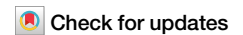


<https://doi.org/10.1038/s44172-025-00470-x>

Bio-inspired acoustic metamaterials for traffic noise control: bridging the gap with machine learning

Jia-Hao Lu^{1,2} , Siqi Ding^{1,2} , Yi-Qing Ni^{1,2} & Shu Li^{1,2}

Acoustic metamaterials (AMMs) represent a transformative approach to sound manipulation, capable of controlling acoustic waves in ways that are not possible with traditional materials. These materials, often inspired by biological structures, leverage complex geometries and innovative designs to enhance sound absorption and control. This review outlines the fundamentals of bio-inspired AMMs, discusses their design and performance characteristics, and highlights the challenges in translating these innovations into practical applications. We also explore the integration of machine learning (ML) techniques with bio-inspired design to optimize AMM for practical implementation. Finally, we propose future research directions aimed at developing broadband AMMs that effectively address the pressing issue of traffic noise, thereby enhancing the overall efficacy of noise control solutions.

Noise pollution has become a major issue affecting human comfort, particularly in environments dominated by traffic noise. While humans can perceive sound frequencies ranging from 20 Hz to 20,000 Hz, frequencies between 400 Hz and 2500 Hz are generally considered most disturbing and are frequently reported as a source of annoyance by residents¹. To address these noise problems, traditional noise control methods primarily involve sound absorption and reflection. Sound absorption relies heavily on structural design, converting acoustic energy into thermal energy through viscous dissipation and thermal conduction on solid surfaces^{2,3}. Conventional sound absorption materials, such as porous absorbers and fibrous materials, usually require substantial thickness to achieve effective absorption at low frequencies, which makes them bulky and less adaptable in applications such as noise control in building interiors⁴, and soundproofing in aircraft cabins and in automotive structures⁵. These materials typically lack broad frequency absorption capabilities and are difficult to tune for specific frequency ranges, limiting their adaptability in dynamic environments where space and performance efficiency is critical.

In view of these limitations, the innovative concept of acoustic metamaterials (AMMs) has been introduced through the advancement of modern technology. Through unique structural arrangement and compositional design, AMMs manifest sound-wave manipulation properties rarely observed in natural materials⁶. Such extraordinary capabilities include exceptional sound attenuation⁷, bandgap isolation⁸, directional emission⁹, negative refraction¹⁰, acoustic cloaking¹¹ and sound tunneling¹². These properties offer diverse and flexible design options for a variety of acoustic

applications and meet numerous engineering requirements. The design of AMMs has traditionally relied on the orderly arrangement of simple geometric shapes to achieve specific acoustic effects^{13,14}. While this approach can provide a certain degree of acoustic control, it falls short in addressing the increasingly complex acoustic demands of modern society. Organisms in nature exhibit unique acoustic shapes and internal structures that can produce acoustic effects beyond what can be achieved with simple geometric arrangements, providing a wealth of design inspiration¹⁵. Bio-inspired AMM design has great potential in solving various noise problems. For instance, the auditory systems and sonar capabilities of some animals demonstrate complex acoustic characteristics that are difficult to replicate in traditional designs^{16–19}.

In addition, with the rapid development of 3D printing and other advanced manufacturing technologies, researchers are now able to reproduce complicated bio-inspired AMMs with greater precision²⁰. This progress not only drives innovations in structural design, but also enables these new materials to more effectively manipulate a broader range of sound frequencies, thereby enhancing the flexibility and efficiency of acoustic control²¹. At the same time, the complexity of the design process continues to increase, and simulation methods are often time-consuming and inefficient, limiting the speed of innovation and design adaptability. To address these challenges, the introduction of machine learning (ML) techniques has brought revolutionary changes to the design and optimization of bio-inspired AMMs^{22–24}. By training on large datasets of initial structural configurations, ML can quickly identify optimal material arrangements and structural designs, predict their performance²⁵, and

¹Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China. ²National Rail Transit Electrification and Automation Engineering Technology Research Center (Hong Kong Branch), Hong Kong, China. ✉e-mail: s.q.ding@connect.polyu.hk; ceyqni@polyu.edu.hk

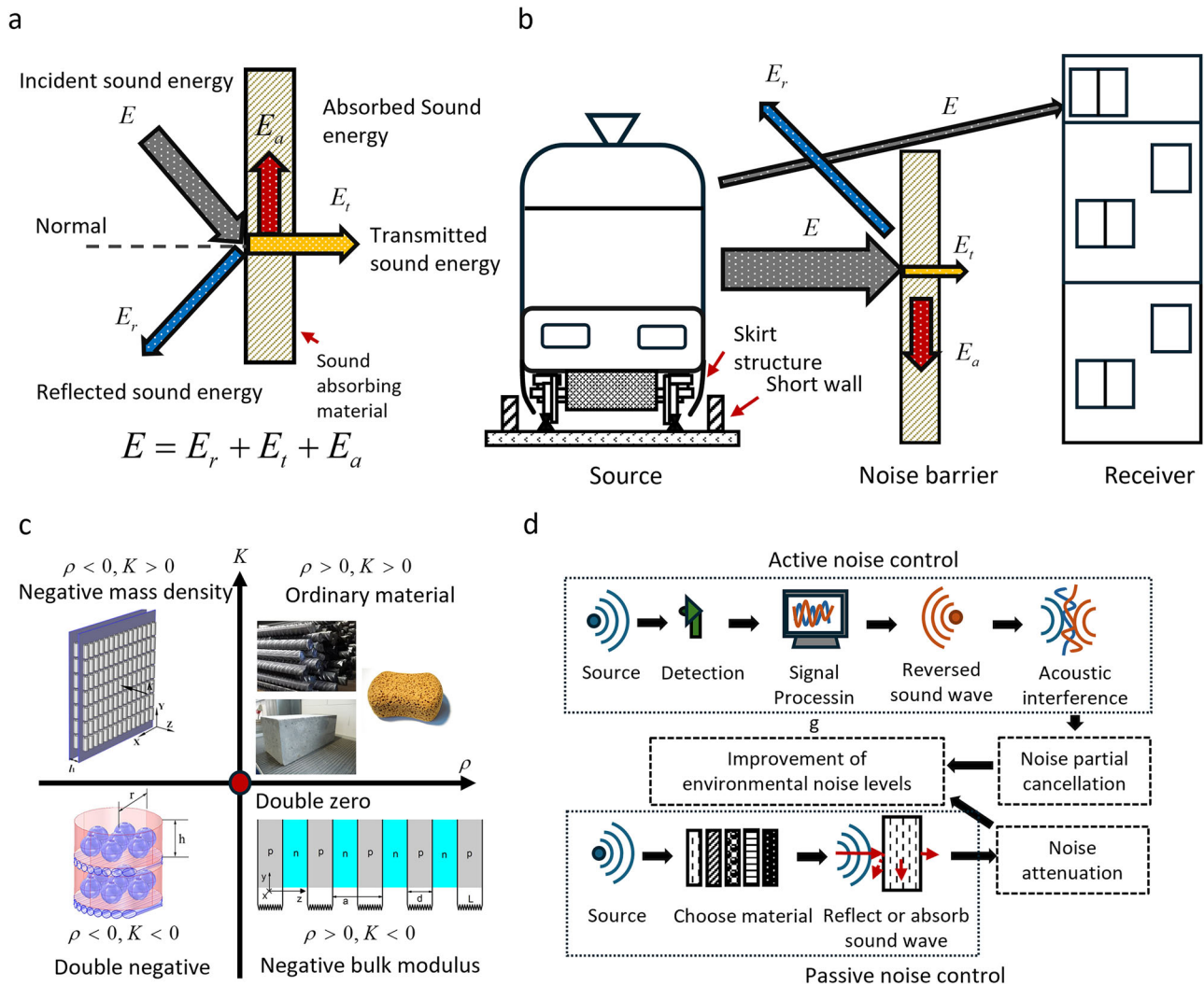


Fig. 1 | Overview of acoustic energy dynamics and key concepts in AMM and noise control. **a** Principle of acoustic energy transmission. **b** Noise propagation and reduction strategies. **c** Negative parameters in mass density and bulk modulus ^{151–153}

Copyright © 2013, AIP Publishing¹⁵¹, Copyright © 2015, AIP Publishing¹⁵², Copyright © 2015, AIP Publishing¹⁵³; **d** Active and passive noise control system in transportation.

accelerate the optimization of design parameters^{26–28}. The application of this technology not only improves design efficiency but also opens up new possibilities for the diversification and complexity of bio-inspired AMMs.

This paper reviews recent advances and prospects in artificial intelligence (AI) and ML-assisted bio-inspired AMMs, with a special emphasis on their potential applications in addressing railway noise challenges. The organization of this paper is as follows: First, we will briefly introduce the fundamental concepts of AMMs, material classifications, and traditional design methods of AMMs. Next, we will focus on classifying bio-inspired AMMs, exploring the commonalities of nature-derived structures that serve as templates for designing sound-absorbing AMMs. Third, we will concentrate on the auxiliary functions of meta-material design through ML methods, including structural optimization and additive techniques. Subsequently, we will review current manufacturing technologies and preparation methods for AMMs. Prior to drawing conclusions, we discuss the limitations of current studies and future research directions.

Fundamental concepts of AMMs and noise control

Sound absorption and noise reduction are critical aspects of managing acoustic environments, particularly in railway transportation. In sound transmission theory, the total sound energy is partitioned into three distinct

components, expressed as

$$E = E_r + E_t + E_a \quad (1)$$

where E_r denotes the reflected sound energy, E_t denotes the transmitted sound energy, and E_a denotes the absorbed sound energy. The principle of sound energy transmission is shown in Fig. 1a. In railway systems, the running train serves as the primary noise source, emitting sound energy that propagates to surrounding structures. Noise mitigation measures, such as skirt structures and short walls along the track, partially reduce noise at the source, while noise barriers are used to impede noise transmission along its propagation path. As depicted in Fig. 1b, when a sound-absorbing noise barrier is installed, most of the sound energy is absorbed within the barrier, with minimal energy being reflected or transmitted. A small fraction of the sound energy may bypass the barrier's apex and reach the building directly, though this constitutes a negligible amount. The primary objective of sound-absorbing noise barriers is to maximize sound energy absorption, which is theoretically represented by maximizing E_a and minimizing E_r and E_t . The effectiveness of such barriers is directly linked to the material's ability to dissipate sound energy, a property quantified by the sound absorption coefficient.

Sound absorption refers to the process by which sound energy is dissipated within materials, thereby reducing the intensity of sound waves. This

phenomenon is quantified using the sound absorption coefficient α , defined as the ratio of absorbed sound energy to the incident sound energy. In this calculation, the transmitted E_t is usually omitted. Thus, the formula for calculating the sound absorption coefficient is given by²⁹

$$\alpha = \frac{E_a}{E_a + E_r} \quad (2)$$

High-performance AMMs can achieve sound absorption coefficients close to unity, indicating their potential to reduce noise levels in railway environments. There is also a method to determine the sound absorption coefficient from acoustic impedance measurements³⁰, given by

$$\alpha = 1 - \left| \frac{(Z/\rho c) \cos \theta - 1}{(Z/\rho c) \cos \theta + 1} \right|^2 \quad (3)$$

where Z is the acoustic impedance of the given material, ρc is the acoustic impedance of the air and θ is the wave incident angle.

On the other hand, noise reduction is often quantified through transmission loss (TL)³¹, which measures the effectiveness of a material in preventing sound from passing through it. The transmission loss can be calculated by:

$$TL = 10 \log_{10} \left(\frac{P_1}{P_2} \right) \quad (4)$$

where P_1 is the sound power incident on the barrier and P_2 is the sound power transmitted through it. The relationship between sound absorption and transmission loss is crucial in railway noise control, as both parameters contribute to the overall acoustic performance of materials used in noise barriers and other structures.

Most conventional materials would be designed to follow the above rules; however, AMMs are engineered materials designed to manipulate sound waves in ways that conventional materials cannot. Two fundamental concepts underpinning the functionality of AMMs are negative mass density and negative bulk modulus, as shown in Fig. 1c. Negative mass density allows for the creation of materials that can exhibit unusual acoustic behaviors, such as reverse sound propagation. This property can be mathematically represented as

$$\rho_{eff} = -\frac{m}{V} \quad (5)$$

$$K_{eff} = -\frac{mc^2}{V} \quad (6)$$

where ρ_{eff} is the effective density, K_{eff} is the effective stiffness, m is the mass of the unit cell, c is the wave velocity, and V is its volume. Similarly, negative bulk modulus enables materials to compress under pressure rather than resist it, leading to enhanced sound absorption capabilities.

In railway noise control, both active and passive sound absorption techniques are employed²⁹, as shown in Fig. 1d. Passive methods, such as the use of AMMs, rely on the inherent properties of materials to absorb sound energy. Active noise control systems, conversely, utilize electronic devices to generate sound waves that interfere with and cancel out unwanted noise. The integration of both approaches can lead to enhanced noise reduction, making it essential to consider both sound absorption and transmission loss when designing effective noise control solutions for railway systems.

When discussing passive sound absorption methods, the microscopic dynamic unit cells of AMMs play a crucial role. These unit cells can be designed with specific geometries and materials to create desired acoustic responses. For instance, by adjusting the dimensions and arrangement of the unit cells, researchers can tailor the effective mass density and bulk modulus of the metamaterial, allowing for precise control over sound wave propagation²⁹. Traditional AMM designs are

usually inspired by fundamental shapes such as triangles and circles, resulting in simple combinations and low-level sound absorbing performance. To improve the noise reduction effect of AMMs, researchers tend to design AMMs to be more complex and detailed. At the same time, some researchers have turned their focus to biomimetic structures in nature. Bio-inspired designs extend the designate dimension in AMMs³², leading to more broadband frequency sound absorbing structures with more precise and smaller scale of acoustic units.

Bio-inspired AMMs for sound absorption

This section introduces AMMs based on various mechanisms of acoustic energy absorption, including cavity resonance, acoustic bandgaps, sound wave extension, metasurfaces, and fractal structures. Each subsection provides bio-inspired AMM examples to illustrate how nature-derived designs inform and enhance AMM technologies.

Cavity resonance absorption

AMMs utilize cavity resonance mechanisms such as Helmholtz resonators³³ (HRs) and microperforated panels (MPPs) have traditionally relied on their ability to target narrow frequency bands by tuning geometric parameters. However, recent bio-inspired advancements have enabled a substantial enhancement of their sound absorption performance, particularly in the broadband and low-frequency range.

The exploration of bio-inspired AMMs utilizing Helmholtz resonators has led to advances in sound absorption and noise control, with various studies highlighting their unique applications and inherent challenges, as shown in Fig. 2. For instance, Zhao and Zhou (2019) introduced an acoustic rainbow catcher that employs Helmholtz resonators arranged in a spiral tube, achieving broadband sound absorption from 1 kHz to 10 kHz. This innovative design leverages resonance effects for spatial-spectral filtering of sound waves, making it particularly suitable for underwater applications due to its compact structure, which reduces the footprint by 70 times and accommodates up to 40 acoustic channels³⁴. However, the manufacturing complexity and environmental noise sensitivity pose challenges to its performance. Complementing this, Gai et al. (2022) investigated honeycomb sandwich AMMs based on Helmholtz resonators, demonstrating excellent sound isolation in the range of 850 to 1600 Hz. This structure effectively combines the lightweight properties of Helmholtz resonance with honeycomb advantages, addressing traditional lightweight materials' shortcomings in low-frequency noise control, although the intricate design and membrane tension control remain limiting factors³⁵. Additionally, Benouhiba et al. (2021) presented an origami-based adjustable Helmholtz resonator, mimicking a water bomb structure, which effectively absorbs low-frequency sound (50–500 Hz) and allows real-time resonant frequency adjustments. Despite its high adjustability and lightweight nature, its performance in high frequency ranges is limited, and it is sensitive to environmental changes³⁶. Li et al. (2023) proposed a bionic multifunctional micro lattice material inspired by bamboo's hollow structure, achieving a sound absorption coefficient of up to 0.99 over a bandwidth of approximately 3.5 kHz. This material exhibits excellent acoustic performance and mechanical strength, although its microporous design may reduce strength and modulus³⁷. Rupin et al. (2019) discussed an active AMM that mimics the cochlea's nonlinear amplification effect through a Helmholtz resonator, demonstrating sound pressure enhancement and frequency selectivity in the range of 300 to 800 Hz³⁸. There are many other designs that exploit this resonant theory, such as AMM based on dragonfly wings³⁹, active AMM that mimic the cochlea⁴⁰, and designs inspired by elastic and viscoelastic bending wave structures of the woodpecker's beak⁴¹.

In addition to the straightforward application of Helmholtz resonators, an MPP paired with a back cavity represents an innovative configuration in AMMs. It is important to distinguish between these two acoustic mechanisms. Helmholtz resonators operate as discrete acoustic elements with a well-defined neck and cavity, while MPPs function through a fundamentally different principle based on distributed acoustic impedance. Classical MPP theory treats the perforated surface not as a collection of

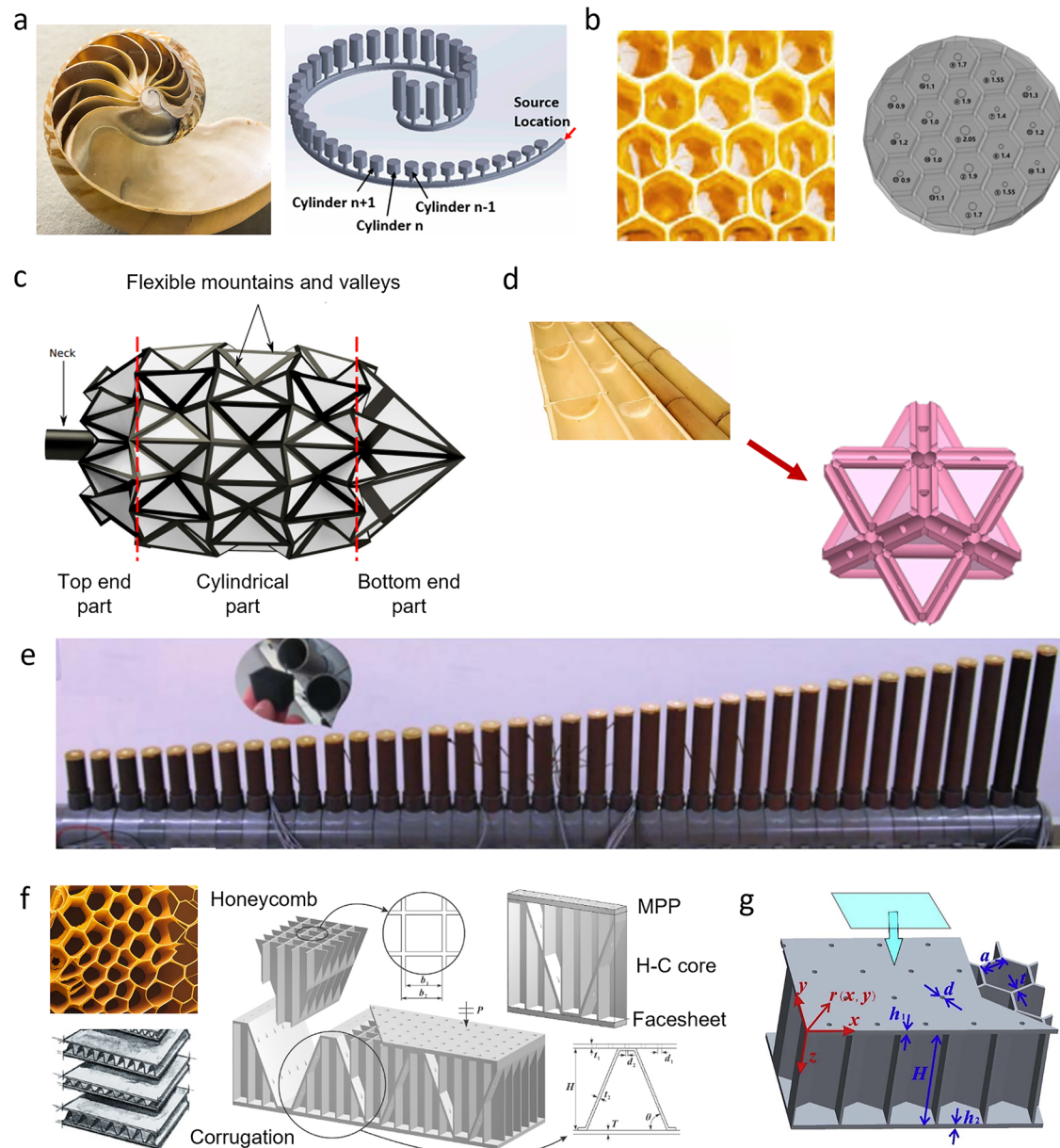


Fig. 2 | Bio-inspired AMM with Helmholtz resonator. **a** Conch-like spiral AMM³⁴, Copyright © 2019 by the authors. **b** Honeycomb sandwich AMM³⁵, Copyright © 2022 Elsevier Ltd. **c** Origami-based AMM³⁶, Copyright © 2021 IOP Publishing Ltd. **d** Bamboo-inspired AMM³⁷, Copyright © 2023, American Chemical Society.

e Cochlea AMM³⁸, Copyright © 2019 The Author(s). **f** honeycomb & corrugation shape AMM⁴², Copyright © 2017, The Author(s). **g** Honeycomb & MPP AMM⁴³, Copyright © 2019 Elsevier Ltd.;

miniature resonators, but as a homogenized acoustic impedance layer that accounts for collective hole-hole interactions across the panel surface. When an MPP is combined with a back cavity, the system exhibits resonant behavior but should not be conceptualized simply as an array of miniature Helmholtz resonators. Rather, it represents a coupled system where the homogenized impedance of the MPP interacts with the back cavity volume.

In practical engineering applications, membrane-like structures utilizing MPPs with back cavities are employed to reduce noise impacts¹³, such as in noise barriers or acoustic liners. Large-area installations are necessary to address more complex noise reduction scenarios. Therefore, periodic or multi-level designs of AMMs based on the combination of MPP units are useful for expanding the acoustic control bandwidth. For instance, Tang et al. (2017) used the Helmholtz resonant cavity principle to design a hybrid AMM⁴². By combining the honeycomb structure with the corrugated structure, it mimics the acoustic properties in nature and achieves excellent broadband low-frequency sound absorption, as shown in Fig. 2f. The

material achieves perfect sound absorption at 580 Hz and has a sound absorption bandwidth of nearly two octaves starting from 290 Hz. Its advantages are light weight, high strength and good low-frequency sound absorption performance, but its disadvantage is its high sensitivity to geometric parameters, which may limit its application flexibility. Similarly, Meng et al. (2019) explored the acoustic properties of a honeycomb sandwich structure using microporous panels⁴³, especially its sound absorption effect combined with the principle of a Helmholtz resonant cavity to form a distributed Helmholtz resonant cavity to enhance low-frequency sound absorption performance as shown in Fig. 2g.

To improve the sound absorption performance of a single MPP structure and expand the range of resonant peaks, it must be arranged into a specific pattern. Achieving broadband sound absorption requires precise design and extensive topological optimizations^{44–46}. Common multilayer structures include parallel structures, in which there are air layers between each MPP layer, and each unit employs a single back cavity to achieve the

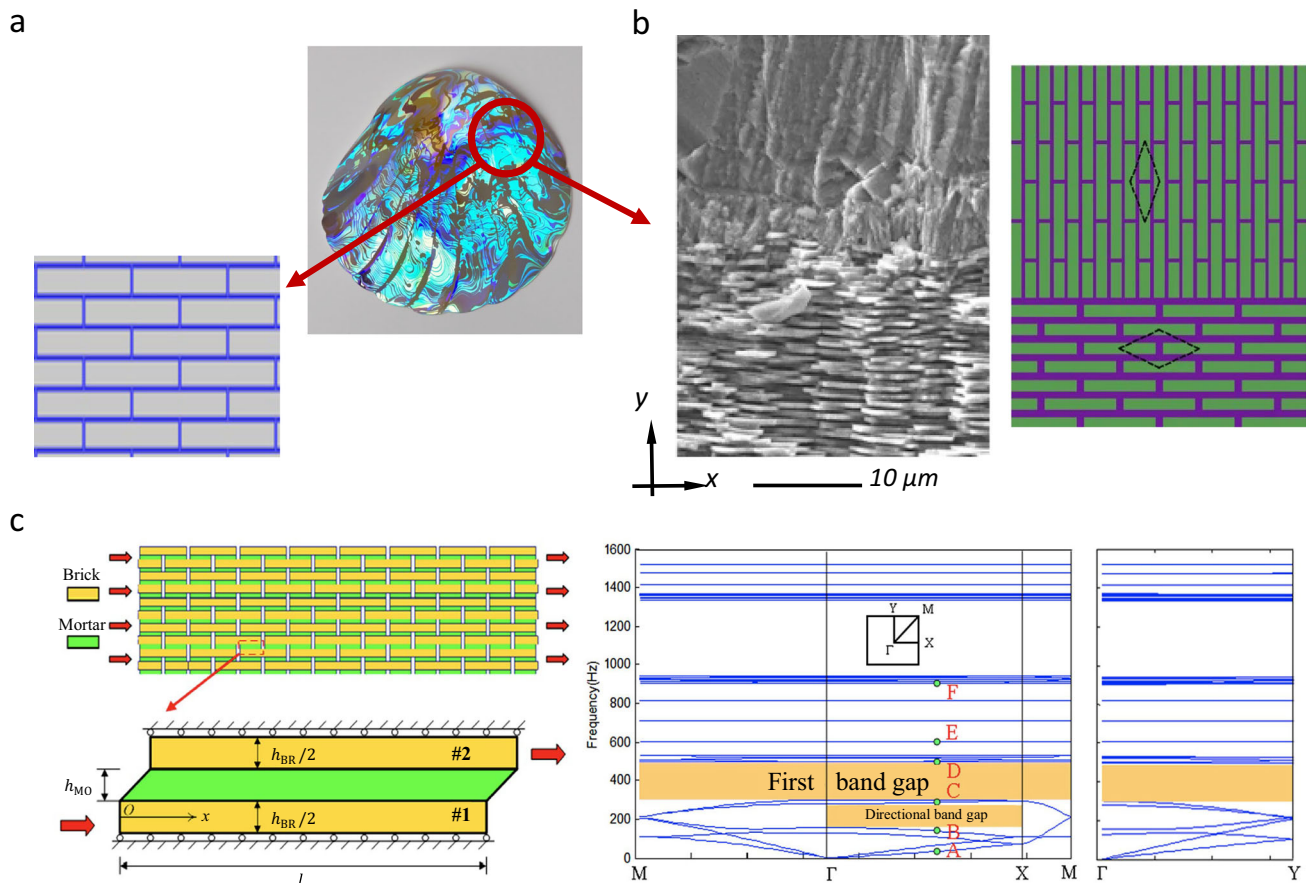


Fig. 3 | Bio-inspired phononic crystals. **a** Nacre-like architecture⁴⁹, Copyright © 2015 Elsevier Ltd. **b** Nacre and biogenic calcite-like AMM⁵⁰, Copyright © 2015, The Author(s). **c** Brick-mortar-like phononic crystals¹⁴³, Copyright © 2014 Elsevier B.V.

resonance effect. This enables each MPP layer to absorb sound waves independently and pass the filtered sound to the next layer, thus achieving the superposition of sound absorption coefficients. The other is a series structure, in which all MPPs are tightly stacked and share a back cavity, and the absorption of sound waves is achieved through the interaction between MPPs⁴⁷. In addition, there is a transition structure, which distributes different resonant frequencies in different MPP layers by adjusting the pore size, perforation rate, back cavity depth and other parameters of the MPP to achieve better broadband sound absorption⁴⁸. In summary, optimizing these structures is crucial to improving the sound absorption performance of a single MPP structure.

Phononic crystal

Phononic crystals achieve bandgap noise attenuation via periodic structures, effectively blocking sound propagation within specific frequency ranges. While foundational phononic crystal theory relies on Bragg scattering and local resonance, recent research emphasizes bio-inspired solutions to overcome frequency range and efficiency limitations.

The ability to finely tune both the band gap frequency and the localized resonance by adjusting periodicity and geometric parameters provides better control over mid- to high-frequency sound waves, making phononic crystals highly versatile in a wide range of acoustic applications. Building on this, researchers have explored biomimetic approaches to enhance the performance of phononic crystals, particularly in the low-frequency domain, by mimicking natural materials such as nacre, shells, and cochlear structures. These designs leverage hierarchical and heterogeneous architectures to achieve multiple bandgaps over an ultra-wide frequency range, opening up new possibilities for noise reduction and sound insulation. As shown in Fig. 3a, b, Chen and Wang (2015) investigated elastic wave

propagation in biomimetic hierarchical composites such as nacre and calcite, demonstrating that these materials can produce multiple bandgaps over an ultra-wide frequency range, particularly in the low-frequency domain⁴⁹. They also studied a biomimetic heterogeneous composite that exploits the bandgap barrier effect for sound wave attenuation, mimicking natural materials such as shells and teeth⁵⁰. This composite features a brick-mortar microstructure that produces multiple attenuation zones from 46 to 285 MHz, providing good vibration mitigation but facing limitations in frequency range and performance under extreme conditions. Additionally, Ma et al. (2016) proposed an AMM inspired by the bionic cochlear outer hair cell structure, achieving low-frequency sound absorption in the ranges of 21–76 Hz and 57–173 Hz⁵¹. This design mimics the outer hair cells of the mammalian cochlea and exhibits excellent low-frequency acoustic performance. Similar results were reported for brick-mortar-like phononic crystals with an ultrawide low-frequency bandgap (301.95–495.79 Hz), as shown in Fig. 3c and a tan band gap width of 1.388 (84.42–467.57 Hz)⁵².

Topological AMM

Topological AMM designs are also based on the manipulation of energy bandgaps. They are distinguished by their unique periodic structures that support topologically protected edge states^{53,54}. These edge states enable sound waves to propagate along the boundaries or defects of the material without reflection, a phenomenon rooted in the principles of topological physics, as shown in Fig. 4. In these materials, energy is localized and dissipated, providing robustness against structural defects and disturbances. One of the most remarkable characteristics of topological AMMs is their immunity to backscattering, which enhances their potential for various acoustic applications, including advanced sound manipulation and noise control. For instance, Poggetto et al. (2021) explored an AMM based on

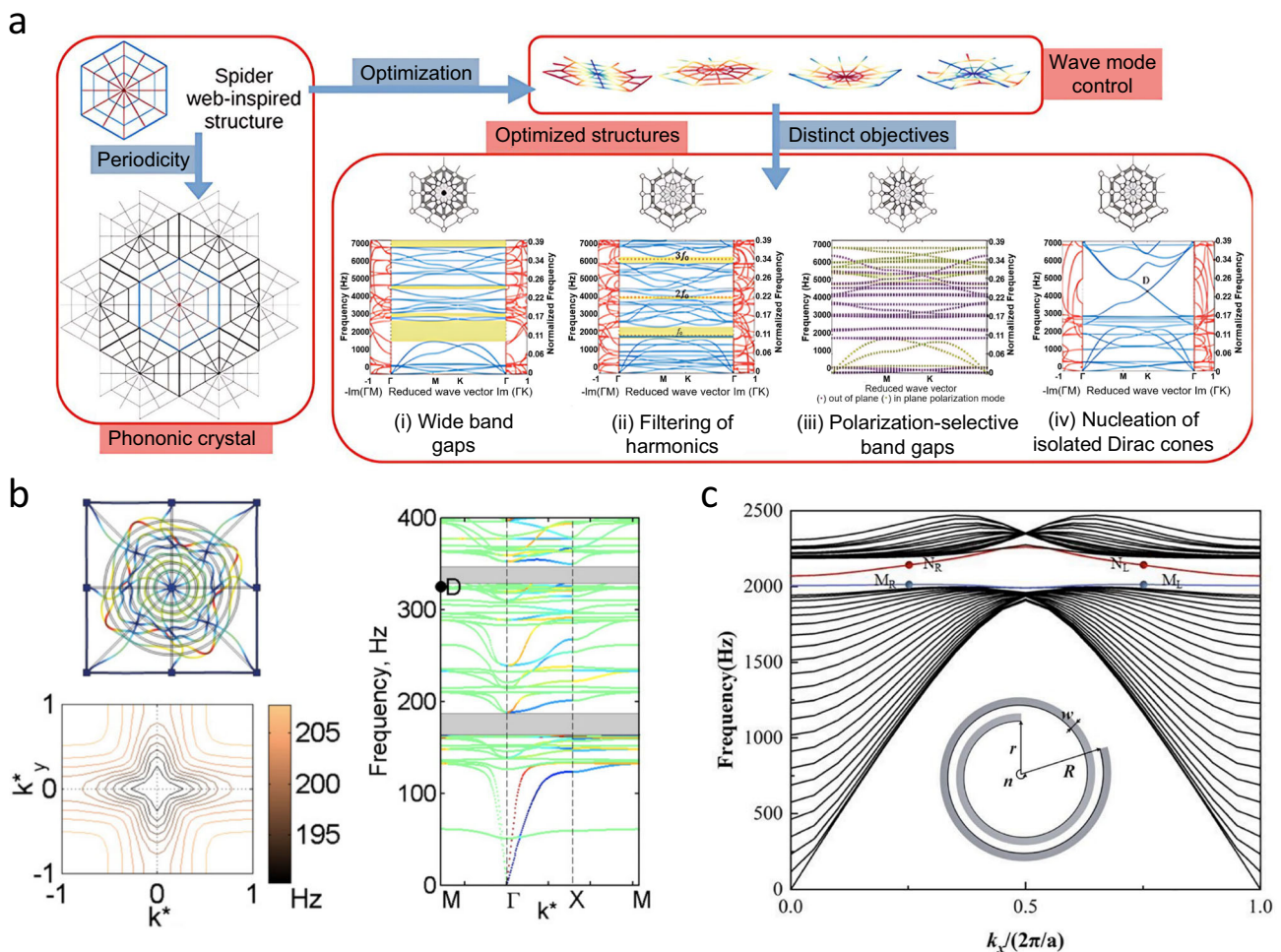


Fig. 4 | Bio-inspired topological AMMs. **a** Spider web-inspired AMM⁵⁵, Copyright © 2021 The Authors. **b** Labyrinthine channels AMM⁵⁷, Copyright © 2017 IOP Publishing Ltd and Deutsche Physikalische Gesellschaft. **c** Archimedean spiral AMM⁵⁸, Copyright © 2022 The Author(s).

spider web structure and achieved a broadband bandgap effect through optimized design⁵⁵. The AMM is inspired by the geometric characteristics of spider webs and uses the change of thread diameter and the addition of local mass to adjust the wave propagation characteristics, forming an effective bandgap in the mid-frequency range such as 2000 Hz and 2500 Hz. Its advantage is that it can be optimized for specific frequencies and provide flexible wave control, but it has high requirements for manufacturing precision and material selection, which may limit the feasibility of practical applications. Krushynska et al. (2017) investigated the use of labyrinthine channels in AMMs, which slow down sound propagation and produce a high refractive index with exceptional material properties⁵⁶. Their study demonstrates that these metamaterials can manipulate sound waves over a broadband frequency range, making them suitable for applications such as subwavelength imaging and sound tunneling⁵⁷. In addition, the introduction of quantum effects in acoustics opens up new avenues for sound manipulation. The development of subwavelength Archimedean spiral elements enables the formation of Dirac cones in the band structure, facilitating topological phase transitions. This approach enhances sound transmission robustness, even around sharp bends, by utilizing topological edge modes, contrasting with traditional Bragg scattering mechanisms that require larger lattice constants⁵⁸.

While phononic crystals primarily rely on Bragg scattering to create acoustic band gaps, topological AMMs leverage the principles of topology to achieve sound wave control. Both approaches share the common goal of manipulating sound waves, yet they employ different mechanisms to achieve this goal. The tunability of phononic crystals can complement the

robustness of topological AMMs, suggesting that integrating these two types of materials could lead to more advanced acoustic applications.

Metasurfaces for sound manipulation

Metasurfaces are a special form of metamaterials, serving as their two-dimensional counterparts^{59–61}. Composed of subwavelength structural units distributed on a plane, metasurfaces enable precise manipulation of wave characteristics, including phase, amplitude, and polarization, through meticulous design of these units. These types of AMMs can achieve ultra-thin designs, with a thickness much smaller than the wavelength of sound waves. Due to their complex surface structures, sound waves can be effectively captured and manipulated. By regulating the phase response of surface units, metasurfaces could control the reflection and transmission of incident sound waves for sound absorption or directional transmission.

An innovative approach is the use of moth wings as sound-absorbing metasurfaces. Neil et al. (2020) explored the natural acoustic properties of moth wings, which are capable of absorbing sound effectively. By analyzing the acoustic topographies of moth wings, the authors identified the mechanisms behind the sound absorption capabilities of moth wings, such as enhanced sound transmission and scattering¹⁶. This bio-inspired design offers potential applications for creating efficient sound-absorbing materials. Further to the previous research, the authors also explored the sound absorption effect achieved by using moth wings as acoustic metasurfaces, as shown in Fig. 5a⁶². These two studies show that moth wings exhibit high acoustic absorption capabilities in the frequency range of 20 kHz to

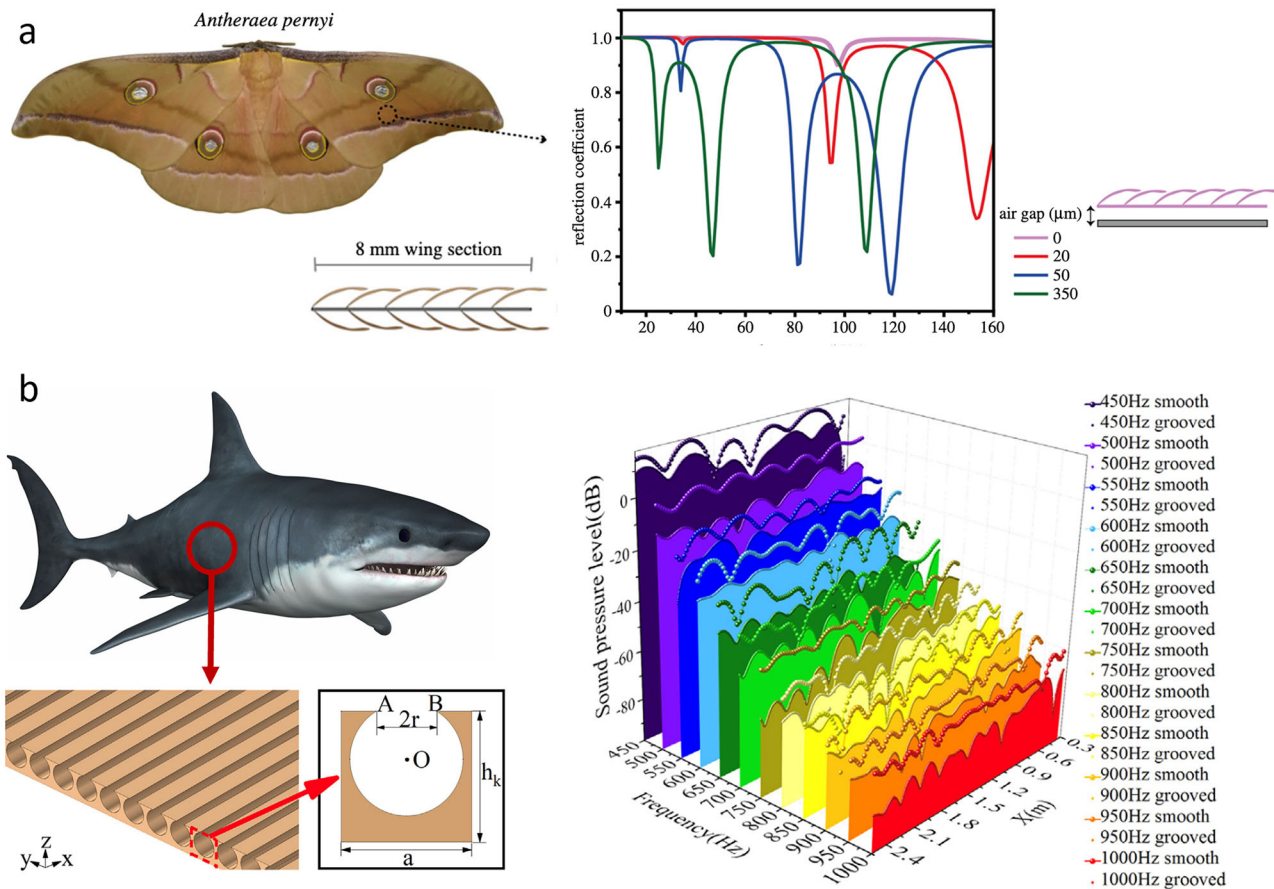


Fig. 5 | Bio-inspired metasurfaces. **a** Moth wing-like metasurface⁶², Copyright © 2022 The Author(s). **b** Shark skin metasurface⁶³, Copyright © 2020 Elsevier Ltd.

160 kHz, showing deep sub-wavelength performance with a reflection coefficient as low as 0.13. The advantages include their ultra-thin characteristics and wide-band sound absorption capabilities.

Another approach involves mimicking animal skin to address aerodynamic noise challenges. Li et al. (2021) investigated the use of biomimetic metasurfaces featuring periodic spherical grooves, inspired by the structure of shark skin, as shown in Fig. 5b⁶³. These metasurfaces effectively reduce noise in the 450–1000 Hz range by leveraging wall suction and slip effects, with a maximum noise reduction of 11.97 dB. This design demonstrates effective low-frequency noise control and holds the potential for complete boundary layer management.

Fractal AMM

Fractal structures have emerged as an important research area in the field of acoustics due to their unique characteristics and potential to enhance acoustic performance^{64,65}. Characterized by self-similarity and hierarchical organization, these structures offer novel ways to manipulate sound waves, with advantages in sound absorption, insulation, and control.

Recent advances in fractal-based AMMs have demonstrated their superior capabilities in sound manipulation, offering substantial improvements over conventional designs. Yan et al. (2024) showed that fractal honeycomb structures exhibit excellent broadband sound absorption properties in the frequency range of 400–1800 Hz⁶⁶, as evidenced in Fig. 6a. This enhanced performance stems from the intricate geometric properties inherent in fractal designs. Based on this, Singh et al. (2022) developed fractal AMMs capable of achieving near-perfect absorption within a specific frequency band (1000 Hz)⁶⁷. The self-similar nature of these fractal configurations is particularly effective in generating multiple bandgaps, thereby achieving broadband sound insulation with exceptional performance in low-frequency ranges⁶⁸.

The hierarchical architecture of fractal designs offers additional advantages in device miniaturization while maintaining acoustic performance. This principle was effectively demonstrated by Man et al. (2021) through developing three-dimensional labyrinthine fractal structures for low-frequency sound suppression⁶⁹. Beyond conventional sound absorption, fractal geometries enable novel wave manipulation phenomena, including negative refraction effects. He et al. (2024) explored this phenomenon and revealed how negative density characteristics in fractal structures can be exploited to achieve advanced sound control applications⁷⁰, as illustrated in Fig. 6b. These capabilities have been further extended by Xiang et al. (2022) who have implemented space-coiling fractal configurations that enable subwavelength-scale control of sound transmission⁷¹.

Multifunctional and composite advances in AMMs

Recent advancements in AMMs have highlighted their multifunctional capabilities, integrating sound absorption with additional mechanical properties, thereby broadening their applications in various engineering fields. Li et al. (2023) introduced a class of multifunctional sound-absorbing and mechanical metamaterials designed through a decoupled mechanism that exhibits excellent sound absorption and enhanced structural performance, achieving coefficients exceeding 0.85 across a frequency range from 0.5 kHz to 6 kHz Multifunctional sound-absorbing and mechanical metamaterials via a decoupled mechanism design approach⁷². Similarly, Li et al. (2023) developed new bamboo-inspired micro-lattice structures that not only provide superior sound absorption but also exhibit damage tolerance and high specific strength³⁷, as shown in Fig. 7a. Wang et al. (2024) fabricated hierarchical metamaterials through additive manufacturing, achieving simultaneous ultra-broadband sound absorption from 0.96 kHz to 6.00 kHz while also providing superior mechanical performance⁷³. In another study,

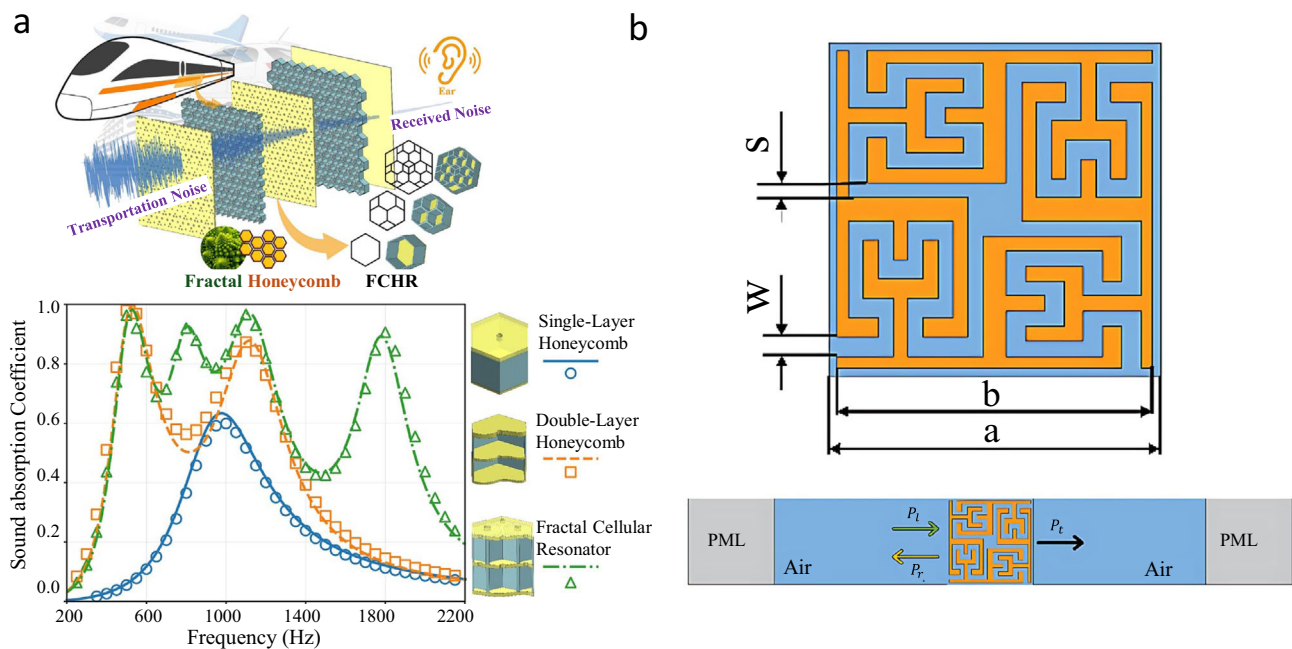


Fig. 6 | Fractal AMMs. a Fractal honeycomb structures⁶⁶, Copyright © 2024 Elsevier Ltd. **b** Self-similar fractal AMM⁷⁰, Copyright © 2023 Elsevier Ltd.

Li et al. (2023) proposed a novel interpenetrating hollow micro-lattice metamaterial that combines outstanding sound absorption capabilities with enhanced mechanical properties, demonstrating absorption coefficients greater than 0.99 across a frequency range from 0.5 kHz to 3.2 kHz and specific strengths surpassing traditional lattice structures⁷⁴, as shown in Fig. 7b.

Composite AMMs are also revolutionizing sound absorption through the innovative integration of various materials and structural designs, which enhances their acoustic performance. For example, Gao et al. (2021) highlights a composite meta-porous structure that achieves sound absorption coefficients exceeding 0.9 within the frequency range of 0 Hz to 6.4 kHz, demonstrating superior broadband absorption capabilities compared to traditional porous materials⁷⁵, as shown in Fig. 7c. Similarly, Zhang and Xin (2023) developed a coiled sound absorber that demonstrates effective sound absorption at frequencies from 241 Hz to over 1,000 Hz, particularly by utilizing the porous material lining to enhance energy dissipation and achieve low-frequency resonance⁶. Guo et al. (2024) introduced the enhanced hierarchical-porous AMM, as shown in Fig. 7d, which achieves broad sound absorption from 760 Hz to as high as 2,160 Hz, leveraging hierarchical structural elements that facilitate both low- and high-frequency sound control⁷⁷. This design illustrates how the combination of hierarchical structures and porous materials can not only optimize absorption efficiency but also expand the operational frequency range to address various acoustic challenges.

Summary

Examples of bio-inspired AMM designs corresponding to various noise control modes are listed in Table 1. Regarding bio-inspired AMM design, many inspirations from nature feature lightweight and high-strength cavities, such as those in honeycombs, bamboo, and turtle shells, which can facilitate the design of Helmholtz resonators by applying the resonance effect to absorb sound waves. In contrast to cavity resonance systems, structures with regular, symmetrical, or periodic arrangements are also widespread, such as nacre and cochlea, which are used to control the energy band range of acoustic energy and are commonly used in the design of phononic crystals. Moreover, spiral biological structures, including conch shells and other labyrinthine and fractal forms, are extensively utilized in AMM design, primarily due to their unique geometries and sound wave

propagation characteristics. These structures typically possess complex spatial arrangements and diverse curvatures, enabling effective manipulation of sound wave propagation paths and frequency responses. By adjusting the angle, radius, and material properties of the spiral, designers can precisely control the refraction, reflection, diffraction and other phenomena of sound waves, thereby achieving sound focusing, dispersion, or isolation. Moreover, the multi-level nature of spiral structures enables them to exhibit excellent acoustic performance in different frequency ranges, indicating great potential for applications in noise control, acoustic stealth, and acoustic imaging. Furthermore, various organisms with potentially inspiring structures can be incorporated into AMM design, highlighting the insights available in bio-inspired AMM development.

Despite the remarkable sound absorption performance of bio-inspired AMMs, most designs described in the publications reviewed in this section are still at the simulation or laboratory experiment stage, indicating that few AMMs have been widely implemented in practice. This situation demonstrates that the precision and extensiveness of the design process poses challenges for creating cost-effective and high-performance AMMs suitable for large-scale applications. Furthermore, there is limited research on traffic noise (400–2500 Hz), while the narrower low- and high-frequency ranges have been the focus of previous studies, which provides rich opportunities for researchers to explore noise control in a wider frequency range covering both low and high frequencies.

Given the complexity and challenges of bio-inspired AMM design, innovative approaches such as AI are increasingly being explored to streamline the design process. The introduction of bionic structures into AMM design leads to more complex and precise configurations, which increases the optimization and computational expenses. Conventional AMM design relies on parametric sweeps for finite element simulations to determine the optimal design, which is a time-consuming and resource-intensive process⁷⁸. With the advancement of AI, a lot of research has emerged focusing on using AI techniques to assist AMM design and accelerate the overall design process⁷⁹. The following section will mainly review how ML can assist AMM design.

Design of AMMs using ML techniques

This section reviews existing AMM designs enhanced by ML techniques. First, general research trends and general concepts of ML

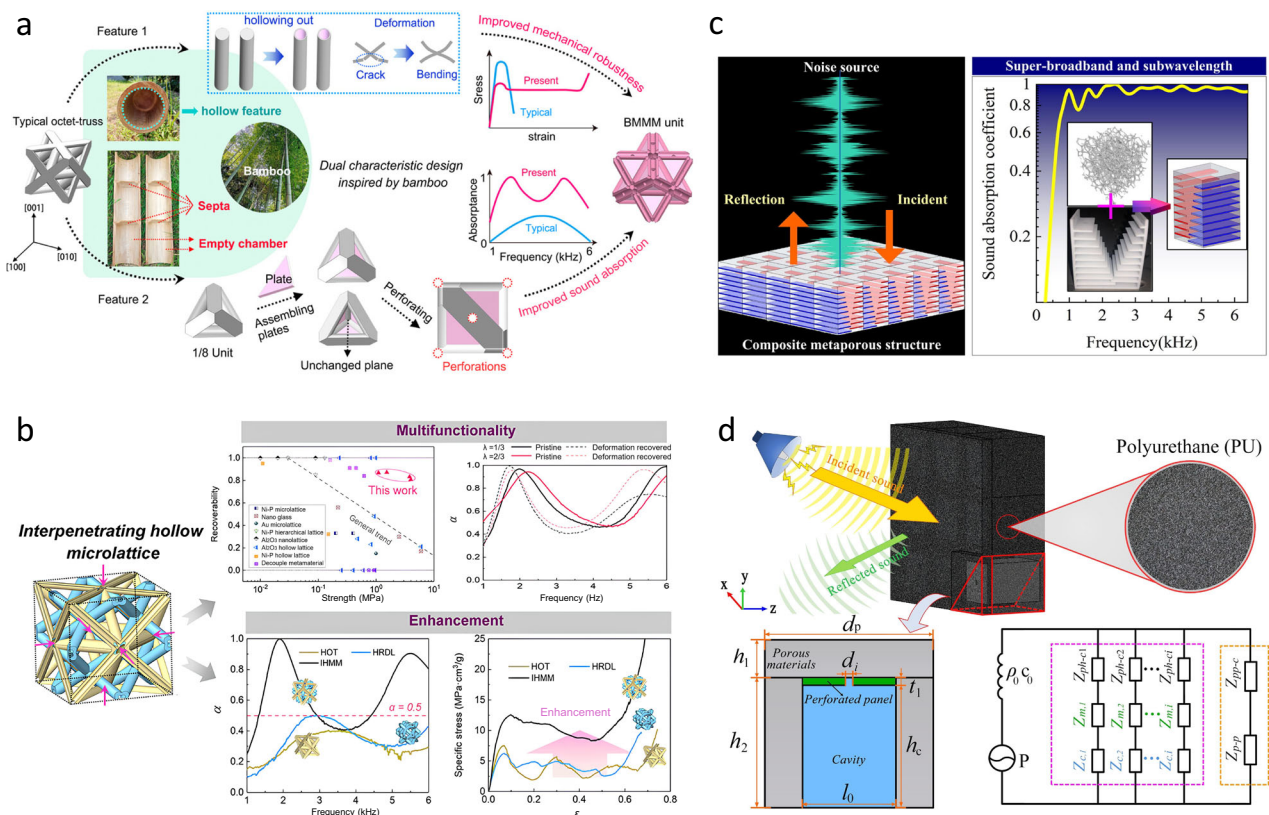


Fig. 7 | Multifunctional and composite AMMs. **a** Bamboo-inspired mechanical-acoustic structures³⁷, Copyright © 2023, American Chemical Society. **b** Mechanical-acoustic interpenetrating hollow micro-lattice metamaterial⁷⁴, Copyright © 2023

American Chemical Society. **c** Composite meta-porous structure⁷⁵, Copyright © 2021 Elsevier Ltd. **d** Enhanced hierarchical-porous AMM⁷⁷, Copyright © 2024, The Authors.

procedures will be examined. Subsequently, two modes of AI-assisted AMM design, including structural parameter optimization and topological optimization, will be discussed in detail. Afterwards, case studies that integrate the concepts of biomimetic AMM with ML techniques will be provided.

General research interests in ML-assisted AMMs design

Integrating ML techniques into the design of AMMs has become an important research area, driven by the need to optimize complex structures inspired by nature. This trend not only enhances the effectiveness of the final product but also brings challenges in simulation and optimization throughout the design process⁸⁰. As the complexity and precision of AMM structures increase, the required computational resources and time also increase, making the design and testing of AMM products more costly compared to conventional methods. To address these challenges and strike a balance between sound absorption performance and R&D costs, researchers are increasingly turning to AI as a valuable tool to streamline simulation and optimization processes. Figure 8 shows the research interests in applying ML to AMM design using the software VOSviewer^{81,82}. From 2021 to 2024, acoustic computational metamaterials accounted for a large proportion, and most of the research focused on the CNN-assisted design of AMMs. A large number of AI applications are used for parameter design, called structural parameter optimization, which is one of the most popular development trends in ML-assisted AMM design and will be mainly reviewed in this section. Apart from applying AI to parameter optimization, generating topology shapes by ML techniques is another mode of designing AMMs to achieve a wider range of bandgaps by broadening the energy strip. After analyzing the trends in ML-assisted AMM design, a targeted review will begin in the next subsection.

Structural parameter optimization and acceleration

ML techniques can enhance the structural design of AMMs through structural parameter optimization^{83–86}. The basic process of this optimization is to create a dataset of structural parameters and sound absorbing performance, most of which comes from a small number of simulation results. Then, the structural parameters are taken as input and the sound absorbing evaluation results such as sound absorption coefficient are used as labels. The next step is to apply the ML model to establish the reflection relationship. After the training process, different optimization algorithms are implemented to search for the best combination of structural parameters to obtain optimal results.

Structural parameter optimization empowered by AI primarily follows the above procedures. For example, Zhang et al. (2024) designed an optimal AMM for use as railway noise barriers with the help of genetic algorithms and neural networks⁸⁷, as shown in Fig. 9a. Their method achieved a bandgap width improvement of 1295 Hz and a sound transmission loss increase of 15 dB in the frequency range of 400–1000 Hz. Similarly, Donda et al. (2021) proposed an ultrathin sound-absorbing acoustic metasurface using CNN and achieved a low frequency of 38.6 Hz with a thickness of only 1.3 cm⁸⁸, demonstrating that their design could achieve perfect sound absorption by reducing model computation time by four orders of magnitude compared to traditional FE simulations, as illustrated in Fig. 9b. This design strategy reduces model computation time by four orders of magnitude compared to traditional finite element simulations. As for other algorithms, Zheng et al. (2020) also proposed an inverse design strategy for low-frequency sound absorbing structures based on the Gaussian-Bayesian method that does not rely on a physical model⁸⁹, as shown in Fig. 9c. For sound absorption in a wide frequency range, Liu et al. (2022) applied CNN to optimize the coupling effect between resonant cavities and achieved wide range sound wave absorption of 860–8000 Hz with an average sound absorption coefficient of higher than 97%⁹⁰.

Table 1 | Summary of bio-inspired AMM designs

Mechanism	Bionic Objects	Sound absorbing performance	Reference
Cavity resonance absorption	Spiral structure of a conch	Achieves wideband sound absorption from 1 kHz to 10 kHz, compact structure, reduces area by 70 times, accommodates up to 40 channels	34
	Honeycomb structure	Exhibits excellent sound insulation within the range of 850 Hz to 1600 Hz	35
	Mammalian cochlea structure	Achieves sound absorption over a wide frequency range from 20 Hz to 20,000 Hz with high sensitivity and frequency selectivity	142
	Origami (water balloon structure)	Effectively absorbs low-frequency sounds from 50 Hz to 500 Hz, allowing real-time adjustment of resonance frequency	36
	Hollow structure of bamboo	Achieves a sound absorption coefficient of up to 0.99, with a bandwidth of about 3.5 kHz	37
	Cochlear	Achieves sound pressure enhancement and frequency selectivity in the range of 300 Hz to 800 Hz	38
	Dragonfly wings	Achieves seismic wave attenuation in the frequency range of 1 Hz to 20 Hz	39
	Cochlear	Achieves sound pressure enhancement and frequency selectivity in the range of approximately 100 Hz to 8 kHz.	40
	Woodpecker's beak	Achieves sound absorption and impacts damping performance in the range of 20 Hz to 8 kHz.	41
Micro-perforated plates with back cavities	Honeycomb and corrugated structure	Reach perfect sound absorption at 580 Hz, with an absorption bandwidth with nearly two octaves from 290 Hz	42
	Honeycomb structure combined with micro-perforated plates	Enhanced low-frequency sound absorption performance	43
Phononic crystals	Nacre structure	Attenuates or eliminates elastic waves within the frequency range of 50–65 kHz	49
	Nacre and biogenic calcite structure	Achieves wide frequency bandgap	50
	Cochlear	Controls elastic wave propagation, enabling waveguiding at desired frequencies	51
	Spider web	Achieves broadband bandgap effects, enhancing sound absorption performance	55
	Brick and mortar	Achieves an ultra-wide low-frequency bandgap (301.95–495.79 Hz)	143
	Brick and mortar	Achieves band gap width of 1.388 (84.42–467.57 Hz)	52
Labyrinthine structure	Labyrinthine	Manipulates sound waves across a wide frequency range	56,57
Quantum effects in acoustics	Subwavelength Archimedean spiral elements	Facilitates topological phase transitions and enhances sound transmission robustness	58
Acoustic metasurfaces	Moth wings	Absorbs sound within the frequency range of 20 kHz to 160 kHz, with notable low-frequency effects	16,62
	Shark skin	Reduces noise in the range of 450 Hz to 1000 Hz, with maximum noise reduction of 11.97 dB	63
Fractal structures	Honeycomb	Broadens sound absorption capability, outperforming traditional materials	66
	Self-similar fractal structure	Achieves near-perfect narrowband absorption, effective at managing low-frequency sounds	67
	Negative index fractal structure	Innovative manipulation of sound waves	70
Other bionic structures	Nacre	Attenuates elastic waves, dissipating energy	144
MEMS acoustic sensors	Fish ear	Provides high sensitivity and linearity in acoustic detection, with better linear response than traditional microphones	145
Multifunctional bionic gradient structure	Glass sponge	Demonstrates advanced mechanical performance with customizable acoustic properties	146

There are many studies on the application of ML in AMM design based on the concept of structural parameters and accelerating the optimization process⁹¹. Nevertheless, dataset preparation can be a challenge because effective training requires sufficient data input, which means that sufficient simulations or experiments are crucial for the confidence of trained ML models, while the process of data collection requires time and computing sources. Another challenge is that the model cannot be generalized to other AMMs due to the characteristics of each structural design, so for each AMM design, the model should be retrained, which is also source consuming. There are also some studies attempting to shorten the training dataset. Ogun et al. explored the effects between datasets of different sizes. Their study indicated that the model could capture some features from a smaller range of resonant frequencies, such as covering 90% of the sound

absorption rate, but the model performance is poor due to lack of information⁹². By increasing the frequency range of interest, model performance improves, but computational cost increases simultaneously. Therefore, the balance between dataset size and computational resources is crucial to optimizing model performance and efficiency in AMM design.

Topological optimization

There are many studies involving the use of ML techniques for topological generation on other AMM modes of phononic crystals^{93–96}. The two-dimensional phononic crystal shapes and relative band structures can be automatically generated through a simulation process to construct a dataset, while the ML model can be used to extract the shape images, which then reflect the sound absorption effect.

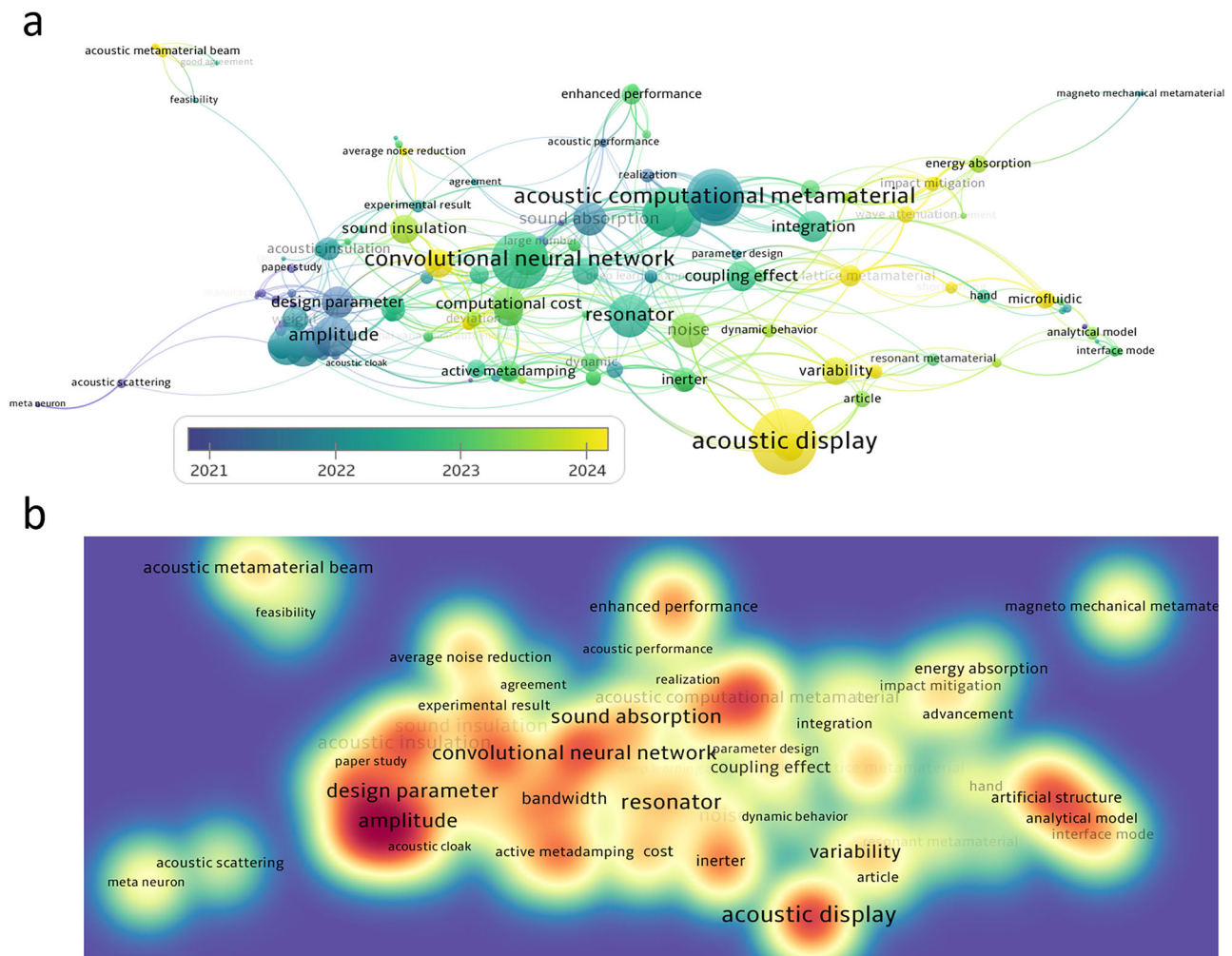


Fig. 8 | Research interests in AMMs using ML techniques. a Network visualization of studies in 2021–2024. **b** Cluster density visualization of the collected studies.

Bacigalupo et al. (2020) introduced radial basis function networks and quasi-Monte Carlo methods for bandgap optimization in quadrat spiral AMM design, allowing for multiple solutions to be generated quickly while reducing computational time by up to 50% compared to more traditional optimization techniques⁹⁷. This method can improve effectiveness and provide multiple solutions quickly. Li et al. (2020) proposed a data-driven method to design a phononic crystal with desired band gaps⁹⁸, as shown in Fig. 10a. This method combines image processing and finite element analysis, extracts topological features by training an autoencoder, and uses an MLP layer to establish the relationship between bandgap and the topological features. This approach does not require real-time calculations, processing high-dimensional design spaces efficiently and achieving design iterations up to 60% faster than traditional methods. Its characteristics are that it does not require real-time calculation and can efficiently process high-dimensional design spaces, but the exploration space is still limited. Similar studies used ML to discover phononic crystal properties, such as using logical regression, artificial neural networks, and RF to find the broadest bandgap⁹⁹. This represents a 5.2-fold improvement over random selection in terms of screening efficiency. Additionally, the MLP model facilitated up to a 50% faster optimization process by quickly correlating structural images with dispersion diagrams as shown in Fig. 10b, highlighting the promising role of ML in revolutionizing the way researchers explore and refine AMM properties. Apart from traditional optimization strategies¹⁰⁰, Luo et al. (2020) explored the inverse design of hierarchical phononic crystal based on reinforcement learning¹⁰¹, aiming to maximize the first-order bandgap

width and achieve a bandgap within a specified frequency range¹⁰². The ML method used is Q-learning¹⁰³, which gradually optimizes the design through interaction with the environment, achieving design optimizations approximately 40% faster than traditional methods, while also ensuring stability and reproducibility in finding optimal solutions, as shown in Fig. 10c. It is efficient and stable and can converge to the same final state under different initial states. The application of ML to optimize phononic crystals also faces similar challenges such as data dependency and low model generalization, which is worth exploring in the future.

There are other studies related to ML-assisted AMM topological optimization, such as using MLP to predict the dispersion relation of phononic crystals and successfully predicting the band structure associated with the unit cell configuration¹⁰⁴. Conditional Generative Adversarial Networks (cGAN) have been used to optimize the transmission loss of AMMs, bringing improvements of up to 20 dB for new metamaterial geometries¹⁰⁵. Deep reinforcement learning has been applied to the inverse design of phononic beams, accurately capturing band structures with a maximum bandgap of 1200 Hz¹⁰⁶. Physics-Informed Neural Network (PINN) has been used to design multifunctional wave control elements to achieve sound absorption from 200 Hz to 2000 Hz without altering the microstructure¹⁰⁷. Additionally, probabilistic deep learning models have also been used to design broadband AMM, which can suppress sound scattering by 15 dB in a wide frequency range from 100 Hz to 1000 Hz¹⁰⁸. Overall, ML technology is revolutionizing the topology optimization methods of AMMs with its efficient optimization capability and exploration of complex design spaces. More and more new ML strategies will be applied to AMM design.

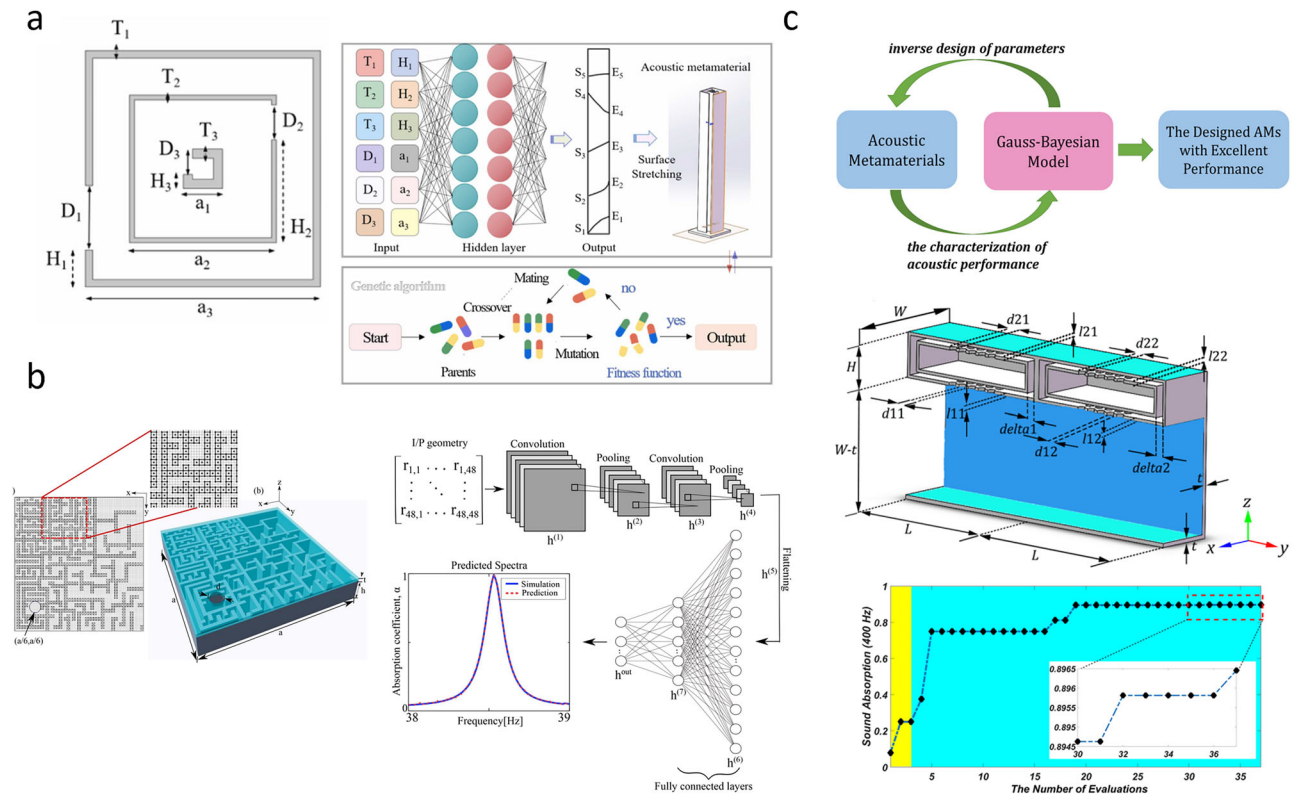


Fig. 9 | Structural parameter optimization for AMM design. **a** Genetic algorithm and neural network⁸⁷, Copyright © 2024 Elsevier Ltd. **b** Convolutional neural network⁸⁸, Copyright © 2021 IOP Publishing Ltd. **c** Gaussian-Bayesian algorithm⁸⁹, Copyright © 2020, AIP Publishing.

Bio-inspired AMMs with ML

Compared with the general structural pattern design empowered by ML, few studies have successfully applied ML to the design of bio-inspired AMMs because the high complexity of the structures requires much more time for simulations in order to obtain sufficient training datasets for ML procedures. One study designed an AMM inspired by turtle shell, achieving high mechanical and sound absorbing performance¹⁰⁹, as shown in Fig. 11. The authors noticed that the turtle shell is damage-resistance and lightweight, while the air cavity inside the shell is suitable for the Helmholtz resonator, so the design strategy is to stack two layers of the redesigned structure into a single unit. The structural parameters of the air cavity can be tuned via MLP to reflect the correction factor for the optimal impedance matching strategy. The bio-inspired AMM in this design achieves broadband sound absorption optimization, with the optimal range from 300–600 Hz to 500–1000 Hz. Meanwhile, it can also achieve a pressure resistance of about 7.74 MPa in the range of 500–1000 Hz, and the total thickness of the structure is only 50 mm. The involvement of ML accelerates the optimization process of the bio-inspired AMM and provides high efficiency to accomplish the impedance matching. Another study used ML to optimize the design of artificial flexible wings that mimic the structure of insect wings and use the principle of deformed materials to achieve controlled dynamic properties. The frequency range of interest in the study is primarily close to 25 Hz¹¹⁰. Therefore, applying bionic models for AMM structural design and combining them with ML for design optimization is a promising research direction. This approach fully exploits the complexity and functionality of natural structures while leveraging the computational power of ML to improve design efficiency and innovation.

Summary

A general summary of ML-assisted AMM designs is given in Table 2. Most studies have focused on high-frequency target ranges, while research on low frequencies remains limited, often resulting in only a few peaks at specific frequencies, narrow bandwidths, or low sound

absorption performance within the desired frequency range. However, with advances in bio-inspired structural design and the application of cutting-edge ML techniques, it is now possible to design a variety of sound-absorbing AMMs that effectively cover both low and high frequencies. This development is particularly important for meeting design requirements in the transportation sector, specifically in the frequency range of 400–2500 Hz. On the other hand, the high cost of computing resources as well as low robustness and generalization remain challenges in introducing ML techniques.

While Table 2 highlights the diverse applications and performance of various algorithms in AMM design, it is essential to consider the inherent strengths and weaknesses of these techniques, as summarized in Table 3. This understanding will guide the selection of appropriate ML methods for effective AMM development and inform subsequent discussions on manufacturing processes that facilitate practical implementation of these advanced materials. For instance, while traditional algorithms such as RF offer computational efficiency and interpretability, they struggle with complex nonlinear relationships. In contrast, advanced models such as cGANs and PINNs introduce innovative design capabilities but require substantial data or computational resources. This balance of strengths and weaknesses underscores the importance of choosing the right ML approach for effective AMM development, paving the way for discussing manufacturing processes that enable practical applications of these advanced materials.

AMM manufacturing technologies

This section reviews AMM manufacturing technologies, focusing on single-step and multi-step approaches. It discusses the advantages and applications of various technologies, especially additive manufacturing^{111–113}, emphasizing their roles in achieving the precision and complexity required for effective AMM manufacturing. Furthermore, this section addresses the assembly methods and their impact on the performance of AMMs in acoustic applications.

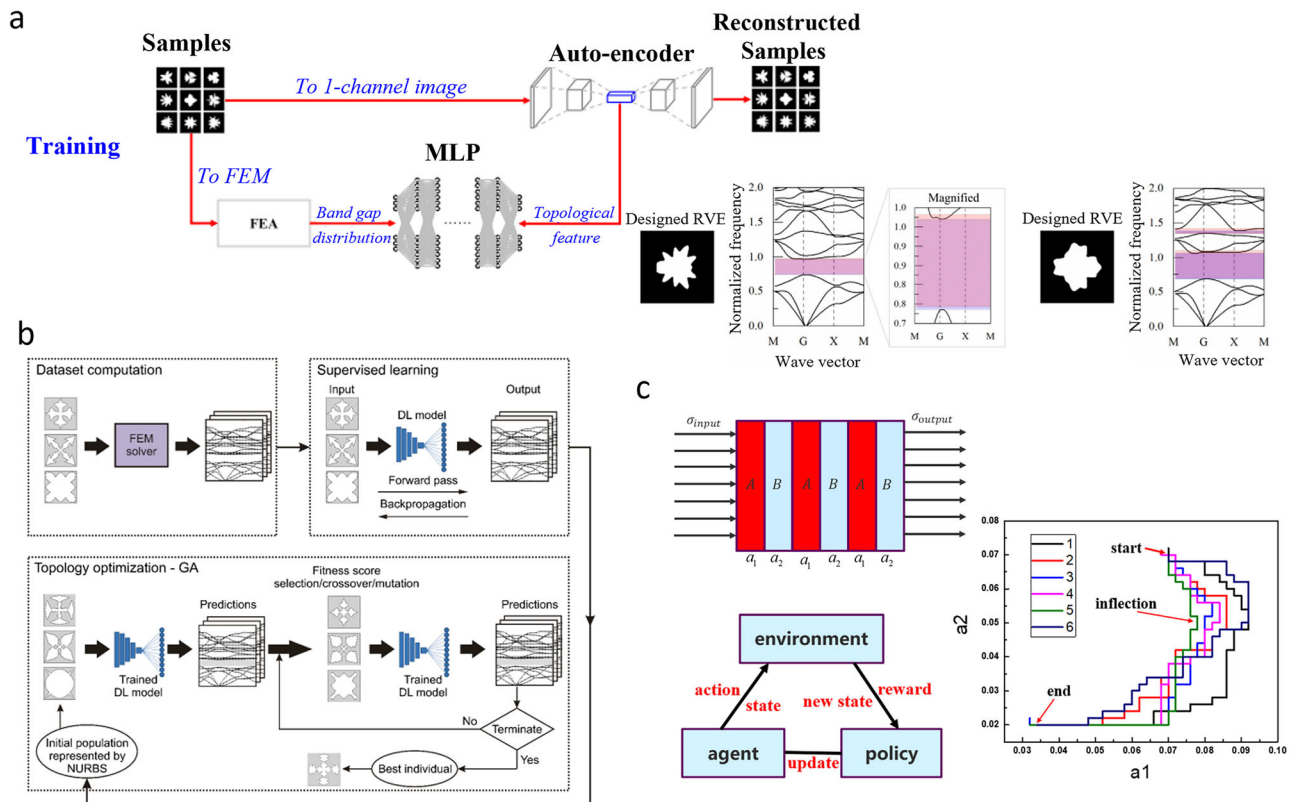


Fig. 10 | Phononic crystal optimization for AMM design. **a** Finite element method with CNN⁹⁸, Copyright © 2019 Elsevier B.V. **b** Finite element method with genetic algorithms and CNN¹⁰⁰, Copyright © 2023 The Authors; **c** AMM optimization using Reinforce Learning¹⁰², Copyright © 2020 Elsevier Ltd.

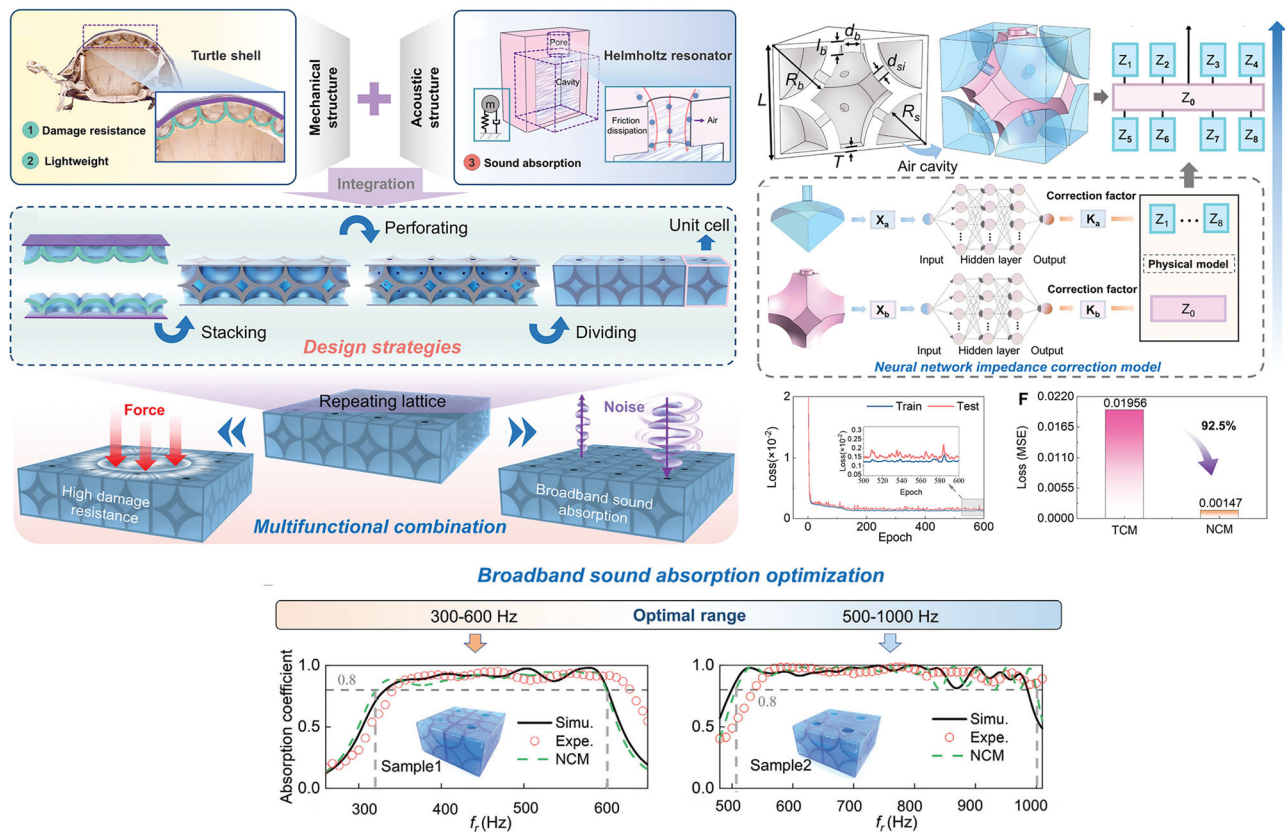


Fig. 11 | Turtle shell inspired mechanical-AMM¹⁰⁹, Copyright © 2024, Wiley-VCH GmbH.

Table 2 | Summary of ML-assisted AMM designs

Algorithm	Application	Sound Absorption performance	Reference
MLP+Genetic algorithms	Design of optimal AMMs for railway noise barriers	Improved acoustic transmission loss by 15 dB in the 400–1000 Hz band; band gap range of 210–1253 Hz	87
Genetic Algorithms	Maximization of low-frequency band gaps in phononic crystals	Maximum relative bandgap size of 48.1%; Cumulative bandgap width can reach 134 kHz	100
Gaussian-based algorithm	Design and representation of porous AMMs for effective sound absorption	Transmission loss peak frequency range of 6276–15600 Hz	147
Gaussian-Bayesian algorithm	Inverse design of low-frequency sound-absorbing structures	High sound absorption at low frequencies 400 Hz ($\alpha = 0.9$)	89
CNN	Design of super-thin sound-absorbing acoustic metasurfaces	860–8000 Hz with average 0.97 coefficient	88
Radial basis function networks quasi-MonteCarlo methods	Bandgap optimization in quadrat spiral AMM design	Maximization of low-frequency band gaps optimization of dispersion properties	97
Autoencoder +MLP	Inverse design of phononic crystals with desired band gaps	Manipulation of acoustic waves with band gaps for noise reduction; applications in filtering, acoustic imaging, and stealth	98
Random forest, logistic regression	Rapid screening of bandgap locations in phononic crystals	Random Forest: 94% accuracy; R^2 values for center frequency and band gap width are 0.66 and 0.85, respectively	99
Reinforcement learning	Inverse design of hierarchical phononic crystals	First-order band gap ranges from 3.2–7.8 kHz	102
Neural Network Correction Model (NCM) MLP+Particle Swarm Optimization Algorithm	Optimization of sound absorption coefficients in AMM design	Average sound absorption coefficient: 0.88 (300–600 Hz); Average sound absorption coefficient: 0.93 (500–1000 Hz); Low thickness: 50 mm; High absorption (>0.8)	109
MLP	Predicting dispersion relations of phononic crystals	Successfully predicts band structures related to unit cell configurations	104
Conditional Generative Adversarial Networks	Optimizing transmission loss of AMMs	Induces transmission loss improvements of up to 20 dB for new metamaterial geometries	105
Deep Reinforcement learning	Inverse design of phononic beams	Accurately captures band structure with a maximum bandgap of 1200 kHz	106
Physics-Informed Neural Network	Designing multifunctional wave control elements	Achieves multifunctionality with sound absorption across 200 Hz to 2000 Hz without altering microstructure	107
Probabilistic Deep Learning models	Designing broadband acoustic cloaks	Suppresses sound scattering with a reduction of 15 dB over a wide frequency range (100 Hz to 1000 Hz)	108

Machining is a traditional single-step manufacturing method that involves removing excess material from raw substrates through processes such as milling and turning to achieve the desired shape of AMMs^{114,115}. This method has advantages in controlling the mechanical properties of materials. It can effectively handle high-strength and hard materials and is suitable for large-scale production. However, achieving optimal sound absorption performance can be challenging. For example, one study investigated the use of compression molding to create PLA-based sound absorbers with kenaf and coconut fiber reinforcements, but the results highlighted difficulty of tailoring these materials to achieve specific acoustic properties¹¹⁶. Similarly, there are designs for absorbers reinforced with natural fibers such as wood, rice straw, and kenaf that are effective but have limited adaptability in tuning their properties^{117,118}. The manufacturing process typically involves complex and time-consuming steps including fiber preparation, blending, and perforation.

3D printing, as an additive manufacturing technology, can directly manufacture complex AMM structures. Common 3D printing methods include fused deposition modeling (FDM)¹¹⁹ and selective laser sintering (SLS)¹²⁰. It is particularly effective in producing low to mid frequency AMMs, with some designs achieving acoustic resonance in the frequency range of 1700 Hz to 6000 Hz in multi-ring configurations¹¹⁹. FDM is favored for its cost-effectiveness and high manufacturing precision, making it suitable for mass production of complex structures. Conversely, SLS offers greater precision and is well suited for low-frequency acoustic applications, where a laser selectively fuses powdered material layer by layer, achieving sound absorption in the frequency range of 1000 kHz to 1792 kHz in specific AMM designs¹²⁰. Many AMMs require a minimum pore size greater than 1 mm due to limitations of conventional FDM and SLA processes, which struggle to guarantee the necessary precision. For example, Zieliński et al. (2022) discuss that while modern additive manufacturing technologies

can produce innovative acoustic materials, the inherent limitations of 3D printing techniques often make it challenging to achieve the desired pore morphologies needed for effective sound absorption FDM facilitates mass production, utilizing heated and extruded thermoplastic materials, where the thermoplastic material is melted and deposited layer by layer¹²¹. Advanced techniques that can achieve finer resolutions often come at a geometric increase in cost, rendering them impractical for large-scale applications, such as sound barriers or noise reduction panels that require extensive parallel use. For instance, Wu et al. (2023) emphasizes the challenges posed by structural complexity in additive manufacturing processes, which can impact the manufacturing cost and feasibility for large applications¹²². Figure 12a–c illustrates the various additive manufacturing technologies used for AMMs, where different additive manufacturing equipment and processes are shown. Recent advances in manufacturing technology have enabled more sophisticated production capabilities. Stereolithography (SLA) builds three-dimensional structures layer by layer using photosensitive resins, where UV lasers cure the resins. It achieves high precision and excellent surface smoothness, making it ideal for manufacturing acoustic components with intricate features^{123,124}.

Fabrication strategies for AMMs encompass a variety of manufacturing methods, each with different cost levels and applicable frequency ranges. As illustrated in Fig. 12d, cost levels vary from very low for FDM to high for techniques. In the transportation sector, FDM stands out for its widespread use in AMM production due to its affordability and practicality, making it an attractive option for applications requiring low-frequency sound manipulation. However, as design complexity increases, particularly in biomimetic structures that incorporate micro-holes and intricate unit geometries, FDM may begin to fail to meet the required precision and detail. In such cases, for more elaborate AMMs that necessitate higher precision and intricate designs, technologies such as SLA and SLS can be employed,

Table 3 | Summary of advantages and disadvantages of using ML techniques

Algorithm	Advantages	Disadvantages	References
Traditional Algorithms (Random Forests, Logistic Regression)	• High computational efficiency • Strong model interpretability • Suitable for smaller data volumes and lower feature dimensions	• Performance may be limited in handling complex nonlinear relationships and high-dimensional design spaces	99,148
Gaussian Process-Based Algorithms (Gaussian Algorithms, Gaussian-Bayesian Algorithms)	• Suitable for handling uncertainty and small-sample data problems • Provides effective predictions and optimizations when data is limited	• Makes strict assumptions about data distribution; performance may decline if data deviates from Gaussian distribution • Computational complexity increases with data size and feature dimensions	87,89,100,147,149
Optimization Algorithms (Genetic Algorithms, Particle Swarm Optimization)	• Excels at global search and finding optimal solutions • Can enhance optimization efficiency when combined with neural networks • Accelerates the design process	• Sensitive to initial parameters and hyperparameters • May require extensive experimentation and tuning • Computational costs can increase in high-dimensional design spaces	109,150
Reinforcement Learning	• Continuously improve design schemes through interaction with the environment • Explores new design spaces; maximizes specific performance metrics	• Training process is complex • Convergence may be slow • Stability of results needs consideration • Requires substantial computational resources	101,102,106
Neural Networks (MLP, CNN, Autoencoder)	• Strong nonlinear fitting capabilities • Suitable for complex structural design • Handles high-dimensional data and complex nonlinear problems	• Requires large amounts of training data and computational resources • Training process is time-consuming	87,88,90,98,104
Advanced Neural Network Models (Conditional Generative Adversarial Networks, Physics-Informed Neural Network, Probabilistic Deep Learning models)	• Introducing new methods and ideas • Generates diverse design schemes under specific conditions • Incorporates physical constraints directly into training • Handles uncertainty in predictions	• Higher complexity • Requires large amounts of data and computational resources for training • Greater demands on model tuning and parameter settings	105,107,108

albeit at a higher cost. These advanced methods enable the production of complex structures that can effectively manipulate sound waves across various frequency ranges, thereby enhancing the functionality and performance of AMMs in practical applications.

While additive manufacturing technologies, such as FDM, SLS, and SLA, offer substantial advantages in producing complex AMMs, their scalability can pose challenges¹²⁵. For instance, although FDM is cost-effective for small batches and simple designs, scaling up production can lead to increased costs due to material and energy consumption¹²⁶. As design complexity rises, especially for biomimetic structures requiring intricate features, the limitations of FDM in achieving the necessary precision may necessitate the use of more advanced—and costly—methods like SLA or SLS. However, these methods, while offering better precision and complexity, also require careful consideration of production costs¹²⁷.

Long-term maintenance is another critical factor that cannot be overlooked. Materials used in AMMs may degrade over time, influenced by environmental conditions such as humidity and temperature fluctuations. This degradation can adversely impact their acoustic performance. Therefore, selecting appropriate materials and designing for durability is crucial¹²⁸. Regular maintenance and monitoring practices will be essential to ensure these materials continue to perform as intended throughout their lifecycle. Moreover, the in situ performance of AMMs often reflects how they will operate under varying environmental conditions. For example, exposure to moisture can change the properties of organic reinforcements used in AMMs, potentially altering their sound absorption capabilities¹²⁹.

Incorporating real-world testing alongside simulation results will provide a better understanding of how these materials perform in practice, bridging the gap between theoretical predictions and actual performance. By addressing these considerations, we can strengthen the engineering relevance of this research and provide more robust guidelines for the practical application of AMMs in various acoustic scenarios.

Current challenges and future perspectives

Despite substantial progress in the field of AMMs, several challenges remain in translating theoretical advances into practical applications, especially in addressing noise pollution in the transportation sector. Traditionally, many AMM designs focused on specific, narrow frequency ranges—often limited to either low or high frequencies—which constrained their effectiveness for broadband noise attenuation in real-world scenarios such as railway noise mitigation. However, recent pioneering studies have developed innovative AMM structures that extend sound absorption to the critical low- to mid-frequency band (400–2500 Hz), which is closely related to traffic and railway noise sources. For example, Liu et al. (2020) engineered a thin micro-perforated panel AMM demonstrating ultra-broadband absorption (average absorption coefficient ≥ 0.9) experimentally verified from 400 Hz to 2500 Hz due to multi-order resonances¹³⁰. Wang et al. (2022) realized strong broadband impedance modulation in non-local acoustic metamaterials, achieving quasi-perfect absorption in deep subwavelength regimes over a broad frequency range¹³¹. Most recently, Mei et al. (2024) integrated low-frequency pipe–plate resonance, mid-frequency multi-order resonance, and

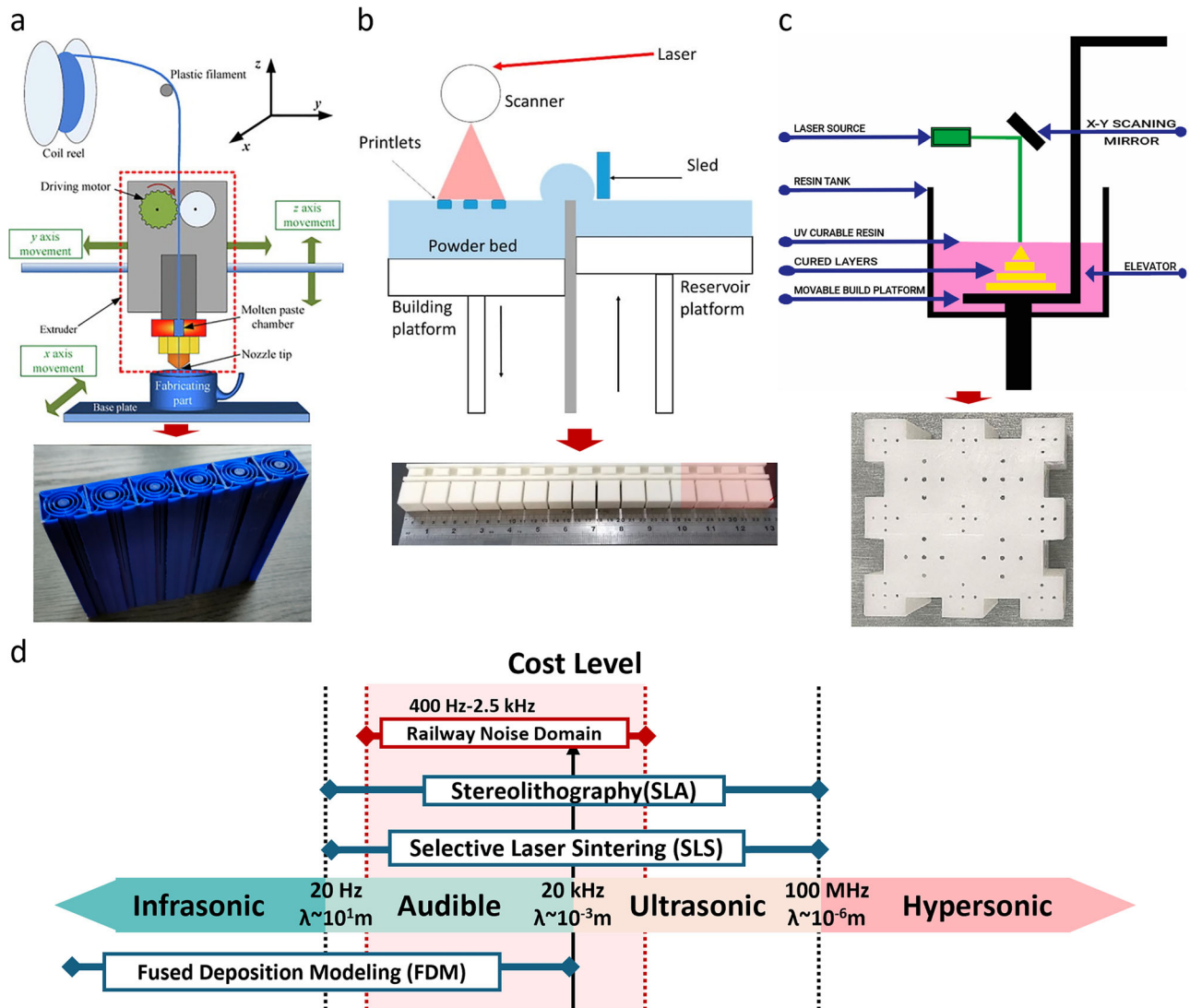


Fig. 12 | General manufacturing strategies and cost level for AMMs. **a** Fused deposition modeling (FDM)^{119,154}, Copyright © 2023 The Author(s)¹¹⁹, Copyright © 2020 Elsevier Ltd.¹⁵⁴. **b** Selective laser sintering (SLS)^{120,155}, Copyright © 2019, The

Author(s)¹²⁰, Copyright © 2021 by the authors¹⁵⁵. **c** Stereolithography (SLA)^{77,123}, Copyright © 2024 The Authors¹²³, Copyright © 2024 The Authors⁷⁷. **d** Summary of fabrication strategies in cost level and applicable frequency range.

high-frequency MPP in a hybrid AMM, resulting in experimental absorption coefficients above 0.93 between 300 Hz and 3600 Hz¹³². These advances extend the working bandwidth of AMMs and provide compelling evidence of their capability to address real-world traffic and railway noise issues. Nonetheless, it is noted that most of these breakthroughs remain at the laboratory or prototype demonstration stage. Performance is primarily reported on idealized samples under controlled conditions, while vital aspects such as scalable fabrication, mechanical robustness, durability, and effectiveness under complex, real-world environments are yet to be fully resolved. This gap between laboratory validation and practical application underscores the key engineering challenges facing the broader deployment of AMMs.

In parallel, contrary to some earlier assumptions, a growing body of literature has explored the design and performance of AMMs integrated with conventional porous materials. Hybrid composite strategies—such as embedding porous layers within resonant metamaterial frameworks or designing multi-scale structures that synergize local resonance and viscous dissipation—have been shown to further widen the effective absorption bandwidth and improve overall performance. Recent studies employing genetic algorithms for optimal design¹³³, hybrid meta-porous architectures⁷⁵, and hierarchical or modulated resonator-porous

composites^{76,77} have achieved substantial improvements and demonstrated that the combination of resonance and porous absorption mechanisms holds considerable promise for broadband noise reduction. However, these composite solutions similarly remain predominantly at the proof-of-concept or prototype level, with critical challenges concerning structural optimization, manufacturability, environmental compatibility, and long-term performance still to be addressed.

Traditional noise reduction methods, such as noise barriers near railway bridges¹³⁴, low barriers beside the track¹³⁵, and train skirts¹³⁶, have been widely used. However, these approaches often fail to provide comprehensive noise control, especially in complex acoustic environments.

The complexity of bio-inspired AMM designs further complicates their practical implementation. Traditional simulation-based optimization methods, while effective, require a great amount of computing resources and time, slowing down the design process. ML offers a promising alternative, but it comes with its own challenges. Developing reliable ML models relies on large, high-quality datasets, which are difficult to obtain due to the time-consuming nature of collecting experimental data and the high computational cost of generating simulation data. Furthermore, the highly specific nature of AMM designs often limits the transferability of trained models, requiring extensive retraining for each new application.

To address these challenges, future research should prioritize the development of broadband AMMs that can effectively absorb sound across the entire frequency spectrum, especially in the understudied low- to mid-frequency range. Advanced AI techniques could play a transformative role in streamlining the design process, enabling more efficient optimization algorithms that reduce computational requirements while maintaining accuracy. Innovative data optimization strategies, such as synthetic data generation and efficient dataset utilization, could also help address current limitations in ML model training. In addition to structural design, future research should also explore the combined effects of material properties on acoustic performance. While most studies focus on geometric configurations, the potential benefits of integrating conventional porous materials into AMM structures remain largely unexplored. This approach could enhance sound absorption while maintaining structural integrity. Furthermore, extending bio-inspired designs to include more complex natural geometries could result in new configurations with superior acoustic properties.

The application of AMMs in railway noise reduction is particularly promising, especially in addressing rolling noise and aerodynamic noise^{87,137,138}. Despite high costs, continued technological advancement and market growth are expected to make AMMs more accessible¹³⁹. AMMs also show potential for improving the acoustic performance of railway ventilation systems such as vents, ducts, and windows. Ventilation AMMs can enhance sound absorption while allowing airflow, improving noise control in these areas^{140,141}. In recent years, the engineering application of AMMs has shown great potential, with several companies and research teams launching related products. For example, commercial AMM-based noise barriers have been reported with sound absorption coefficients exceeding 0.7 and thicknesses under 50 mm, offering efficient and compact solutions for urban traffic noise management [see, e.g., https://www.imeta-center.com/pro12_4/1.html]. Specialized AMM products have also been developed for noise control in power transmission facilities and for acoustic environmental design in public spaces. In addition, products such as modular acoustic panels and silencers for HVAC systems, based on metamaterial principles, have been introduced for small-scale noise control applications [see, e.g., <https://metacoust.com/products/>]. While these advances highlight the diverse applications of AMMs for noise control, their widespread adoption still faces challenges such as the need for highly customized designs, the lack of standardized production models, and cost control issues. As technology advances and costs decrease, AMMs are likely to achieve broader application across a variety of fields, potentially transforming future noise control technology.

Future research should focus on the development of robust, field-ready broadband AMMs and their composites, leveraging advances in both architectural design and material science. This should be complemented by the establishment of scalable, reliable manufacturing solutions and standardized testing protocols. Additionally, further exploration of hybrid AMM-porous concepts, bio-inspired topologies, and data-driven design frameworks will be critical in closing the gap between laboratory achievement and engineering reality. Efforts to systematically study durability, environmental resilience, and integration with existing infrastructure will also be essential for the practical translation of AMM-based technologies.

Overall, the rapid progress in broadband AMM design—including the successful demonstration of high-efficiency absorption in the challenging low-mid frequency range and the emerging synergy with porous materials—marks a pivotal step forward. Nonetheless, systematic research is still required to surmount remaining barriers and realize the full potential of AMMs in large-scale, real-world noise control applications.

Conclusions

This review systematically explores the progress and challenges in the development of bio-inspired AMMs, with a particular focus on their applications in addressing railway noise. The integration of advanced manufacturing technologies and ML has greatly propelled the development of bio-inspired AMMs, especially in addressing railway noise challenges.

While traditional design methods often struggle with the complexity and computational demands of AMM optimization, ML techniques have emerged as a powerful tool to streamline the process, enabling faster and more efficient identification of optimal structural configurations. Despite these advances, challenges such as data requirements, generalization issues, and the need for wider frequency range absorption remain. Future research should focus on developing broadband AMMs, optimizing datasets for ML, and exploring more complex bio-inspired designs. By addressing these limitations, the field can move closer to practical, large-scale applications, ultimately enhancing noise control solutions in transportation and beyond.

Data availability

No datasets were generated or analyzed during the current study.

Received: 22 February 2025; Accepted: 7 July 2025;

Published online: 29 July 2025

References

- Ouis, D. Annoyance from road traffic noise: a review. *J. Environ. Psychol.* **21**, 101–120 (2001).
- Yang, M. & Sheng, P. Sound absorption structures: from porous media to acoustic metamaterials. *Annu. Rev. Mater. Res.* **47**, 83–114 (2017).
- Amares, S., Sujatmika, E., Hong, T. W., Durairaj, R. & Hamid, H. A review: characteristics of noise absorption material. *J. Phys.: Conf. Ser. (ICADME)* **908**, 012005 (2017).
- Tao, Y., Ren, M., Zhang, H. & Peijs, T. Recent progress in acoustic materials and noise control strategies—a review. *Appl. Mater. Today* **24**, 101141 (2021). **This review provides an overview of recent advancements in acoustic materials and noise control strategies, highlighting progress in acoustic metamaterials (AMMs) and their applications in effective noise reduction.**
- Ang, L. Y. L., Koh, Y. K. & Lee, H. P. Acoustic metamaterials: a potential for cabin noise control in automobiles and armored vehicles. *Int. J. Appl. Mech.* **08**, 1650072 (2016).
- Lee, S. H., Park, C. M., Seo, Y. M., Wang, Z. G. & Kim, C. K. Acoustic metamaterial with negative modulus. *J. Phys.: Condens. Matter* **21**, 175704 (2009).
- Kumar, S. & Lee, H. P. Recent advances in acoustic metamaterials for simultaneous sound attenuation and air ventilation performances. *Crystals* **10**, 686 (2020).
- Jiang, H. et al. Band gaps and vibration isolation of a three-dimensional metamaterial with a star structure. *Materials* **13**, 3812 (2020).
- Qian, J., Sun, H., Yuan, S. & Liu, X. Enhanced directional acoustic emission based on anisotropic metamaterials. *Appl. Phys. Lett.* **114**, 013506 (2019).
- Park, C. M. & Lee, S. H. Zero-reflection acoustic metamaterial with a negative refractive index. *Sci. Rep.* **9**, 3372 (2019).
- Chen, H. & Chan, C. T. Acoustic cloaking in three dimensions using acoustic metamaterials. *Appl. Phys. Lett.* **91**, 183518 (2007).
- Liu, A., Zhou, X., Huang, G. & Hu, G. Super-resolution imaging by resonant tunneling in anisotropic acoustic metamaterials. *J. Acoustical Soc. Am.* **132**, 2800–2806 (2012).
- Ma, G. & Sheng, P. Acoustic metamaterials: From local resonances to broad horizons. *Sci. Adv.* **2**, e1501595 (2016).
- Liao, G. et al. Acoustic metamaterials: A review of theories, structures, fabrication approaches, and applications. *Adv. Mater. Technol.* **6**, 2000787 (2021).
- Aydın, G. & San, S. E. Breaking the limits of acoustic science: A review of acoustic metamaterials. *Mater. Sci. Eng.: B* **305**, 117384 (2024).
- Neil, T. R., Shen, Z., Robert, D., Drinkwater, B. W. & Holderied, M. W. Moth wings are acoustic metamaterials. *Proc. Natl Acad. Sci. USA* **117**, 31134–31141 (2020).

17. Ji, G. et al. Nano-fibrous composite sound absorbers inspired by owl feather surfaces. *Appl. Acoust.* **156**, 151–157 (2019).
18. Dong, E. et al. Bioinspired metagel with broadband tunable impedance matching. *Sci. Adv.* **6**, eabb3641 (2020).
19. Ma, Y. & Ye, W. Biomimetic coupling structure increases the noise friction and sound absorption effect. *Materials* **16**, 7148 (2023).
20. Sharma, R. et al. Recent advances in 3D printing properties of natural food gels: Application of innovative food additives. *Food Chem.* **432**, 137196 (2024).
21. Periferakis, A. et al. Use of biomaterials in 3D printing as a solution to microbial infections in arthroplasty and osseous reconstruction. *Biomimetics* **9**, 154 (2024).
22. Tezsezen, E., Yigci, D., Ahmadpour, A. & Tasoglu, S. AI-based metamaterial design. *ACS Appl. Mater. Interfaces* **16**, 29547–29569 (2024).
23. Zhu, C., Bamidele, E. A., Shen, X., Zhu, G. & Li, B. Machine learning aided design and optimization of thermal metamaterials. *Chem. Rev.* **124**, 4258–4331 (2024).
24. Cerniauskas, G., Sadia, H. & Alam, P. Machine intelligence in metamaterials design: a review. *Oxf. Open Mater. Sci.* **4**, itae001 (2024).
25. Zhang, H. et al. Learning to inversely design acoustic metamaterials for enhanced performance. *Acta Mech. Sin.* **39**, 722426 (2023).
26. Dal Poggetto, V. F. Bioinspired acoustic metamaterials: From natural designs to optimized structures. *Front. Mater.* **10**, 1176457 (2023).
27. Yang, Y. et al. Structural design and electromagnetic wave absorbing performance optimization of lightweight foam cement-based metamaterials. *Constr. Build. Mater.* **438**, 137191 (2024).
28. Guo, H. et al. Parametric modeling and deep learning-based forward and inverse design for acoustic metamaterial plates. *Mech. Adv. Mater. Struct.* **31**, 12986–12996 (2024).
29. Crocker, M. J. *Handbook of Acoustics* (John Wiley & Sons, 1998).
30. London, A. The determination of reverberant sound absorption coefficients from acoustic impedance measurements. *J. Acoustical Soc. Am.* **22**, 263–269 (1950).
31. Norton, K. A. Transmission loss in radio propagation. *Proc. IRE* **41**, 146–152 (1953).
32. Giorgio, I., Spagnuolo, M., Andreus, U., Scerrato, D. & Bersani, A. M. In-depth gaze at the astonishing mechanical behavior of bone: a review for designing bio-inspired hierarchical metamaterials. *Math. Mech. Solids* **26**, 1074–1103 (2021).
33. Tang, P. K. & Sirignano, W. A. Theory of a generalized Helmholtz resonator. *J. Sound Vib.* **26**, 247–262 (1973).
34. Zhao, L. & Zhou, S. Compact acoustic rainbow trapping in a bioinspired spiral array of graded locally resonant metamaterials. *Sensors* **19**, 788 (2019).
35. Gai, X.-L. et al. Acoustic properties of honeycomb like sandwich acoustic metamaterials. *Appl. Acoust.* **199**, 109016 (2022).
36. Benouhiba, A., Rougeot, P., Andreff, N., Rabenorosoa, K. & Ouisse, M. Origami-based auxetic tunable Helmholtz resonator for noise control. *Smart Mater. Struct.* **30**, 035029 (2021).
37. Li, Z., Wang, X., Li, X., Wang, Z. & Zhai, W. New class of multifunctional bioinspired microlattice with excellent sound absorption, Damage Tolerance, and High Specific Strength. *ACS Appl. Mater. Interfaces* **15**, 9940–9952 (2023). **This study presents a new class of multifunctional bio-inspired micro-lattices that exhibit excellent sound absorption, damage tolerance, and high specific strength, providing a valuable example for the design of advanced AMMs.**
38. Rupin, M., Lerosey, G., de Rosny, J. & Lemoult, F. Mimicking the cochlea with an active acoustic metamaterial. *N. J. Phys.* **21**, 093012 (2019).
39. Miniaci, M., Krushynska, A., Bosia, F. & Pugno, N. M. Large scale mechanical metamaterials as seismic shields. *N. J. Phys.* **18**, 083041 (2016).
40. Maurel, A., Mercier, J.-F. & Montagnat, M. Critical investigation of calculation methods for the elastic velocities in anisotropic ice polycrystals. *Cryosphere* **10**, 3063–3070 (2016).
41. Raut, M. S. & Gopalakrishnan, S. Elastic and viscoelastic flexural wave motion in woodpecker-beak-inspired structures. *Bioinspiration Biomim.* **16**, 046021 (2021).
42. Tang, Y. et al. Hybrid acoustic metamaterial as super absorber for broadband low-frequency sound. *Sci. Rep.* **7**, 43340 (2017). **This study combines MPP and honeycomb sandwich structures to achieve high sound absorption performance while maintaining thickness advantages, suggesting that similar hybrid configurations could be considered in the design of acoustic metamaterials for railway noise reduction to broaden the absorption frequency range.**
43. Meng, H., Galland, M.-A., Ichchou, M., Xin, F. X. & Lu, T. J. On the low frequency acoustic properties of novel multifunctional honeycomb sandwich panels with micro-perforated faceplates. *Appl. Acoust.* **152**, 31–40 (2019).
44. Li, W., Meng, F., Chen, Y., Li, Y. F. & Huang, X. Topology optimization of photonic and phononic crystals and metamaterials: a review. *Advcd Theory Sims* **2**, 1900017 (2019).
45. Zhang, X., Li, Y., Wang, Y. & Luo, Y. Ultra-wide low-frequency bandgap design of acoustic metamaterial via multi-material topology optimization. *Compos. Struct.* **306**, 116584 (2023).
46. Noguchi, Y., Yamada, T., Izui, K. & Nishiwaki, S. Topology optimization for hyperbolic acoustic metamaterials using a high-frequency homogenization method. *Comput. Methods Appl. Mech. Eng.* **335**, 419–471 (2018).
47. Xiang, N., Fackler, C. J., Hou, Y. & Schmitt, A. A. Bayesian design of broadband multilayered microperforated panel absorbers. *J. Acoustical Soc. Am.* **151**, 3094–3103 (2022).
48. Yang, W. et al. 3D printing of polymeric multi-layer micro-perforated panels for tunable wideband sound absorption. *Polymers* **12**, 360 (2020).
49. Chen, Y. & Wang, L. Multiband wave filtering and waveguiding in bio-inspired hierarchical composites. *Extrem. Mech. Lett.* **5**, 18–24 (2015).
50. Chen, Y. & Wang, L. Bio-inspired heterogeneous composites for broadband vibration mitigation. *Sci. Rep.* **5**, 17865 (2015).
51. Ma, F., Wu, J. H., Huang, M. & Zhang, S. Cochlear outer hair cell bio-inspired metamaterial with negative effective parameters. *Appl. Phys. A* **122**, 525 (2016).
52. Yin, J., Peng, H. J., Zhang, S., Zhang, H. W. & Chen, B. S. Design of nacreous composite material for vibration isolation based on band gap manipulation. *Comput. Mater. Sci.* **102**, 126–134 (2015).
53. Xue, H., Yang, Y. & Zhang, B. Topological acoustics. *Nat. Rev. Mater.* **7**, 974–990 (2022).
54. Chen, Y. et al. Various topological phases and their abnormal effects of topological acoustic metamaterials. *Interdiscip. Mater.* **2**, 179–230 (2023).
55. Dal Poggetto, V. F., Bosia, F., Miniaci, M. & Pugno, N. M. Optimization of spider web-inspired phononic crystals to achieve tailored dispersion for diverse objectives. *Mater. Des.* **209**, 109980 (2021).
56. Krushynska, A. O., Bosia, F., Miniaci, M. & Pugno, N. M. Spider web-structured labyrinthine acoustic metamaterials for low-frequency sound control. *N. J. Phys.* **19**, 105001 (2017).
57. Miniaci, M., Krushynska, A., Movchan, A. B., Bosia, F. & Pugno, N. M. Spider web-inspired acoustic metamaterials. *Appl. Phys. Lett.* **109**, 071905 (2016).
58. Yang, T. et al. Acoustic edge mode in spiral-based metamaterials at subwavelength scale. *Results Phys.* **42**, 106008 (2022).
59. Hu, J., Bandyopadhyay, S., Liu, Y. & Shao, L. A review on metasurface: from principle to smart metadevices. *Front. Phys.* **8**, 586087 (2021).

60. Colombi, A. et al. Elastic wave control beyond band-gaps: shaping the flow of waves in plates and half-spaces with subwavelength resonant rods. *Front. Mech. Eng.* **3**, 10 (2017).
61. Ryoo, H. & Jeon, W. Broadband sound absorption using multiple hybrid resonances of acoustic metasurfaces. *Int. J. Mech. Sci.* **229**, 107508 (2022).
62. Neil, T. R., Shen, Z., Robert, D., Drinkwater, B. W. & Holderied, M. W. Moth wings as sound absorber metasurface. *Proc. R. Soc. A.* **478**, 20220046 (2022).
63. Li, M., Wu, J. H. & Yuan, X. Y. Wall suction & slip effect of spherical-grooved bionic metasurface for controlling the aerodynamic noise. *Appl. Acoust.* **171**, 107537 (2021).
64. Dai, H. et al. Review and prospects of metamaterials used to control elastic waves and vibrations. *Front. Phys.* **10**, 1069454 (2022).
65. Zhao, X., Liu, G., Zhang, C., Xia, D. & Lu, Z. Fractal acoustic metamaterials for transformer noise reduction. *Appl. Phys. Lett.* **113**, 074101 (2018).
66. Yan, H., Xie, S., Zhang, F., Jing, K. & He, L. Semi-self-similar fractal cellular structures with broadband sound absorption. *Appl. Acoust.* **217**, 109864 (2024). **This study utilizes a multi-layer honeycomb biomimetic approach to design broadband AMMs aimed at sound absorption and noise reduction in railway applications, providing guidance for the implementation of effective acoustic solutions in railway infrastructure.**
67. Singh, S. K., Prakash, O. & Bhattacharya, S. Novel fractal acoustic metamaterials (FAMs) for multiple narrow-band near-perfect absorption. *J. Appl. Phys.* **132**, 035105 (2022).
68. Liu, Y. et al. Fractal acoustic metamaterials with subwavelength and broadband sound insulation. *Shock Vib.* **2019**, 1894073 (2019).
69. Man, X. et al. Engineering three-dimensional labyrinthine fractal acoustic metamaterials with low-frequency multi-band sound suppression. *J. Acoustical Soc. Am.* **149**, 308–319 (2021).
70. He, C., Li, Z., Wu, G. & Tao, M. Fractal acoustic metamaterials with near-zero index and negative properties. *Appl. Acoust.* **217**, 109825 (2024).
71. Xiang, L., Wang, G. & Zhu, C. Controlling sound transmission by space-coiling fractal acoustic metamaterials with broadband on the subwavelength scale. *Appl. Acoust.* **188**, 108585 (2022).
72. Li, Z., Li, X., Wang, Z. & Zhai, W. Multifunctional sound-absorbing and mechanical metamaterials via a decoupled mechanism design approach. *Mater. Horiz.* **10**, 75–87 (2023).
73. Wang, Z., Guo, Z., Li, Z. & Zeng, K. Design, manufacture, and characterisation of hierarchical metamaterials for simultaneous ultra-broadband sound-absorbing and superior mechanical performance. *Virtual Phys. Prototyp.* **18**, e2111585 (2023).
74. Li, Z., Li, X., Wang, X., Wang, Z. & Zhai, W. Interpenetrating hollow microlattice metamaterial enables efficient sound-absorptive and deformation-recoverable capabilities. *ACS Appl. Mater. Interfaces* **15**, 24868–24879 (2023).
75. Gao, N., Wu, J., Lu, K. & Zhong, H. Hybrid composite meta-porous structure for improving and broadening sound absorption. *Mech. Syst. Signal Process.* **154**, 107504 (2021).
76. Zhang, W. & Xin, F. Coiled-up structure with porous material lining for enhanced sound absorption. *Int. J. Mech. Sci.* **256**, 108480 (2023).
77. Guo, Z. et al. Hierarchical-porous acoustic metamaterials: A synergic approach to enhance broadband sound absorption. *Mater. Des.* **241**, 112943 (2024). **This study explores a combination of porous structures and AMMs, demonstrating that this synergy can achieve excellent sound absorption across a broad frequency range.**
78. Ogun, O. & Kennedy, J. Comparison of traditional and deep learning optimisation for the design of acoustic metamaterials. In: *INTER-NOISE and NOISE-CON Congress and Conference Proceedings* Vol. 270 (ed. Bahtiarian, M.) 1352–1362 (Institute of Noise Control Engineering, 2024).
79. Lee, D., Chen, W., Wang, L., Chan, Y. & Chen, W. Data-driven design for metamaterials and multiscale systems: a review. *Adv. Mater.* **36**, 2305254 (2024).
80. Kennedy, J. & Lim, C. W. Machine learning and deep learning in phononic crystals and metamaterials—a review. *Mater. Today Commun.* **33**, 104606 (2022).
81. Van Eck, N. & Waltman, L. Software survey: VOSviewer, a computer program for bibliometric mapping. *scientometrics* **84**, 523–538 (2010).
82. Kumar, R. et al. Service innovation research: a bibliometric analysis using VOSviewer. *Competitiveness Rev.: Int. Bus. J.* **34**, 736–760 (2024).
83. Jin, Y. et al. Intelligent on-demand design of phononic metamaterials. *Nanophotonics* **11**, 439–460 (2022).
84. He, L. et al. Machine learning assisted intelligent design of meta structures: a review. *Microstructures* **3**(2023).
85. Chen, A. et al. Machine learning-assisted low-frequency and broadband sound absorber with coherently coupled weak resonances. *Appl. Phys. Lett.* **120**, 033501 (2022).
86. Hu, Z. et al. Machine learning-enabled inverse design of shell-based lattice metamaterials with optimal sound and energy absorption. *Virtual Phys. Prototyp.* **19**, e2412198 (2024).
87. Zhang, X. et al. Reverse optimization design of OAM sound barrier based on acoustic metamaterials. *Constr. Build. Mater.* **432**, 136600 (2024). **This study provides forward and reverse design methods for AMMs, aiming to offer noise solutions for the construction industry and highlighting their potential in reducing noise for railways.**
88. Donda, K. et al. Ultrathin acoustic absorbing metasurface based on deep learning approach. *Smart Mater. Struct.* **30**, 085003 (2021).
89. Zheng, B., Yang, J., Liang, B. & Cheng, J. Inverse design of acoustic metamaterials based on machine learning using a Gauss–Bayesian model. *J. Appl. Phys.* **128**, 134902 (2020).
90. Liu, L. et al. Broadband acoustic absorbing metamaterial via deep learning approach. *Appl. Phys. Lett.* **120**, 251701 (2022).
91. Yago, D., Sal-Anglada, G., Roca, D., Cante, J. & Oliver, J. Machine learning in solid mechanics: Application to acoustic metamaterial design. *Numer. Meth Eng.* **125**, e7476 (2024).
92. Jain, A. et al. Overview and importance of data quality for machine learning tasks. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 3561–3562 (ACM, Virtual Event, 2020).
93. Chen, J. et al. Application of machine learning on the design of acoustic metamaterials and phonon crystals: A review. *Smart Mater. Struct.* **33**, 073001 (2024).
94. Zhang, X., Xing, J., Liu, P., Luo, Y. & Kang, Z. Realization of full and directional band gap design by non-gradient topology optimization in acoustic metamaterials. *Extrem. Mech. Lett.* **42**, 101126 (2021).
95. Dong, H.-W. et al. Systematic design and realization of double-negative acoustic metamaterials by topology optimization. *Acta Materialia* **172**, 102–120 (2019).
96. Li, Y., Zhang, X., Tian, Q. & Luo, Y. Topological design of soft substrate acoustic metamaterial for mechanical tuning of sound propagation. *Compos. Struct.* **346**, 118399 (2024).
97. Bacigalupo, A., Gnecco, G., Lepidi, M. & Gambarotta, L. Machine-learning techniques for the optimal design of acoustic metamaterials. *J. Optim. Theory Appl.* **187**, 630–653 (2020).
98. Li, X. et al. Designing phononic crystal with anticipated band gap through a deep learning based data-driven method. *Comput. Methods Appl. Mech. Eng.* **361**, 112737 (2020).
99. Sadat, S. M. & Wang, R. Y. A machine learning based approach for phononic crystal property discovery. *J. Appl. Phys.* **128**, 025106 (2020).
100. Kudela, P. et al. Deep learning aided topology optimization of phononic crystals. *Mech. Syst. Signal Process.* **200**, 110636 (2023).

- This research integrates machine learning, topology optimization, and genetic algorithms to effectively design phononic crystals, enhancing their acoustic properties.**
101. Kaelbling, L. P., Littman, M. L. & Moore, A. W. Reinforcement learning: a survey. *J. Artif. Intell. Res.* **4**, 237–285 (1996).
 102. Luo, C., Ning, S., Liu, Z. & Zhuang, Z. Interactive inverse design of layered phononic crystals based on reinforcement learning. *Extrem. Mech. Lett.* **36**, 100651 (2020).
 103. Clifton, J. & Laber, E. Q-learning: theory and applications. *Annu. Rev. Stat. Appl.* **7**, 279–301 (2020).
 104. Liu, C.-X. & Yu, G.-L. Predicting the dispersion relations of one-dimensional phononic crystals by neural networks. *Sci. Rep.* **9**, 15322 (2019).
 105. Gurbuz, C. et al. Generative adversarial networks for the design of acoustic metamaterials. *J. Acoustical Soc. Am.* **149**, 1162–1174 (2021).
 106. Maghami, A. & Hosseini, S. M. Automated design of phononic crystals under thermoelastic wave propagation through deep reinforcement learning. *Eng. Struct.* **263**, 114385 (2022).
 107. Chen, J., Chen, Y., Xu, X., Zhou, W. & Huang, G. A physics-guided machine learning for multifunctional wave control in active metabeams. *Extrem. Mech. Lett.* **55**, 101827 (2022).
 108. Ahmed, W. W., Farhat, M., Zhang, X. & Wu, Y. Deterministic and probabilistic deep learning models for inverse design of broadband acoustic cloak. *Phys. Rev. Res.* **3**, 013142 (2021).
 109. Feng, J. et al. Broadband sound absorption and high damage resistance in a turtle shell-inspired multifunctional lattice: neural network-driven design and optimization. *Small* **20**, 2403254 (2024). **This study combines biomimicry with the design of AMM, optimizing multifunctional materials using machine learning to achieve excellent sound absorption and damage resistance.**
 110. Zhilyaev, I., Krushinsky, D., Ranjbar, M. & Krushynska, A. O. Hybrid machine-learning and finite-element design for flexible metamaterial wings. *Mater. Des.* **218**, 110709 (2022).
 111. Fan, J. et al. A review of additive manufacturing of metamaterials and developing trends. *Mater. Today* **50**, 303–328 (2021).
 112. Zhao, T., Chen, Y., Zhang, K. & Hu, G. Tunable network sound absorber based on additive manufacturing. *J. Acoustical Soc. Am.* **150**, 94–101 (2021).
 113. Boulvert, J. et al. Acoustic modeling of micro-lattices obtained by additive manufacturing. *Appl. Acoust.* **164**, 107244 (2020).
 114. Kaiyu, J., Jian, W., Minjie, W., Chunzheng, D. & Binzhou, C. Forming and machining technology for metamaterials. In: *2022 IEEE MTT-S International Microwave Workshop Series on Advanced Materials and Processes for RF and THz Applications (IMWS-AMP)* (ed. Xue, Q.) 1–3 (IEEE, 2022).
 115. Pereira, T., Kennedy, J. V. & Potgieter, J. A comparison of traditional manufacturing vs additive manufacturing, the best method for the job. *Procedia Manuf.* **30**, 11–18 (2019).
 116. Chin Vui Sheng, D. D., Yahya, M. N. B. & Che Din, N. B. Sound absorption of microperforated panel made from coconut fiber and polylactic acid composite. *J. Nat. Fibers* **19**, 2719–2729 (2022).
 117. Chin, D. D. V. S., Yahya, M. N. B., Din, N. B. C. & Ong, P. Acoustic properties of biodegradable composite micro-perforated panel (BC-MPP) made from kenaf fibre and polylactic acid (PLA). *Appl. Acoust.* **138**, 179–187 (2018).
 118. Daeipour, Z., Safdari, V. & Nurbakhsh, A. Evaluation of the acoustic properties of wood-plastic-chalk composites. *Eng., Technol. Appl. Sci. Res.* **7**, 1540–1545 (2017).
 119. Szczepanski, G., Podlesna, M., Morzynski, L. & WŁUDARCZYK, A. Investigation of the acoustic properties of a metamaterial with a multi-ring structure. *Arch. Acoust.* **48**, 497–507 (2023).
 120. Beli, D., Fabro, A. T., Ruzzene, M. & Arruda, J. R. F. Wave attenuation and trapping in 3D printed cantilever-in-mass metamaterials with spatially correlated variability. *Sci. Rep.* **9**, 5617 (2019).
 121. Zieliński, T. G. et al. Taking advantage of a 3D printing imperfection in the development of sound-absorbing materials. *Appl. Acoust.* **197**, 108941 (2022).
 122. Wu, L., Xue, J., Tian, X., Liu, T. & Li, D. 3D-printed metamaterials with versatile functionalities. *Chin. J. Mech. Eng.: Addit. Manuf. Front.* **2**, 100091 (2023).
 123. Husna, A., Ashrafi, S., Tomal, A. A., Tuli, N. T. & Rashid, A. B. Recent advancements in stereolithography (SLA) and their optimization of process parameters for sustainable manufacturing. *Hybrid. Adv.* **7**, 100307 (2024).
 124. Kirihaara, S., Miyamoto, Y. & Kajiyama, K. Fabrication of ceramic–polymer photonic crystals by stereolithography and their microwave properties. *J. Am. Ceram. Soc.* **85**, 1369–1371 (2002).
 125. Thomas, D. S. & Gilbert, S. W. Costs and cost effectiveness of additive manufacturing. *NIST Spec. Publ.* **1176**, 12 (2014).
 126. Jung, S., Kara, L. B., Nie, Z., Simpson, T. W. & Whitefoot, K. S. Is additive manufacturing an environmentally and economically preferred alternative for mass production? *Environ. Sci. Technol.* **57**, 6373–6386 (2023).
 127. Paxton, N. C., Zhao, J. & Sauret, E. Polymer 3D printing in perspective: assessing challenges and opportunities in industrial translation against the metal benchmark. *Int. J. Adv. Manuf. Technol.* **133**, 59–80 (2024).
 128. Su, J. et al. Achieving sustainability by additive manufacturing: a state-of-the-art review and perspectives. *Virtual Phys. Prototyp.* **19**, e2438899 (2024).
 129. Wright, W. J., Darville, J., Celik, N., Koerner, H. & Celik, E. In-situ optimization of thermoset composite additive manufacturing via deep learning and computer vision. *Addit. Manuf.* **58**, 102985 (2022).
 130. Liu, C. R., Wu, J. H., Yang, Z. & Ma, F. Ultra-broadband acoustic absorption of a thin microperforated panel metamaterial with multi-order resonance. *Compos. Struct.* **246**, 112366 (2020).
 131. Zhou, Z., Huang, S., Li, D., Zhu, J. & Li, Y. Broadband impedance modulation via non-local acoustic metamaterials. *Natl. Sci. Rev.* **9**, nwab171 (2022).
 132. Mei, Z. et al. Broadening sound absorption bandwidth via multi-order resonances. *Int. J. Mech. Sci.* **280**, 109493 (2024).
 133. Yuan, T. et al. Optimal design of subwavelength broadband acoustic porous composite metasurface based genetic algorithm. *J. Sound Vib.* **586**, 118498 (2024).
 134. Morgan, P. A., Hothersall, D. C. & Chandler-Wilde, S. N. Influence of shape and absorbing surface—a numerical study of railway noise barriers. *J. Sound Vib.* **217**, 405–417 (1998).
 135. Zou, C., Wang, Y., Zhang, X. & Tao, Z. Vibration isolation of over-track buildings in a metro depot by using trackside wave barriers. *J. Build. Eng.* **30**, 101270 (2020).
 136. Frid, A. Skirts and barriers for reduction of wayside noise from railway vehicles—an experimental investigation with application to the BR185 locomotive. *J. Sound Vib.* **267**, 709–719 (2003).
 137. Talotte, C., Gautier, P.-E., Thompson, D. J. & Hanson, C. Identification, modelling and reduction potential of railway noise sources: a critical survey. *J. Sound Vib.* **267**, 447–468 (2003).
 138. Chen, Z.-W. et al. Reducing the aerodynamic drag of high-speed trains by air blowing from the nose part: Effect of blowing speed. *J. Wind Eng. Ind. Aerodyn.* **238**, 105429 (2023).
 139. Yang, M. & Sheng, P. Acoustic metamaterial absorbers: the path to commercialization. *Appl. Phys. Lett.* **122**, 260504 (2023).
 140. Zhang, X. et al. Modular reverse design of acoustic metamaterial and sound barrier engineering applications: High ventilation and broadband sound insulation. *Thin-Walled Struct.* **196**, 111498 (2024).

141. Arjunan, A., Baroutaji, A., Robinson, J., Vance, A. & Arafat, A. Acoustic metamaterials for sound absorption and insulation in buildings. *Build. Environ.* **251**, 111250 (2024).
142. Ma, F., Wu, J. H., Huang, M., Fu, G. & Bai, C. Cochlear bionic acoustic metamaterials. *Appl. Phys. Lett.* **105**, 213702 (2014).
143. Yin, J., Huang, J., Zhang, S., Zhang, H. W. & Chen, B. S. Ultrawide low frequency band gap of phononic crystal in nacreous composite material. *Phys. Lett. A* **378**, 2436–2442 (2014).
144. De Maio, U., Greco, F., Luciano, R., Sgambitterra, G. & Pranno, A. Microstructural design for elastic wave attenuation in 3D printed nacre-like bioinspired metamaterials lightened with hollow platelets. *Mech. Res. Commun.* **128**, 104045 (2023).
145. Zhou, C. et al. Design of a novel medical acoustic sensor based on MEMS bionic fish ear structure. *Micromachines* **13**, 163 (2022).
146. Wu, J. et al. Multi-feature bionic gradient hierarchical lattice metamaterials with multi-synergistic crushing mechanisms. *Int. J. Mech. Sci.* **283**, 109383 (2024).
147. Casaburo, A., Magliacano, D., Petrone, G., Franco, F. & De Rosa, S. Gaussian-based machine learning algorithm for the design and characterization of a porous meta-material for acoustic applications. *Appl. Sci.* **12**, 333 (2021).
148. Jordan, M. I. & Mitchell, T. M. Machine learning: trends, perspectives, and prospects. *Science* **349**, 255–260 (2015).
149. Seeger, M. Gaussian processes for machine learning. *Int. J. Neur. Syst.* **14**, 69–106 (2004).
150. Zhang, Y., Wang, S. & Ji, G. A comprehensive survey on particle swarm optimization algorithm and its applications. *Math. Probl. Eng.* **2015**, 1–38 (2015).
151. Chen, H., Zeng, H., Ding, C., Luo, C. & Zhao, X. Double-negative acoustic metamaterial based on hollow steel tube meta-atom. *J. Appl. Phys.* **113**, 104902 (2013).
152. Chen, H., Zhai, S., Ding, C., Luo, C. & Zhao, X. Acoustic metamaterial with negative mass density in water. *J. Appl. Phys.* **118**, 094901 (2015).
153. Hou, Z. & Assouar, B. M. Tunable solid acoustic metamaterial with negative elastic modulus. *Appl. Phys. Lett.* **106**, 251901 (2015).
154. Solomon, I. J., Sevel, P. & Gunasekaran, J. A review on the various processing parameters in FDM. *Mater. Today.: Proc.* **37**, 509–514 (2021).
155. Gueche, Y. A., Sanchez-Ballester, N. M., Cailleaux, S., Bataille, B. & Soulaïrol, I. Selective laser sintering (sls), a new chapter in the production of solid oral forms (sofs) by 3D printing. *Pharmaceutics* **13**, 1212 (2021).

Acknowledgements

The work described in this paper was supported by a grant from the Innovation and Technology Commission of the Hong Kong Special Administrative Region Government (Grant No. K-BBY1) and the Start-Up Fund for Research Assistant Professors under the Strategic Hiring Scheme of The Hong Kong Polytechnic University (P0051104).

Author contributions

Jia-Hao Lu drafted the manuscript. Siqi Ding revised the manuscript, contributed to the study design, and secured funding. Yi-Qing Ni supervised the research and reviewed the manuscript. Shu Li assisted with the literature and data collection.

Competing interests

Siqi Ding is acting as Guest Editor for a relevant collection in Communications Engineering, but was not involved in the editorial review of, nor the decision to publish this article. All other authors declare no competing financial or non-financial interests.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s44172-025-00470-x>.

Correspondence and requests for materials should be addressed to Siqi Ding or Yi-Qing Ni.

Peer review information *Communications Engineering* thanks Xiuyuan Peng, Tongyang Shi, and the other, anonymous, reviewer for their contribution to the peer review of this work. Primary Handling Editors: [Rosamund Daw]. Peer reviewer reports are available.

Reprints and permissions information is available at <http://www.nature.com/reprints>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2025