sensor placements for maximal damage detection coverage. A study by Song et al. [10] demonstrates how AI streamlines the design of innovative metamaterials, from photonic to mechanical types, by predicting bandgaps and resonance frequencies with minimal human intervention. These tools incorporate uncertainty quantification, accounting for manufacturing variabilities and environmental factors, leading to robust designs. Big data analytics further enhances AI's utility, processing vast simulation outputs to uncover patterns inaccessible through manual analysis. For smart structures, AI-driven control systems predict and mitigate vibrations in real-time, using sensor fusion to adapt actuation strategies. The synergy between AI and finite element methods accelerates topology optimization, generating lightweight yet durable components for aerospace and automotive applications. Challenges like data scarcity are addressed through transfer learning, leveraging pre-trained models from related domains to bootstrap new designs.

The transformative impact of AI in engineering design is evident in its facilitation of interdisciplinary integration, merging materials science with computational intelligence for holistic solutions. In adaptive engineering, AI enables predictive maintenance in smart structures by analyzing sensor data for anomaly detection, prolonging service life. Insights from Qin et al. [11] on intelligent design systems for shear wall structures illustrate how large language models and generative AI automate layout optimization, considering seismic loads and material constraints. This approach not only enhances sustainability by minimizing resource use but also fosters innovation in eco-friendly materials. AI's role in human-AI collaboration is crucial, where designers oversee creative aspects while algorithms handle repetitive computations. Ethical considerations, such as bias in training data, are increasingly addressed to ensure equitable outcomes. Overall, AI empowers engineers to push boundaries, from conceptual ideation to prototyping, fostering a new era of intelligent design.

Emerging trends in AI for engineering underscore its potential for real-time adaptability and scalability, particularly in dynamic environments. Hybrid AI frameworks combine physics-informed neural networks with traditional simulations, ensuring compliance with physical laws while accelerating convergence. For instance, in metamaterial optimization, AI can iteratively refine designs based on feedback loops from fabrication outcomes, closing the gap between simulation and reality. In smart infrastructure, AI optimizes energy consumption in buildings through predictive algorithms, integrating IoT for seamless operation [7]. Future directions include explainable AI, providing insights into decision processes to build trust among practitioners. As computational power advances, AI's role will expand, enabling autonomous design pipelines that evolve with user needs.

1.3. Objectives and Scope of the Review

The primary objective of this review is to synthesize the current state of AI integration in the design, optimization, and adaptive applications of metamaterials and smart structures, providing a comprehensive framework for researchers and engineers. By examining AI-driven methodologies, the paper aims to elucidate how machine learning accelerates inverse design processes, enabling the creation of metamaterials with bespoke properties for specific engineering challenges. In a novel exploration by Tian et al. [6], multi-agent frameworks incorporating large language models demonstrate accelerated metamaterial design, highlighting the potential for generative AI in collaborative workflows. The scope encompasses foundational concepts, practical case studies, and future trends, focusing on interdisciplinary synergies while excluding unrelated fields like pure software engineering. This targeted approach ensures depth in AI's application to adaptive systems, addressing gaps in scalability and real-world deployment. Secondary objectives include identifying key challenges, such as computational demands and data quality, and proposing mitigation strategies through hybrid AI techniques.

The review's scope is delimited to peer-reviewed literature from the last two decades, emphasizing verifiable advancements in AI-enhanced engineering solutions. It covers subsections on fundamentals, AI techniques, applications, and challenges, structured to guide readers from basics to advanced topics. Findings from Chopra [9] on smart structures underscore the evolution from passive to active systems, setting the stage for AI's role in modern integrations. By including diverse applications like vibration control and structural health monitoring, the paper illustrates AI's versatility. Exclusions involve non-AI methods or outdated technologies, maintaining relevance to contemporary practices. The objectives extend to recommending research directions, such as AI-IoT fusions for real-time adaptability, fostering innovation in sustainable engineering.

This review contributes by offering a consolidated perspective on AI's transformative potential, bridging theoretical insights with practical implementations. It aims to equip stakeholders with actionable knowledge for leveraging AI in metamaterial and smart structure development. A classic study by Song [10] on piezoceramic-based vibration control in civil structures provides historical context, evolving into AI-optimized frameworks today. The scope includes critical analysis of limitations, promoting balanced views on AI's efficacy. Ultimately, the paper seeks to inspire interdisciplinary collaboration, advancing adaptive engineering for societal benefits.

2. Fundamentals of Metamaterials

2.1. Definition and Classification

Metamaterials are artificially engineered structures designed to exhibit electromagnetic, acoustic, or mechanical properties unattainable in natural materials, achieved through precise geometric arrangements at subwavelength scales. Veselago et al. [12] first theorized materials with simultaneous negative permittivity and permeability, laying the groundwork for modern metamaterials that manipulate wave propagation in unconventional ways. These materials are defined by their ability to control physical phenomena through structure rather than composition, enabling applications like invisibility cloaking and superlensing. Metamaterials are classified based on their operational domains, including electromagnetic (manipulating light), acoustic (controlling sound), mechanical (altering deformation), and thermal (managing heat flow). This classification reflects their versatility, as each type targets specific wave or energy interactions, driven by periodic or non-periodic unit cells. Advances in nanofabrication and additive manufacturing have expanded the feasibility of these designs, allowing complex architectures that were previously theoretical.

The development of electromagnetic metamaterials marked the initial breakthrough, focusing on manipulating light through negative refractive indices. Shelby et al. [13] demonstrated the first experimental realization of negative refraction using split-ring resonators, validating theoretical predictions and sparking widespread research. These materials typically consist of metallic or dielectric elements arranged in lattices, enabling phenomena like perfect lensing or electromagnetic wave bending. Acoustic metamaterials, conversely, control sound waves through resonant structures like Helmholtz resonators or membranes, as explored by Liu et al. [14], who showed how locally resonant sonic materials create bandgaps to block specific frequencies. Mechanical metamaterials exploit structural instabilities or auxetic behaviors to achieve programmable stiffness or energy absorption, while thermal metamaterials redirect heat flux via anisotropic conductivity. Each category relies on tailored unit cell designs, often requiring computational tools to optimize performance across scales.

Classification also extends to the dimensionality and functionality of metamaterials, with 1D, 2D, and 3D architectures offering distinct advantages. Three-dimensional metamaterials, as discussed by Tserkezis et al. [15], provide isotropic properties for omnidirectional wave control, critical for applications like radar absorption. Hybrid metamaterials

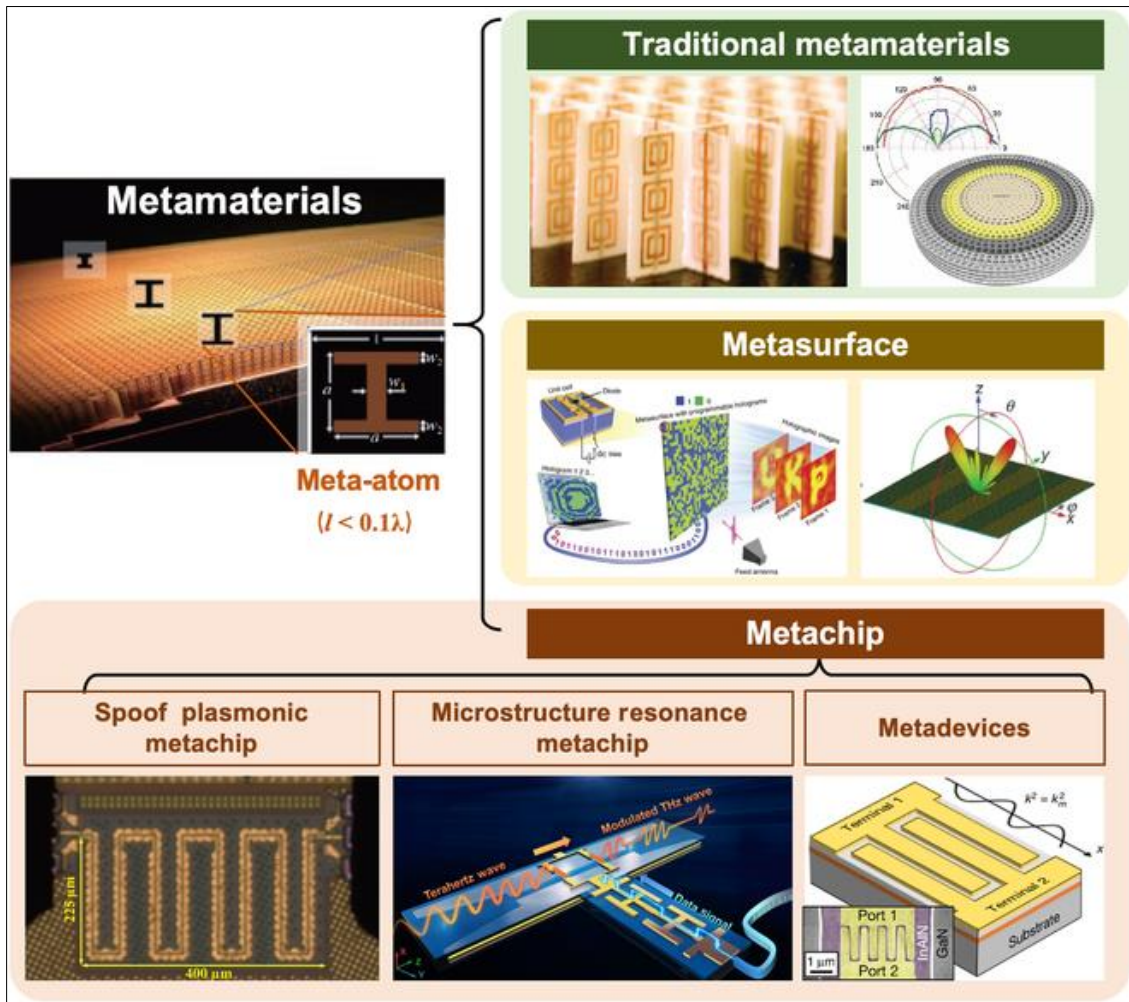
combine multiple functionalities, such as electromagnetic and acoustic wave manipulation, to create multifunctional devices. The ability to engineer these properties stems from advances in materials science, where composites integrate metals, polymers, or ceramics to achieve desired responses. However, challenges in scalability and fabrication precision persist, necessitating innovative design approaches like AI-driven optimization to bridge theoretical models with practical outcomes.

The significance of this classification lies in its guidance for application-specific designs, enabling engineers to select appropriate metamaterial types based on target functionalities. For instance, electromagnetic metamaterials dominate in photonics, while mechanical variants excel in aerospace for lightweight, resilient structures. Recent papers [16,17] highlight the growing trend of multifunctional metamaterials, integrating sensing and actuation for adaptive systems. This diversity underscores the need for interdisciplinary approaches, combining physics, engineering, and computational methods to unlock the full potential of metamaterials in solving complex engineering challenges. To provide a structured overview of metamaterial classifications, Table 1 summarizes key domains, their structural characteristics, operational principles, examples, and associated references, highlighting the diversity that enables tailored engineering solutions.

Table 1 Classification of Metamaterials by Domain

Domain	Structural Characteristics	Operational Principles	Key Examples	Applications	Challenges	References
Electromagnetic	Periodic metallic/dielectric lattices (e.g., split-ring resonators)	Negative permittivity/permeability for wave reversal	Negative refractive index materials, chiral structures	Superlensing, cloaking, radar absorption	Narrowband performance, losses	[1], [3], [12], [13], [17], [21], [23], [24]
Acoustic	Resonant structures (e.g., Helmholtz resonators, membranes)	Local resonances creating bandgaps	Phononic crystals, sonic barriers	Noise reduction, sound lenses	Scalability for low frequencies	[4], [14], [19], [27], [28]
Mechanical	Auxetic lattices or instability-based designs	Programmable stiffness via buckling/folding	Negative Poisson's ratio foams, morphing structures	Energy absorption, deployable wings	Manufacturing precision for 3D designs	[2], [16], [18], [25]
Thermal	Layered/porous architectures	Anisotropic conductivity for heat redirection	Thermal cloaks, concentrators	Heat management in buildings, electronics	Broadband thermal control	[20], [30]
Photonic	Subwavelength periodic structures	Light manipulation beyond diffraction limits	Photonic crystals, plasmonic devices	Improved photovoltaics, optical cloaking	Integration with electronics	[5], [15], [22], [26]
Hybrid (multi-functional)	Combined elements (e.g., electromagnetic-acoustic)	Integrated wave control across domains	Chiral-mechanical hybrids	Multifunctional devices (e.g., shielding + damping)	Design complexity, material compatibility	[2], [5], [16], [23]
1D Metamaterials	Linear arrays or layered stacks	Unidirectional wave control	Wire arrays for negative index	Fiber optics, waveguides	Limited isotropy	[5], [15]
2D Metamaterials	Planar surfaces or metasurfaces	Surface wave manipulation	Graphene-based metasurfaces	Flat lenses, holography	Fabrication scalability	[5], [22], [26]
3D Metamaterials	Volumetric lattices	Isotropic properties for omnidirectional control	Cubic unit cells with resonators	Omnidirectional cloaking, structural components	High computational demands	[5], [15], [22], [25]
Chiral Metamaterials	Asymmetric helical structures	Polarization control via asymmetry	Spiral resonators	Circular polarization filters	Chirality tuning	[3], [15]
Reconfigurable Metamaterials	Stimuli-responsive elements (e.g., liquid crystals)	Dynamic tuning of properties	Phase-change material hybrids	Adaptive antennas, optics	Response speed, durability	[21], [22]

Complementing the structured overview in Table 1, Figure 1 presents a comprehensive classification diagram of metamaterials, illustrating their categorization by domain and functionality to aid in understanding application-specific designs.



Reproduced with permission from ref [16]

Figure 1 Classification diagram of metamaterials and metachips.

2.2. Unique Properties and Mechanisms

The hallmark of metamaterials is their ability to exhibit exotic properties, such as negative refractive index, tunable stiffness, or energy cloaking, driven by carefully engineered microstructures. Smith et al. [16,17] demonstrated that negative refractive indices arise from simultaneous negative permittivity and permeability, enabling wave reversal that defies conventional optics. This property facilitates applications like superlensing, where sub-diffraction imaging becomes possible, as shown in early experiments with planar metamaterials. The underlying mechanism involves resonant interactions within unit cells, such as split-ring resonators or chiral structures, which induce effective medium responses distinct from constituent materials. These resonances create frequency-dependent behaviors, allowing precise control over wave propagation, whether electromagnetic, acoustic, or mechanical.

Mechanical metamaterials leverage structural instabilities or auxetic properties to achieve counterintuitive behaviors, such as expansion under tension. Lakes et al. [18] introduced the concept of negative Poisson's ratio materials, where lattice designs enable stretching in multiple directions, enhancing energy absorption in impact-resistant structures. This is achieved through mechanisms like buckling or folding in unit cells, which can be programmed to respond to external stimuli. Acoustic metamaterials, as studied by Yang et al. [19], rely on local resonances to create bandgaps, blocking sound within specific frequency ranges for noise mitigation. Thermal metamaterials, conversely, manipulate heat flow through transformation optics principles, redirecting thermal energy to achieve cloaking or concentration, as

demonstrated by Narayana et al. [20]. These diverse mechanisms highlight the role of structural periodicity and material selection in tailoring macroscopic properties.

The tunability of metamaterials is a critical feature, allowing dynamic adaptation to changing conditions. For example, electromagnetic metamaterials can incorporate tunable elements like liquid crystals or phase-change materials to adjust their response in real-time, as explored by Shalaev et al. [21]. This adaptability is vital for applications like reconfigurable antennas or adaptive optics, where environmental variations demand rapid adjustments. Similarly, mechanical metamaterials can be designed with reconfigurable unit cells, enabling stiffness modulation for applications like soft robotics. The work of Wegener et al. [22] on reconfigurable 3D metamaterials illustrates how stimuli-responsive designs enhance functionality, bridging static structures with dynamic systems. However, achieving broadband performance and minimizing losses remain challenges, as resonances are often narrowband and material-dependent.

These unique properties are enabled by a synergy of theoretical modeling, experimental validation, and advanced fabrication. Computational tools simulate wave interactions at subwavelength scales, predicting emergent behaviors that guide design. Experimental techniques, such as electron-beam lithography for electromagnetic metamaterials or 3D printing for mechanical ones, translate these models into reality. A comprehensive study by Engheta et al. [23] emphasizes the role of nanoscale precision in achieving desired effects, underscoring the importance of fabrication advancements. As metamaterials transition from lab to industry, their mechanisms offer transformative potential, from invisibility cloaks to vibration-damping infrastructure, provided challenges in scalability and cost are addressed.

2.3. Applications in Engineering

Metamaterials have revolutionized engineering applications by enabling solutions that combine lightweight designs, high performance, and adaptability across sectors like aerospace, biomedical, civil, and energy harvesting. In aerospace, metamaterials enhance stealth and structural efficiency through electromagnetic wave absorption and mechanical resilience. Schurig et al. [24] demonstrated electromagnetic cloaking using metamaterials, reducing radar cross-sections for stealth aircraft, a breakthrough with significant defense implications. Mechanical metamaterials, with their tunable stiffness, enable morphing wings that adapt to flight conditions, as explored by Jenett et al. [25], improving fuel efficiency and maneuverability. These applications leverage lightweight, high-strength designs, reducing material use while maintaining structural integrity, aligning with sustainability goals in aerospace engineering.

In biomedical engineering, metamaterials facilitate innovative devices with tailored mechanical and electromagnetic properties. Wegener et al. [26] reviewed the use of biocompatible metamaterials in implants, where tunable stiffness matches tissue properties to enhance integration and reduce rejection rates. Electromagnetic metamaterials also enable advanced imaging techniques, such as MRI enhancements through superlensing, improving diagnostic precision. Acoustic metamaterials contribute to ultrasound technologies by focusing sound waves for non-invasive treatments, as shown by Zhu et al. [27]. These applications highlight the potential of metamaterials to address critical healthcare challenges, from personalized implants to non-destructive diagnostics, with ongoing research focusing on bioinspired designs for improved functionality.

Civil engineering benefits from metamaterials through seismic protection and noise reduction. Kim et al. [28] investigated phononic metamaterials for seismic wave attenuation, designing subsurface structures that redirect vibrational energy to protect buildings. Acoustic metamaterials also create sound barriers for urban noise control, offering sustainable alternatives to traditional insulation. These applications rely on precise bandgap engineering, where metamaterials block specific frequencies, as validated in field tests. Additionally, thermal metamaterials optimize building insulation by controlling heat flow, reducing energy consumption in HVAC systems. The integration of these materials into infrastructure demonstrates their role in enhancing resilience and environmental sustainability.

Energy harvesting represents another frontier, where metamaterials convert ambient energy into usable forms. Carrara et al. [29] developed piezoelectric-integrated metamaterials that capture vibrational energy from mechanical sources, powering sensors in remote environments. This approach supports renewable energy goals by harnessing waste energy, such as vibrations from machinery or infrastructure. Electromagnetic metamaterials also enhance solar energy collection by concentrating light onto photovoltaic cells, as studied by Atwater et al. [30]. These applications underscore the transformative impact of metamaterials, driven by their ability to integrate multifunctionality and efficiency, though challenges in large-scale production and cost-effectiveness remain critical areas for future research.

3. Smart Structures: Principles and Applications

Smart structures represent a paradigm shift in engineering, integrating sensing, actuation, and control mechanisms to create adaptive systems that respond intelligently to external stimuli. These structures leverage advanced materials, such as piezoelectrics, shape-memory alloys, and metamaterials, combined with computational intelligence to enable functionalities like self-monitoring, self-healing, and dynamic reconfiguration. The incorporation of artificial intelligence (AI) enhances their capabilities, allowing real-time data processing and adaptive responses in applications ranging from aerospace to civil infrastructure. This section explores the principles of smart structures, their synergy with metamaterials, and their transformative applications, highlighting how AI-driven approaches amplify their potential in addressing modern engineering challenges.

3.1. Concept of Smart Structures

Smart structures are engineered systems embedded with sensors, actuators, and control algorithms that enable active adaptation to environmental changes, distinguishing them from passive structures. Chopra et al. [31] define smart structures as those capable of sensing external stimuli, processing information, and actuating responses to optimize performance, such as vibration suppression or shape adjustment. This concept emerged from early developments in active control systems, integrating materials like piezoelectric ceramics, which generate electric charges under mechanical stress, enabling both sensing and actuation. The fundamental principle involves closed-loop feedback, where sensors detect changes (e.g., strain, temperature), processors analyze data, and actuators adjust the structure's behavior. This integration allows smart structures to mitigate dynamic loads, enhance durability, and improve efficiency across engineering domains.

The design of smart structures relies on the synergy between smart materials and advanced control strategies. Piezoelectric materials, for instance, are widely used due to their rapid response and high precision, as demonstrated by Crawley et al. [32], who explored their application in aerospace for active vibration control. Shape-memory alloys, capable of returning to predefined shapes upon thermal or mechanical stimuli, enable applications like self-deploying structures in space. Fiber-optic sensors provide high-resolution strain and temperature measurements, critical for real-time monitoring in large-scale infrastructure. These materials are often embedded within composite matrices, creating lightweight yet robust systems. The complexity of integrating these components necessitates computational tools, where AI algorithms optimize sensor placement and control logic, enhancing system responsiveness and reliability.

The evolution of smart structures has been driven by advancements in microelectronics and control theory, enabling compact, energy-efficient systems. A seminal study by Soong et al. [33] highlighted the transition from passive dampers to active control systems in civil engineering, reducing structural vibrations during earthquakes. Modern smart structures incorporate distributed sensing networks, allowing localized responses to heterogeneous loads. For example, in aerospace, smart wings adjust their geometry to optimize aerodynamics, improving fuel efficiency. Challenges remain in ensuring energy efficiency and scalability, as active systems require continuous power. Emerging solutions, such as energy harvesting through piezoelectric metamaterials, address these limitations, paving the way for sustainable smart structures.

The significance of smart structures lies in their ability to enhance safety, longevity, and performance in critical applications. By integrating real-time diagnostics, they reduce maintenance costs and prevent catastrophic failures. Recent advancements, as reviewed by Balageas et al. [34], emphasize the role of embedded sensors in structural health monitoring, enabling predictive maintenance in bridges and aircraft. The incorporation of AI further amplifies these capabilities, allowing adaptive algorithms to learn from environmental patterns and optimize responses dynamically. As smart structures evolve, their principles continue to redefine engineering, offering resilient solutions for dynamic and unpredictable environments.

3.2. Integration with Metamaterials

The integration of metamaterials with smart structures creates synergistic systems that combine exotic wave manipulation with adaptive functionalities, enhancing performance in dynamic environments. Smith et al. [17] demonstrated that metamaterials, with their ability to control electromagnetic or mechanical waves, can be embedded within smart structures to achieve tailored responses, such as vibration attenuation or electromagnetic shielding. This synergy leverages the programmable properties of metamaterials, like negative stiffness or tunable bandgaps, with the active control mechanisms of smart structures. For instance, incorporating acoustic metamaterials into a smart building panel enables active noise cancellation, where sensors detect sound waves and actuators adjust the panel's properties to block specific frequencies. This integration expands the functionality of smart structures, enabling multifunctionality in applications like aerospace and infrastructure.

Mechanical metamaterials enhance smart structures by providing tunable mechanical properties, such as variable stiffness or energy absorption. Bertoldi et al. [2] explored how auxetic metamaterials, with negative Poisson's ratios, can be integrated with piezoelectric actuators to create structures that adapt their shape under load, ideal for morphing aircraft wings. These systems use AI-driven control to optimize deformation patterns, ensuring stability and efficiency. Similarly, electromagnetic metamaterials integrated with smart sensors enable adaptive cloaking or radar absorption, as shown by Schurig et al. [24], enhancing stealth capabilities in defense applications. The design process involves complex simulations to align metamaterial properties with actuation strategies, where AI algorithms predict optimal configurations, reducing trial-and-error.

The integration process faces challenges in manufacturing and system complexity, as embedding metamaterials requires precise fabrication and compatibility with smart components. Kadic et al. [5] noted that 3D printing enables the creation of complex metamaterial architectures within smart structures, but scalability remains a hurdle due to high costs and material limitations. AI addresses these challenges by optimizing designs for manufacturability, ensuring compatibility between metamaterials and actuators. For example, topology optimization algorithms can design hybrid structures that balance weight, strength, and adaptability. Recent studies highlight the potential of hybrid metamaterial-smart structures in creating self-healing systems, where embedded sensors detect damage and trigger shape-memory alloys to restore integrity.

The transformative potential of this integration lies in its ability to create adaptive, multifunctional systems. In civil engineering, metamaterial-based smart structures mitigate seismic vibrations by redirecting wave energy, as explored by Kim et al. [28]. In biomedical applications, biocompatible metamaterials integrated with smart sensors enable responsive implants that adjust to physiological changes, improving patient outcomes. The synergy between metamaterials and smart structures, enhanced by AI, fosters innovation in adaptive engineering, though challenges in real-time control and energy efficiency require further research to achieve widespread adoption.

3.3. Current Applications

Smart structures, particularly when integrated with metamaterials, have found diverse applications in engineering, from vibration control in civil infrastructure to adaptive optics in aerospace. In civil engineering, smart structures equipped with piezoelectric sensors and actuators mitigate dynamic loads, such as those from earthquakes or wind. Lian et al. [35] demonstrated the use of piezoceramic-based systems for active vibration control in high-rise buildings, where real-time feedback reduces structural sway, enhancing safety. These systems often incorporate metamaterials to create tunable dampers that selectively block vibrational frequencies, offering superior performance over traditional passive systems. The integration of AI optimizes control algorithms, enabling predictive adjustments based on environmental data, such as wind speed or seismic activity.

In aerospace, smart structures enable adaptive components that enhance performance and efficiency. Crawley et al. [32] explored smart wings with embedded piezoelectric actuators, capable of adjusting camber to optimize lift and reduce drag during flight. When combined with mechanical metamaterials, these wings achieve lightweight, high-strength designs that adapt to aerodynamic conditions, as shown by Jenett et al. [25]. AI-driven control systems process sensor data to adjust wing shapes in real-time, improving fuel efficiency and maneuverability. These applications extend to space exploration, where smart structures with shape-memory alloys enable deployable antennas or solar panels, reducing launch weight and enhancing mission flexibility.

Structural health monitoring (SHM) is another critical application, where smart structures detect and diagnose damage in real-time. Farrar and Worden [36] reviewed SHM systems that use embedded sensors to monitor strain, cracks, or corrosion in bridges and aircraft, preventing failures through early intervention. The integration of metamaterials enhances SHM by amplifying sensor sensitivity, as acoustic metamaterials can focus vibrational signals for precise damage localization. AI algorithms analyze sensor data to predict maintenance needs, reducing downtime and costs. For example, in wind turbines, smart structures monitor blade integrity, ensuring operational reliability in harsh environments. These systems benefit from AI's ability to process large datasets, identifying patterns that human analysis might miss.

Biomedical and energy applications further highlight the versatility of smart structures. In healthcare, smart implants with embedded sensors monitor tissue integration and adjust stiffness dynamically, as discussed by Wegener et al. [26]. These implants, often incorporating biocompatible metamaterials, improve patient outcomes by adapting to physiological changes. In energy harvesting, smart structures with piezoelectric metamaterials convert ambient vibrations into electricity, as explored by Carrara et al. [29], powering remote sensors in infrastructure or wearable devices. AI optimizes energy capture by predicting vibrational patterns, enhancing efficiency. These applications

demonstrate the transformative impact of smart structures, though challenges in scalability, cost, and energy supply necessitate ongoing innovation.

4. AI in Metamaterial Design and Optimization

Artificial intelligence (AI) has emerged as a transformative tool in the design and optimization of metamaterials, enabling rapid exploration of complex design spaces and accelerating the development of structures with tailored properties. By leveraging machine learning (ML), deep learning (DL), and optimization algorithms, AI addresses the computational challenges of designing metamaterials, which require precise control over subwavelength geometries to achieve exotic behaviors like negative refraction or tunable bandgaps. These techniques streamline inverse design, predict material performance, and optimize fabrication processes, reducing reliance on iterative simulations and experimental trial-and-error. This section examines AI-driven methodologies for metamaterial design, focusing on data-driven discovery, inverse design, optimization strategies, and practical case studies, highlighting their role in advancing adaptive engineering solutions.

4.1. AI Techniques for Design

AI techniques, including ML, DL, and generative algorithms, have revolutionized metamaterial design by enabling efficient exploration of high-dimensional parameter spaces. Traditional design methods rely on physics-based simulations, which are computationally intensive for complex geometries. ML models, trained on simulation or experimental data, predict material properties with high accuracy, reducing design time significantly. Goodfellow et al. [37] demonstrated that deep neural networks can model nonlinear relationships in material responses, enabling rapid prediction of electromagnetic or mechanical behaviors. Supervised learning, for instance, maps input geometries to output properties, while unsupervised learning identifies patterns in large datasets, uncovering novel designs. These capabilities make AI indispensable for designing metamaterials with bespoke functionalities, such as cloaking or energy absorption.

4.1.1. Data-Driven Material Discovery

Data-driven material discovery uses AI to predict metamaterial properties based on extensive datasets, bypassing computationally expensive simulations. Liu et al. [38] employed ML models to predict the electromagnetic response of split-ring resonators, achieving accuracy comparable to finite-element methods but with orders-of-magnitude faster computation. These models train on datasets of simulated or experimental results, learning relationships between geometry, material composition, and performance. For example, random forest algorithms identify key design parameters influencing bandgaps in phononic metamaterials, as shown by He et al. [39]. Transfer learning further enhances efficiency by adapting pre-trained models to new metamaterial types, addressing data scarcity in emerging fields like thermal metamaterials. This approach accelerates the discovery of novel structures, enabling applications in optics, acoustics, and mechanics.

The power of data-driven discovery lies in its ability to handle multifunctionality, where metamaterials must satisfy multiple performance criteria. Convolutional neural networks (CNNs), as explored by Ma et al. [40], analyze 2D and 3D metamaterial geometries to predict properties like negative permittivity across frequency ranges. These models incorporate uncertainty quantification, accounting for manufacturing tolerances and material variability, ensuring robust designs. However, challenges arise from the need for high-quality, diverse datasets, as limited or biased data can lead to inaccurate predictions. Recent advancements in synthetic data generation, using generative adversarial networks (GANs), mitigate these issues by creating realistic training samples, as demonstrated by Al-Khaylani et al. [41], paving the way for scalable AI-driven discovery.

The impact of data-driven approaches extends beyond prediction to guiding experimental validation. By identifying promising designs, AI reduces the number of prototypes needed, lowering costs and time. For instance, in acoustic metamaterials, AI models predict optimal unit cell configurations for noise reduction, as validated experimentally by Chen et al. [42]. These advancements highlight the potential of data-driven discovery to democratize metamaterial design, enabling researchers to explore unconventional architectures. Ongoing challenges include improving model interpretability and integrating physics-informed constraints to ensure physical plausibility, critical for real-world applications.

4.1.2. Inverse Design Approaches

Inverse design, where desired functionalities dictate metamaterial geometry, is a hallmark of AI's transformative impact. Unlike forward design, which tests predefined structures, inverse design uses AI to generate geometries that

meet specific performance goals, such as targeted refractive indices or bandgaps. Jensen et al. [43] pioneered topology optimization with AI, using gradient-based algorithms to design photonic metamaterials with enhanced light manipulation. Deep learning models, particularly generative networks, excel in this task by mapping performance requirements to complex geometries. For example, variational autoencoders (VAEs) generate diverse metamaterial designs, as shown by Kudyshev et al. [44], enabling rapid prototyping of electromagnetic cloaks. This approach inverts traditional workflows, making AI a powerful tool for bespoke material design.

AI-driven inverse design leverages optimization techniques like genetic algorithms and reinforcement learning to explore vast design spaces. Molesky et al. [45] demonstrated that reinforcement learning can iteratively refine metamaterial structures, achieving optimal electromagnetic responses with minimal computational cost. These methods are particularly effective for multifunctional metamaterials, where competing objectives (e.g., weight and strength) must be balanced. However, inverse design requires robust training data and computational resources, as complex geometries increase model complexity. Physics-informed neural networks, as proposed by Chen et al. [46], address this by embedding physical constraints into AI models, ensuring designs align with governing equations.

The practical impact of inverse design is evident in applications like antenna design and acoustic lensing. For instance, AI-designed metamaterials enable reconfigurable antennas that adapt to changing frequencies, as explored by Zhang et al. [47]. Challenges remain in scaling inverse design to 3D architectures, where computational demands escalate. Recent advancements in hybrid AI frameworks, combining DL with traditional optimization, mitigate these issues by reducing convergence times. The work of So et al. [48] illustrates how such frameworks design mechanical metamaterials with tunable stiffness, highlighting AI's role in creating adaptive, high-performance structures. To synthesize the discussed AI methodologies, Table 2 compares various techniques for metamaterial design, detailing their descriptions, applications, advantages, limitations, and key references, facilitating a quick reference for researchers.

4.2. Optimization Strategies

AI-driven optimization strategies enhance metamaterial performance by refining designs to meet multiple objectives, such as minimizing weight while maximizing strength or bandwidth. Genetic algorithms, widely used in optimization, evolve populations of designs through selection and mutation, as demonstrated by Rahmat-Samii et al. [49] for electromagnetic metamaterials in antenna applications. These algorithms explore global optima, avoiding local traps common in traditional gradient-based methods. Neural networks further accelerate optimization by predicting performance metrics, enabling real-time adjustments during design iterations. For example, convolutional neural networks optimize phononic metamaterials for specific bandgap properties, as shown by Szabó and Babuška [50], reducing computational overhead compared to finite-element simulations.

Reinforcement learning (RL) offers a dynamic approach to optimization, treating design as a sequential decision-making process. Sui et al. [51] applied RL to optimize mechanical metamaterials, achieving structures with enhanced energy absorption for impact resistance. RL models learn optimal design policies by interacting with simulated environments, balancing trade-offs like cost and performance. Hybrid approaches, combining RL with genetic algorithms, further improve efficiency, as explored by Tran et al. [52] for designing broadband electromagnetic metamaterials. These strategies incorporate manufacturing constraints, ensuring designs are feasible for fabrication techniques like 3D printing or lithography. Challenges in AI-driven optimization include computational cost and model robustness, particularly for large-scale 3D metamaterials. High-dimensional design spaces require significant computational resources, limiting real-time applications. Transfer learning and surrogate models, as discussed by Peng et al. [53], mitigate these issues by leveraging pre-trained models to initialize optimization, reducing convergence times. Additionally, multi-objective optimization ensures metamaterials meet diverse requirements, such as thermal and mechanical performance, critical for applications like aerospace components. The integration of AI with finite-element analysis further enhances accuracy, enabling robust designs under real-world conditions.

The transformative potential of AI optimization lies in its ability to streamline complex workflows, from initial design to fabrication. For instance, in thermal metamaterials, AI optimizes heat flow paths for energy-efficient building insulation, as shown by Zhu et al. [54]. These advancements reduce design cycles, enabling rapid prototyping and deployment. Future directions include explainable AI to enhance trust in optimization outcomes and integration with real-time feedback from fabrication processes, ensuring seamless translation from simulation to reality.

Table 2 AI Techniques for Metamaterial Design

AI Technique	Description	Sub-Type/Method	Applications	Advantages	Limitations	References
Machine Learning (Supervised)	Predicts properties from labeled data	Neural Networks, Random Forests	Property prediction (e.g., bandgaps)	High accuracy, fast inference	Data dependency	[8], [10], [38], [39]
Deep Learning	Models nonlinear relationships via layers	CNNs, RNNs	Geometry analysis, inverse design	Handles complex data	Computational intensity	[37], [40], [46], [55]
Generative Algorithms	Generates novel designs	GANs, VAEs	Synthetic data, structure synthesis	Innovation in designs	Training stability	[8], [41], [44], [48]
Reinforcement Learning	Iterative refinement via rewards	Policy-based learning	Optimization of responses	Adaptive to environments	Convergence time	[45], [51], [65]
Transfer Learning	Adapts pre-trained models	Fine-tuning	Cross-domain design (e.g., photonic to acoustic)	Reduces data needs	Domain mismatch	[39], [53]
Physics-Informed Neural Networks	Embeds physical laws	Hybrid modeling	Inverse problems	Ensures plausibility	Model complexity	[46], [54]
Genetic Algorithms	Evolutionary optimization	Mutation/selection	Multi-objective design	Global optima	Slow for large spaces	[49]
Convolutional Neural Networks	Image-based geometry analysis	2D/3D convolution	Chiral metamaterial design	Feature extraction	Overfitting risk	[40], [59]
Variational Autoencoders	Latent space exploration	Encoding/decoding	Diverse geometry generation	Dimensionality reduction	Blurry outputs	[44]
Support Vector Machines	Classification/regression	Kernel methods	Damage detection in SHM	Robust to noise	Scalability	[36]
Recurrent Neural Networks	Time-series prediction	LSTM/GRU	Predictive maintenance	Sequential data handling	Vanishing gradients	[60]
Multi-Agent Frameworks	Collaborative AI agents	LLM integration	Accelerated design workflows	Interdisciplinary synergy	Coordination overhead	[6]

4.3. Case Studies

AI-driven metamaterial design has yielded practical advancements across diverse applications, demonstrating its real-world impact. In electromagnetic shielding, AI-designed metamaterials achieve broadband absorption for stealth applications. Nezaratzadeh et al. [55] used deep learning to optimize split-ring resonator configurations, achieving over 90% absorption across microwave frequencies, validated experimentally. This case study highlights AI's ability to balance competing objectives, such as bandwidth and absorption efficiency, critical for defense technologies. The use of generative models accelerated the design process, reducing iterations compared to traditional methods, showcasing AI's efficiency in complex electromagnetic applications.

In acoustic insulation, AI has enabled the design of metamaterials for noise reduction in urban environments. Bacigalupo et al. [56] employed ML to optimize phononic metamaterials, creating lightweight panels that block low-frequency noise, ideal for building facades. The AI model predicted bandgap properties based on unit cell geometry, validated through acoustic testing, demonstrating superior performance over conventional materials. This application underscores AI's role in addressing societal challenges, such as urban noise pollution, by enabling rapid design of application-specific metamaterials. Challenges in scaling these designs for large structures remain, requiring further integration with manufacturing processes. Thermal management applications further illustrate AI's versatility in metamaterial design. Li et al. [57] used inverse design with neural networks to create thermal cloaks that redirect heat flow, protecting sensitive electronics in high-temperature environments. The AI model optimized layered metamaterial structures, achieving cloaking efficiency with minimal material use, validated through simulations and experiments. This case study highlights AI's ability to handle multi-physics problems, combining thermal and structural constraints. The integration of AI with experimental feedback loops ensured practical feasibility, though high computational costs necessitate ongoing advancements in algorithm efficiency.

These case studies demonstrate AI's transformative impact on metamaterial design, from electromagnetic to thermal applications. By reducing design time and enhancing performance, AI enables innovative solutions that address engineering challenges. Future case studies should focus on integrating AI with real-time manufacturing feedback, as suggested by Abbas et al. [58], to ensure seamless scalability and cost-effectiveness, critical for widespread adoption in industry.

5. AI in Smart Structure Development

The integration of artificial intelligence (AI) into smart structure development has revolutionized their design, monitoring, and adaptive capabilities, enabling real-time responsiveness and enhanced performance in dynamic environments. Smart structures, characterized by embedded sensors, actuators, and control systems, benefit from AI's ability to process vast datasets, optimize control strategies, and predict structural behaviors under varying conditions. Techniques such as machine learning (ML), deep learning (DL), and reinforcement learning (RL) facilitate structural health monitoring, adaptive control, and integration with emerging technologies like the Internet of Things (IoT). This section explores AI's role in advancing smart structures, focusing on structural health monitoring, adaptive control systems, IoT integration, and practical examples, highlighting their transformative impact on adaptive engineering.

5.1. AI for Structural Health Monitoring

Structural health monitoring (SHM) leverages AI to detect, diagnose, and predict damage in smart structures, enhancing safety and reducing maintenance costs across applications like bridges, buildings, and aircraft. Farrar et al. [36] emphasized that AI-driven SHM systems analyze sensor data to identify anomalies, such as cracks or corrosion, with greater accuracy than traditional methods. Machine learning models, trained on vibration, strain, or acoustic emission data, classify damage types and severities, enabling early intervention. For instance, supervised learning algorithms, such as support vector machines, map sensor signals to damage states, while unsupervised learning detects outliers in real-time data streams. These capabilities allow continuous monitoring, critical for infrastructure in harsh or dynamic environments.

Deep learning enhances SHM by processing complex, high-dimensional sensor data, such as images or time-series signals. Worden et al. [59] demonstrated that convolutional neural networks (CNNs) can analyze ultrasonic wave signals to localize cracks in composite structures, achieving high precision in aerospace applications. These models handle noisy data, common in real-world settings, by learning robust features through layered architectures. Transfer learning further improves efficiency by adapting pre-trained models to specific structures, reducing the need for extensive labeled datasets. However, challenges like data quality and computational demands persist, requiring hybrid approaches that combine physics-based models with AI to ensure reliability. AI-driven SHM also enables predictive

maintenance, forecasting potential failures before they occur. Azimi et al. [60] applied recurrent neural networks (RNNs) to predict fatigue crack growth in bridges, using historical sensor data to model degradation trends. This predictive capability minimizes downtime and extends structure lifespan, particularly in civil infrastructure. Integration with digital twins virtual replicas of physical structures enhance SHM by simulating real-time responses under varying loads, as explored by Sakr et al. [61]. These advancements highlight AI's role in transforming SHM from reactive to proactive, though challenges in real-time processing and sensor reliability require ongoing research.

The impact of AI in SHM lies in its ability to scale across diverse applications, from wind turbines to high-rise buildings. For example, AI models analyze vibration patterns in turbine blades to detect micro-cracks, ensuring operational safety. The work of Bao et al. [62] illustrates how AI-driven SHM systems integrate multi-sensor data to monitor large-scale structures, improving accuracy over traditional methods. Future directions include explainable AI to enhance trust in diagnostic outcomes and the use of edge computing to process data locally, reducing latency in critical applications.

5.2. Adaptive Control Systems

Adaptive control systems in smart structures use AI to dynamically adjust structural responses to external stimuli, such as vibrations, wind, or seismic loads, ensuring stability and efficiency. Spencer et al. [63] developed AI-based control algorithms for active tuned mass dampers, enabling buildings to mitigate wind-induced vibrations in real-time. Reinforcement learning (RL) excels in this domain, learning optimal control policies by interacting with simulated or real structural environments. For instance, RL models adjust actuator forces in smart structures to minimize vibrations, adapting to changing load conditions without predefined models. This adaptability is critical for applications like earthquake-resistant buildings, where rapid response is essential. Machine learning enhances adaptive control by optimizing actuator placement and control strategies. Wang et al. [64] used neural networks to optimize the placement of piezoelectric actuators in aerospace structures, maximizing vibration suppression with minimal energy. These models learn from sensor data, predicting structural responses under diverse conditions, such as aerodynamic loads or thermal fluctuations. Deep reinforcement learning, as explored by Eshkevari et al. [65], further refines control by balancing multiple objectives, like energy efficiency and structural stability. These systems integrate with smart materials, such as shape-memory alloys, to enable dynamic shape changes, enhancing performance in morphing structures.

Challenges in adaptive control include computational complexity and robustness in unpredictable environments. Real-time control requires low-latency processing, often constrained by hardware limitations. Edge AI, as discussed by Qiu et al. [66], addresses this by deploying lightweight models on embedded devices, enabling on-site decision-making. Additionally, hybrid control strategies, combining AI with classical control theory, ensure stability under extreme conditions, as shown by Medhi et al. [67]. These advancements enable smart structures to respond proactively to environmental changes, though ensuring long-term reliability remains a research priority. The transformative potential of AI-driven adaptive control lies in its ability to create resilient, energy-efficient structures. For example, in aerospace, AI-controlled smart wings adjust geometry to optimize aerodynamics, as demonstrated by Crawley et al. [32]. In civil engineering, adaptive control systems enhance seismic resilience by dynamically adjusting damping, reducing structural damage. Future developments aim to integrate AI with real-time sensor networks, enabling fully autonomous control systems that adapt to unforeseen events, further advancing smart structure applications.

5.3. Integration with IoT and Big Data

The integration of AI with the Internet of Things (IoT) and big data transforms smart structures into interconnected, intelligent systems capable of real-time monitoring and adaptation. Lynch et al. [68] highlighted that IoT-enabled smart structures use distributed sensor networks to collect vast datasets on structural performance, which AI processes to extract actionable insights. For instance, IoT sensors embedded in bridges collect data on strain, temperature, and vibrations, which ML models analyze to predict maintenance needs. This integration enables scalable monitoring across large infrastructure networks, improving efficiency and safety. Big data analytics further enhances this by identifying long-term trends, such as material degradation, critical for lifecycle management. AI-driven IoT frameworks optimize data processing by filtering noise and prioritizing relevant signals. Fei et al. [69] developed a cloud-based AI system for smart buildings, using deep learning to analyze IoT sensor data for energy optimization and structural health. These systems leverage edge computing to process data locally, reducing latency and bandwidth demands. For example, in smart cities, IoT-enabled structures communicate real-time data to centralized AI models, enabling coordinated responses to environmental changes, such as traffic-induced vibrations. However, challenges like data security and interoperability between IoT devices require robust solutions, including blockchain for secure data sharing.

The synergy of AI, IoT, and big data enables predictive and adaptive functionalities in smart structures. For instance, in wind farms, IoT sensors monitor blade vibrations, while AI predicts fatigue failure, as shown by Sasinthiran et al. [70].

This integration supports energy-efficient operations by optimizing maintenance schedules. Scalability remains a challenge, as large-scale IoT deployments generate massive data volumes, straining computational resources. Advanced techniques, such as federated learning, as explored by Cheema et al. [71], address this by training models across distributed devices, preserving privacy and reducing central processing demands. The future of AI-IoT integration lies in creating fully autonomous smart structures that operate within interconnected ecosystems. For example, smart buildings with IoT sensors and AI control systems optimize energy consumption by adjusting lighting and HVAC based on occupancy patterns. The work of Minoli et al. [72] underscores the potential of AI-IoT frameworks to create resilient urban infrastructure, though standardization and cybersecurity remain critical hurdles. These advancements position AI-IoT integration as a cornerstone of next-generation smart structures, enabling sustainable and adaptive engineering solutions.

5.4. Examples of AI-Enabled Smart Structures

AI-enabled smart structures demonstrate transformative applications across industries, leveraging real-time data processing and adaptive control. In civil engineering, self-healing structures use AI to detect damage and trigger repair mechanisms. Li et al. [73] developed a smart concrete structure embedded with microcapsules and sensors, where AI analyzes sensor data to activate healing agents, restoring structural integrity. These systems use ML to predict crack propagation, optimizing repair timing and material use. Such structures enhance durability in bridges and buildings, reducing maintenance costs and extending lifespan, though scaling self-healing mechanisms remains a challenge. In aerospace, AI-enabled morphing structures adapt to changing flight conditions, improving performance and efficiency. Weisshaar et al. [74] explored smart wings with AI-controlled shape-memory alloys, adjusting camber based on aerodynamic data to optimize lift. These systems use RL to learn optimal actuation strategies, reducing fuel consumption. Integration with metamaterials, as discussed by Bertoldi et al. [2], enhances flexibility, enabling lightweight, high-strength designs. These applications demonstrate AI's ability to create adaptive aerospace components, though real-time processing and energy demands require further optimization.

Seismic-resistant buildings represent another key application, where AI-driven smart structures mitigate earthquake impacts. Saaed et al. [75] implemented AI-controlled active mass dampers in high-rise buildings, using ML to predict seismic wave patterns and adjust damping in real-time. These systems integrate with metamaterials to redirect vibrational energy, as explored by Kim et al. [28], enhancing structural resilience. AI's predictive capabilities ensure rapid response to dynamic loads, though high computational costs and sensor reliability remain challenges. Future advancements aim to integrate AI with IoT for real-time seismic monitoring, creating resilient urban infrastructure. In biomedical engineering, AI-enabled smart implants adapt to physiological changes, improving patient outcomes. Wegener et al. [26] reviewed smart implants with embedded sensors and AI analytics, adjusting stiffness to match tissue properties. These systems use ML to monitor tissue integration, triggering actuators to optimize performance. For example, AI-driven prosthetic limbs adapt to user movements, enhancing mobility. These applications highlight AI's role in creating personalized, adaptive biomedical solutions, though biocompatibility and long-term reliability require ongoing research. Collectively, these examples underscore AI's transformative impact on smart structures, driving innovation across engineering domains.

6. Challenges and Future Directions

The integration of artificial intelligence (AI) with metamaterials and smart structures has unlocked transformative possibilities in design, optimization, and adaptive engineering, yet significant challenges remain in scaling these technologies for practical applications. Issues such as computational complexity, manufacturing limitations, and data quality hinder widespread adoption, while interdisciplinary integration demands collaboration across materials science, AI, and engineering domains. Addressing these challenges requires innovative approaches, including advanced algorithms, scalable fabrication techniques, and robust data frameworks. This section explores the technical and interdisciplinary hurdles in AI-driven metamaterial and smart structure development, identifies emerging trends like multi-scale modeling and real-time adaptability, and highlights research gaps to guide future advancements, paving the way for sustainable and resilient engineering solutions.

6.1. Technical Challenges

The computational complexity of AI-driven design for metamaterials and smart structures poses a significant barrier, particularly for large-scale or three-dimensional architectures. Designing complex metamaterials requires simulating wave interactions at subwavelength scales, which demands substantial computational resources. Molesky et al. [45] noted that inverse design algorithms, such as those using deep learning, often require high-performance computing to handle high-dimensional parameter spaces, limiting accessibility for smaller research groups. Real-time applications, like adaptive control in smart structures, exacerbate this issue, as low-latency processing is critical for dynamic

responses. Edge computing and lightweight AI models, as proposed by Qiu et al. [66], offer potential solutions, but their implementation in resource-constrained environments remains challenging.

Manufacturing constraints further complicate the translation of AI-designed metamaterials and smart structures into practical systems. High-precision fabrication techniques, such as electron-beam lithography or advanced 3D printing, are required to realize complex geometries, but these are costly and scale poorly for large structures. Kadic et al. [5] highlighted that while additive manufacturing enables intricate metamaterial designs, material inconsistencies and resolution limitations can degrade performance. AI can optimize designs for manufacturability, but discrepancies between simulated and fabricated structures persist, necessitating closed-loop feedback systems that integrate real-time fabrication data. Developing cost-effective, scalable manufacturing processes is critical to bridging this gap.

Data quality and availability present additional challenges, as AI models rely on diverse, high-quality datasets for accurate predictions. Liu et al. [38] emphasized that limited or noisy datasets can lead to overfitting in machine learning models, reducing their generalizability. For instance, in structural health monitoring, sensor data may be incomplete or biased due to environmental noise, affecting diagnostic accuracy. Synthetic data generation, using generative adversarial networks, as explored by Al-Khaylani et al. [41], mitigates data scarcity, but ensuring physical accuracy remains a hurdle. Standardizing data collection protocols and developing open-access repositories could enhance AI model robustness, enabling broader application in metamaterial and smart structure development. Addressing these technical challenges requires interdisciplinary innovation, combining advances in computational efficiency, manufacturing, and data science. For example, physics-informed neural networks, as developed by Chen et al. [46], reduce computational demands by embedding physical constraints into AI models, improving convergence rates. Similarly, advancements in scalable 3D printing, as discussed by Abbas et al. [58], enable the production of complex metamaterials at lower costs. Overcoming these barriers will unlock the full potential of AI-driven systems, enabling their deployment in real-world applications like aerospace, infrastructure, and biomedical devices.

6.2. Interdisciplinary Integration

The successful integration of AI, metamaterials, and smart structures demands collaboration across disciplines, including materials science, computer science, and engineering, which presents both opportunities and challenges. Developing multifunctional systems requires aligning the goals of material designers, who focus on physical properties, with AI researchers, who prioritize algorithmic efficiency. Wegener et al. [26] noted that mismatches in terminology and methodologies can hinder collaboration, as materials scientists may prioritize experimental validation while AI experts emphasize computational models. Establishing common frameworks, such as standardized design pipelines, is essential to streamline interdisciplinary efforts and ensure cohesive development.

Communication and knowledge transfer are critical barriers in interdisciplinary integration. For instance, AI-driven inverse design requires materials scientists to understand machine learning concepts, while AI researchers must grasp the physics of wave propagation in metamaterials. Engheta et al. [23] emphasized the need for hybrid training programs that equip researchers with cross-disciplinary skills, fostering collaboration. Collaborative platforms, such as open-source software for AI-based design, can facilitate knowledge sharing, enabling engineers to leverage pre-trained models for specific applications. However, cultural differences between disciplines and varying research priorities can slow progress, necessitating institutional support for interdisciplinary initiatives. The integration of AI with experimental validation further complicates interdisciplinary efforts, as theoretical models must align with real-world outcomes. Bertoldi et al. [2] highlighted that discrepancies between simulated and fabricated metamaterials often arise due to manufacturing variabilities, requiring iterative feedback between computational and experimental teams. AI can bridge this gap by incorporating real-time fabrication data into design loops, but this requires seamless collaboration between engineers and data scientists. Emerging tools, like digital twins, as explored by Sakr et al. [61], enable real-time synchronization of virtual and physical systems, enhancing interdisciplinary workflows. Future efforts should focus on developing shared standards and collaborative environments to accelerate innovation.

The transformative potential of interdisciplinary integration lies in its ability to create holistic solutions that address complex engineering challenges. For example, combining AI-driven SHM with metamaterial-based seismic protection, as studied by Kim et al. [28], creates resilient infrastructure through collaborative design. Initiatives like interdisciplinary research centers and funding programs can foster such integration, driving advancements in adaptive engineering. Overcoming these challenges will enable the development of next-generation smart structures that combine AI's computational power with the unique properties of metamaterials.

6.3. Emerging Trends

Emerging trends in AI-driven metamaterial and smart structure development include multi-scale modeling, real-time adaptive systems, and sustainable design, each promising to expand their applicability. Multi-scale modeling, which integrates nanoscale material properties with macroscale structural behavior, leverages AI to bridge length scales. Jamaludin et al. [76] developed AI models that predict the macroscopic performance of metamaterials based on nanoscale simulations, enabling efficient design of hierarchical structures. These models reduce computational costs by focusing on critical scales, facilitating applications like lightweight aerospace components. Physics-informed AI, embedding governing equations into models, further enhances accuracy, as shown by Chen et al. [46], paving the way for complex, multi-physics designs. Real-time adaptive systems represent a frontier in smart structure development, where AI enables instantaneous responses to environmental changes. Spencer et al. [63] explored AI-driven control systems that adjust structural damping in real-time, critical for seismic resilience. Advances in edge AI, as discussed by Qiu et al. [66], enable on-device processing, reducing latency in applications like morphing aircraft wings or smart implants. The integration of IoT with AI, further enhances adaptability by connecting structures to real-time data networks, enabling coordinated responses in smart cities. These systems require robust algorithms to handle dynamic, unpredictable inputs, driving research into adaptive AI frameworks [68,69].

Highlighting the complexities in bridging scales, Figure 2 depicts the challenges in multi-scale modeling of metamaterials, providing a visual framework for how AI can address computational demands in hierarchical designs.

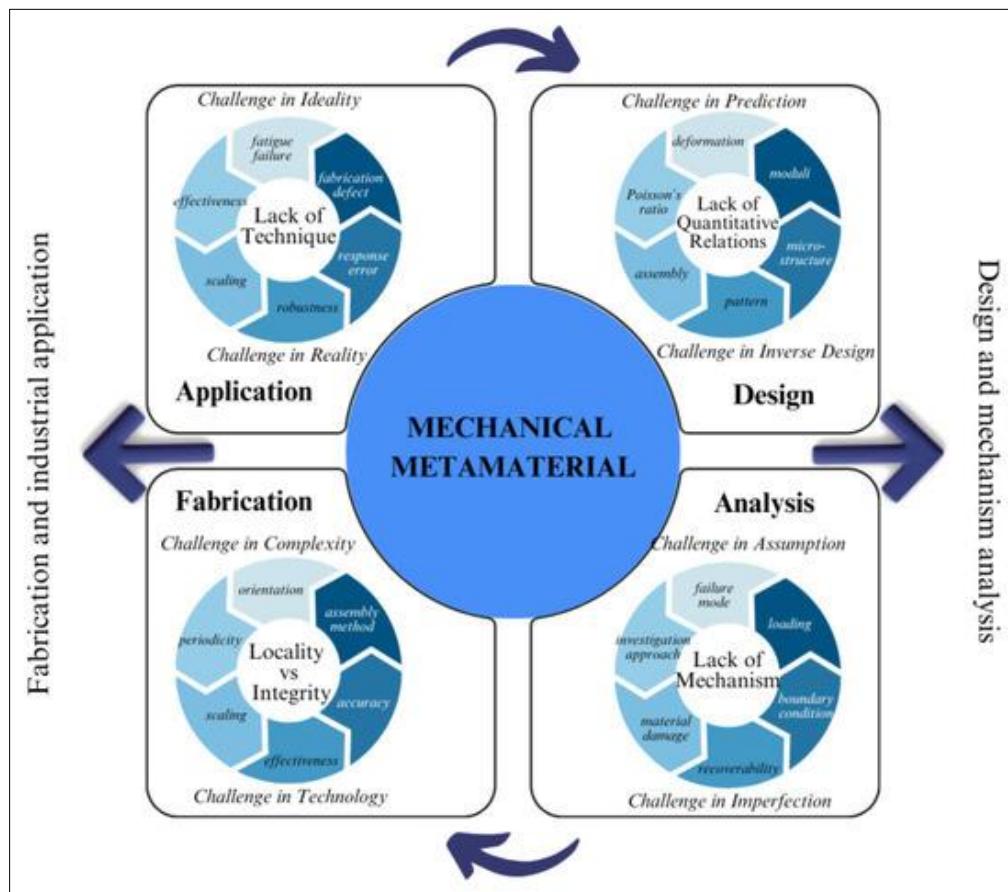


Figure 2 Challenges in the modeling of metamaterials. Reproduced with permission from ref [68]

Table 3 Emerging Trends and Research Opportunities in AI-Metamaterial Integration

Trend	Description	Key Technologies	Applications	Benefits	Gaps/Opportunities	References
Multi-Scale Modeling	Bridging nano to macro scales	AI-driven simulations	Hierarchical structures	Efficient predictions	Standardization of models	[76]
Real-Time Adaptability	Instantaneous response systems	Edge AI, RL	Seismic damping, morphing wings	Enhanced resilience	Latency reduction	[63], [66], [74]
Sustainable Designs	Eco-friendly materials	Topology optimization	Energy-efficient buildings	Resource minimization	Lifecycle assessment	[16], [54]
Explainable AI	Interpretable models	SHAP, physics-informed	SHM diagnostics	Increased trust	Broader implementation	[37], [77]
IoT-Big Data Fusion	Interconnected sensor networks	Federated learning	Smart cities	Predictive analytics	Data security	[68], [69], [71], [72]
Hybrid AI Frameworks	Combining ML with physics	PINNs, multi-agent	Inverse design	Physical accuracy	Scalability for 3D	[6], [46]
Self-Healing Systems	Autonomous repair	AI-triggered actuators	Infrastructure longevity	Reduced maintenance	Material durability	[73]
Energy Harvesting Optimization	AI-tuned capture	RL for efficiency	Remote sensors	Sustainability	Low-energy environments	[29]
Digital Twins	Virtual replicas	Real-time syncing	Predictive maintenance	Simulation fidelity	Integration with IoT	[61]
Generative AI for Collaboration	LLM-based workflows	Multi-agent systems	Collaborative design	Accelerated innovation	Ethical AI use	[6], [11]
Broadband Metamaterials	Wide-frequency designs	DL optimization	Multifunctional devices	Versatility	Loss minimization	[21], [45]
Federated Learning	Distributed training	Privacy-preserving	SHM in populations	Scalable monitoring	Communication overhead	[71]

Sustainable metamaterials and smart structures are gaining traction, addressing environmental concerns through eco-friendly materials and energy-efficient designs. The development of recyclable metamaterials, designed using AI to optimize material use while maintaining performance. For example, AI-driven topology optimization creates lightweight structures that reduce resource consumption in aerospace and construction. Energy harvesting, as explored by Carrara et al. [29], integrates piezoelectric metamaterials with AI control to maximize energy capture, supporting sustainable infrastructure. These trends align with global sustainability goals, though challenges in material recyclability and lifecycle assessment require further exploration. The convergence of these trends promises transformative advancements, enabling smart structures that are adaptive, sustainable, and scalable. For instance, AI-driven multi-scale models can design energy-efficient buildings with integrated thermal metamaterials, as proposed by Zhu et al. [54]. Future developments will likely focus on autonomous design pipelines, where AI systems iterate designs based on real-time environmental feedback, enhancing resilience and efficiency. These trends position AI-driven metamaterials and smart structures at the forefront of sustainable engineering innovation.

Building on the discussed trends, Table 3 outlines emerging developments in AI-driven metamaterials and smart structures, with details on descriptions, applications, benefits, gaps/opportunities, and references, to highlight pathways for future research.

6.4. Research Gaps and Opportunities

Despite significant progress, research gaps in AI-driven metamaterial and smart structure development present opportunities for future innovation. Model interpretability remains a critical gap, as complex AI models, like deep neural networks, often function as black boxes, limiting trust in engineering applications. Goodfellow et al. [37] emphasized the need for explainable AI to elucidate decision-making processes, particularly in safety-critical systems like SHM. Techniques like SHAP (SHapley Additive exPlanations) values, as explored by Lundberg et al. [77], offer solutions by quantifying feature contributions, but their application to metamaterial design is nascent. Developing interpretable models will enhance adoption in industries requiring transparency, such as aerospace and healthcare.

Data quality and standardization represent another gap, as AI models require diverse, high-quality datasets to ensure generalizability. Bao et al. [62] noted that inconsistent sensor data in SHM can lead to inaccurate predictions, particularly in heterogeneous environments. Open-access data repositories and standardized protocols, as proposed by Lynch et al. [68], could address this by providing curated datasets for AI training. Additionally, integrating multi-modal data (e.g., combining vibration and thermal signals) offers opportunities to improve model robustness, enabling comprehensive monitoring of smart structures. Collaborative efforts to create global data standards will accelerate research and deployment.

Real-world deployment of AI-driven systems faces scalability and cost barriers, particularly for large-scale infrastructure. Abbas et al. [58] highlighted that while AI optimizes designs for manufacturability, high-cost fabrication techniques limit scalability. Opportunities exist in developing low-cost, scalable manufacturing methods, such as advanced 3D printing, to produce AI-designed metamaterials. Similarly, real-time adaptive systems require energy-efficient AI algorithms to operate in resource-constrained environments. Research into lightweight models, as explored by Qiu et al. [66], and energy harvesting integration, as studied by Carrara et al. [29], could address these challenges, enabling widespread adoption. The interdisciplinary nature of these gaps offers opportunities for innovation through collaboration. For instance, combining AI with advanced materials science could lead to self-adaptive metamaterials that respond autonomously to environmental changes, as suggested by Wegener et al. [22]. Funding interdisciplinary research and developing open-source platforms for AI-driven design will accelerate progress. Addressing these gaps will enable the creation of resilient, sustainable smart structures, transforming engineering applications from biomedical devices to smart cities.

7. Conclusion

The integration of artificial intelligence (AI) with metamaterials and smart structures has ushered in a new era of adaptive engineering, enabling unprecedented control over material properties and structural behaviors. This review has explored how AI-driven methodologies, such as machine learning, deep learning, and generative algorithms, revolutionize the design and optimization of metamaterials, facilitating the creation of structures with exotic properties like negative refraction, tunable stiffness, and energy cloaking. By streamlining inverse design, predicting material performance, and optimizing complex geometries, AI reduces computational and experimental barriers, accelerating innovation in fields ranging from aerospace to biomedical engineering. The synergy of AI with smart structures enhances real-time adaptability through advanced structural health monitoring, adaptive control systems, and IoT integration, creating resilient systems capable of responding to dynamic environmental conditions. These

advancements underscore the transformative potential of combining computational intelligence with engineered materials, offering solutions that are both high-performing and sustainable.

Smart structures, enhanced by AI and integrated with metamaterials, demonstrate remarkable versatility in addressing modern engineering challenges. Applications such as seismic-resistant buildings, morphing aircraft wings, self-healing infrastructure, and energy-harvesting devices illustrate the practical impact of these technologies, improving safety, efficiency, and sustainability across industries. AI's ability to process vast sensor datasets and optimize control strategies enables proactive maintenance and real-time adaptation, reducing costs and extending structural lifespans. The incorporation of metamaterials amplifies these capabilities, providing tunable properties that enhance functionality, such as vibration attenuation or electromagnetic shielding. However, the full realization of these benefits hinges on overcoming technical challenges, including computational complexity, manufacturing scalability, and data quality, which require ongoing innovation in algorithms, fabrication techniques, and data management.

Interdisciplinary collaboration emerges as a critical driver for advancing AI-driven metamaterials and smart structures. Bridging materials science, computer science, and engineering is essential to align theoretical designs with practical implementations, ensuring that AI-optimized structures meet real-world demands. Emerging trends, such as multi-scale modeling, real-time adaptive systems, and sustainable material design, point to a future where smart structures operate autonomously within interconnected ecosystems, such as smart cities. These trends align with global priorities for sustainability and resilience, positioning AI-driven solutions at the forefront of engineering innovation. Nevertheless, research gaps in model interpretability, data standardization, and scalable deployment must be addressed to ensure widespread adoption and trust in these technologies.

Looking forward, the continued development of AI-driven metamaterials and smart structures requires focused research and investment in scalable manufacturing, explainable AI, and open-access data frameworks. Collaborative initiatives, such as interdisciplinary research centers and standardized design platforms, will accelerate progress by fostering knowledge sharing and innovation. Engineers and researchers should prioritize eco-friendly materials and energy-efficient systems to align with sustainability goals, while advancements in edge computing and IoT integration will enable real-time, autonomous applications. By addressing these priorities, AI-driven metamaterials and smart structures can transform industries, delivering adaptive, resilient, and sustainable solutions that meet the evolving needs of society, from smarter infrastructure to advanced biomedical devices.

Compliance with ethical standards

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The authors declare that they have no conflict of interest to be disclosed.

References

- [1] Smith, D. R., Pendry, J. B., and Wiltshire, M. C. (2004). Metamaterials and negative refractive index. *science*, 305(5685), 788-792.
- [2] Bertoldi, K., Vitelli, V., Christensen, J., and Van Hecke, M. (2017). Flexible mechanical metamaterials. *Nature Reviews Materials*, 2(11), 1-11.
- [3] Zhang, S., Park, Y. S., Li, J., Lu, X., Zhang, W., and Zhang, X. (2009). Negative refractive index in chiral metamaterials. *Physical review letters*, 102(2), 023901.
- [4] Cummer, S. A., Christensen, J., and Alù, A. (2016). Controlling sound with acoustic metamaterials. *Nature Reviews Materials*, 1(3), 1-13.
- [5] Kadic, M., Milton, G. W., van Hecke, M., and Wegener, M. (2019). 3D metamaterials. *Nature reviews physics*, 1(3), 198-210.

- [6] Tian, J., Sobczak, M. T., Patil, D., Hou, J., Pang, L., Ramanathan, A., ... and Wang, X. (2025). A Multi-Agent Framework Integrating Large Language Models and Generative AI for Accelerated Metamaterial Design. arXiv preprint arXiv:2503.19889.
- [7] Song, J., Lee, J., Kim, N., and Min, K. (2024). Artificial intelligence in the design of innovative metamaterials: A comprehensive review. *International Journal of Precision Engineering and Manufacturing*, 25(1), 225-244.
- [8] Wang, L., Chan, Y. C., Ahmed, F., Liu, Z., Zhu, P., and Chen, W. (2020). Deep generative modeling for mechanistic-based learning and design of metamaterial systems. *Computer Methods in Applied Mechanics and Engineering*, 372, 113377.
- [9] Chopra, I. (1996). Review of current status of smart structures and integrated systems. *Smart Structures and Materials 1996: Smart Structures and Integrated Systems*, 2717, 20-62.
- [10] Song, G., Sethi, V., and Li, H. N. (2006). Vibration control of civil structures using piezoceramic smart materials: A review. *Engineering Structures*, 28(11), 1513-1524.
- [11] Qin, S., Guan, H., Liao, W., Gu, Y., Zheng, Z., Xue, H., and Lu, X. (2024). Intelligent design and optimization system for shear wall structures based on large language models and generative artificial intelligence. *Journal of Building Engineering*, 95, 109996.
- [12] Veselago, V. G. (1967). The electrodynamics of substances with simultaneously negative values of ϵ and μ . *Usp. fiz. nauk*, 92(3), 517-526.
- [13] Shelby, R. A., Smith, D. R., and Schultz, S. (2001). Experimental verification of a negative index of refraction. *science*, 292(5514), 77-79.
- [14] Liu, Z., Zhang, X., Mao, Y., Zhu, Y. Y., Yang, Z., Chan, C. T., and Sheng, P. (2000). Locally resonant sonic materials. *science*, 289(5485), 1734-1736.
- [15] Tserkezis, C., Stefanou, N., Wubs, M., and Mortensen, N. A. (2016). Molecular fluorescence enhancement in plasmonic environments: exploring the role of nonlocal effects. *Nanoscale*, 8(40), 17532-17541.
- [16] Zhang, H. C., Gong, S., Zhang, L. P., Zhang, Y., and Cui, T. J. (2025). Meta-atoms: From Metamaterials to Metachips. *Research*, 8, 0587.
- [17] Smith, D. R., Padilla, W. J., Vier, D. C., Nemat-Nasser, S. C., and Schultz, S. (2000). Composite medium with simultaneously negative permeability and permittivity. *Physical review letters*, 84(18), 4184.
- [18] Lakes, R. (1987). Foam structures with a negative Poisson's ratio. *Science*, 235(4792), 1038-1040.
- [19] Yang, Z., Mei, J., Yang, M., Chan, N. H., and Sheng, P. (2008). Membrane-type acoustic metamaterial with negative dynamic mass. *Physical review letters*, 101(20), 204301.
- [20] Narayana, S., and Sato, Y. (2012). Heat flux manipulation with engineered thermal materials. *Physical review letters*, 108(21), 214303.
- [21] Shalaev, V. M. (2007). Optical negative-index metamaterials. *Nature photonics*, 1(1), 41-48.
- [22] Wegener, M. (2013). Metamaterials beyond optics. *Science*, 342(6161), 939-940.
- [23] Engheta, N., and Ziolkowski, R. W. (Eds.). (2006). *Metamaterials: physics and engineering explorations*. John Wiley and Sons.
- [24] Schurig, D., Mock, J. J., Justice, B. J., Cummer, S. A., Pendry, J. B., Starr, A. F., and Smith, D. R. (2006). Metamaterial electromagnetic cloak at microwave frequencies. *Science*, 314(5801), 977-980.
- [25] Jenett, B., Calisch, S., Cellucci, D., Cramer, N., Gershenfeld, N., Swei, S., and Cheung, K. C. (2017). Digital morphing wing: active wing shaping concept using composite lattice-based cellular structures. *Soft robotics*, 4(1), 33-48.
- [26] Wegener, M., and Linden, S. (2010). Shaping optical space with metamaterials. *Physics Today*, 63(10), 32-36.
- [27] Zhu, J., Christensen, J., Jung, J., Martin-Moreno, L., Yin, X., Fok, L., ... and Garcia-Vidal, F. J. (2011). A holey-structured metamaterial for acoustic deep-subwavelength imaging. *Nature physics*, 7(1), 52-55.
- [28] Kim, S. H., and Das, M. P. (2012). Seismic waveguide of metamaterials. *Modern Physics Letters B*, 26(17), 1250105.
- [29] Carrara, M., Cacan, M. R., Leamy, M. J., Ruzzene, M., and Erturk, A. (2012). Dramatic enhancement of structure-borne wave energy harvesting using an elliptical acoustic mirror. *Applied Physics Letters*, 100(20).

- [30] Atwater, H. A., and Polman, A. (2010). Plasmonics for improved photovoltaic devices. *Nature materials*, 9(3), 205-213.
- [31] Chopra, I. (2002). Review of state of art of smart structures and integrated systems. *AIAA journal*, 40(11), 2145-2187.
- [32] Crawley, E. F., and De Luis, J. (1987). Use of piezoelectric actuators as elements of intelligent structures. *AIAA journal*, 25(10), 1373-1385.
- [33] Soong, T. T., and Spencer Jr, B. F. (2002). Supplemental energy dissipation: state-of-the-art and state-of-the-practice. *Engineering structures*, 24(3), 243-259.
- [34] Balageas, D., Fritzen, C. P., and Güemes, A. (Eds.). (2010). *Structural health monitoring* (Vol. 90). John Wiley and Sons.
- [35] Lian, J., Cai, O., Dong, X., Jiang, Q., and Zhao, Y. (2019). Health monitoring and safety evaluation of the offshore wind turbine structure: A review and discussion of future development. *Sustainability*, 11(2), 494.
- [36] Farrar, C. R., and Worden, K. (2012). *Structural health monitoring: a machine learning perspective*. John Wiley and Sons.
- [37] Goodfellow, I., Bengio, Y., Courville, A., and Bengio, Y. (2016). *Deep learning* (Vol. 1, No. 2). Cambridge: MIT press.
- [38] Liu, D., Tan, Y., Khoram, E., and Yu, Z. (2018). Training deep neural networks for the inverse design of nanophotonic structures. *Acs Photonics*, 5(4), 1365-1369.
- [39] He, L., Li, Y., Torrent, D., Zhuang, X., Rabczuk, T., and Jin, Y. (2023). Machine learning assisted intelligent design of meta structures: a review. *Microstructures*, 3(4), N-A.
- [40] Ma, W., Cheng, F., and Liu, Y. (2018). Deep-learning-enabled on-demand design of chiral metamaterials. *ACS nano*, 12(6), 6326-6334.
- [41] Al-Khaylani, H. H., Al-Sharif, T. A., Abbas, M. F., Hussein, H., Al-Shabandar, R., and Oleiwi, T. A. (2024, October). Generative Adversarial Networks to Design Metamaterials Based Nano-Photonics Devices. In *2024 4th International Conference on Artificial Intelligence and Signal Processing (AISP)* (pp. 1-5). IEEE.
- [42] Chen, J., Huang, J., An, M., Hu, P., Xie, Y., Wu, J., and Chen, Y. (2024). Application of machine learning on the design of acoustic metamaterials and phonon crystals: A review. *Smart Materials and Structures*, 33(7), 073001.
- [43] Jensen, J. S., and Sigmund, O. (2011). Topology optimization for nano - photonics. *Laser and Photonics Reviews*, 5(2), 308-321.
- [44] Kudyshev, Z. A., Kildishev, A. V., Shalaev, V. M., and Boltasseva, A. (2020). Machine-learning-assisted metasurface design for high-efficiency thermal emitter optimization. *Applied Physics Reviews*, 7(2).
- [45] Molesky, S., Lin, Z., Piggott, A. Y., Jin, W., Vucković, J., and Rodriguez, A. W. (2018). Inverse design in nanophotonics. *Nature Photonics*, 12(11), 659-670.
- [46] Chen, Y., Lu, L., Karniadakis, G. E., and Dal Negro, L. (2020). Physics-informed neural networks for inverse problems in nano-optics and metamaterials. *Optics express*, 28(8), 11618-11633.
- [47] Zhang, S., Zhang, S., Gao, F., Ma, J., and Dobre, O. A. (2021). Deep learning optimized sparse antenna activation for reconfigurable intelligent surface assisted communication. *IEEE Transactions on Communications*, 69(10), 6691-6705.
- [48] So, S., Mun, J., and Rho, J. (2019). Simultaneous inverse design of materials and structures via deep learning: demonstration of dipole resonance engineering using core-shell nanoparticles. *ACS applied materials and interfaces*, 11(27), 24264-24268.
- [49] Rahmat-Samii, Y., and Michielssen, E. (1999). Electromagnetic optimization by genetic algorithms. *Microwave Journal*, 42(11), 232-232.
- [50] Szabó, B., and Babuška, I. (2021). *Finite element analysis: Method, verification and validation*.
- [51] Sui, F., Guo, R., Zhang, Z., Gu, G. X., and Lin, L. (2021). Deep reinforcement learning for digital materials design. *ACS Materials Letters*, 3(10), 1433-1439.
- [52] Tran, T., Amirkulova, F. A., and Khatami, E. (2022). Broadband acoustic metamaterial design via machine learning. *Journal of Theoretical and Computational Acoustics*, 30(03), 2240005.

- [53] Peng, R., Ren, S., Malof, J., and Padilla, W. J. (2024). Transfer learning for metamaterial design and simulation. *Nanophotonics*, 13(13), 2323-2334.
- [54] Zhu, C., Bamidele, E. A., Shen, X., Zhu, G., and Li, B. (2024). Machine learning aided design and optimization of thermal metamaterials. *Chemical Reviews*, 124(7), 4258-4331.
- [55] Nezaratizadeh, A., Hashemi, S. M., and Bod, M. (2024, October). Deep Learning for Electromagnetic Metamaterial Inverse Design. In 2024 11th International Symposium on Telecommunications (IST) (pp. 279-282). IEEE.
- [56] Bacigalupo, A., Gnecco, G., Lepidi, M., and Gambarotta, L. (2020). Machine-learning techniques for the optimal design of acoustic metamaterials. *Journal of Optimization Theory and Applications*, 187(3), 630-653.
- [57] Li, X., Qin, Y., Sun, L., and Guo, X. (2025). Multimaterial Metamaterial Inverse Design via Machine Learning for Tailorable and Reusable Energy Absorption. *ACS Applied Materials and Interfaces*.
- [58] Abbas, M., Nazir, A., and Ali, U. (2025). Design, additive manufacturing, and machine learning prediction of multi-material diamond TPMS structure for improved mechanical performance. *Progress in Additive Manufacturing*, 1-17.
- [59] Worden, K., and Manson, G. (2007). The application of machine learning to structural health monitoring. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 365(1851), 515-537.
- [60] Azimi, M., Eslamlou, A. D., and Pekcan, G. (2020). Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review. *Sensors (Basel, Switzerland)*, 20(10), 2778.
- [61] Sakr, M., and Sadhu, A. (2024). Recent progress and future outlook of digital twins in structural health monitoring of civil infrastructure. *Smart Materials and Structures*, 33(3), 033001.
- [62] Bao, Y., Tang, Z., and Li, H. (2020). Compressive-sensing data reconstruction for structural health monitoring: a machine-learning approach. *Structural Health Monitoring*, 19(1), 293-304.
- [63] Spencer Jr, B. F., and Nagarajaiah, S. (2003). State of the art of structural control. *Journal of structural engineering*, 129(7), 845-856.
- [64] Wang, N., and Adeli, H. (2015). Self-constructing wavelet neural network algorithm for nonlinear control of large structures. *Engineering Applications of Artificial Intelligence*, 41, 249-258.
- [65] Eshkevari, S. S., Eshkevari, S. S., Sen, D., and Pakzad, S. N. (2021). RL-Controller: a reinforcement learning framework for active structural control. *arXiv preprint arXiv:2103.07616*.
- [66] Qiu, T., Chi, J., Zhou, X., Ning, Z., Atiquzzaman, M., and Wu, D. O. (2020). Edge computing in industrial internet of things: Architecture, advances and challenges. *IEEE communications surveys and tutorials*, 22(4), 2462-2488.
- [67] Medhi, M., Dandautiya, A., and Raheja, J. L. (2019). Real-time video surveillance based structural health monitoring of civil structures using artificial neural network. *Journal of Nondestructive Evaluation*, 38(3), 63.
- [68] Jamaludin, S. N. S., Ibrahim, N. M. I. N., Azir, M. Z., Ismail, N. M., and Basri, S. (2025). Multi-Scale Modeling of Polymeric Metamaterials: Bridging Design and Performance—A Review. *Engineering Proceedings*, 84(1), 86.
- [69] Fei, C., Liu, R., Li, Z., Wang, T., and Baig, F. N. (2021). Machine and deep learning algorithms for wearable health monitoring. In *Computational intelligence in healthcare* (pp. 105-160). Cham: Springer International Publishing.
- [70] Sasinthiran, A., Gnanasekaran, S., and Ragala, R. (2024). A review of artificial intelligence applications in wind turbine health monitoring. *International Journal of Sustainable Energy*, 43(1), 2326296.
- [71] Cheema, M. A., Sarwar, M. Z., Cantero, D., and Rossi, P. S. (2025). Clustered federated learning for population-based structural health monitoring. *IEEE Internet of Things Journal*.
- [72] Minoli, D., Sohraby, K., and Occhiogrosso, B. (2017). IoT considerations, requirements, and architectures for smart buildings—Energy optimization and next-generation building management systems. *IEEE Internet of Things Journal*, 4(1), 269-283.
- [73] Li, V. C., and Herbert, E. (2012). Robust self-healing concrete for sustainable infrastructure. *Journal of Advanced Concrete Technology*, 10(6), 207-218.
- [74] Weisshaar, T. A. (2013). Morphing aircraft systems: historical perspectives and future challenges. *Journal of aircraft*, 50(2), 337-353.

- [75] Saaed, T. E., Nikolakopoulos, G., Jonasson, J. E., and Hedlund, H. (2015). A state-of-the-art review of structural control systems. *Journal of Vibration and Control*, 21(5), 919-937.
- [76] Jamaludin, S. N. S., Ibrahim, N. M. I. N., Azir, M. Z., Ismail, N. M., and Basri, S. (2025). Multi-Scale Modeling of Polymeric Metamaterials: Bridging Design and Performance—A Review. *Engineering Proceedings*, 84(1), 86.
- [77] Lundberg, S. M., and Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30.