

Numerical Simulation Engines and Deep Learning Architectures for Inverse Design of Multilayer Metamaterials

Motores de Simulación Numérica y Arquitecturas de Aprendizaje Profundo para el Diseño Inverso de Metamateriales Multicapa

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Abstract

The inverse design of multilayer metamaterials —artificial structures with engineered electromagnetic, acoustic, thermal, or mechanical properties— represents a high-dimensional optimisation challenge that has driven the integration of deep learning into computational photonics and materials science. This paper presents a systematic literature review conducted under the PRISMA 2020 protocol, aimed at mapping the numerical simulation methods employed as forward engines or training data generators within deep learning-assisted inverse design pipelines. Starting from 392 records retrieved from Scopus and Web of Science over the 2010–2025 period, a multi-stage screening process based on a heuristic prioritisation index termed CARS (Citation-Adjusted Relevance Score) identified 44 core articles. Eleven distinct numerical methods were identified and organised into two conceptual layers: classical simulation engines (finite element method, topology optimisation, guided-mode expansion, adjoint method, and

Summary: Introduction, Materials and Methods, Results and Discussion, Conclusions.

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genetic algorithms) and deep learning architectures (tandem CNN, transformer, GAN, PINN, and diffractive neural networks). Results show a strong dominance of the electromagnetic-photonics domain (72%), accelerated growth of deep learning-based publications from 2022 onward, and a clear trend toward hybrid physics, data and learning pipelines. The review concludes by proposing a prioritised experimental roadmap for future research.

Keywords: metamaterials, inverse design, deep learning, numerical simulation, systematic review, topology optimisation.

Resumen

El diseño inverso de metamateriales multicapa —estructuras artificiales con propiedades electromagnéticas, acústicas, térmicas o mecánicas diseñadas a medida— constituye un problema de optimización de alta dimensionalidad que ha impulsado la integración del aprendizaje profundo en la fotónica computacional y la ciencia de materiales. Este artículo presenta una revisión sistemática de la literatura realizada siguiendo el protocolo PRISMA 2020, orientada a mapear los métodos de simulación numérica empleados como motores directos o generadores de datos de entrenamiento dentro de flujos de trabajo de diseño inverso asistido por aprendizaje profundo. A partir de 392 registros recuperados de Scopus y Web of Science en el periodo 2010–2025, un proceso de cribado multietapa basado en un índice heurístico de priorización denominado CARS (Citation-Adjusted Relevance Score) permitió identificar 44 artículos centrales. Se identificaron once métodos numéricos distintos, organizados en dos capas conceptuales: motores clásicos de simulación (método de elementos finitos, optimización topológica, expansión en modos guiados, método adjunto y algoritmos genéticos) y arquitecturas de aprendizaje profundo (CNN en tándem, transformer, GAN, PINN y redes neuronales difractivas). Los resultados evidencian un predominio del dominio electromagnético-fotónico (72 %), un crecimiento acelerado de las publicaciones basadas en aprendizaje profundo a partir de 2022, y una tendencia clara hacia flujos híbridos que combinan física, datos y aprendizaje. La revisión concluye proponiendo una hoja de ruta experimental priorizada para futuras investigaciones.

Palabras clave: metamateriales, diseño inverso, aprendizaje profundo, simulación numérica, revisión sistemática, optimización topológica.

Introduction

Multilayer metamaterials are periodic or quasi-periodic artificial structures whose effective electromagnetic, acoustic, thermal, or mechanical response depends on the geometry, thickness, and material properties of each constituent layer (Lin et al., 2018; Liu et al., 2024). Because their response arises from structural rather than chemical composition, they can be engineered to exhibit properties unavailable in nature: negative refractive index, near-perfect absorption, acoustic bandgaps, or programmable heat flux.

The inverse design problem—recovering layer parameters from a desired spectral or field response—is fundamentally ill-posed, nonlinear, and one-to-many: multiple geometries may produce the same target response (Ma et al., 2020; Naseri & Hum, 2021). Classical approaches iterate between a forward solver, such as a finite element or transfer-matrix code, and an optimisation heuristic, requiring thousands of computationally expensive simulations.

Deep learning offers an alternative: trained once on a synthetic dataset of forward simulations, a deep learning model can infer designs in milliseconds at inference time (Jia et

al., 2022; Lininger et al., 2021). Despite rapid progress, however, the field lacks a comprehensive synthesis of which numerical simulation methods have been most productive as training data generators, and how these map to deep learning architectures and application domains. This gap is the motivation for the present work.

Objectives and contributions

The general objective of this research is to systematically identify and classify the numerical simulation methods used in the inverse design of multilayer metamaterials, with emphasis on their role as data generators for training deep learning architectures. The specific contributions are as follows:

1. A PRISMA 2020 systematic review of 392 records yielding a corpus of 44 core articles on numerical methods for multilayer metamaterial inverse design.
2. A quantitative analysis of method frequency, application domains, and temporal trends over the 2010–2025 period.
3. A taxonomy of eleven numerical methods and deep learning architectures organised according to their function within the design pipeline.
4. A prioritised experimental roadmap, presented explicitly as a research direction derived from the synthesised evidence rather than as a validated outcome.

Related work

Deep learning for photonic inverse design

The application of neural networks to nanophotonic and metamaterial design has grown rapidly since 2018. Work by Liu et al. (2022) demonstrated that fully connected networks could map optical spectra to nanostructure parameters for single-layer gratings. Chen et al. (2019) extended this approach to graphene-based photonic metamaterials using an adaptive neural network, while Lininger et al. (2021) showed that convolutional tandem models generalise adequately to multilayer thin-film stacks.

An important observation across this body of work is that the inverse design problem is ill-conditioned: multiple layer configurations can produce nearly identical spectra. Tandem architectures address this difficulty by pre-training a forward network that enforces physical consistency (Jia et al., 2022; Zhu et al., 2022). Approaches based on generative adversarial networks (Hodge et al., 2020; Naseri & Hum, 2021) follow a different route, learning the full distribution of valid designs rather than a point estimate, which can accommodate the one-to-many character of the inverse problem.

Optimisation Methods for Metamaterial Design

Classical optimisation methods predate deep learning in the metamaterial design literature. Topology optimisation, originally developed for structural mechanics, has been applied to multilayer photonic structures by Lin et al. (2018) for metaoptic lens design and by Fu et al. (2016) for broadband perfect absorbers. The reliance of topology optimisation on adjoint gradients (Mansouree et al., 2020) makes it suitable for problems with thousands of design variables, but its computational cost per iteration limits the number of designs that can be evaluated, preventing its practicality as a standalone dataset generator.

Genetic algorithms (Cao et al., 2024; Jiang et al., 2023) avoid gradient computation and accommodate discrete design variables, such as integer layer counts or discrete material choices, but scale poorly beyond approximately fifty variables. For this reason, in the reviewed literature they are typically employed in combination with a surrogate model that replaces expensive forward simulations.

Forward Simulation Engines

The choice of forward simulation engine strongly influences the feasibility of large-scale dataset generation. The transfer-matrix method (García-Esteban et al., 2021) and guided-mode expansion (Zanotti et al., 2024) are semi-analytical and compute the optical response of periodic multilayer stacks in milliseconds per structure. Finite-difference time-domain and finite element methods provide full-wave simulations at a cost of minutes to hours per structure (Peralta & Fachinotti, 2017), which can make them impractical for generating the 10^5 samples typically required to train a deep learning model.

Materials and Methods

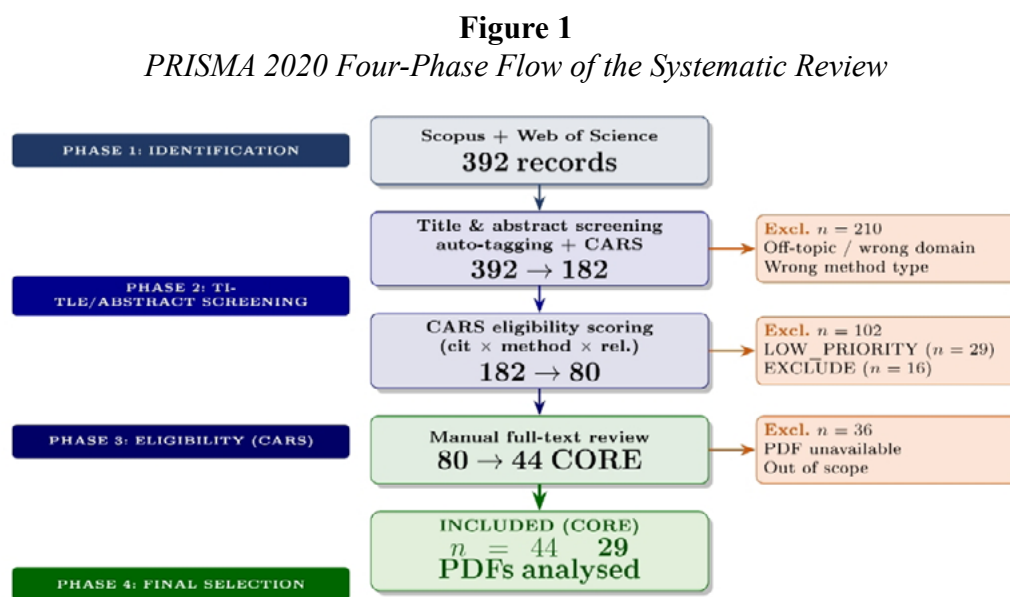
Search strategy and databases

Records were retrieved from Scopus and Web of Science in January 2026 using Boolean combinations of the terms multilayer metamaterial, inverse design, neural network, deep learning, topology optimisation, finite element method, and adjoint method, together with domain terms (electromagnetic, acoustic, thermal, mechanical). No temporal restriction was applied; the effective range of retrieved records spans 2010–2025.

The resulting corpus of 44 articles is intentionally narrow by design. The review targets a highly specific intersection: structures that are multilayer metamaterials and are addressed through inverse design using a numerical simulation or optimisation method. This triple constraint excludes the large body of work on single-interface metasurfaces, bulk metamaterial characterisation, and forward-only simulation studies. Within this niche, 44 included articles provide the evidence base used to characterise methodological trends, domain distributions, and dominant pipeline patterns (Page et al., 2021).

PRISMA 2020 Screening protocol

The review was conducted following the PRISMA 2020 guidelines (Page et al., 2021). The four-phase flow is illustrated in Figure 1. Screening files were managed through seven successive workbooks implementing automated tagging, CARS computation, and manual full-text verification.



Note. Adapted from the PRISMA 2020 protocol (Page et al., 2021). Databases consulted: Scopus and Web of Science, 2010–2025.

CARS (Citation-Adjusted Relevance Score)

Each record was assigned to a composite prioritisation index weighting three orthogonal dimensions, according to Equation 1:

$$\text{CARS} = 0.40 \cdot \text{cit_pct} + 0.35 \cdot \text{meth} + 0.25 \cdot \text{rel} \quad (1)$$

Where $\text{cit_pct} \in [0, 1]$ is the annual citation percentile of each record, normalised within its publication-year cohort (that is, a 2024 article is compared only with other 2024 articles in the set), so that recent records are not penalised relative to older ones. The meth component $\in \{0.30, 0.65, 0.85, 1.00\}$ is an ordinal score of methodological specificity: 0.30 for records with no recognised method keywords; 0.65 for a single general keyword; 0.85 for a specific deep learning keyword; and 1.00 for combinations including DEEP_LEARNING together with at least one complementary methodological term. Finally, $\text{rel} \in \{0.20, 1.00\}$ is a binary thematic relevance indicator, set to 1.00 when the title or abstract explicitly addresses the inverse design of multilayer structures, and 0.20 otherwise.

The weight assignment was determined through a heuristic calibration process: the three weights were varied over a grid and evaluated against a manually labelled gold-standard set of twenty records (ten highly relevant and ten irrelevant) until the resulting ranking correctly placed all ten relevant records within the top 20 % of scores. The final weights reflect the practical judgement that citation impact provides one indirect signal for prioritising influential studies in a field without standardised benchmarks, that methodological specificity is the most decisive criterion for inclusion, and that thematic alignment, while necessary, operates as a binary gate rather than a fine discriminant.

It must be stated explicitly that CARS constitutes an operationally designed heuristic prioritisation tool, and not a universal bibliometric index. It was conceived specifically to manage the large-volume, multi-keyword screening challenge of this review, and its weights should not be interpreted as absolute importance estimates transferable to other literature searches. Its function is analogous to that of a scoring rubric: transparent, reproducible within this study, and open to recalibration in future replications.

Table 1
CARS Classification of the 182 Records that passed title and abstract careening

Class	Cars range	N	%	Role in the review
CORE	≥ 75	44	24.2	Primary synthesis corpus
HIGH_VALUE	60–74	36	19.8	Background context (deferred)
SUPPORTING	45–59	47	25.8	Supplementary references (deferred)
LOW_PRIORITY	< 45	29	15.9	Excluded from synthesis
EXCLUDE	—	16	8.8	Off-topic after title screening
Not scored	—	10	5.5	Duplicate or missing metadata
Total Phase 2		182	100	

Note. Non-scored records were retained by Phase 2 but lacked sufficient metadata for CARS computation; all were manually reviewed and ultimately excluded at Phase 4. Prepared by the authors.

Exclusion Breakdown and Full-Text Access

Table 2 details the reasons for exclusion at each phase, accounting for the transitions $392 \rightarrow 182 \rightarrow 80 \rightarrow 44$.

Table 2
Exclusion breakdown by phase and reason

Phase	Exclusion reason	n	Retained
2 – Screening	Off-topic (no metamaterial design)	121	182
	Wrong material type (single-layer, bulk)	58	
	Language other than English	31	
3 – CARS	Low CARS: LOW_PRIORITY (< 45)	29	80
	Low CARS: EXCLUDE (off-scope)	16	
	CARS 45–74 (HIGH_VALUE/SUPPORTING, deferred)	57	
4 – Full text	HIGH_VALUE below CORE threshold (deferred)	36	44
Total excluded		348	44 CORE

Note. Prepared by the authors based on the screening workbooks available in the public repository.

Regarding full-text access, of the 44 core articles, 29 full texts were retrieved and analysed in depth; the remaining 15 could not be accessed because Universidad de las Fuerzas Armadas ESPE, as a public university, does not hold institutional subscriptions to all publisher platforms, primarily paywalled content from Elsevier and IEEE Xplore. These 15 articles were nonetheless retained in the corpus: their inclusion was supported by complete title, abstract, and citation metadata, as well as by cross-referencing their key contributions through citations contained in the 29 accessible full texts. This limitation is explicitly acknowledged as a threat to internal validity.

Results and Discussion

Temporal distribution

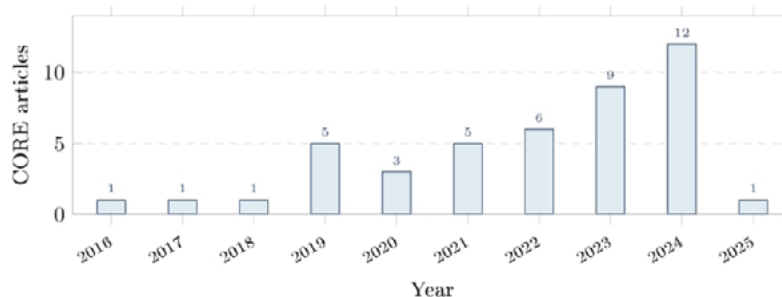
Table 3 and Figure 2 reveal a pronounced acceleration from 2022 onward, with 2024 alone accounting for 27% of the entire corpus. This behaviour reflects the convergence between mature deep learning architectures —particularly Transformer and deep convolutional networks— and the availability of large synthetic datasets generated by semi-analytical solvers (Cai et al., 2023; Teng et al., 2023).

Table 3
Annual distribution of core articles (2016–2025)

YEAR	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	TOTAL
Articles	1	1	1	5	3	5	6	9	12	1	44
% corpus	2	2	2	11	7	11	14	20	27	2	100

Note. Prepared by the authors.

Figure 2
Temporal distribution of core articles (2016–2025)



Note. The number of core articles increases markedly from 2022 onward. Prepared by the authors.

Taxonomy of computational methods and architecture

Eleven distinct methods were identified and organised into two conceptually differentiated layers of the inverse design pipeline. Layer A groups the classical simulation methods, that is, physics-based forward engines that generate the training data —spectrum, displacement field, or temperature map— from a given structural configuration. Layer B groups the deep learning architectures, namely data-driven models that learn to invert the forward map, enabling millisecond inference at deployment time.

This separation is useful for pipeline design: the choice of Layer A engine influences the volume and fidelity of the dataset, while Layer B architecture influences inverse accuracy and generalisation capability. Table 4 presents the complete taxonomy structured accordingly.

Table 4
Computational methods and architectures identified in the 44 core articles, separated by layer

Method	N	Period / domain	Role in the pipeline
Layer A — Classical Simulation (Forward Engines)			
Topology Optimisation	7	2016–24 / EM, Ac, Me	Material density distribution; adjoint gradients
Adjoint Method	2	2019–20 / EM	Efficient gradient in high-dimensional spaces
Finite Element Method	3	2017–23 / Th, Me	Full 3D PDE solver; validation engine
Genetic Algorithm	4	2013–25 / EM, Me	Derivative-free search for discrete layer stacks
Isogeometric Optimisation	2	2022–24 / Me	Spline-based CAD-exact shape optimisation
Layer B — Deep Learning Architectures			
CNN + Optimisation	12	2020–24 / EM, Th, Ac	Spectral forward surrogate; drives tandem loop
Tandem DNN	8	2021–24 / EM, Th	Bidirectional network; resolves one-to-many mapping
Transformer	5	2023–25 / EM	Multi-head attention on broadband spectra
GAN	4	2019–21 / EM	Generative one-to-many geometry synthesis
PINN	3	2021–24 / EM, Ac	Physics (PDE) constraints in the loss function
Diffractive Neural Network	2	2019–20 / EM	Optical layers as neural layers; end-to-end training

Note. EM = electromagnetic/photonic; Th = thermal; Ac = acoustic; Me = mechanical. Prepared by the authors.

Domain distribution and cross-analysis

Table 5 cross-tabulates methods with application domains. The electromagnetic-photonic domain dominates the corpus with 32 of 44 articles (72.7%), concentrating convolutional network-based approaches. The mechanical domain relies more heavily on classical simulation —finite elements, genetic algorithms, and isogeometry— while the acoustic domain exhibits the fastest recent growth, suggesting a potential research opportunity in deep learning-assisted acoustic metamaterial design.

Table 5
Method occurrences across core articles by application domain

Method	Em/phot.	Thermal	Acoustic	Mech.	Total
CNN + Optimisation	9	2	1	0	12
Tandem DNN	6	1	0	1	8
Transformer	5	0	0	0	5
GAN	4	0	0	0	4
PINN	2	0	1	0	3
Diffraction Neural Network	2	0	0	0	2
Topology Optimisation	3	1	2	1	7
Adjoint Method	2	0	0	0	2
Finite Element Method	0	1	0	2	3
Genetic Algorithm	3	0	0	1	4
Isogeometric Optimisation	0	0	0	2	2
Total	36	5	4	7	52

Note. The total sum exceeds 44 because articles employing multiple methods are counted in each of them. Prepared by the authors.

Method–architecture combinations

The dominant pattern identified in the corpus is the convolutional forward-inverse tandem loop, present in twelve articles, in which a convolutional network pre-trained on forward simulations is concatenated with a dense inverse network that maps target spectra to layer parameters (Lininger et al., 2021; Wang et al., 2023; Xiong et al., 2023). It should be noted that the individual studies differ in their datasets, target spectral ranges, and evaluation metrics; direct cross-study performance comparisons are therefore indicative rather than conclusive.

The second most prominent pattern is synthesis based on generative adversarial networks, present in four articles, where the generator directly produces stack geometries (Hodge et al., 2020; Naseri & Hum, 2021). The third corresponds to the Transformer-type spectral model, present in five articles, which in the reviewed studies were applied to long-range spectral dependencies in broadband terahertz and near-infrared problems, although comparative evaluation under equivalent conditions remains an open research task (Cai et al., 2023; Teng et al., 2023).

Physics-informed approaches incorporate Maxwell’s equations or elasticity equations into the training loss function. The reviewed works report dataset reductions of up to one order of magnitude relative to their own purely data-driven baselines (Noureen et al., 2023; Yago et al., 2024); whether this advantage generalises across different layer geometries and solvers requires further study.

Key trends

From standalone networks to hybrid pipelines

Early studies, between 2019 and 2021, deployed simple dense networks trained on small datasets (Chen et al., 2019; García-Esteban et al., 2021). From 2022 onward, the dominant pipeline combined a physics-based forward solver—capable of generating between 10^4 and 10^6 simulations—with a deep learning surrogate model trained on that data (Hu et al., 2024; Knightley et al., 2023). This shift substantially improves generalisation by separating the data generation problem, addressed through numerical simulation, from the inference problem, solved through deep learning.

Emergence of attention mechanisms

The Transformer architecture, originally proposed for natural language processing, has been adapted to spectral inverse design since 2023 (Cai et al., 2023; Teng et al., 2023). Its capacity to capture global correlations across spectral bands may be advantageous in broadband problems where resonances interact throughout the entire spectrum. The self-attention mechanism allows the model to simultaneously weight contributions from all spectral positions, unlike convolutional networks, which operate with local receptive fields that must be stacked to achieve global coverage. In the context of multilayer metamaterials this is particularly relevant, given that a resonance in one spectral band is physically coupled to adjacent bands through the interference conditions between layers.

Physics-constrained learning as a data-reduction strategy

Physics-informed networks and adjoint-integrated networks reduce the required number of forward simulations by incorporating partial differential equation constraints directly into the loss function (Noureen et al., 2023). This is particularly relevant for three-dimensional finite element forward models, where each simulation may take hours. Within their respective experimental settings, the reviewed works individually report training-data reductions relative to their own baselines, with accuracy impacts that the authors characterise as acceptable (Noureen et al., 2023; Yago et al., 2024); the magnitude of these gains is problem-specific and should not be generalised without comparable experimental conditions.

Threats to Validity

Internal validity

The CARS index introduces a citation-count bias that may underrepresent recent high-quality work published within two years of the search date. To partially mitigate this effect, the `cit_pct` component was normalised within the publication-year cohort rather than globally. The two-layer classification of method family may likewise obscure architectural variations within each family; future work should apply a finer-grained taxonomy. The manual relevance indicator, assigned by a single reviewer, introduces reviewer subjectivity; a dual-review protocol with inter-rater agreement assessed using Cohen's kappa measurement is recommended for future replications.

A further threat is partial full-text coverage: 15 of the 44 core articles, equivalent to 34%, could not be retrieved in full for the institutional access reasons already stated. These articles were retained based on abstract and metadata evidence but nuances visible only in the full text—experimental protocols, exact dataset sizes, architecture hyperparameters—may have been missed.

External validity and database bias

The review covers only Scopus and Web of Science. Both databases offer solid coverage of peer-reviewed journals and conference proceedings from Springer, IEEE, and Elsevier, but present limited indexing of: machine learning conference proceedings such as NeurIPS, ICLR, and ICML, where architecturally innovative work is often published before its journal versions; preprint repositories such as arXiv, which may contain the most recent results from the 2024–2025 period; and regional or Spanish-language journals relevant to the Ecuadorian and Latin American research context.

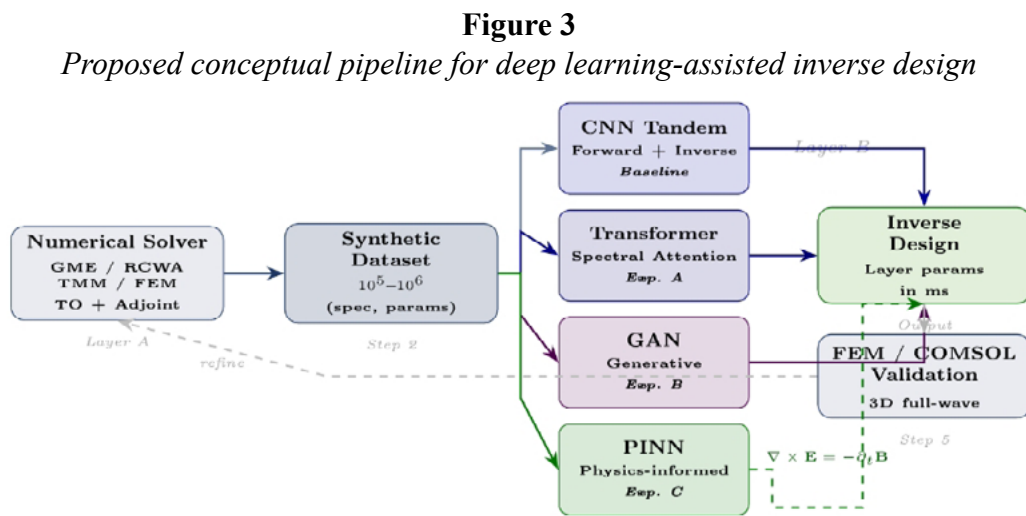
Language and grey literature bias

The search was restricted to English-language records. Although English is the dominant language of scientific publication in this domain, relevant contributions may also have been

published in Chinese and other languages. Likewise, technical reports, doctoral theses, patents, and software documentation were excluded. For a domain that depends on computational tools, this exclusion may underrepresent emerging engineering practices. Future reviews should consider complementary searches in ProQuest Dissertations relevant institutional repositories.

Proposed experimental pipeline

Based on the systematic analysis, the following experimental pipeline is proposed as a research direction for the development of a deep learning training framework oriented to the inverse design of multilayer metamaterials. It must be emphasised that this pipeline has not been implemented or validated; it represents the logical next step derived from the evidence synthesised in the review, and each stage corresponds directly to methods identified in the analysed corpus. Figure 3 illustrates the proposed conceptual architecture.



Note. Layer A corresponds to the numerical solver generating the synthetic dataset; Layer B groups the four deep learning architectures evaluated in parallel. Prepared by the authors.

The first stage corresponds to the forward engine. The guided-mode expansion method implemented in Legume (Zanotti et al., 2024) would be employed to generate between 10^5 and 10^6 input-output pairs, relating layer parameters to reflectance and transmittance spectra for periodic multilayer structures. This method is orders of magnitude faster than full-wave finite element analysis for this geometry class, enabling the large-scale datasets generation.

The second stage consists of dataset construction through systematic Latin hypercube sampling of the layer-parameter space—thickness, fill factor, and refractive index—combined with random geometry augmentation to maximise parameter-space coverage and avoid distribution bias.

The third stage establishes the baseline through a tandem convolutional network: a pre-trained forward model is concatenated with a fully connected inverse network following the architecture of Lininger et al. (2021), during inverse training to promote physical consistency. The fourth and fifth stages contemplate comparative experiments with a spectral-attention transformer model and with a physics-informed network, respectively, followed by validation against full-wave finite element simulations on an independent test set.

Conclusions

This work presented a systematic review under the PRISMA 2020 protocol of 392 records, of which 44 constituted the core corpus, aimed at identifying computational methods and deep learning architectures employed in the inverse design of multilayer metamaterials through deep learning pipelines. The principal findings are as follows.

First, the tandem convolutional network constitutes the dominant architecture, present in 12 of the 44 articles (27%), combining a convolutional forward surrogate with an inverse network; it was therefore selected as the baseline for the proposed experimental pipeline.

Second, transformer-based spectral models represent an emerging trend in the reviewed corpus, with five articles between 2023 and 2025, showing promising results in broadband terahertz and near-infrared problems thanks to multi-head attention over spectral sequences.

Third, the electromagnetic-photonic domain dominates the corpus with 72% of the core articles, while the acoustic domain exhibits the fastest recent growth, suggesting an opportunity for future research.

Fourth, the hybrid strategy articulating physics, data, and learning—guided-mode expansion for large-scale data generation, deep learning for fast inference, and physics-informed networks for data-efficient learning—emerges as the most productive pipeline architecture according to the evidence gathered.

Finally, the open-source Legume implementation of the guided-mode expansion method (Zanotti et al., 2024) and the adjoint-coupled topology optimisation framework emerge as the most scalable forward engines for training-set generation. These findings directly inform the experimental design of the ongoing doctoral research, oriented to the inverse design of multilayer electromagnetic and photonic metamaterials.

Acknowledgements and Declarations

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Data Availability

To support reproducibility and transparency, all screening records, individual CARS scores, inclusion and exclusion decisions, classification workbooks, and the Python pipeline used for automated keyword tagging and CARS computation are publicly available at the following repository: https://colab.research.google.com/drive/1iPGWpBodtOuO_ojaZrm1JE_F4a1-Av93?usp=drive_link

Author Contributions

Following the CRediT taxonomy, the individual contributions were as follows. Laura Malache: conceptualisation, methodology, data curation, writing of the original draft. Federico Rodas: conceptualisation, investigation, formal analysis, writing, review and editing, supervision. Osmani Mujica Pérez: investigation, visualisation, review and editing.

Declaration on the Use of Artificial Intelligence

The authors declare that, in the preparation of this article, artificial intelligence tools have been used. Specifically, Claude (Anthropic) was employed for the following tasks: automated keyword tagging and CARS index computation over the 392 retrieved records, in the Materials and Methods section; extraction and tabulation of method, domain, and year fields from bibliographic metadata, in the Results section; and assistance with document editing and formatting. All scientific interpretation, synthesis, and conclusions are the sole responsibility of the authors. The artificial intelligence model did not generate any scientific claims that are not verifiable in the cited literature.

Conflict of Interest

The authors declare no conflicts of interest relevant to the content of this article.

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