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Review

Artificial intelligence for shallow geothermal systems: A review of ground heat exchanger performance modeling

Danial Sheini Dashtgoli [a,b,c,*], Guillermo A. Narsilio [c], Qusi I. Alqawasmeh [d], Michela Giustiniani [b], Martina Busetti [b], Claudia Cherubini [a,b]

[a] Department of Mathematics, Informatics, and Geosciences, University of Trieste, Trieste, 34128, Italy
[b] National Institute of Oceanography and Applied Geophysics - OGS, Sgonico, Trieste, 34010, Italy
[c] Department of Infrastructure Engineering, The University of Melbourne, Parkville, VIC, 3010, Australia
[d] Civil Engineering Department, Faculty of Engineering, University of Petra, Amman, 11196, Jordan

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ABSTRACT

Shallow geothermal systems are increasingly recognized as a reliable and low-carbon solution for space heating and cooling, with ground heat exchangers (GHEs) serving as the core component for thermal energy exchange between buildings and the subsurface. The performance of GHEs, across boreholes, horizontal trenches, and energy geostructure configurations, is governed by complex, nonlinear interactions involving soil thermal properties, groundwater flow, material configurations, and system design parameters. Conventional modeling techniques often fall short in capturing these nonlinear and site-specific behaviors. In this context, artificial intelligence (AI) has emerged as a powerful tool for improving predictive accuracy, system optimization, and real-time decision-making in geothermal applications. This review presents a systematic assessment of AI applications in shallow GHE technologies, aiming to bridge the gap between geothermal engineering and modern data-driven modeling approaches. A total of 59 peer-reviewed studies were analyzed and classified according to GHE type, main application domain, and AI methodology. The review also includes AI-assisted interpretation of thermal response tests, which play a critical role in characterizing ground thermal properties prior to GHE system design. The analysis reveals two overarching patterns: (i) research efforts are heavily concentrated on borehole thermal-performance prediction, whereas thermomechanical behavior in energy geostructures and system-level operational optimization remain comparatively underexplored; and (ii) modern AI techniques such as physics-informed learning, uncertainty-aware models, reinforcement learning, and digital-twin concepts are rarely adopted, highlighting a clear methodological gap relative to broader AI advances. These findings outline emerging opportunities for next-generation AI frameworks that are physics-aware, uncertainty-quantified, and operationally adaptive.

1. Introduction

Ground heat exchangers (GHEs) are subsurface heat exchange systems that provide ground-source heating and cooling by utilizing the relatively stable underground temperature (Aresti et al., 2018). They are the key component of shallow geothermal heat pump systems, transferring heat between buildings and the ground (Cui et al., 2024a). Common GHE configurations include vertical borehole heat exchangers (BHEs) drilled into the ground, and horizontal ground loops buried at shallow depth (Aresti et al., 2018). Recent innovations also embed GHEs into civil structures, so-called energy geostructures such as foundation piles, tunnel linings, retaining walls, and pavement systems, allowing them to serve as both structural elements and heat exchangers (Loveridge et al., 2020). These systems offer sustainable thermal energy with lower greenhouse gas emissions, but their performance depends on complex ground thermal processes and site-specific factors such as soil thermal properties, groundwater flow, and seasonal

* Corresponding author. Department of Mathematics, Informatics, and Geosciences, University of Trieste, Trieste, 34128, Italy.
E-mail address: dsheinidashtgoli@ogs.it (D. Sheini Dashtgoli).
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loads. Accurately predicting GHE performance and optimizing designs is challenging; as many scenarios lack analytical solutions (e.g. heat transport with groundwater advection or non-linear coil geometries), requiring computationally intensive numerical simulations (Shoji et al., 2022). Artificial Intelligence (AI) methods are increasingly used in such cases. AI techniques can learn complex relationships from data and serve as fast surrogate models, drastically reducing simulation time (Sheini Dashtgoli et al., 2024a, 2026a; Liu et al., 2024; Mojtahedi et al., 2025). They also excel at multi-parameter, multi-objective optimization, helping engineers identify optimal designs that balance energy efficiency and cost. In recent years, a surge of research has applied AI to GHE performance prediction, design optimization, and economic feasibility analysis. These data-driven methods offer promising alternatives to computationally expensive numerical models, enabling faster and more adaptive solutions for complex geothermal systems. This review provides a comprehensive and critical synthesis of current knowledge in this domain, highlighting how AI is advancing GHE technology and where further research is needed.

2. Modern AI techniques for GHE modeling: A focused overview

This section provides a concise introduction to the key AI algorithms used for GHE modeling, starting with classical machine learning (ML) methods, followed by modern deep leaning (DL) architectures, and concluding with advanced and emerging AI techniques that address the multi-scale, data-limited, and physically complex nature of shallow geothermal systems.

2.1. Classical ML models for GHE prediction

Classical ML methods form the foundation of early GHE modeling, offering transparent structures and low computational cost. Linear and polynomial regression provide simple parametric baselines for modeling thermal relationships, with polynomial terms enabling limited nonlinear fitting (Ostertagová, 2012; Su et al., 2012). Support vector regression (SVR) extends traditional regression by introducing margin-based loss and kernel functions, allowing flexible nonlinear modeling with strong generalization (Sheini Dashtgoli et al., 2024b; Rao et al., 2023). Decision trees (DT) partition data into hierarchical rule structures and are valued for their interpretability, though they tend to overfit unless regularized (Duan and Xiao, 2024; Karrari et al., 2025). A major advancement in classical ML is ensemble learning, in which multiple weak learners are combined to improve robustness (Khan et al., 2024). Random forest (RF) aggregates numerous decorrelated decision trees built on bootstrapped samples, reducing variance and enhancing stability in heterogeneous subsurface datasets (Iranzad and Liu, 2025; Mao et al., 2024). Extreme gradient boosting (XGBoost) refines this approach by sequentially training trees to correct prior errors using gradient-based optimization and regularization, achieving high accuracy on nonlinear geotechnical data with efficient computation (Chen and Guestrin, 2016; Arif Ali et al., 2023; Sheini Dashtgoli et al., 2024c). Artificial neural networks (ANNs), although part of the broader neural network family, have historically functioned as classical non-linear predictors in geothermal and geotechnical engineering, relying on multilayer feedforward structures and backpropagation to approximate thermal behavior (Dike et al., 2018; Moayedi et al., 2020). Classical ML methods remain strong baselines in GHE modeling due to their interpretability and efficiency, motivating the transition to more expressive deep-learning and physics-integrated techniques presented in Sections 2.2 and 2.3.

2.2. Deep learning architectures

Deep learning (DL) offers flexible nonlinear mappings that can capture the multi-scale relationships present in shallow GHE systems. Unlike classical models, DL architectures can learn both sequential patterns (such as thermal response test (TRT) and depth-dependent temperature) and high-dimensional feature interactions (such as borehole spacing, geology, and flow conditions). The following groups summarize the main DL approaches relevant to GHE prediction.

2.2.1. Convolutional neural networks

Among DL architectures, convolution-based models provide a natural way to capture localized patterns in GHE datasets. Convolutional neural networks (CNNs), although originally developed for images, are increasingly applied to geothermal tabular data using 1D convolutions and pseudo-2D feature maps (Yang et al., 2023; Zhang et al., 2021b; Zhu et al., 2021). By extracting local interaction patterns, such as depth-wise thermal gradients or short-range borehole coupling, CNNs are effective for both sequential and spatially structured inputs (Gupta et al., 2022; Li et al., 2022). Temporal convolutional networks (TCNs) build on these ideas with dilated convolutions for larger receptive fields (Dudukcu et al., 2023; Fan et al., 2023). More recently, transfer learning (TL) strategies have been explored to reuse convolutional feature extractors trained on related thermal or geotechnical tasks, helping reduce data requirements in domains with limited field measurements (Shima et al., 2024).

2.2.2. Recurrent models for sequential data

For patterns where ordering and temporal or depth-wise progression matter, recurrent architectures are more suitable. Sequential datasets, such as time series measurements, temporally sampled signals, or depth-indexed logs commonly encountered in GHE studies, require models capable of learning ordered dependencies. Recurrent neural networks (RNNs) and their gated variants, long short-term memory (LSTM) and gated recurrent units (GRU), capture directional relationships and nonlinear transitions more effectively than classical autoregressive approaches, making them well-suited for structured sequential patterns (Das et al., 2023; Wang et al., 2024b).

2.2.3. Attention-based and transformer architectures

Because CNNs emphasize local features and RNNs struggle with long-range dependencies due to their sequential processing, attention-based models offer a more flexible mechanism for capturing global relationships (Han et al., 2024; Jiang et al., 2022a; Shih et al., 2024). Transformer architectures use self-attention to learn interactions across all depth or temporal positions (Ge et al., 2024; Youwai and Thongnoo, 2025), overcoming these locality and memory constraints. Their strong performance on irregularly sampled, multivariate forecasting tasks in recent engineering studies (He et al., 2025) highlights their potential for next-generation GHE performance modeling.

2.2.4. Hybrid models

Hybrid DL architectures combine complementary mechanisms to address the individual limitations of CNNs, RNNs, and attention models. CNN–LSTM and CNN–GRU hybrids integrate convolutional feature extraction with recurrent sequence modeling, enabling accurate representation of nonlinear temporal behavior and coupled spatial–temporal patterns (Demiss and Elsaigh, 2024; Kong et al., 2019). More advanced hybrids incorporate attention mechanisms to improve feature weighting and capture long-range dependencies more effectively (Ma et al., 2019; Yang et al., 2021).

Together, these hybrid architectures provide flexible and expressive modeling frameworks, particularly suited for complex GHE-related sequential and spatial–temporal behaviors.

2.3. Advanced and emerging AI methods

Although classical ML and DL models offer strong statistical prediction capabilities, they remain limited when GHE systems require physical consistency, uncertainty awareness, or reliable behavior with sparse data. Advanced and emerging AI methods address these gaps by integrating physics, characterizing uncertainty, augmenting limited datasets, enabling decision processes, and supporting real-time adaptation. This section briefly introduces these methods to provide a clear orientation before their detailed discussion.

2.3.1. Physics-integrated learning

Physics-integrated ML refers to methods that incorporate physical laws directly into neural network training, ensuring predictions remain consistent with governing physical processes (e.g., heat conduction-convection and thermo-mechanical soil–structure interaction) even when field observations are sparse. Unlike conventional statistical models that rely solely on data patterns and do not enforce physical constraints, these approaches introduce physics as an explicit structural component of learning. In geothermal applications, where subsurface measurements are limited, heterogeneous, and strongly constrained by physics, this paradigm provides a principled alternative to purely data-driven modeling. This subsection is organized into four methodological groups: PDE-constrained networks, variational physics-learning, physics-guided neural architectures, and operator-learning models.

2.3.1.1. PDE-constrained neural networks. Physics-informed neural networks (PINNs) incorporate partial differential equation (PDE) residuals, boundary conditions, and constitutive laws directly into the loss function using automatic differentiation, enabling simultaneous data fitting and physics enforcement (Fig. 1a) (Cai et al., 2021; Piere Canilandi et al., 2025). Extended physics-informed neural networks (XPINNs) partition the physical domain into multiple subregions with localized physics losses, improving convergence in stiff, nonlinear, or geometrically complex geothermal problems (Toscano et al., 2025).

2.3.1.2. Variational physics-learning. Variational approaches in Fig. 1b, replace pointwise PDE residuals with weak-form or energy-functional losses, resulting in improved numerical stability for elliptic and parabolic systems and reduced sensitivity to collocation sampling (León et al., 2025; Rojas et al., 2024).

2.3.1.3. Physics-guided neural networks (PGNNs). Physics-guied neural networks incorporate ddomain knowledge through architectural constraints, invariances, or regularization terms inspired by physical behavior. By restricting the hypothesis space, such as embedding monotonicity, conservation structures, or physics-aware penalty terms, PGNNs mitigate overfitting with sparse datasets while maintaining physical consistency (Fig. 1c) (Faroughi et al., 2024; Sheini Dashtgoli et al., 2026b).

2.3.1.4. Operator learning models. Operator learning methods map entire function spaces, such as permeability fields to temperature distributions, rather than solving individual PDE instances (Fig. 1d). Architectures such as deep operator networks (DeepONets), Fourier neural operators (FNO), and physics-informed Kolmogorov–Arnold Networks provide fast emulation of large families of PDE solutions and are particularly well for parametric sweeps, scenario testing, and computationally intensive simulation workflows (Azizzadenesheli et al., 2024; Gonon et al., 2024; Koh and Kim, 2025; Kovachki et al., 2024).

The four main physics-integrated learning approaches each have distinct limitations. PINNs struggle with high-frequency or multi-scale solutions and are highly sensitive to noisy or incomplete data (Luo et al., 2025). Variational PINNs remain dependent on the choice of test-space basis functions, and their loss may converge to zero even when the true PDE error remains large (Rojas et al., 2024). PGNNs can violate physical laws because their training is purely statistical, and they fail to generalize with sparse datasets (Luo et al., 2025). Operator learning models such as DeepONet and FNO are limited to structured data and simple geometries, and their error convergence is fundamentally algebraic rather than exponential (Faroughi et al., 2024).

2.3.2. Uncertainty-aware and trustworthy AI

Modern geothermal workflows increasingly require AI models that deliver predictions, indicate the reliability of those predictions, and assess how safely the models can be deployed. This

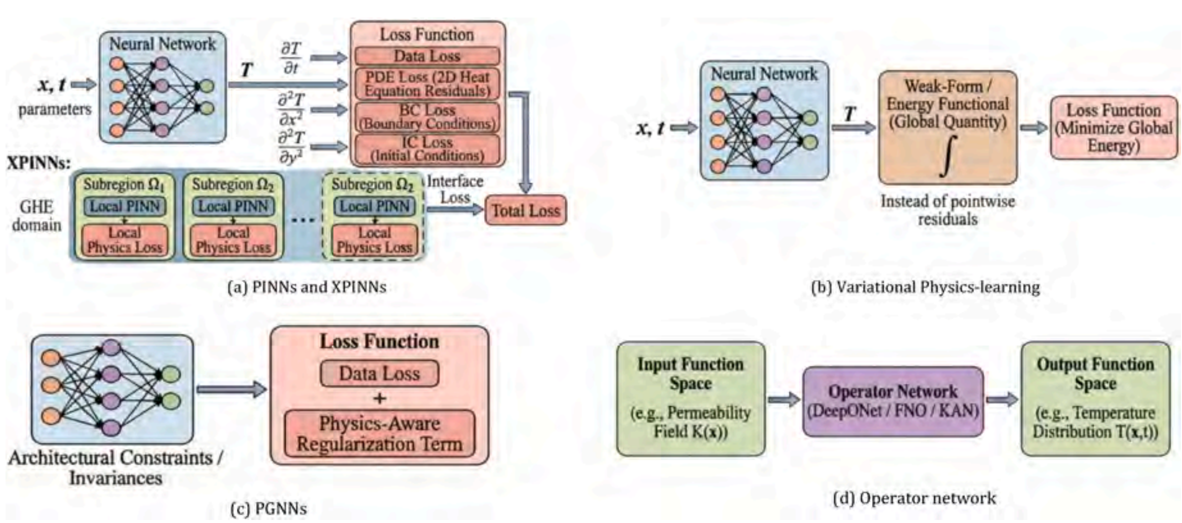

Fig. 1. Schematic illustrations of physics-aware learning frameworks: (a) PINNs/XPINNs, (b) variational physics-learning, (c) PGNNs with architectural constraints, and (d) operator-learning networks.

section introduces two complementary perspectives: methods that quantify predictive uncertainty, and frameworks that ensure models behave robustly and transparently in real-world conditions.

2.3.2.1. Bayesian neural networks (BNNs). Accurate predictions alone are insufficient in geothermal engineering, where sparse, noisy, and heterogeneous subsurface data make model output reliability critical. BNNs address this by producing predictive distributions instead of single estimates, enabling practitioners to distinguish epistemic uncertainty from limited data and aleatory uncertainty from inherent thermal variability (Fig. 2). Recent studies consistently show that calibrated uncertainty intervals support more reliable engineering decisions than deterministic predictions (Alqarafi et al., 2024; Tyralis and Papacharalampous, 2024). Recent scientific-ML studies emphasize that trustworthy deployment requires calibrated models, distribution-aware metrics, and evaluation under noise and perturbations (Siddique et al., 2022). These aspects are crucial for geothermal applications, where uncertainty estimates influence system design, performance evaluation, and long-term operational decisions.

2.3.2.2. Trustworthy machine learning. Trustworthy machine learning (TML) offers a broader perspective by defining the conditions under which ML models can be safely deployed in engineering settings. The literature repeatedly emphasizes key principles: robustness to noise and perturbations, interpretability through attribution or sensitivity analysis, and generalization under distribution shift. These principles form the basis for dependable model behavior (Thuraisingham, 2022; Li et al., 2023; Wei and Liu, 2025). They are especially relevant in geothermal applications, where digital twins must function under evolving subsurface conditions, irregular sensor behavior, and incomplete measurements. As monitoring systems move toward continuous and distributed sensing, concerns such as data integrity, security, privacy, and resilience to data poisoning become increasingly important for long-term reliability (Phoon, 2024; Wei and Liu, 2025b). These considerations are essential for maintaining consistency when models process streaming field data or interact with remote devices. Together, uncertainty-aware methods and TML provide the foundation for next-generation geothermal models that are not only calibrated and uncertainty-aware but also robust, interpretable, and reliable under real operational variability.

2.3.3. Generative AI

Generative AI consists of models that learn data distributions and generate new samples, enabling reconstruction, augmentation, and latent-pattern discovery when datasets are limited. These methods have also demonstrated the ability to recover coherent statistical structures from weakly labeled or unlabeled data (Chen et al., 2024a; Wang et al., 2024b). The following subsections introduce three major generative frameworks –adversarial, diffusion-based, and variational – and their relevance to scientific modeling.

2.3.3.1. Generative adversarial networks (GANs). GANs are a major class of deep generative models that learn complex data distributions through an adversarial game between two networks: a generator that maps latent noise to synthetic samples, and a discriminator that distinguishes real from generated data (Fig. 3) (Ahmad et al., 2024; Bao et al., 2024; Islam et al., 2024; Parsa-Pajouh, 2025). This feedback loop enables the generator to progressively capture the statistical structure of the training distribution (Alqahtani et al., 2021; Pan et al., 2019) and the minimax formulation allows GANs to model multimodal and highly nonlinear patterns without requiring explicit likelihoods (Saxena and Cao, 2022). GAN architectures adapt to multiple data types: convolution-based designs excel for image-like or spatial fields by learning local and hierarchical patterns (Pan et al., 2019), while recurrent or hybrid variants target sequential signals, though long-range dependencies remain difficult (Zhang et al., 2022; Zhang et al., 2022). Beyond generic synthesis, GANs can reproduce high-dimensional spatial structures and generate physically coherent fields, supporting data augmentation and uncertain-parameter representation (Barsha and Eberle, 2025; Chen et al., 2023a). Recent geophysical work shows that GANs can preserve multiscale and anisotropic subsurface patterns more effectively than variational autoencoders or interpolation methods (Baharuddin and John, 2025). Although adversarial training remains prone to instability, mode collapse, and generator–discriminator imbalance (Cobbinah et al., 2025), their ability to capture nonlinear, multimodal behavior and produce realistic synthetic fields makes GANs a practical tool for enriching geothermal datasets and compensating for sparse or heterogeneous subsurface measurements.

2.3.3.2. Diffusion models. Diffusion models offer a structured generative framework in which data are progressively perturbed through a forward noising process and then reconstructed by learning the reverse denoising dynamics. This approach enables

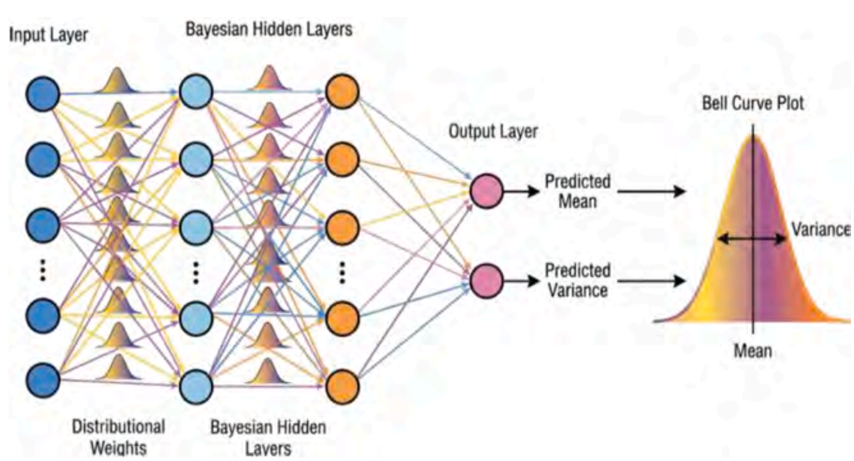

Fig. 2. Conceptual structure of a Bayesian neural network illustrating distributional weights, Bayesian hidden layers, and outputs providing predictive mean and variance.

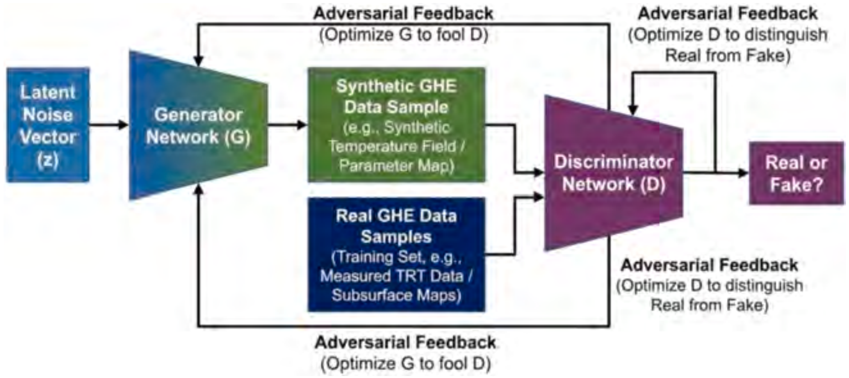

Fig. 3. Overview of a GAN framework generating synthetic GHE data while the discriminator distinguishes real from synthetic samples.

the model to approximate complex and multimodal probability distributions with stable training behavior, an advantage highlighted in comprehensive theoretical analyses of diffusion-based generative modeling (Chen et al., 2024b). Recent developments demonstrate that diffusion models perform well on scientific datasets, including heterogeneous tabular data with complex feature interactions and multimodal distributions that challenge classical generative methods (Li et al., 2025; Shi et al., 2025). Their flexibility in capturing joint distributions without predefined assumptions makes them a promising tool for high-dimensional structured data. However, adapting them to geothermal contexts, requires careful feature encoding, noise scheduling, and sampling strategies for mixed numerical and categorical tabular inputs (Wang et al., 2024a). For sequential or time-dependent data, conditioning mechanisms must preserve temporal dependencies throughout the forward and reverse processes (Su et al., 2025). Ensuring statistical validity and physical plausibility remains essential, as emphasized in broader evaluations of augmentation workflows (Cui et al., 2024b; Leng et al., 2025). A schematic (non-real) illustration of the diffusion-model workflow for both numerical tabular data and image-based fields is shown in Fig. 4.

2.3.3.3. Variational autoencoder (VAE). VAE is a probabilistic extension of the classical autoencoder that learns smooth, low-dimensional latent representations of high-dimensional data through an encoder–decoder architecture (Wei et al., 2020). As shown in Fig. 5, unlike deterministic autoencoders, VAEs encode each input as a distribution with learnable mean and variance, enabling sampling-based reconstruction and making them true generative models capable of producing plausible variations of physical fields (Akkem et al., 2024). VAEs have been successfully used to model complex subsurface features, including fractures and non-Gaussian structures, while conditional variants help maintain physical plausibility by linking generation to relevant operational constraints (Bacsa et al., 2025; Chen et al., 2023a, 2023b; Lotfollahi et al., 2020; Nakata et al., 2025). They support dimensionality reduction, prior-model construction, uncertainty-aware prediction, and data-assimilation workflows in geoscience (Chen et al., 2023c). Their main limitation is the tendency toward overly smooth or blurry outputs due to Gaussian latent assumptions, which can mask sharp geological boundaries (Deng et al., 2024).

2.3.4. Large language models (LLMs)

LLMs are transformer-based models that learn rich semantic structures from large text corpora and can be adapted to engineering tasks through prompting, retrieval augmentation, or lightweight fine-tuning (Fan et al., 2025; Wang et al., 2025). Recent studies in geoscience show that LLMs can integrate heterogeneous sensing data and geological knowledge using vector embeddings and knowledge-graph reasoning (Xu et al., 2024), and they effectively process mixed-format technical inputs such as logs, reports,

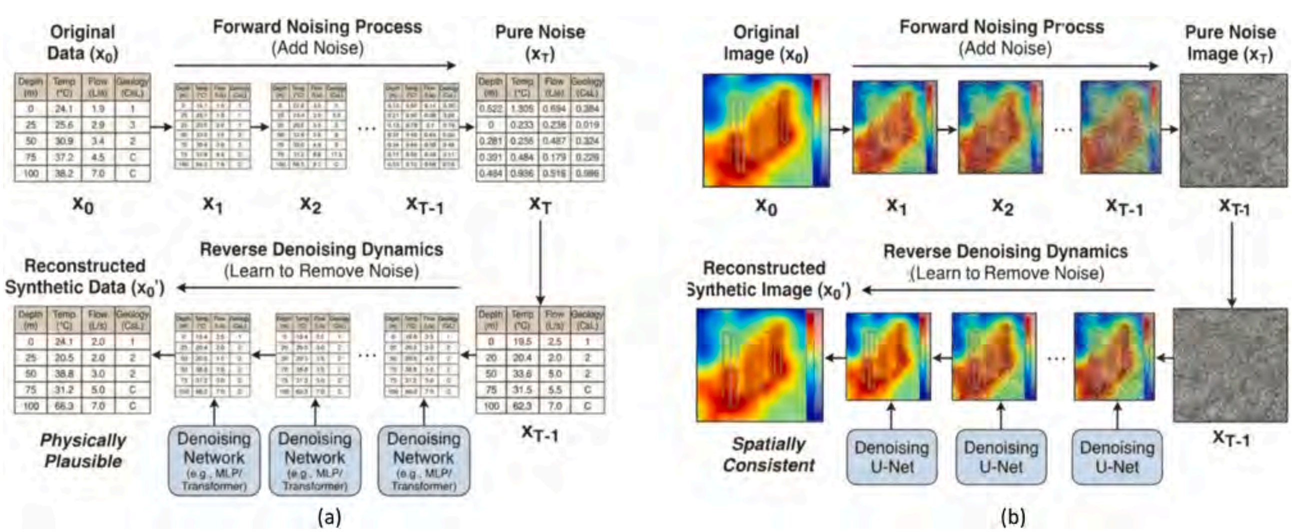

Fig. 4. Schematic illustration of a diffusion-model workflow: (a) Example for numerical tabular data, and (b) Example for image-based fields.

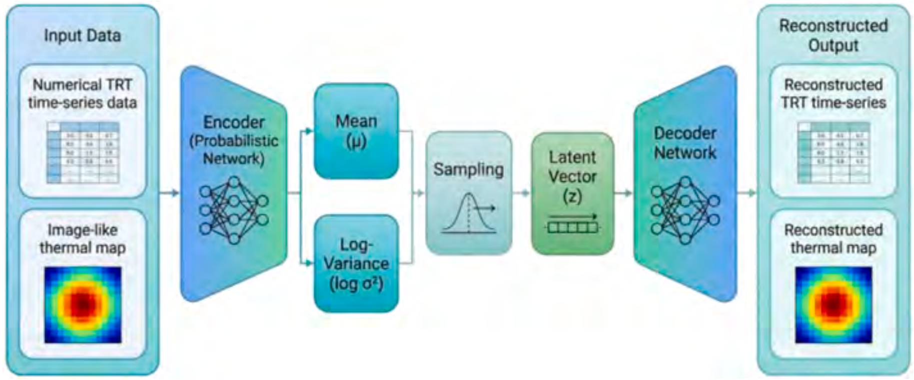

Fig. 5. Schematic of a VAE that encodes GHE data into a latent space and reconstructs time-series or thermal maps through probabilistic sampling.

and serialized numerical tables (Kumar, 2024; Ouko et al., 2025). Their main strengths are unifying textual and numerical information and operating reliably in data-sparse scenarios where classical ML struggles. Key limitations persist, including hallucination, inconsistent numerical reasoning, strong prompt sensitivity, and the absence of embedded physical constraints, highlighting the need for strict validation and domain oversight (Chen et al., 2024a; Fan et al., 2025; Xu et al., 2025). Although not yet applied to GHE modeling, recent geothermal studies show that LLMs can already support complex computational workflows, indicating clear potential for future integration into advanced geo-energy modeling ecosystems (Harsuko et al., 2025). Fig. 6 provides, as an illustrative example, a schematic of how an LLM could process heterogeneous GHE data sources and generate structured engineering outputs.

2.3.5. Reinforcement learning (RL)

RL offers a sequential decision-making framework in which an agent learns optimal actions through interaction and reward feedback, formalized by Markov Decision Processes that represent system states, actions, transition dynamics, and rewards (Fig. 7) (Gutiérrez-Oribio et al., 2025; Stavrev and Ginchev, 2024). In engineering and energy systems, RL agents typically use numerical simulators or surrogate models to generate experience for policy improvement (Hu et al., 2024a). Two main algorithmic families dominate practice: value-based methods such as Q-learning and deep Q-networks for discrete operational decisions (Clifton and Laber, 2020; Hanif et al., 2025; Yang et al., 2024), and policy-gradient or actor–critic approaches that provide more stable

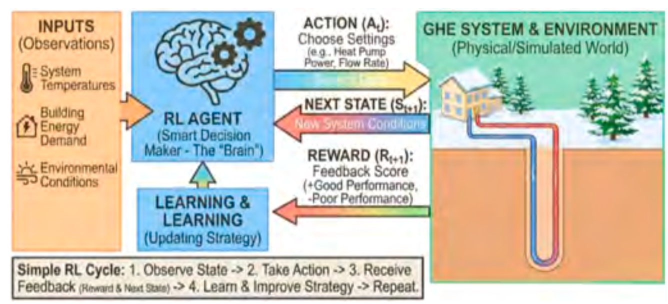

Fig. 7. Reinforcement learning framework where an agent optimizes GHE operation by interacting with system states, actions, and reward feedback.

performance in nonlinear, continuous-control environments (Michailidis et al., 2025a; Prudencio et al., 2023). Key challenges remain, including the need for large simulated training episodes, sensitivity to reward design, and transfer gaps between simulated and real environments (Abdalla et al., 2023; Yu et al., 2025). Despite these limitations, RL remains a promising approach for shallow geothermal systems because of its interaction-driven learning capability, adaptability to evolving dynamics, and effectiveness in managing delayed thermal responses. This makes it particularly suitable for dynamic load management, real-time optimization, and long-term decision-making.

2.3.6. Digital twins for real-time modeling

Digital twins create a continuously updated virtual counterpart of a physical system by integrating sensor data with computational

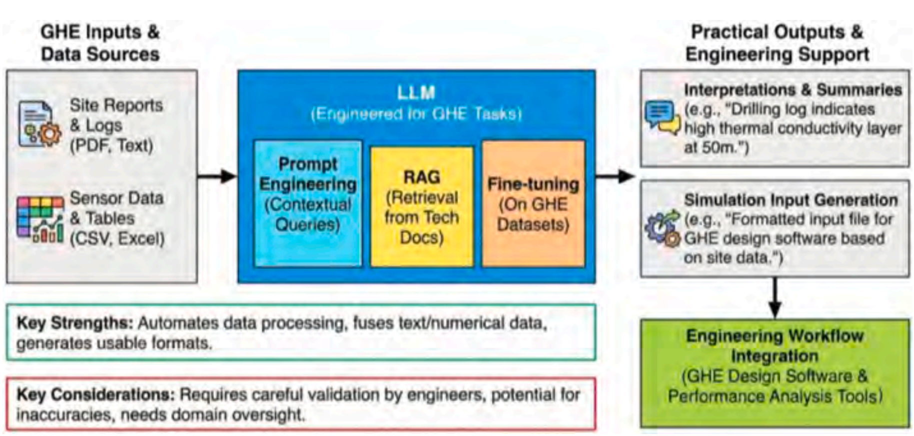

Fig. 6. Illustrative schematic showing how an LLM processes mixed geothermal inputs into structured engineering outputs.

models, using three linked components: the instrumented physical asset, a virtual model (for example, a thermo-hydraulic–mechanical model), and a synchronization layer that enables real-time bidirectional data exchange (Fig. 8) (Guan and Wang, 2024; Pang et al., 2024; Semeraro et al., 2025). Their real-time capability relies on fast surrogate models that approximate high-fidelity simulations and can be adaptively refined as new observations arrive (Lyu et al., 2025; Mahmoud et al., 2025), along with data assimilation techniques, Bayesian updating, filtering, and probabilistic state estimation, which align the virtual model with evolving field measurements (Cotoarbă et al., 2025; Tao et al., 2024). These features enable real-time performance monitoring, rapid scenario evaluation, anomaly detection, and predictive maintenance. Key challenges remain, including dependence on dense and reliable sensor networks, communication stability, and the risk of surrogate-model drift when system behavior moves beyond the training domain (Adebiyi et al., 2024; Kreuzer et al., 2024; Song et al., 2024). Data assimilation can become unstable under sparse or noisy measurements, and integrating heterogeneous datasets remains difficult (Guan and Wang, 2024). Even so, digital twins provide a robust foundation for responsive, data-driven, and uncertainty-aware decision support in geothermal systems.

3. Analysis of AI applications in GHEs

Building on the methodological and algorithmic foundations outlined in the preceding sections, this section reviews how AI has been applied within the GHE domain. First, the research methodology is introduced, and the data collection process is described. Second, trends in AI adoption are analyzed, with particular attention to the increase in publications and the development of applied algorithms. Finally, the utilization of AI across various types of GHEs is examined.

3.1. Research method and data collection

To assess the adoption of AI algorithms in the design and performance prediction of GHE systems, a systematic search was conducted in the Web of Science Core Collection using targeted keywords related to AI, ML, DL, and GHE. As of March 18, 2025, the search initially returned 112 articles, which were individually reviewed to confirm their explicit focus on AI applications in GHE systems. After a rigorous screening process, 59 peer-reviewed journal articles were selected for comprehensive analysis, ensuring a focused review of AI methodologies in GHE research. These studies reflect the diverse implementation of AI across various GHE configurations, including BHEs, horizontal ground heat exchangers (HGHEs), and energy geostructures that integrate geothermal functionality within civil infrastructure. In the context of energy geostructures, AI has been used to enhance the performance of energy piles, energy tunnels, energy walls, and geothermal pavements. The following sections provide an in-depth discussion of these applications, detailing how AI advances GHE technology through predictive modeling, system optimization, and data-driven decision-making.

3.2. Trends in AI applications for GHEs: research growth and algorithm evolution

Fig. 9a illustrates the trend in publications on the integration of AI in GHE research from 2008 to 2025, compared with the overall number of AI-related publications during the same period. Until 2021, studies combining AI and GHE were minimal, rarely exceeding two publications per year. However, a notable increase occurred in 2022, with annual growth rates of 250%, 43%, and 60% recorded in 2022, 2023, and 2024, respectively. Meanwhile, the total number of publications in the broader field of AI also showed continuous growth, rising steadily from approximately 87,000 in 2010 to over 240,000 by 2022. This parallel growth underscores not only the accelerating interest in applying AI within the GHE domain but also reflects a broader global surge in AI-related research. Fig. 9b shows the distribution of GHE-related studies by field of application. BHE accounts for the majority with 32 studies (58.2%). HGHE comprises 5 studies (9.1%). Energy geostructures, including energy piles (10 studies), geothermal pavements (4 studies), energy tunnels (2 studies), and energy walls (2 studies), collectively represent 32.7% of the total (18 studies). This highlights that while BHE systems dominate the literature, energy geostructures as a group also constitute a significant portion, indicating their growing relevance in geothermal energy research. Even in areas with higher publication counts, such as BHEs, HGHEs, energy piles, and geothermal pavements, research remains limited, with significant room for further advancement. Energy tunnels and energy walls are among the least explored, with only two studies each, emphasizing the need for more research. Additionally, other energy geostructures, such as energy slabs and energy retaining walls, are either underrepresented or entirely absent, presenting further opportunities for investigation.

Fig. 10a shows the evolving trends in AI algorithms used in GHE research from 2008 to 2025. Early research was limited and primarily relied on ANN, which remained dominant for much of the

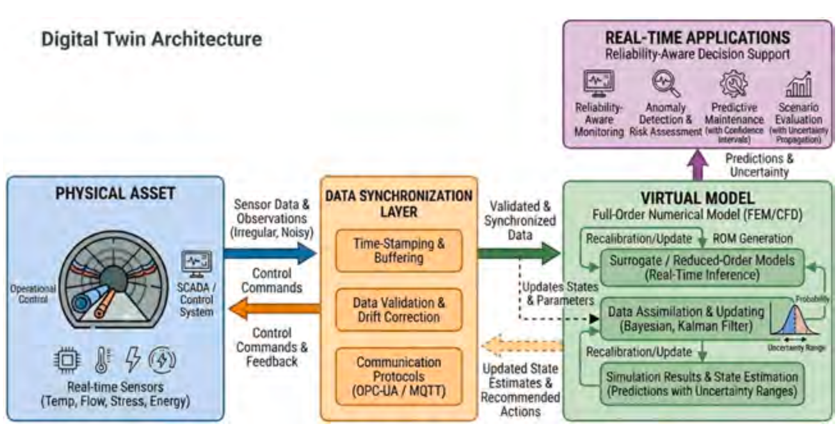

Fig. 8. Schematic digital-twin workflow illustrating sensor data acquisition, synchronization, virtual modeling, and real-time decision support for GHE systems.

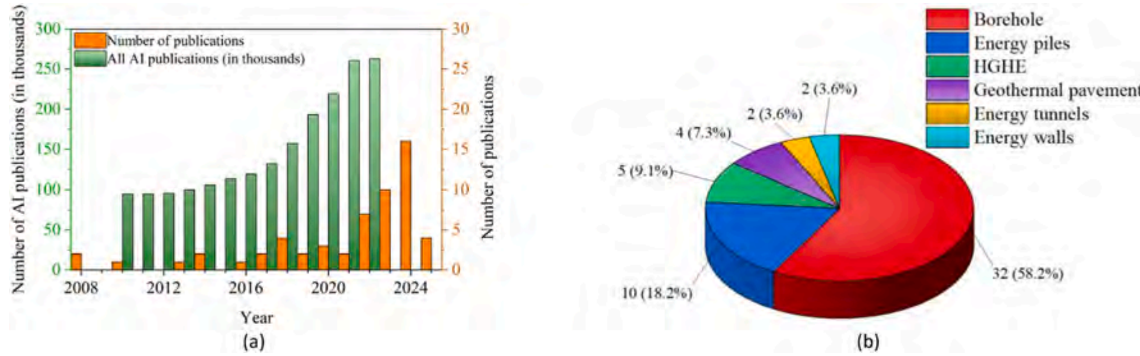

Fig. 9. (a) Trends in AI applications in GHE research (2008–2025) (this study) compared to overall AI publications (Maslej et al., 2024), and (b) Distribution of AI studies across GHE types.

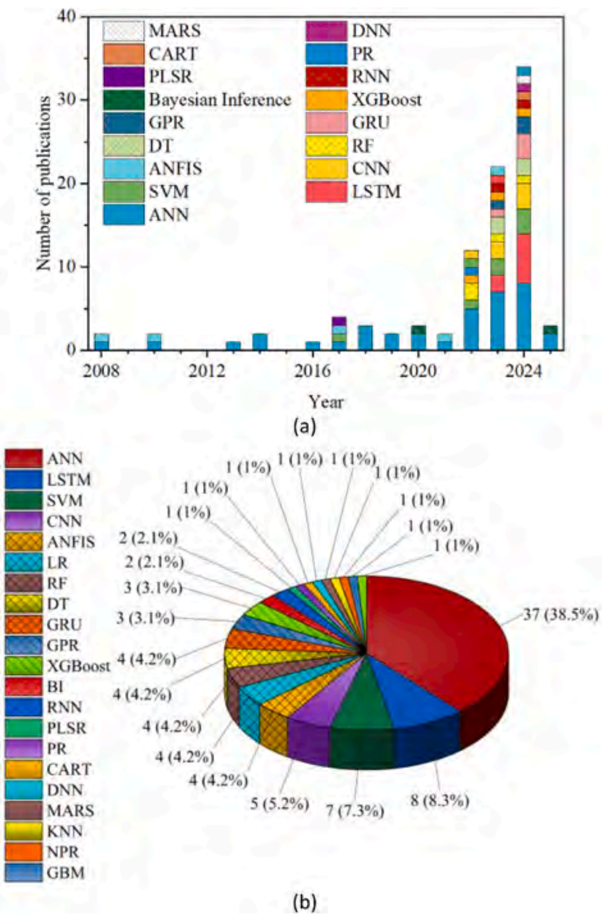

Fig. 10. (a) Temporal trends in AI algorithms in GHE-related research, and (b) Frequency distribution of AI algorithms used in GHE studies.

period. No until 2022 did a notable diversification in AI methods begin to appear. From 2022 onward, there was increasing adoption of sequential and recurrent models, particularly LSTM and GRU, followed by RNN in 2024. These models indicate a shift toward time-series analysis and forecasting applications in geothermal systems. In parallel, CNN appeared in 2023, highlighting its relevance for spatial data processing and pattern recognition within GHE contexts. Tree-based ensemble algorithms such as RF and XGBoost also gained popularity after 2022 due to their robustness and interpretability. SVM, present across several years, continued to play a key role in classification and regression tasks. Emerging methods like reinforcement learning (RL) and Bayesian inference (BI) were introduced in 2023 and 2024, reflecting growing interest in adaptive control and uncertainty-aware modeling. Meanwhile, ANFIS has maintained a steady presence throughout the years, valued for its interpretability and hybrid fuzzy-neural architecture. Overall, while ANN (38.9%, 37 studies) remains the most widely used algorithm, it is followed by LSTM (8.4%, 8 studies) and SVM (7.4%, 7 studies). Other notable methods include CNN (5.3%, 5 studies), ANFIS, LR, RF, DT, and GRU (each with 4 studies, 4.2%) (b). The emergence of BI, RNN, and XGBoost further highlights the ongoing diversification and sophistication of AI methods applied in GHE research.

3.3. AI applications across GHE types

This section summarizes AI applications across the main GHE types and groups the reviewed studies by their primary task and methodology. The goal is to highlight cross-type trends and consolidate the evidence in focused summary tables.

3.3.1. Borehole heat exchangers

Vertical ground heat exchangers or BHEs, are essential components of closed-loop geothermal systems, especially in areas with limited land or unsuitable soil conditions for horizontal heat exchangers (Aresti et al., 2018). These systems typically use single or double U-tube and coaxial configurations, each with trade-offs in thermal and hydraulic performance (Harris et al., 2022; Zanchini et al., 2010). Borehole performance depends on pipe arrangement, backfill material, installation depth, and grout thermal properties, requiring careful material selection to improve efficiency improvements (Dong et al., 2024; Düber et al., 2023; Jiang et al., 2022b; Magdic et al., 2023; Zhang et al., 2022). Fig. 11 shows a schematic representation of a BHE system, illustrating heat extraction from ground for space heating in winter and heat rejection to ground for space cooling in summer.

Traditional numerical models, though reliable, are often impractical for real-time applications. AI-based approaches offer faster, more efficient solutions, enabling improved system design and operation. A key AI application in BHE research is thermal response prediction, particularly in estimating g-functions, which define borehole heat transfer characteristics. Conventional models are computationally intensive, but Pasquier et al. (2018) showed that ANNs can predict short-term g-functions 10,000 times faster than traditional numerical methods, with negligible error. Additionally, Cimmino et al. (2024) improved g-function discretization, reducing errors by 97% while significantly lowering computation time. AI has also been applied to system efficiency evaluation and predictive control. Esen and Inalli (2010) used ANN and ANFIS to

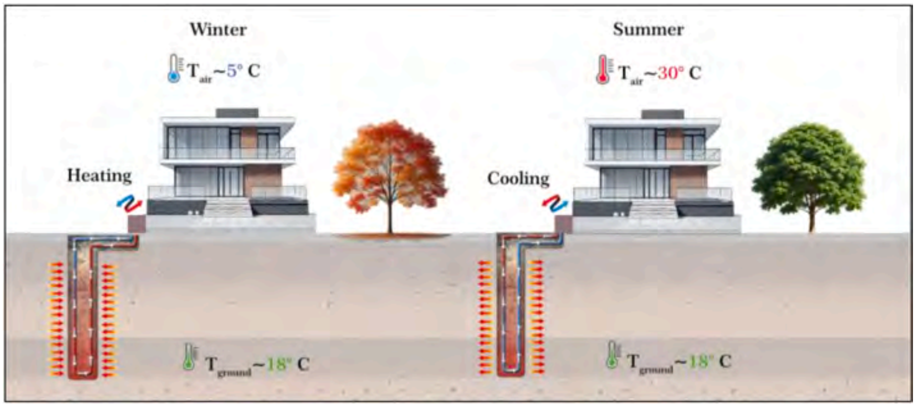

Fig. 11. BHE system illustrating building heating in winter and building cooling in summer.

predict the coefficient of performance (COP) in GSHPs, showing that ANFIS outperformed ANN in accuracy and reliability (Fig. 12).

Mahmoud et al. (2025) introduced a digital twin model that integrates formal concept analysis and relation concept analysis to enhance predictive maintenance and performance monitoring (Fig. 13).

In geothermal system optimization, AI has been used to enhance cost-efficiency and adaptive control. Ahmed et al. (2023)

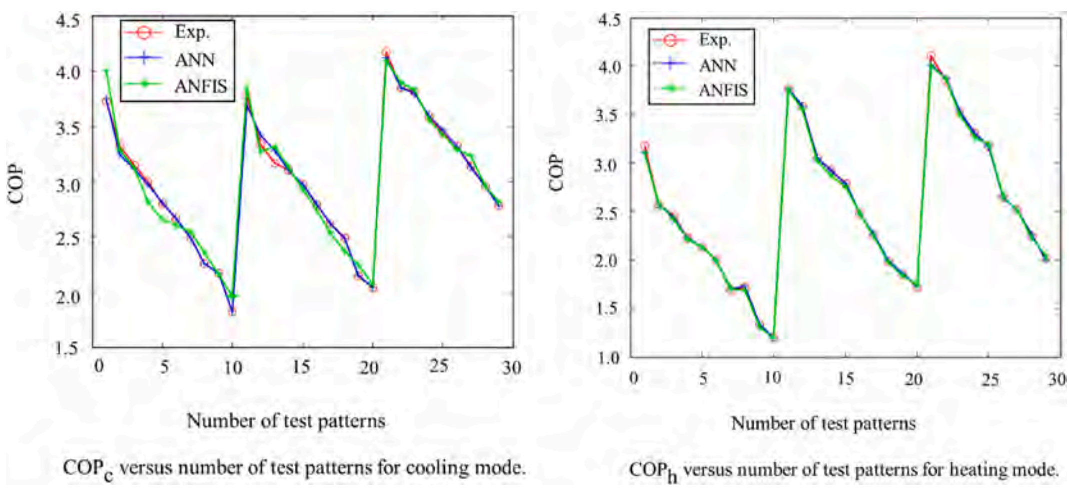

Fig. 12. Prediction of COP (c: cooling; h: heating) for BHE using ANN and ANFIS (Esen and Inalli, 2010).

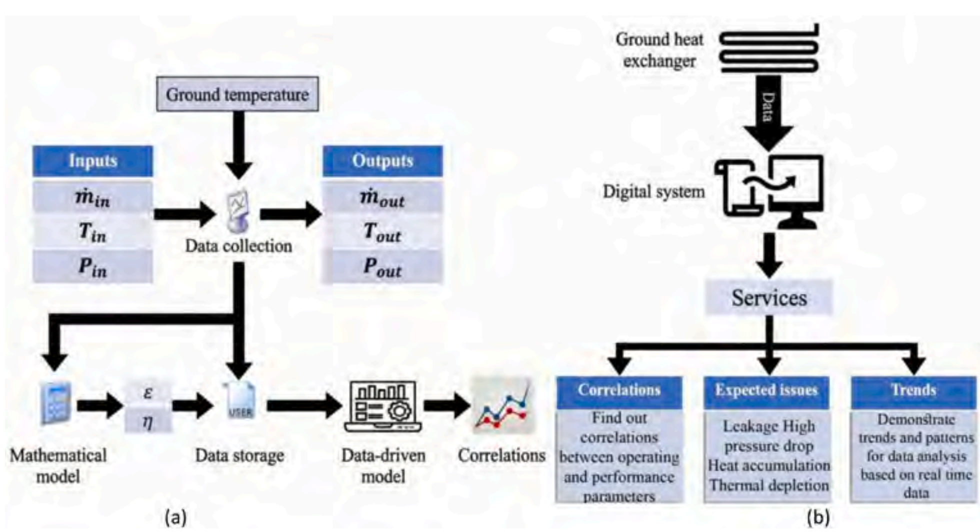

Fig. 13. Digital twin for BHEs (Mahmoud et al., 2025) (a) The digital system layout for a GHE, and (b) The services provided by the digital system.

optimized the performance of borehole-coupled heat pumps (BCHPs) using ANNs, reducing costs by 20%. Similarly, Puttige et al. (2022) applied AI to optimize hybrid ground source heat pumps (GSHPs), achieving significant cost reductions and CO2 savings. Energy usage prediction and load forecasting have also improved with AI. King et al. (2024) used a CNN-RNN hybrid model to predict long-term BHE outlet temperatures, achieving high accuracy (coefficient of determination $R^2 = 98.75\%$), making it a valuable tool for predictive geothermal control (Fig. 14).

AI has also been used in boreholes and soil thermal property estimation. Pasquier and Marcotte (2020) combined BI with ANN to estimate borehole thermal resistance, reducing uncertainty by 16% and accelerating calculations 2500 times. Similarly, Li and Peng (2025) applied Bayesian optimization, achieving less than 2% error in borehole resistance predictions. Overall, AI applications in BHEs have impacted geothermal modeling by offering faster computations, improved efficiency, and enhanced predictive accuracy. A summary of AI-based studies applied to BHEs is presented in Table 1.

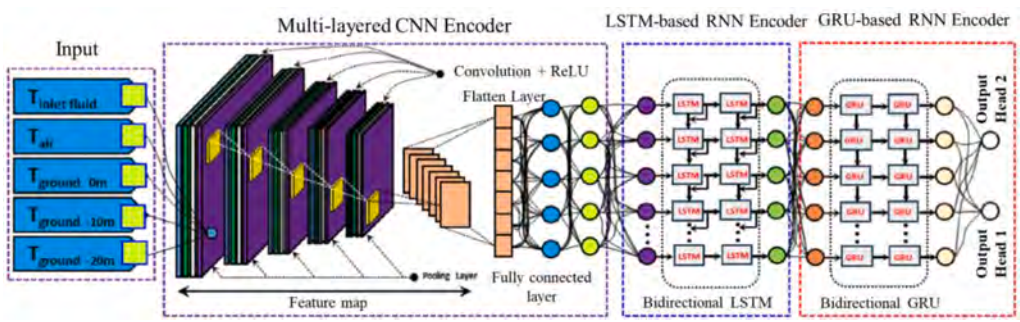

Fig. 14. Typical architecture comprising a multi-layered CNN encoder, an LSTM-based RNN encoder, and a GRU-based RNN decoder (King et al., 2024).

Table 1
Summary of AI-based studies applied to BHEs.

Reference	Specific Topic	Algorithms	Inputs	Outputs	Insights
Pasquier et al. (2018)	Short-term g-function construction for BHEs	ANN	Thermal properties (soil conductivity, grout conductivity, heat capacity), borehole geometry (radius, depth, pipe spacing), fluid circulation rate, and simulation time	Short-term thermal response (g-function values) for the borehole outlet temperature	ANN-based g-function construction achieved millisecond predictions, 10,000x faster than numerical methods, with a max absolute error of 0.006 °C.
Shoji et al. (2022)	Fast G-function computation for BHE design	ANN	Borehole temperature, heat injection rate, groundwater flow, geometric parameters	G-function approximation for BHE performance prediction	ANN reduced computational time by 90%
Cimmino et al. (2024)	Optimal discretization of geothermal boreholes	ANN	Borehole depth, borehole spacing, borehole geometry, soil thermal properties, steady-state borehole wall temperatures	Optimal discretization strategy for BHE segments, prediction of g-function values	ANN-based discretization cut g-function error by 97% and reduced computation time by 4 orders of magnitude, improving geothermal design efficiency.
Mahmoud et al., 2025	Digital twin modeling for GHEs	Formal concept analysis (FCA), Relation concept analysis (RCA)	Ground temperature, inlet/outlet fluid temperatures, flow rates, pressures	GHE effectiveness (ε), efficiency (η), predictive alerts (issues detection), trend analysis, correlations between parameters	DT improved monitoring and predictive maintenance, detecting leakage, pressure drops, and heat accumulation, while FCA and RCA optimized GHE performance.
Esen and Inalli (2010)	Performance evaluation of vertical GSHP	ANN, ANFIS	Borehole depth, pipe diameter, flow rate, load demand	Predicted COP for different borehole configurations	ANN and ANFIS showed high accuracy ($R^2 = 0.9999$), with ANFIS outperforming ANN in reliability.
Fannou et al. (2014)	Performance modeling of DX geothermal heat pumps	ANN, MLP, Levenberg-Marquardt (LM)	Inlet/outlet temperatures and pressures of geothermal evaporator, condenser inlet water temperature, compressor discharge pressure	Heating capacity (kW), compressor power consumption (kW)	ANN (LM, 28 neurons) achieved $R^2 = 0.9994$ for compressor power and 0.9989 for heating capacity, enhancing real-time DX heat pump control.
Kose and Petlenkov (2016)	Neural network-based system identification for GSHPs	nonlinear Autoregressive model with eXogenous inputs (NARX)	Inlet/outlet temperatures, borehole depth, operational heat loads, ambient temperature, historical data	Predicted ground temperature (°C), GSHP energy efficiency, system optimization parameters	NARX NN achieved the lowest MAE (0.0168), improving GSHP control strategies and real-time optimization.
Zhuang et al. (2017)	Predicting heat transfer in GCHP systems	- Partial least squares regression- SVR- M5 model Tree	Borehole parameters: arrangement, radius, depth, vertical spacing, column spacing, number, thermal conductivity coefficient - U-tube parameters: nominal external diameter, spacing - Ground parameters: temperature, thermal conductivity - Circulating liquid parameters: flow rate, composition	Predicted heat transfer performance of GHE over 10 years - Estimated average heat exchange rate, ground temperature variations, and inlet temperature of heat pump unit	SVR and M5 Model Tree accurately predicted GHE heat transfer; M5 had the best RMSE (0.09) and MAE (0.06).

Table 1 (*continued*)

Reference	Specific Topic	Algorithms	Inputs	Outputs	Insights
Lee et al. (2019)	ANN-based performance prediction for BHEs in MPC	ANN- LM	Previous outlet fluid temperatures, current and previous heat extraction rates, cumulative heat extraction	Predicted outlet fluid temperature (°C) of BHE	ANN (R^2 = 0.9999, RMSE = 0.0053 °C, CVRMSE = 0.04%) performed 569x faster than numerical models, making MPC feasible.
Kharseh et al. (2020)	Estimating ground temperature around BHEs using ANN	ANN - LM	Groundwater velocity - Ground diffusivity - Ground porosity - Heat injection rate - Distance from borehole - Time elapsed	Predicted ground temperature around BHEs	ANN (99% accuracy) optimized borehole spacing, reducing thermal interference and improving nonlinear heat transfer modeling.
Pasquier and Marcotte (2020)	Bayesian inference & ANN for TRT heat capacity estimation	ANN, Bayesian Inference	Ground thermal properties (conductivity, heat capacity), borehole thermal response data, inlet/outlet temperatures, flow rate	Estimated volumetric heat capacity (MJ/m^3·K), thermal conductivity, borehole thermal resistance	Bayesian inference with ANN cut TRT heat capacity uncertainty by 16.3% (ground) and 13.8% (grout), accelerating likelihood computations 2500x.
Ahmed et al., 2023	ML-based design & control of BCHP systems	ANN, SVM, DT, Deep Learning Models	Borehole depth, groundwater flow, soil thermal properties, operational heat loads, system configurations	Optimized BCHP performance, predictive control strategies, energy savings (%)	ANN optimization cut BCHP costs by 20%, boosted efficiency, and enabled real-time adaptive control.
Gang and Wang (2013)	Predictive ANN models for hybrid GSHP control	ANN, LM	Inlet/outlet water temperatures, ground temperature, heat pump operational parameters, cooling load, historical temperature data	Predicted exit water temperature from BHE (°C)	ANN-based control reduced energy use, improving efficiency (absolute error <0.2 °C) vs. schedule-based methods.
Gang et al. (2014)	ANN-based control for hybrid GSHP systems	ANN-LM	Inlet/outlet water temperatures, ground temperature, cooling load, operation time, historical temperature data	Predicted exit water temperature from BHE (°C), energy savings (%)	ANN-based control improved HGSHP efficiency, achieving RMS <0.5 and better thermal balance.
Puttige et al. (2020)	Hybrid analytical-ANN modeling for BHEs	Hybrid ANN model	Inlet temperatures, mass flow rates of current and past 24-h period, analytical model output (borehole wall temperature, heat load), hours since last analytical output	Heat loads of borehole groups (kW)	Hybrid ANN cut RMSE to 6% (vs. 22% for analytical, 12% for best pure ANN), integrating long-term analytical with short-term ANN accuracy.
Puttige et al. (2022)	Optimization of hybrid GSHPs in district heating/cooling	ANN	Borehole inlet temperatures, mass flow rates, ground thermal properties, historical heat extraction/injection rates	Hourly heat extraction/injection rate of BHE (kW), compressor power consumption (kW)	ANN hybrid model (MAE <5%) reduced errors, saving € 64,000 annually and cutting CO_2 by 92 tons/year while stabilizing ground temperature.
Ahmed and Zhang, 2023	Impact analysis of hybrid deep learning for BHEs	Hybrid DL models: LSTM-CNN, GRU-CNN, CNN-LSTM, CNN-GRU; Shapley Additive Explanations (SHAP)	Inlet/outlet fluid temperatures, mass flow rate, ambient temperature, solar radiation, wind speed	Outlet fluid temperature (°C)	LSTM-CNN (RMSE = 0.37 °C) achieved top accuracy; SHAP identified inlet temperature as most influential, avoiding overfitting.
King et al. (2024)	Long-term BHE outlet temperature forecasting using CNN-RNN	CNN, RNN	Inlet fluid temperature, ambient air temperature, subsurface temperatures at 0m, 10m, and 20m depths	Predicted outlet fluid temperature (°C)	CNN-RNN outperformed LSTM, CNN, and Simple RNN (R^2 = 98.75%, RMSE = 0.818, MAE = 0.642, AARE = 0.0305), improving long-term predictions.
Hemmatabady et al. (2022)	Enviro-economic optimization of solar-geothermal systems	ANN + multi-objective optimization	Borehole configuration, thermal properties, energy demand, economic costs	Optimized geothermal and hybrid system layouts	Solar-assisted geothermal systems cut emissions by 60%.
Fu et al. (2023)	Optimizing heat extraction in Spiral Fin Coaxial BHEs	GA, BPNN, Q-learning-based marine predator algorithm	Structural parameters (fin height, pitch, number of fins, vortex generator spacing, inner tube insertion depth), operating conditions (inlet/outlet temperatures, flow rate)	Optimized heat extraction rate (W), maximum fluid temperature increase (K), improved efficiency (%)	Optimized SFCBHE boosted heat extraction by 30.8% and max temperature by 26.8K, with GA–BPNN–QLMPA improving efficiency.
Chaoran and Chanjuan (2024)	Surrogate modeling for GSHP heat extraction optimization	XGBoost, particle swarm optimization (PSO)	Borehole depth, runtime, standby time, inlet/outlet temperatures, ambient temperature	Heat extraction rate (kWh), optimized COP, maximum extractable heat (Qedge)	XGBoost (R^2 = 0.990) cut computation time, while PSO optimized COP and predicted auxiliary heating needs.
Alexis Sazon et al. (2024)	Operational optimization of solar-assisted GSHPs	ANN	Evaporator fluid flow rate and temperature, gas cooler fluid flow rate and temperature, gas cooler pressure, desired setpoint temperature	Heat pump power consumption (W), total heat output (W), gas cooler outlet temperature (°C), evaporator outlet temperature (°C)	ANN surrogate model ran 6–15x faster than Modelica, reducing weekly costs by 12–58% via real-time optimization.
King and Yune (2024)	BHE thermal resistance prediction & optimization	Deep feedforward neural network (DFNN)-GA	Thermal conductivity of pipe, grout, ground; borehole depth, pipe diameter, fluid velocity, heat transfer rate	Predicted borehole thermal resistance (Rb,3D) and internal resistance (Ra,3D)	DFNN-GA (R^2 = 99.15%) outperformed RSM (R^2 = 87.90%), improving BHE thermal resistance predictions.

(*continued on next page*)

Table 1 (*continued*)

Reference	Specific Topic	Algorithms	Inputs	Outputs	Insights
Li and Peng (2025)	Multi-objective optimization for BHE parameter estimation	Bayesian Inference	Ground thermal properties (conductivity, heat capacity, borehole thermal resistance, grout properties), measured inlet/outlet fluid temperatures	Estimated borehole thermal resistance (m·K/W), soil thermal conductivity (W/m·K), grout thermal diffusivity (m^2/s), and soil thermal diffusivity (m^2/s)	Stepwise optimization achieved <2% error for borehole resistance, <4% for soil conductivity, validating Bayesian inference.
Chen et al. (2018)	ANN-based depth prediction for BHEs	ANN	Soil thermal conductivity, grout conductivity, inlet water temperature, heat flux	Predicted borehole depth	ANN (LM) achieved high accuracy in vertical GHE depth prediction.
Tang et al. (2022)	Heat exchange capacity prediction for infrastructure BHEs	PR, LR, RF, ANN	Groundwater level, soil thermal conductivity, grout thermal conductivity, carrying fluid type and velocity, inlet temperature, shank spacing, borehole length, pipe thermal conductivity, average surrounding temperature, grout diameter, U-pipe configuration	Heat extraction rate (HER) (W/m)	PR (RMSE = 1.74 W/m, R^2 = 0.99) accurately predicted HER, outperforming traditional models.
Liu et al. (2023)	Long-term GSHP performance prediction	ANN	Climate data, ground temperature, borehole configuration, load demand	Predicted seasonal energy efficiency ratio (SEER), COP, and annual energy savings	ANN predicted GSHP performance over 10 years with minimal deviation.
Piotrowska-Woroniak et al. (2024)	Comparative study of brine temperature models	ANN, CART, MARS	Outdoor air temperature, solar irradiance, brine flow rate, heating season month	Predicted brine temperature	ANN (R^2 = 0.99, CVRMSE = 4.6%) outperformed other models in brine temperature forecasting.
Ahmad et al., 2024	Deep learning prediction for BCHP heating & cooling	LSTM, Bidirectional LSTM, GRU, CNN	Inlet fluid temperature, mass flow rate	Outlet fluid temperature (°C) of borehole heat exchanger	BD-LSTM achieved lowest MAPE (0.22%), highlighting sensor data quality's critical role in AI predictions.
Ahmed et al. (2024)	Input impact analysis for AI-based BHE temperature prediction	LSTM, GRU, CNN, Bidirectional LSTM, SHAP	Inlet/outlet fluid temperatures, ambient temperature, mass flow rate, solar radiation, wind velocity	Outlet fluid temperature (°C)	BD-LSTM (MAPE = 2.68%) with SHAP analysis identified inlet temp and mass flow rate as key variables, minimizing unnecessary inputs.
Previati and Crosta (2024)	Surrogate modeling for regional-scale geothermal potential assessment considering groundwater flow (open loop)	ANN, GPR, DT, SVM	Aquifer porosity, groundwater velocity, saturation, thermal conductivity, heat demand, borehole depth	Thermal exchange potential (W/m), heat extraction/injection rates	ANN surrogate model (R^2 > 0.999, RMSE = 2.0e-3) mapped geothermal potential rapidly, with groundwater flow improving efficiency 3x and raw potential 50x.
Richter et al. (2024)	Sensitivity & uncertainty analysis optimizing the design parameters of BHEs	GPR	BHE length, thermal conductivity (pipes, grout, soil), heat demand, groundwater flow characteristics (thickness and position), subsurface temperatures, refrigerant properties, pipe dimensions	Mean BHE fluid temperature, minimum fluid temperature, sensitivity, and uncertainty indices (Sobol indices)	AI proxy modeling reduced sensitivity analysis effort, identifying groundwater flow and heat demand as key factors for shallow geothermal optimization.
Javadi et al. (2019)	Thermal analysis & optimization of triple helix GHEs	ANN, Multiple Linear Regression)MLR(	- Helix pitch - Helix diameter - Helical coil length - Distance between centers of inner and outer helical coil branches - Distance between centers of inner/outer helical coil branches	- Predicted outlet fluid temperature - Heat exchange rate - Pressure drop - Thermal resistance - Effectiveness - Thermal performance capability	ANN (R^2 = 98.99%) reduced pressure drop by 27%, increasing GHE thermal efficiency, outperforming regression models in real-time adaptability.

3.3.2. *Horizontal ground heat exchangers*

HGHEs play a significant role in GSHP systems by providing a cost-effective and efficient means of thermal exchange. Their performance depends on installation depth, pipe configuration, soil properties, material selection, and optimization strategies related to system design and operation. HGHEs are typically buried at depths of 1–3 m, with deeper installations offering more stable temperatures but increasing excavation costs (Fujii et al., 2012; Selamat et al., 2016). Straight-pipe layouts require more space and offer lower efficiency, while slinky and spiral coils enhance heat transfer per trench length, reducing land requirements (Florides and Kalogirou, 2007; Hou et al., 2022). Soil thermal properties significantly influence efficiency. Moist, high-conductivity soils improve performance, while dry, sandy soils require high-conductivity backfill materials such as sand-bentonite mixtures (Congedo et al., 2012; Kupiec et al., 2015). Pipe material selection also impacts efficiency, with high-density polyethylene pipes widely used for durability, while copper pipes offer 16% greater heat transfer at a higher cost (Congedo et al., 2012). Recent advancements include computational fluid dynamics (CFD) simulations and thermal response tests (TRTs), which refine pipe spacing, flow control, and trench layouts for better efficiency (Hou et al., 2022; Pu et al., 2018). Recent studies introduced horizontal coaxial ground heat exchangers (HCGHEs), which improve heat transfer and reduce installation costs using advanced drilling techniques (Akram et al., 2024). Numerical models comparing slinky, spiral, and U-tube designs have identified slinky configurations as the most efficient (Jahan et al., 2024). New hybrid numerical models using proper orthogonal decomposition reduce computational costs while maintaining accuracy, improving real-time optimization (Tong et al., 2024). A schematic of an HGHE system exchanging heat with the ground for seasonal heating and cooling is presented in Fig. 15.

AI has improved HGHE performance prediction and system optimization, enabling faster and more accurate modeling. Esen et al. (2008a) applied ANNs to predict GCHP performance,

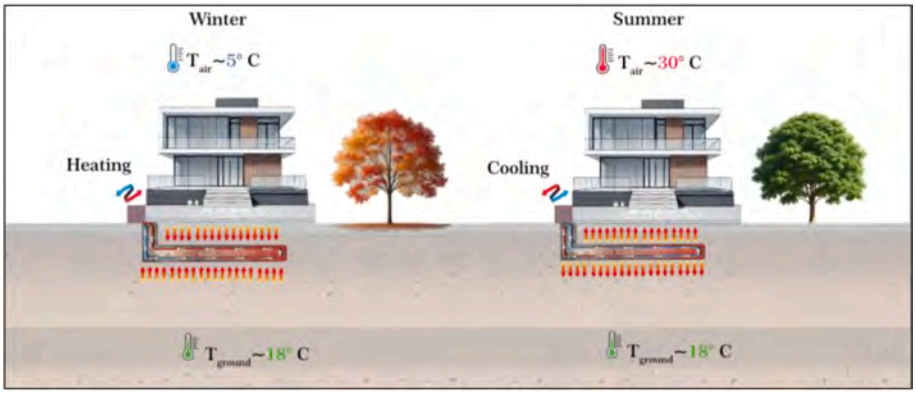

Fig. 15. HGHE system showing building heating in winter and building cooling in summer.

achieving $R^2 = 0.9999$ and significantly outperforming conventional methods. Esen et al. (2008b) used ANFIS models to predict heating COP, demonstrating high reliability with near-zero error. AI has also contributed to design optimization; Jeon et al. (2018) employed ANNs and LR to refine spiral-coil trench configurations, improving heat transfer efficiency while reducing computational effort by 80%. In broader applications, Zhou et al. (2024) showed that ANN-based rural GCHP predictions ran 100 times faster than a transient system simulation tool (TRNSYS), enabling efficient system design. Overall, AI has streamlined geothermal modeling, improved predictive accuracy, and optimized HGHE configurations, making it a valuable tool for system performance enhancement. A summary of AI-driven studies in HGHE research is presented in Table 2.

3.3.3. *Energy geostructures*

Energy geostructures are innovative systems in which civil infrastructure elements – such as foundations, tunnels, retaining walls, and pavements – also serve as heat exchangers. These structures can harvest or dissipate thermal energy to provide heating or cooling while maintaining their primary structural function (Loveridge et al., 2020). AI applications are essential in this emerging field, as energy geostructures present multi-physics challenges: coupling thermal performance with structural behavior, managing large-scale systems with heterogeneous conditions, and requiring adaptive control to balance energy efficiency and safety. AI and optimization algorithms advance energy geostructure technology in several ways:

3.3.3.1. Energy piles. Energy piles have emerged as a promising sustainable solution for heating and cooling buildings by leveraging geothermal energy through structural foundations, thereby reducing geothermal system costs by eliminating the need for purpose-drilled boreholes (Batini et al., 2015; Fadejev et al., 2017; Mohamad et al., 2021). Significant efforts have been made to enhance their thermal performance, including innovative approaches such as integrating phase change materials into pile fillings (Bandeira Neto et al., 2024). Multiple studies have emphasized the importance of ground characteristics, demonstrating that accurate assessment of natural soil layering, hydrothermal spatial variability, and groundwater flow substantially impact energy pile performance and can lead to notable underestimation or overestimation if these factors are disregarded (Alqawasmeh et al., 2024, 2025). Additionally, investigations into the thermo-mechanical behavior of energy piles, both at the soil–structure interface and at the group level, have revealed that

Table 2
Summary of AI-based studies applied to HGHEs.

Reference	Specific topic	Algorithms	Inputs	Outputs	Insights
Esen et al. (2008a)	Forecasting GCHP performance using ANN with statistical data weighting	ANN	- Air temperatures entering/leaving the condenser unit - Water-antifreeze solution temperatures entering/leaving the HGHE - Ground temperatures at 1 m and 2 m depths	Predicted coefficient of performance (COP) of the GCHP system	SWP-ANN ($R^2 = 0.9999$, RMS error = 0.002) outperformed standard ANN models.
Esen et al. (2008b)	Modeling GCHP performance with ANFIS	ANFIS	- Air temperatures entering/leaving the condenser unit - Ground temperatures at 1 m and 2 m depths	Predicted heating coefficient of performance (COPS)	ANFIS (Gaussian membership, $R^2 = 0.9999$) proved highly reliable for GCHP prediction.
Esen et al. (2017)	Experimental & ANN-based modeling of solar-assisted GSHP	ANN - ANFIS	Pipe configuration, heat pump coefficient of performance (COP), solar energy input	Predicted COPsys and COPhp	ANFIS (RMSE = 0.074, $R^2 = 0.9999$) outperformed ANN, cutting error by 45%. Horizontal slinky GHE (COPsys = 2.88, COPhp = 3.55) outperformed vertical slinky in efficiency and heat transfer.
Zhou et al. (2024)	Performance prediction of rural GCHPs	ANN	Climate data, soil type, pipe configuration, load demand	Predicted COP and outlet temperature of HGHX	ANN predicted COP with <5% error, ran 100x faster than TRNSYS, enabling rapid rural GCHP design.
Jeon et al. (2018)	Scale factor optimization for spiral-coil HGHX design	ANN, LR	GHE configuration, soil thermal properties, weather conditions	Optimized scale factor for HGHX trench design	ANN ($R^2 = 0.98$) improved heat transfer efficiency while reducing computational effort by 80%.

cyclic temperature changes induce critical mechanical responses, influencing structural stability and thermal efficiency (Laloui and Sutman, 2021; Mimouni and Laloui, 2015). The optimization of pile design parameters, such as pipe arrangements, concrete admixtures, and fluid flow rates, has been extensively explored, showing marked improvements in thermal efficiency and mechanical performance when properly optimized (Batini et al., 2015; Mohamad et al., 2021). Given the complexity and variability in energy pile design and performance identified by recent studies, accurate and rapid prediction methods are essential to optimize design, operation, and reliability. Fig. 16 illustrates the role of an energy pile system in harnessing ground energy for both heating and cooling across seasons.

In response to the computational challenges posed by diverse influencing factors such as soil heterogeneity, groundwater conditions, thermo-mechanical interactions, and pile design parameters, AI applications, particularly data-driven prediction models, have increasingly been integrated into geothermal energy systems to enable efficient, reliable, real-time predictions and decision-making. Performance prediction is a key AI application in energy piles. Makasis et al. (2018) used MLR to estimate fluid temperature variations in an energy pile system, considering thermal load, thermal storage, previous-step fluid temperature, and energy pile geometries as input variables (Fig. 17). Their model achieved $R^2 > 0.99$, RMSE <0.6 °C, and MAE <0.2 °C, while reducing computational time from 1.5 to 7 h to approximately 4 s. This improvement enabled rapid and accurate temperature variation predictions over a five-year period, making MLR an efficient alternative to more complex numerical simulations for energy pile thermal modeling.

Similarly, Zhang et al. (2023) used a CNN-LSTM hybrid model to predict outlet water temperature, outperforming standard ANN and RNN models by 2.3%–5.7% and demonstrating AI's effectiveness in handling dynamic thermal conditions (Fig. 18). AI has also been used to thermo-mechanical behavior prediction, which is critical for structural integrity. Pei et al. (2022) developed an ANN model for long-term thermally induced pile head displacement, achieving $R^2 = 0.975$, RMSE = 0.084 mm, and reducing computational time from hours to seconds, enabling rapid design optimization.

For system optimization, AI has improved cooling efficiency, COP, and heat exchange performance. Nazmabadi et al. (2022) used genetic algorithms (GA) and non-parametric regression (NPR) to optimize spiral-coil energy pile cooling, achieving a 50% increase in cooling load and a 30% improvement in COP. Chen et al. (2023) combined PSO with ANN models, significantly improving heat pump system performance, with RMSE = 0.037 and $R^2 = 0.991$, demonstrating AI's adaptability to varying environmental conditions. For long-term geothermal performance forecasting, Lee et al. (2025) developed an ANN model for steel pipe heat exchanger (SPHX) piles, achieving a 1.53% prediction error and improving GSHP feasibility. Kong et al. (2024) applied ANN models for seasonal energy prediction, achieving 92.3% accuracy in building thermal load forecasts while reducing monitoring costs. AI has also contributed to pile capacity estimation; Kumar and Samui (2022) used RF, SVM, GBM, and XGBoost for pile group capacity prediction, with GBM identifying key cone penetration test (CPT) parameters influencing pile strength with $R^2 = 0.808$. In summary, AI applications in energy piles have streamlined system modeling, enhanced predictive accuracy, and optimized thermo-mechanical performance, making them a crucial tool for geothermal and structural engineering advancements. Table 3 provides a comprehensive overview of AI-based approaches used in energy pile research.

3.3.3.2. Energy tunnels. Energy tunnels have attracted as an innovative geothermal technology, integrating heat exchange pipes within tunnel linings to harness geothermal and aerothermal energy for heating, cooling, and de-icing (Barla et al., 2019; Dai et al., 2023; Stemmle et al., 2022). Recent studies have examined various different aspects, such as heat exchange mechanisms affected by groundwater flow and tunnel airflow, which significantly influence thermal performance (Bidarmaghz and Narsilio, 2018; Dai et al., 2023b; Ma et al., 2021). Several full-scale experiments and numerical simulations have confirmed the feasibility and effectiveness of these systems, demonstrating achievable thermal yields of about 5–6 W/m^2 per degree Celsius difference between fluid and ground temperatures, and highlighting the critical roles of soil properties and structural configuration (Barla et al., 2016; Insana and Barla, 2020). Despite their promising energy potential and the advantage of large heat exchange surfaces, energy tunnels remain relatively underutilized compared to other geostructures, mainly due to limited practical experience and the need for optimized techno-economic assessments (Barla et al., 2016; Stemmle et al., 2022). Given the complexity of energy tunnel systems, which are influenced by groundwater conditions, tunnel airflow, and structural characteristics, accurate and efficient prediction tools are essential. Fig. 19 presents a schematic of an energy tunnel system utilizing ground energy for thermal exchange.

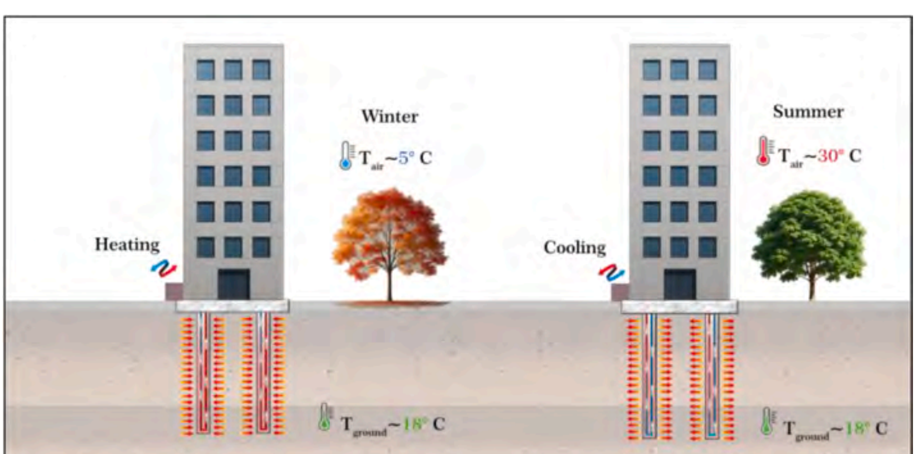

Fig. 16. Energy piles system showing an example of building heating in winter and building cooling in summer.

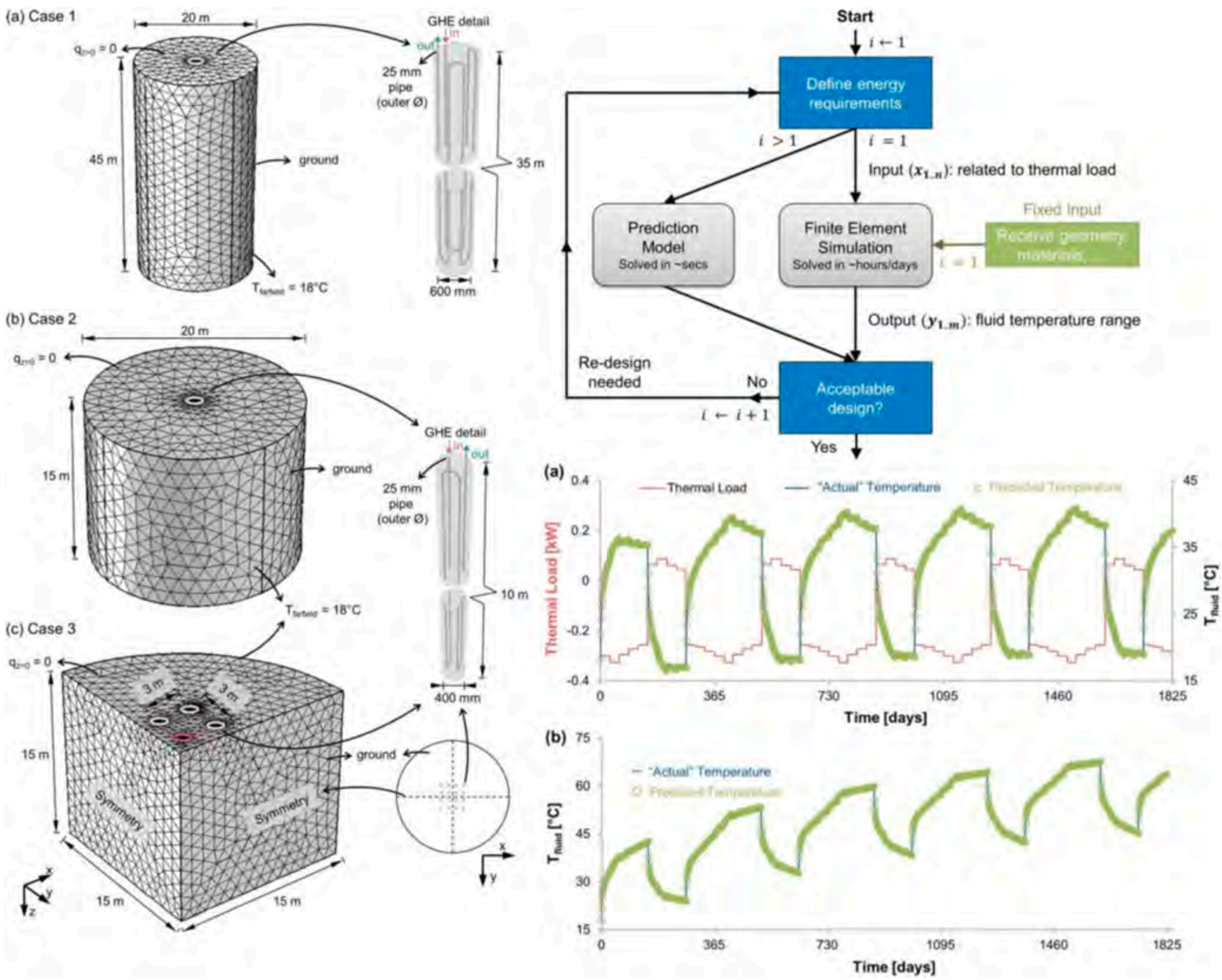

Fig. 17. AI-assisted thermal performance prediction of energy piles using MLR, validated against FE simulations (Makasis et al., 2018).

Despite the potential of AI-based approaches for rapid and reliable predictions, research integrating AI into energy tunnel performance remains limited, with only a few recent studies exploring this area. This scarcity highlights significant opportunities for further research to fully leverage AI in optimizing energy tunnel design and operations. A critical aspect of energy tunnel performance is the ability to accurately predict heat flux, which determines the efficiency of thermal energy exchange. Hu and Kong (2024) applied multiple ML algorithms, including RF, DT, KNN, SVM, and ANN, to predict heat flux (W/m^2) in energy tunnels (Fig. 20). Their model used ground temperature, groundwater velocity, air temperature, pipe burial depth, pipe spacing, wind speed, and inlet temperature as input variables. Among the tested models, RF achieved the highest accuracy with R^2 = 0.983, RMSE = 2.47 W/m^2, and MAE = 1.89 W/m^2, outperforming other ML techniques. A sensitivity analysis identified pipe burial depth and inlet temperature as the most influential parameters, providing insights for improving energy tunnel design and operational strategies.

Accurate long-term temperature prediction is essential for optimizing energy tunnel operations. Ma et al. (2024) developed an ANN-based model to predict daily outlet temperatures using tunnel air temperature, inlet temperature, fluid flow rate, and previous day outlet temperature as inputs (Fig. 21). Their model significantly reduced prediction time from hours to minutes, achieving RMSE = 0.92 °C, MAE = 0.67 °C, and R^2 = 0.976. This demonstrates the effectiveness of ANN in forecasting thermal behavior, enabling for more efficient energy management and real-time control of geothermal heat exchange in tunnels. AI has proven to be a powerful tool for improving the predictive accuracy and operational efficiency of energy tunnels. RF models have been particularly effective for heat flux estimation, while ANN models provide fast and reliable long-term temperature predictions. A detailed summary of AI applications in energy tunnel research is presented in Table 4.

3.3.3.3. *Energy walls.* Energy walls have emerged as an innovative geothermal solution, integrating heat exchange pipes within retaining wall structures to efficiently harness renewable thermal energy and reduce the initial installation costs associated with traditional geothermal systems (Makasis and Narsilio, 2022; Zhong et al., 2022). Recent experimental and numerical studies have demonstrated the potential of energy walls for both thermal and thermo-mechanical performance, highlighting their dual function in structural support and thermal energy provision (Zhong et al., 2022). Field investigations on pilot projects, such as

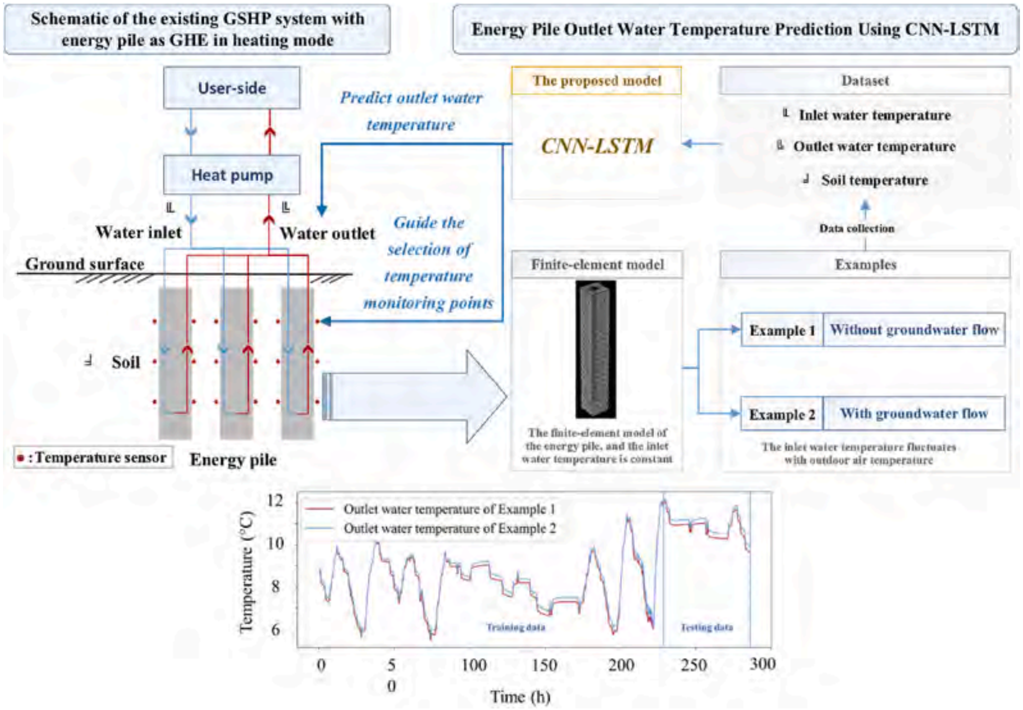

Fig. 18. CNN-LSTM model for predicting outlet water temperature in energy piles under varying groundwater conditions (Zhang et al., 2023).

Table 3
Summary of AI-based studies applied to energy geostructures-energy piles.

Reference	Specific topic	Algorithms	Inputs	Outputs	Insights
Makasis et al. (2018)	Thermal energy estimation for energy piles	MLR	Thermal load, thermal storage, fluid temperature from previous step, energy pile geometries	Predicted fluid temperature in energy pile system	The AI model achieved RMSE <0.6 °C, MAE <0.2 °C, and $R^2 > 0.99$, reducing computation time from 1.5 to 7 h to ~4 s while accurately predicting temperature variations over 5 years.
Nazmabadi et al. (2022)	Optimization of spiral-coil energy pile cooling performance	Non-parametric regression (NPR), GA	Ground-water heat exchanger (GWHE) diameter, GWHE pitch, ground-air heat exchanger)GAHE(diameter, inlet air velocity	Optimal energy pile cooling load per unit depth, annual COP	The optimized design increased cooling load by 50%, improved COP by 30% for double GAHE pipes and 16 percent for single GAHE pipes, and reduced soil temperature rise from 46.97 °C to 33.86 °C over 15 years.
Zhang et al. (2023)	Outlet water temperature prediction for GSHP System	CNN-LSTM Hybrid model, CNN, LSTM, ANN, simple RNN	Inlet and outlet water temperatures, STF data	Predicted outlet water temperature of the energy pile	The CNN-LSTM model achieved RMSE 0.096, MAE 0.078, MAPE 0.723, and R^2 96.252%, outperforming LSTM, CNN, ANN, and Simple RNN by 2.3% to 5.7%.
Pei et al. (2022)	Long-term thermomechanical displacement prediction	ANN	Thermal load distribution, time, material properties, geometry	Predicted thermally induced pile head displacement	The ANN model achieved RMSE 0.084 mm, MAE 0.062 mm, and R^2 0.975 while reducing computation time from hours to seconds for rapid design optimization.
Chen et al. (2023a)	Energy pile heat pump system performance prediction	PSO-ANN	Ambient temperature, room temperature, humidity, power consumption	Predicted COP	The PSO-ANN model achieved RMSE 0.037, MAE 0.029, and R^2 0.991, outperforming empirical models and ensuring robust predictions with limited sensor data.
Imtiyaz et al. (2023)	Thermal conductance prediction for energy piles	GPR, SVR, RF, DT, MLP, XGBoost	Number of tubes, inner tube diameter, thickness of tube, thermal conductivity of tube, pile, and soil, water velocity	Predicted energy pile thermal conductance	The GPR model achieved R^2 0.994 and RMSE 1.886, outperforming other ML models and identifying pile thermal conductivity as the key performance factor.
Kong et al. (2024)	Seasonal performance and building thermal load prediction	ANN	Ambient temperature, room temperature, humidity, power consumption	Predicted seasonal COP and building thermal load	The ANN model for COP prediction achieved RMSE 0.052, MAE 0.041, and R^2 0.982, predicting building thermal load with 92.3% accuracy and reducing monitoring costs.
Lee et al. (2025)	Data-driven prediction of long-term thermal performance for SPHX energy piles	ANN	Thermal conductivity (concrete, ground formations), flow rate of working fluid, initial ground temperature	Average heat exchange amount (W)	The ANN model for SPHX energy piles had a 1.53% prediction error, outperforming analytical methods and improving GSHP feasibility and optimization.
Kumar and Samui (2022)	Predicting the group capacity of energy piles based on cone penetration test (CPT) data using ML	RF, SVM, GBM, XGBoost	- Average cone resistance- Minimum cone resistance- Average of minimum cone resistance- Cone resistance- Young's modulus	Predicted pile group capacity for energy piles	The GBM model achieved R^2 0.808, identifying key CPT parameters, influencing pile capacity with the highest accuracy among tested models.
Kumar and Samui (2024)	Reliability-based load and resistance factor design	1D-CNN, LSTM, Bi-LSTM	CPT data, pile geometry, load resistance factors	Predicted factored resistance and load capacity for energy piles	The Bi-LSTM model for heating achieved $R^2 = 0.984$, RMSE = 0.019, RMSLE = 0.006, while LSTM for cooling had $R^2 = 0.982$, RMSE = 0.019, RMSLE = 0.007, enhancing energy pile load and resistance predictions over empirical methods.

instrumented energy soldier piled walls, have shown that thermal loading induces measurable but manageable mechanical responses, with minimal residual axial strains due to the structural rigidity and thermo-elastic behavior of the walls (Zhong et al., 2024). Studies have also emphasized the importance of design parameters such as pile spacing, wall depth, pipe configuration, and boundary conditions, indicating that optimized spacing and sufficient depth significantly enhance thermal performance (Makasis et al., 2020). Additionally, numerical analyses have underscored the critical impact of groundwater flow and thermal interaction with adjacent underground spaces on overall system efficiency, highlighting the necessity of accurately accounting for hydrogeological conditions and thermal boundaries during the design phase (Makasis et al., 2020; Zhong et al., 2023). Despite these advancements, the literature on energy retaining walls remains limited, indicating the need for further experimental studies, field data acquisition, and the development of standardized design guidelines to facilitate broader adoption of this promising technology. Energy walls present distinct design challenges due to complex interactions involving structural elements, groundwater flow, and thermal boundaries. While recent experimental and numerical studies have addressed some fundamental aspects, traditional simulation methods remain computationally expensive and limited in accurately capturing real-time behavior. AI has recently begun to bridge this gap, offering rapid, precise predictions of thermal and structural responses. Although a few pioneering studies have integrated AI into energy wall research, the field remains largely unexplored, leaving substantial

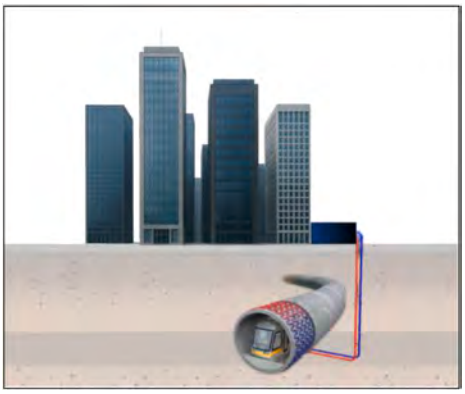

Fig. 19. Schematic of an energy tunnel system using ground energy.

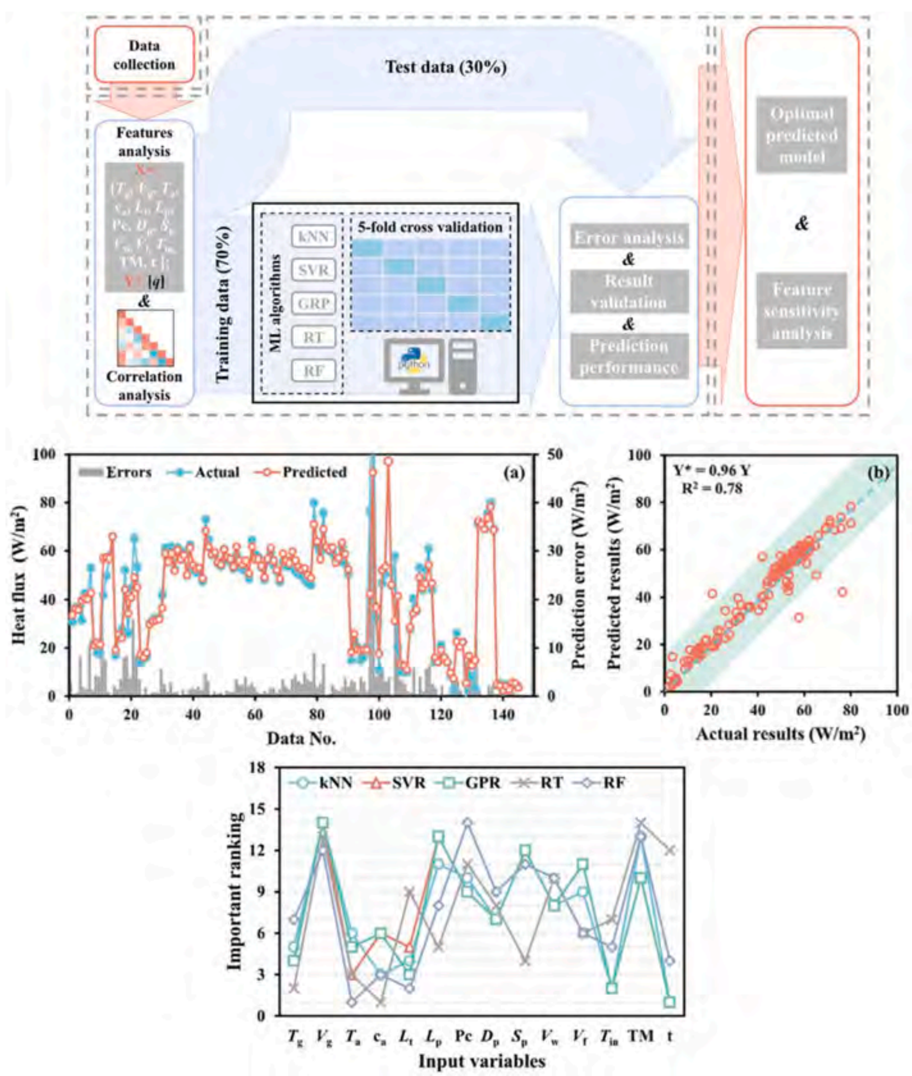

Fig. 20. AI workflow and results for heat flux prediction in energy tunnels, with RF model showing highest accuracy (Hu and Kong, 2024).

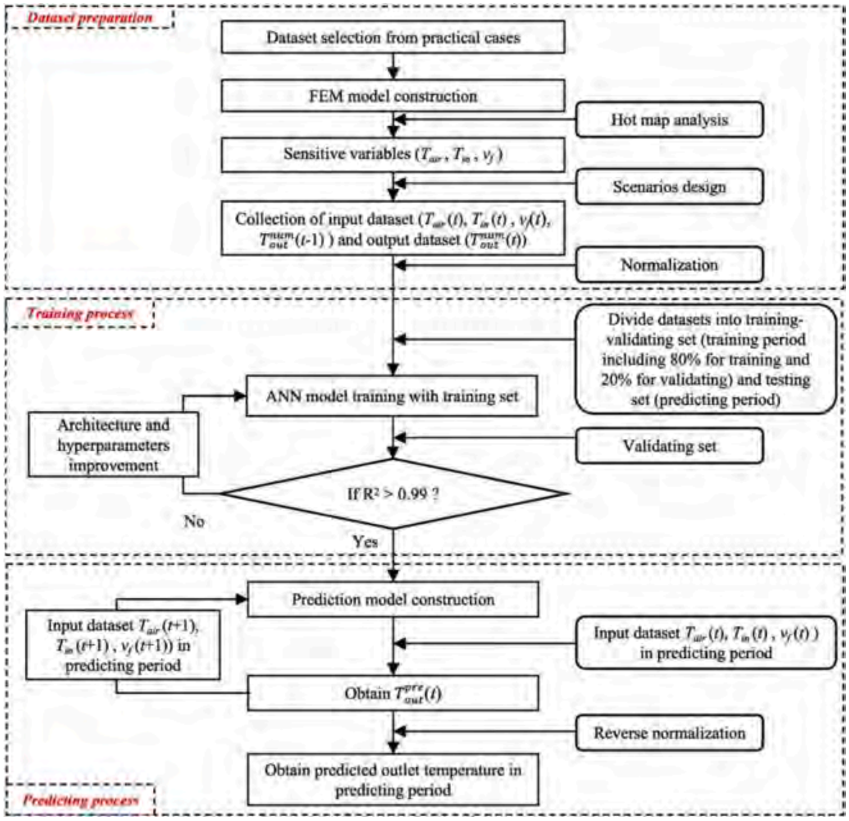

Fig. 21. ANN-based workflow for long-term outlet temperature prediction in energy tunnels, enabling fast and accurate thermal forecasting (Ma et al., 2024).

Table 4
Summary of AI-based studies applied to energy geostructures-energy tunnels.

Reference	Specific Topic	Algorithms	Inputs	Outputs	Insights
Hu and Kong (2024)	Heat performance prediction for energy tunnels	RF, DT, KNN, SVM, ANN	Ground temperature, groundwater velocity, air temperature, pipe burial depth, pipe spacing, wind speed, inlet temperature	Predicted heat flux (W/m^2) of energy tunnels	RF achieved R^2 0.983, RMSE 2.47 W/m^2, and MAE 1.89 W/m^2, outperforming other ML models. Sensitivity analysis identified pipe burial depth and inlet temperature as the key parameters.
Ma et al. (2024)	Long-term thermal performance prediction	ANN	Tunnel air temperature, inlet temperature, fluid flow rate, previous day outlet temperature	Predicted daily outlet temperature (°C)	ANN reduced prediction time from hours to minutes, achieving RMSE 0.92 °C, MAE 0.67 °C, and R^2 0.976, demonstrating strong predictive capability for operational optimization.

opportunities to extend AI methods to enhance energy wall design, optimization, and risk mitigation. AI-driven models have been used to improve thermal performance prediction and assess thermomechanical behavior, providing faster, more accurate solutions compared to conventional methods. Accurate thermal performance prediction is crucial for optimizing energy walls in underground environments. Hu et al. (2024b) developed an SVR model to predict outlet temperature, heat exchange power, thermal saturation, and overall system effectiveness (Fig. 22). The model used heating time, air temperature, inlet temperature, flow rate, tank temperature, heating load, pipe burial depth, and wall temperature (on both the ground side and excavation side) as inputs. The SVR model achieved RMSE = 0.92 °C, MAE = 0.67 °C, and R^2 = 0.976, demonstrating strong predictive capability. A key finding was that soil-side pipes provided 15% higher heat exchange power compared to excavation-side pipes, while increasing the heating load yielded minimal efficiency gains, highlighting the importance of optimizing pipe placement for maximum heat transfer. In addition to thermal behavior, energy walls must withstand structural and thermo-mechanical stresses, particularly when interacting with tunnels and underground utilities.

Hu et al. (2023) applied a regression tree (RT) model to predict short-term thermally induced stress in energy retaining piles (Fig. 23). The model included operation mode, inlet temperature, pile temperature, pile temperature in the previous hour, and thermally induced stress in the previous hour as inputs. The RT model achieved R^2 > 0.95, accurately predicting short-term thermo-mechanical response. The study found that tunnel excavation reduced axial thermally induced stress in the energy pile wall by 50%, redistributed soil pressure, and increased bending moments at the tunnel's top and bottom, revealing significant structural implications for energy walls near tunnels. However, the study noted that long-term predictions require additional training data, emphasizing the need for further AI model refinement. A detailed summary of AI applications in energy wall research is presented in Table 5.

3.3.3.4. Geothermal pavement. Geothermal pavements incorporate heat exchanger systems within pavement structures, enabling

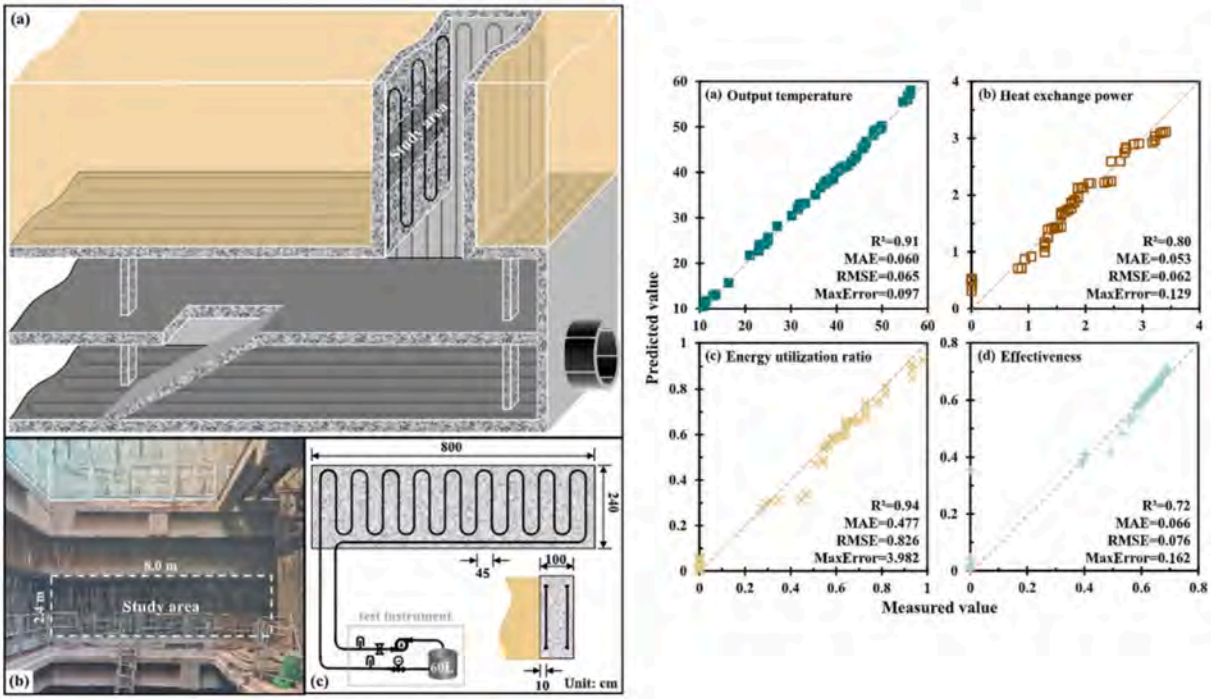

Fig. 22. SVR-based prediction of thermal performance in energy walls, showing strong accuracy across key outputs and emphasizing the impact of pipe placement on heat exchange efficiency (Han et al., 2024).

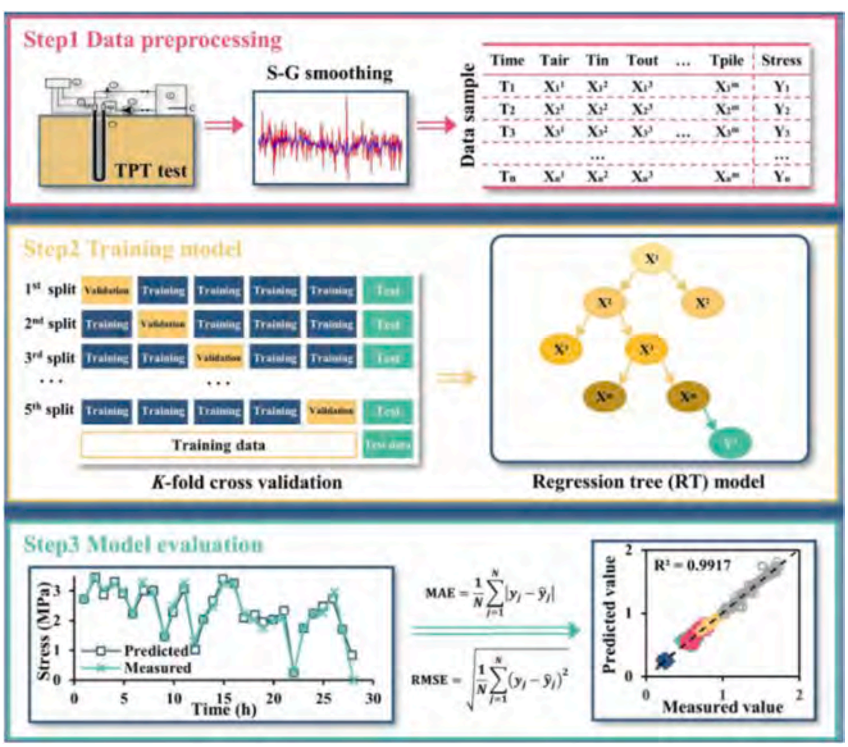

Fig. 23. Schematic and error analysis of an RT model for predicting short-term thermally induced stress in energy piles, showing high accuracy and structural insights near tunnels (Hu et al., 2023).

thermal energy harvesting and enhancing pavement durability. Their performance depends on pipe embedment depth, material composition, thermal conductivity, and dynamic loading conditions (Al-Qadami et al., 2022; Arulrajah et al., 2021; Baumgärtel et al., 2021; Gu et al., 2022; Motamedi et al., 2021). AI-driven models have significantly improved the prediction of thermal and mechanical performance, enabling faster and more accurate simulations than conventional methods. Efficient heat collection is

Table 5
Summary of AI-based studies applied to energy geostructures - energy walls.

Reference	Specific topic	Algorithms	Inputs	Outputs	Insights
Hu et al. (2024a)	AI-enhanced thermal performance prediction in underground spaces.	SVR	Heating time, air temperature, inlet temperature, flow rate, tank temperature, heating load, pipe burial depth, wall temperature (ground side & excavation side)	Predicted outlet temperature, heat exchange power, thermal saturation degree, effectiveness	The SVR model achieved RMSE 0.92 °C, MAE 0.67 °C, and R^2 0.976. Soil-side pipes provided 15% higher heat exchange power than excavation-side pipes, while increasing heating load had minimal efficiency gains.
Hu et al. (2023)	ML-based prediction of energy pile wall thermomechanical response under utility tunnel influence.	Regression tree (RT) mode	- Operation mode - Inlet temperature - Pile temperature - Pile temperature in the previous hour - Thermally induced stress in the previous hour	Predicted thermally induced stress of the energy retaining pile	The RT model achieved $R^2 > 0.95$, accurately predicting short-term thermomechanical response. Tunnel excavation reduced axial thermally induced stress in the energy pile wall by 50%, redistributed soil pressure, and increased bending moments at the tunnel's top and bottom. Long-term predictions require additional training data.

a key function of geothermal pavements, requiring optimization of pipe embedment depth, supply temperature, and pavement structure. Ghalandari et al. (2023) developed an ANN model to predict heat harvesting capacity (GJ/m^2) and outlet water temperature (°C) based on pipe depth, inlet supply temperature, pipe section length, and pavement temperature. The model achieved $R^2 = 0.987$, RMSE = 1.45 GJ/m^2, and MAE = 0.89 GJ/m^2, demonstrating strong predictive accuracy. The study found that optimal pipe embedment minimized failure risk while maintaining high thermal efficiency, achieving up to 1.17 GJ/m^2 of annual heat harvesting, making geothermal pavements a viable renewable energy solution. The mechanical behavior of geothermal pavements is affected by thermal expansion, cyclic loading, and material properties. Ghorbani et al. (2021) used ANFIS to predict the resilient modulus (MR) of demolition waste materials in geothermal pavements, incorporating thermal conductivity, confining stress, deviator stress, and moisture content as inputs. The model achieved $R^2 = 0.99$, RMSE = 12.4 MPa, accurately predicting MR values. Results showed that recycled concrete aggregate had the highest MR (381 MPa), improving pavement stability and reducing rutting, highlighting the potential of recycled materials in sustainable pavement designs. In addition to modulus prediction, Ghorbani et al. (2021) applied ANNs to estimate deformation behavior under thermal and dynamic loads, considering temperature, load cycles, and material type (recycled concrete, crushed brick, waste rock, reclaimed asphalt pavement). The ANN model reduced computation time by 80% and identified distinct shakedown responses: recycled concrete aggregate remained stable (Range A) across all temperatures, while reclaimed asphalt pavement exhibited incremental collapse (Range C) at 35 °C and 50 °C, providing critical insights for material selection in geothermal pavements. AI models have also been used to optimize cement content in geothermal pavement materials, balancing mechanical performance and sustainability. For example, García et al. (2025) developed an ANN model to predict cement consumption in clayey waste-cement mixtures, using curing temperature, mechanical strength (compressive and tensile), resilient modulus, deviatoric stress, and porosity as inputs. The model achieved minimal prediction error (RMSE = 0.0051), accurately estimating cement content and resilient modulus. Results showed that higher curing temperatures increased resilient modulus by 18%, demonstrating how AI can optimize material mix designs for improved performance in geothermal pavements. AI applications in geothermal pavements have enhanced thermal efficiency, mechanical stability, and material optimization, supporting the development of more durable and energy-efficient road structures. ANN models have been particularly effective for heat harvesting and deformation prediction, while ANFIS and ANN approaches have improved material property estimation. These advancements streamline geothermal pavement design, improve predictive accuracy, and reduce computational costs, making AI an essential tool for sustainable pavement engineering. Table 6 outlines key applications of artificial intelligence in geothermal pavement research.

3.3.4. AI in thermal response test

TRT is a crucial in-situ method for assessing subsurface thermal properties and evaluating the efficiency of GHEs (Fig. 24). While TRT is not directly a GHE technology, it plays a fundamental role in their initial design and optimization by providing essential thermal characterization of the ground. Accurate TRT results help calibrate numerical models, optimize BHE configurations, and minimize uncertainties in geothermal system performance predictions. As the application of AI expands in geothermal energy research, its integration into TRT analysis enhances predictive accuracy, reduces computational effort, and provides deeper insights into complex thermal interactions. This method is widely used for measuring subsurface thermal properties and evaluating the GHEs performance. TRTs involve injecting heat through circulating fluid within pipes and monitoring temperature responses to estimate parameters such as ground thermal conductivity, borehole thermal resistance, and undisturbed ground temperature (Jensen-Page et al., 2018; Zhang et al., 2021a). Accurate TRT data are vital for designing geothermal systems, minimizing uncertainties, and optimizing economic efficiency (Raymond et al., 2011). The interpretation process of traditional TRTs commonly uses analytical solutions such as the infinite line source model (ILSM), which simplifies subsurface conditions as homogeneous and neglects the influence of groundwater flow, both of which can introduce significant inaccuracies. Recent research has highlighted the limitations of these assumptions. For instance, Alqawasmeh et al. (2024) demonstrated that ignoring soil stratification and groundwater flow can lead to thermal yield underestimations of up to 19.6% and long-term thermal accumulation exceeding 48%. These inaccuracies become more critical in energy piles and shallow geothermal systems under unbalanced thermal loading. Furthermore, groundwater flow, neglected in ILSM, has been shown to enhance convective heat transfer and improve long-term system performance. In response, new modeling approaches such as multilayer analytical solutions, advanced FEM-based simulations (Jensen-Page et al., 2019; Motamedi et al., 2021) and distributed TRTs using fiber-optic sensors have emerged to provide depth-resolved thermal conductivity profiles (Raymond et al., 2011). Group TRT studies have also emphasized the importance of considering thermal interference among GHEs (Bandeira Neto et al., 2023). While these advancements offer greater accuracy, they are often computationally intensive. Consequently, AI is increasingly

Table 6
Summary of AI-based studies applied to energy geostructures-geothermal pavements.

Reference	Specific topic	Algorithms	Inputs	Outputs	Insights
Ghalandari et al. (2023)	Thermo-mechanical feasibility of pavement solar collectors	ANN	Pipe embedment depth, inlet supply temperature, pipe section length, pavement temperature	Predicted heat harvesting capacity (GJ/m^2), outlet water temperature (°C)	The ANN model achieved R^2 0.987, RMSE 1.45 GJ/m^2, and MAE 0.89 GJ/m^2. Optimal pipe embedment minimized failure risk while maintaining high thermal efficiency, yielding up to 1.17 GJ/m^2 annually.
Ghorbani et al., 2021	Resilient modulus prediction of demolition waste in geothermal pavements	ANFIS	Thermal conductivity, physical properties, confining stress, deviator stress, moisture content	Predicted MR of geothermal pavement materials	The ANFIS model achieved R^2 0.99 with RMSE 12.4 MPa. Recycled concrete aggregate had the highest MR (~381 MPa), enhancing stability and reducing rutting in geothermal pavements.
Ghorbani et al., 2021	Deformation prediction of recycled materials under thermal and dynamic loads	ANN	Temperature, load cycles, material type (recycled concrete aggregate, crushed brick, waste rock, and reclaimed asphalt pavement), moisture content	Predicted permanent strain of geothermal pavement materials	The ANN model cut computation time by 80 percent. Plastic shakedown (Range A) occurred in recycled concrete at all temperatures, while reclaimed asphalt showed incremental collapse (Range C) at 35 °C and 50 °C.
García et al. (2025)	Cement consumption estimation in clayey waste-cement mixtures for geothermal pavements	ANN	Curing temperature, mechanical strength (compressive and indirect tensile strength), resilient modulus, deviatoric stress, cell pressure, porosity, plasticity index, organic matter content, methylene blue index, dry density	Predicted cement consumption in mixtures, resilient modulus (MPa)	The ANN model had a minimal prediction error (RMSE 0.0051), accurately estimating cement content and resilient modulus. Higher curing temperatures boosted modulus by 18 percent, optimizing geothermal pavement designs.

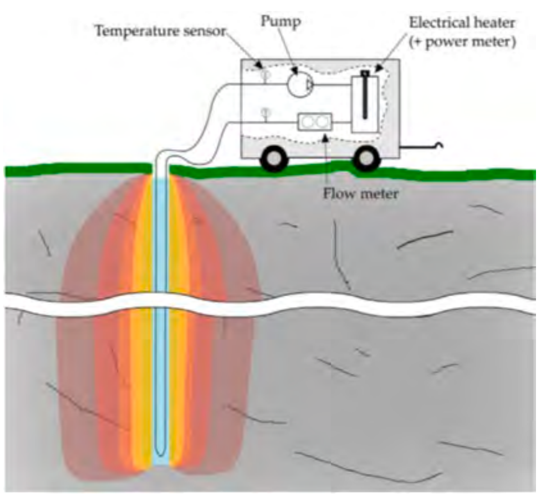

Fig. 24. Standard experimental configuration for conducting a TRT (Mazzotti Pallard and Lazzarotto, 2021).

explored as a complementary tool to improve prediction speed and efficiency without sacrificing accuracy.

Early AI applications, such as those by Popov et al. (2016), used GA and PSO for borehole thermal property estimation. These methods demonstrated greater accuracy than traditional analytical approaches, with PSO achieving faster convergence. A significant advancement was made by Pasquier and Marcotte (2020), who integrated ANN with BI for parameter estimation, improving accuracy and addressing residual autocorrelation in TRT data. Bourhis et al. (2021) built on these methods using XGBoost and ensemble learning, achieving highly accurate predictions for ground temperature and thermal conductivity, especially for site-specific assessments. As computational power increased, more sophisticated models emerged. Dong et al. (2024) and Zhang et al. (2022) enhanced TRT analysis by incorporating ANN and Kalman filtering to reduce measurement errors and improve volumetric heat capacity estimations. Meanwhile, Jacques and Pasquier (2023) refined BI with ANN for standing column well TRT, offering precise hydraulic and thermal parameter estimations essential for groundwater-influenced systems. Recent breakthroughs in 2024 have advanced AI applications further. Zhang et al. (2024) used DNNs to identify soil thermal properties and groundwater seepage velocity from TRT data, significantly improving estimation accuracy (Fig. 25). Their model used TRT experimental data as input, including thermal conductivity, volumetric heat capacity, and seepage velocity, and achieved maximum identification errors of 5.3%, 5.21%, and 5.78%, respectively. Additionally, increasing TRT duration from 50 to 100 h reduced uncertainty by 65.7%, enhancing the reliability of AI-driven parameter identification. Fig. 25 illustrates the AI-based parameter estimation process in their research, showing the DNN model structure and its multi-step optimization approach for improving prediction accuracy.

Additionally, Li et al. (2024) demonstrated that ensemble learning, particularly the XGBoost-RF model, offers both high accuracy ($R^2 = 0.9809$) and computational efficiency in predicting in-situ soil thermal conductivity, outperforming traditional numerical simulations, which are often limited by high computational costs and complexity. Despite these advancements, challenges remain, especially in addressing uncertainties caused by measurement errors, geological heterogeneity, and external environmental influences. AI-driven TRT analysis continues to evolve, with ongoing efforts focused on integrating hybrid models, improving real-time adaptability, and refining uncertainty quantification methodologies to further enhance the reliability and applicability of AI in geothermal energy systems. Table 7 summarizes the main applications of AI in the analysis and interpretation of TRT.

3.3.5. Cross-study comparison of AI algorithms

Table 8 summarizes task-specific performance patterns observed across the studies reviewed in this work. Because each publication uses different datasets, sensing resolutions, and operational conditions, direct accuracy comparisons are not meaningful Instead, the table highlights recurring tendencies reported within individual studies addressing similar GHE tasks.

Across BHE outlet temperature prediction, reviewed studies consistently show that ANNs deliver fast and accurate short-term forecasts, LSTM and GRU models better capture thermal-history effects, and CNN–RNN hybrids offer the most stable long-horizon predictions. For heat extraction and heat transfer rate prediction, classical ML models (SVR, M5) provide strong baselines, while ANN-based hybrid optimization schemes achieve superior

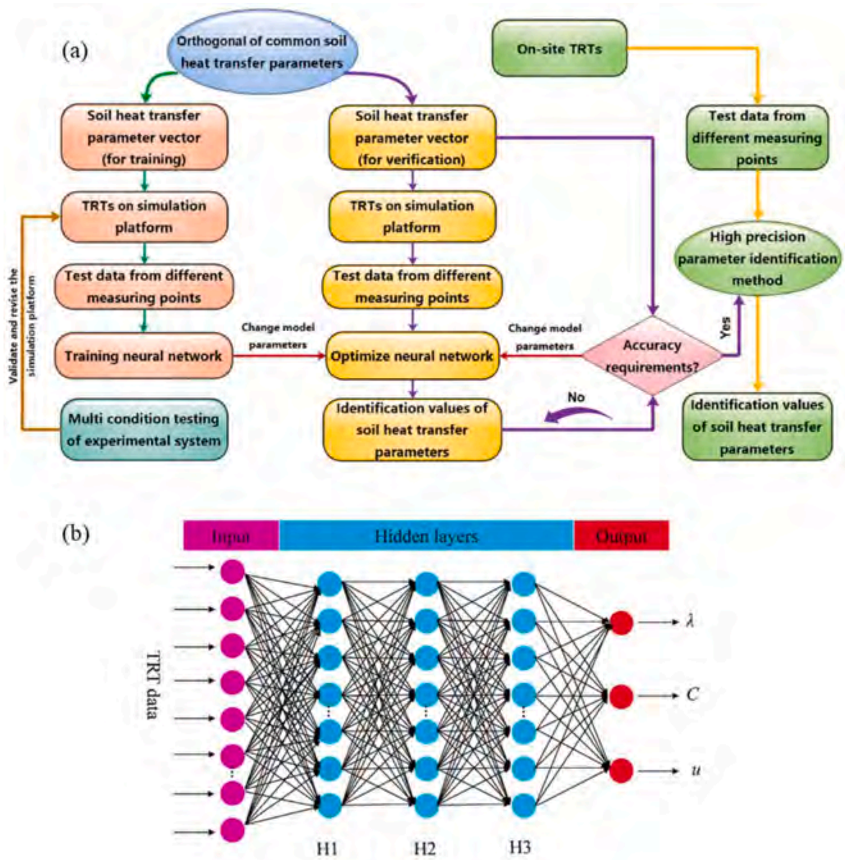

Fig. 25. (a) AI-based parameter identification process for TRT data, and (b) DNN model for predicting soil thermal properties and seepage velocity (Zhang et al., 2024).

performance in highly nonlinear conditions. In thermal resistance and parameter estimation tasks, probabilistic or hybrid approaches (Bayesian inference, DFNN–GA) outperform standalone ANNs due to improved uncertainty handling. For COP prediction, ANFIS repeatedly outperforms ANN and linear baselines, reflecting its suitability for nonlinear thermomechanical interactions. In thermomechanical forecasting for energy piles and walls, temporal DL models (Bi-LSTM) perform best when long-term thermal loading matters, whereas tree-based models (RF, XGBoost, RT) remain reliable for static or small structured datasets. In regional surrogate modeling, ANNs provide the fastest regressions, while GPR offers superior uncertainty quantification when confidence bounds are required. Overall, the patterns emerging from the reviewed literature indicate two consistent insights: (1) algorithm suitability is task and data-structure dependent, and (2) the field lacks true benchmarking, meaning current trends reflect methodological appropriateness and data availability rather than intrinsic algorithm superiority.

3.3.6. Practical considerations for deploying AI in GHE engineering

AI offers significant potential for improving the design, monitoring, and operational optimization of GHEs. However, applying these capabilities from controlled research environments to real engineering practice remains challenging. Several practical bottlenecks, often not addressed in model-centric AI studies, directly affect deployment feasibility and long-term system reliability.

3.3.6.1. Data acquisition limitations remain the primary constraint. Field measurements for BHEs and energy geostructures require intrusive and costly instrumentation, particularly when installing subsurface temperature strings, flow meters, distributed fiber-optic sensors, or long-term monitoring probes. Operational datasets are often sparse, unevenly sampled, or affected by sensor drift, noise contamination, and inconsistent calibration, which complicate AI model training and reduce prediction confidence (Akteruzzaman, 2025; Bramm et al., 2025). Even high-frequency monitoring systems experience dropouts and latency, producing asynchronous multichannel signals that challenge real-time AI pipelines (Jabeen et al., 2025; Sepúlveda-Oviedo et al., 2025).

3.3.6.2. Geological and operational variability further limits model transferability. AI models trained on one site rarely generalize to others because of differences in stratigraphy, moisture regimes, hydraulic gradients, or operational cycles. As a result, purely data-driven approaches often underperform in field conditions unless supplemented by physics-informed or physics-derived features, such as thermal diffusivity indicators, analytical borehole response functions, or synthetic data generated from calibrated numerical models, which improve robustness and physical interpretability (Ghorbani Bam et al., 2025; Ray, 2025).

3.3.6.3. Systems integration presents another major barrier. AI modules must interface with Supervisory Control and Data Acquisition (SCADA) or Building Automation Systems (BAS), which often operate at low sampling frequencies, exhibit communication latency, or rely on legacy protocols that do not support high-bandwidth data streaming. These limitations are particularly critical for digital twin implementations in BHEs: reliable twins require synchronized thermal and hydraulic data, stable telemetry, and predictable sampling intervals. In field environments, delays

Table 7
Summary of AI-based studies applied to TRT.

Reference	Specific topic	Algorithms	Inputs	Outputs	Insights
Zhang et al. (2024)	Identification of soil thermal properties and groundwater seepage from TRT data using AI for BHEs	DNN	TRT experimental data, Soil thermal conductivity, Volumetric heat capacity, Groundwater seepage velocity	Estimated thermal properties of soil and seepage velocity	The AI-based model improves parameter estimation accuracy compared to conventional analytical methods. The uncertainty in identification decreases with increased test duration, and adversarial training enhances model robustness
Zhang et al. (2022)	Effect of temperature measurement error on thermal parameter estimation in TRTs for BHEs	ANN	TRT experimental data, Soil thermal conductivity, Volumetric heat capacity, Temperature noise level	Estimated soil thermal parameters	ANN improves accuracy over traditional models, especially for volumetric heat capacity. Regression fitting of noise data enhances model stability.
Li et al. (2024)	Forecasting regional in-situ thermal conductivity of soil using AI models for BHEs	XGBoost, RF, Gradient boosting decision trees, AdaBoost	TRT experimental data, Geological properties, Groundwater parameters, Soil thermal properties	Predicted in-situ thermal conductivity for BHEs	XGBoost-RF achieved the best accuracy ($R^2 = 0.9809$), outperforming numerical simulations. SHAP analysis confirmed that weighted thermal conductivity and groundwater parameters were the most influential features.
Dong et al. (2022)	ANN-based prediction of in-situ thermal conductivity for BHEs	ANN with backpropagation	TRT experimental data, Geological parameters (stratigraphy, soil properties), Hydrogeological parameters (groundwater flow, aquifer thickness, permeability)	Predicted in-situ thermal conductivity for BHEs	The ANN model achieved $R^2 = 0.968$, significantly outperforming empirical models. Weighted thermal conductivity and groundwater characteristics were key predictors, reducing the need for full-scale TRT measurements.
Bourhis et al., 2021	ML enhancement of TRT (BHEs) data for geothermal potential assessment	XGBoost	TRT experimental data, Borehole location, Geological characteristics, Borehole depth, Borehole diameter	Predicted ground temperature, thermal conductivity, borehole resistance	XGBoost-based models achieved high accuracy (MAE <0.7 °C for temperature, <0.2 W/(m·K) for thermal conductivity). Site-specific predictions are more accurate than regional-scale mapping.
Pasquier and Marcotte (2020)	BI with ANN for TRT parameter estimation	ANN, BI	TRT experimental data, Borehole parameters, Ground thermal properties	Estimated volumetric heat capacity, thermal conductivity, borehole resistance	ANN significantly accelerates Bayesian inference for TRT, improving parameter accuracy. Residual autocorrelation must be accounted for in TRT data analysis.
Jacques and Pasquier (2023)	ANN-based BI for hydraulic and thermal parameter estimation in standing column Well TRT	ANN, BI	TRT experimental data, Geological stratigraphy, Hydrostratigraphic unit parameters, Groundwater flow properties	Estimated hydraulic conductivity, thermal conductivity, volumetric heat capacity	ANN-enhanced Bayesian inference allows faster and more precise estimation of subsurface properties. High hydraulic conductivity enhances advective heat transfer, affecting parameter identification.

Table 8
Cross-study synthesis of AI algorithm performance across similar GHE tasks.

Task	Algorithm families used	Observed cross-study tendencies	General insight for GHE modeling
BHE outlet-temperature prediction	ANN, LSTM, GRU, CNN, CNN–RNN, Bi-LSTM	ANN models → fastest and effective for short-term behavior. Sequential DL (LSTM/GRU) → better at capturing temporal dependencies. CNN–RNN hybrids → most stable for long-horizon forecasts.	Model suitability depends on prediction horizon: ANN (short-term), temporal DL (long-term). No universal best model.
Heat extraction/ heat-transfer rate prediction	SVR, PLSR, M5 Tree, ANN, GA-BPNN, hybrid GA/QL schemes	Classical ML (SVR, M5) → strong baseline accuracy. ANN + evolutionary hybrids → better for nonlinear regimes. Optimization-coupled models → best for design-oriented tuning.	Hybrid ANN + optimization consistently handles nonlinear heat-transfer complexity better than pure classical ML.
Thermal resistance (Rb) & parameter estimation	ANN, Bayesian inference, DFNN–GA	Bayesian + ANN → strongest for uncertainty handling. DFNN–GA → highest accuracy for Rb/Ra estimation. ANN alone → fast but less robust for physical parameter inference.	Parameter-estimation tasks benefit from probabilistic or hybrid ML frameworks, not standalone ANN models.
COP prediction (GSHP/HGHE)	ANN, ANFIS, LR	ANFIS → consistently highest accuracy and stability. ANN → good speed and acceptable accuracy. LR → lowest performance, used as baseline.	Fuzzy-rule systems (ANFIS) outperform ANN in COP prediction due to their structured nonlinear mapping.
Thermomechanical prediction in energy piles/walls	ANN, RT, RF, SVM, XGBoost, LSTM, Bi-LSTM	ANN → effective for short-term deformation. RT/RF/SVM → stable for small datasets. Bi-LSTM → most accurate for long-term thermomechanical response. XGBoost → strong when shallow but interaction-rich inputs exist.	When thermal history matters → temporal DL (LSTM/ Bi-LSTM). For instantaneous/static prediction → tree-based ML is more reliable.
Regional potential mapping/ surrogate modeling	ANN, GPR, DT, SVM	ANN → fastest with near-perfect fits. GPR → strongest for uncertainty quantification in sparse data. DT/SVM → acceptable but weaker generalization.	ANN enables fast surrogates; GPR is preferred where uncertainty intervals are essential for decision-making.

or missing values frequently desynchronize the virtual model, undermining the system's predictive capability (Ali et al., 2025; Taheri Hosseinkhani, 2025).

3.3.6.4. Computational constraints are equally important. Many advanced AI techniques, including deep operator learning, diffusion models, and high-capacity deep networks, require computational resources far beyond those available in typical field-level or embedded hardware. Consequently, real-time or near–real-time inference generally depends on lightweight architectures or hierarchical surrogate models that can function under strict latency and energy constraints (Michailidis et al., 2025b).

3.3.6.5. Economic considerations further complicate adoption. GHE installations already involve substantial capital costs. Incorporating AI frameworks adds expenses related to sensor deployment, high-performance computing (HPC), cloud-based analytics, long-term data storage, and system maintenance. These recurring operational costs underscore the importance of developing low-cost, data-efficient AI methods capable of operating with reduced sensing requirements (Alves et al., 2025; Taheri Hosseinkhani, 2025). While the preceding subsections outline the practical bottlenecks of deploying AI in GHE systems, it is important to recognize that these limitations coexist with substantial benefits demonstrated across the reviewed studies. AI models provide notable improvements in predictive accuracy, computational speed, and the ability to represent nonlinear thermo-hydraulic interactions that are difficult to capture using conventional analytical or numerical formulations. However, their effectiveness remains strongly dependent on data availability and quality, deep models present interpretability challenges, and generalization across heterogeneous geological settings is not yet assured. Real-time implementation is further limited by sensing infrastructure, computational resources, and integration with SCADA-based operational systems. This balanced summary clarifies both the strengths and the practical limitations of AI adoption in GHE engineering.

Despite these challenges, several practical engineering pathways can facilitate real-world deployment: (1) Hybrid modeling workflows that combine AI with validated numerical simulators (such as COMSOL Multiphysics®-based thermal models, analytical BHE solutions, or reduced-order PDE solvers) enable pre-calibration using synthetic datasets and reduce reliance on extensive field measurements. (2) Physics-informed and uncertainty-aware architectures improve robustness with sparse or noisy data, making them suitable for sites with limited sensing infrastructure. (3) Tiered digital-twin frameworks, in which high-fidelity models run offline and lightweight surrogates operate in real time, address computational limitations while preserving predictive accuracy. (4) Modular SCADA-AI interfaces with buffering, time-alignment, and fault-tolerant data assimilation lower the risk of model desynchronization in field environments. (5) Adaptive sensing strategies, such as sparse sensor placement optimization or periodic calibration scheduling, reduce long-term operational costs while maintaining data quality.

Overall, bridging the laboratory–field gap requires improved sensing strategies, physics-aware model design, computationally efficient architectures, and robust SCADA integration. These engineering considerations define a realistic path toward deploying trustworthy, scalable, and operationally viable AI systems in real-world GHE applications.

4. Present gaps and future directions

A comprehensive evaluation of current AI applications in GHE systems reveals an uneven landscape regarding research maturity, coverage of physical processes, and methodological depth. As shown in Fig. 26, most existing work focuses on BHEs, where neural networks and hybrid DL models have been widely used to predict outlet temperature, g-function values, and heating/cooling capacity. Despite this progress, several physically important aspects, such as pipe configuration, grout and backfill properties, groundwater-driven heat advection, and long-term seasonal cycling, remain insufficiently represented. Coaxial BHEs and water-flow–coupled thermal behavior have received particularly limited attention, even though they are increasingly relevant in modern system design.

HGHEs have been explored far less extensively, with most studies focusing on COP prediction despite the strong dependence of system behavior on trench geometry, pipe spacing, soil moisture dynamics, and spatial heterogeneity. Energy piles represent a growing research area, but existing AI models for thermal output, COP, and thermomechanical deformation rarely incorporate cyclic thermal loading, soil–structure interaction, or soil heterogeneity, which are key factors for actual engineering design. Energy tunnels, energy walls, and geothermal pavements remain at early stages of investigation, with only isolated studies addressing simplified thermal outputs while neglecting complex multiphysics interactions such as airflow–ground heat exchange, groundwater influence, dynamic boundary conditions, thermoelastic cycling, or long-term material degradation.

To clearly differentiate between well-studied, exploratory, and unaddressed topics, Table 9 organizes the gaps across GHE types into three categories: (i) mature application domains, dominated by traditional ANN/CNN-based thermal-performance prediction; (ii) early-stage exploratory areas, including thermomechanical coupling in energy piles and moisture-dependent behavior in HGHEs; and (iii) untapped research opportunities, where advanced AI techniques could play a transformative role.

4.1. Cross-cutting methodological gap

Beyond system-specific limitations, a second and more fundamental gap concerns the types of AI methods used in GHE research. Although modern AI has advanced rapidly in physics-based modeling, uncertainty quantification, operator learning, generative modeling, and real-time digitalization, almost all published GHE studies rely on classical ML or early deep-learning architectures. As a result:

(1) Physics-integrated learning (PINNs, XPINNs, VPINNs) has remained almost entirely unused, despite its ability to embed governing heat-transfer physics and improve generalization across geological settings.
(2) Uncertainty-aware modeling (BNNs, distribution-aware learning) is absent, even though thermal property estimation and TRT interpretation depend critically on uncertainty quantification.
(3) Operator learning models have yet to be explored for rapid scenario generation or reduced-order emulation of multiphysics simulations.
(4) RL has not been applied, despite its natural suitability for dynamic load control, thermal cycling strategies, and adaptive operation.
(5) Generative AI is entirely missing, even though sparse field data and incomplete TRT measurements would greatly benefit from physically constrained data augmentation and sensor-gap reconstruction.
(6) LLMs remain unexplored, although recent studies in geo-engineering demonstrate their potential for integrating

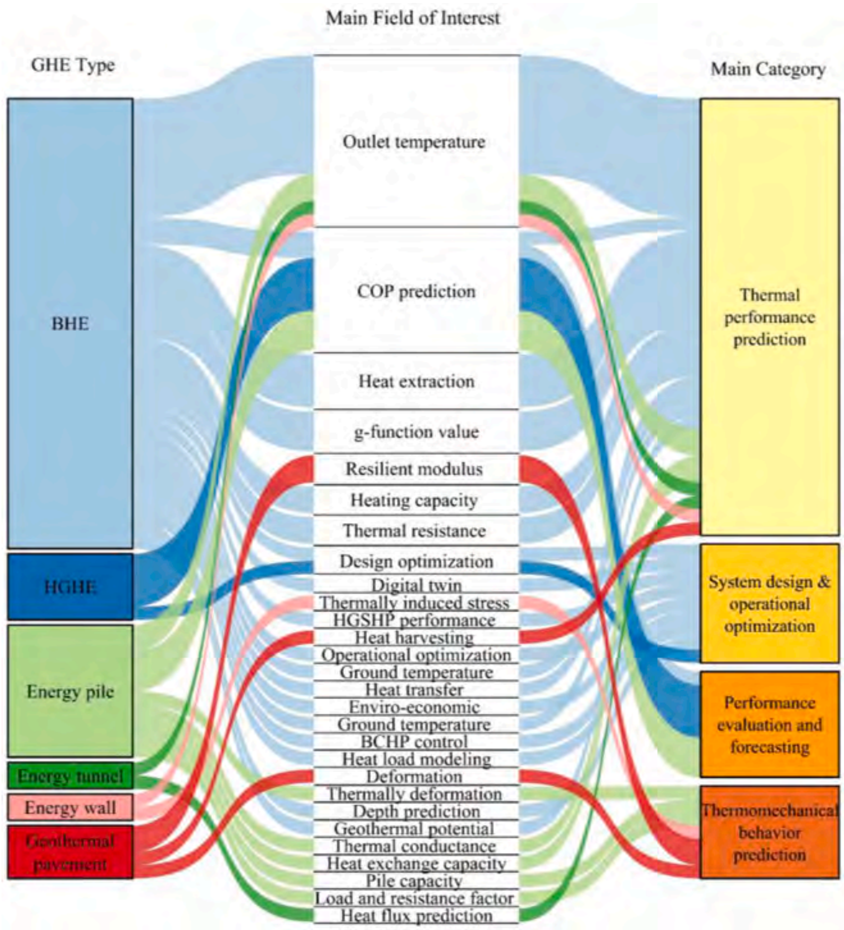

Fig. 26. Alluvial diagram showing the distribution of AI applications in different GHE types, main fields of interest, and main research categories.

heterogeneous logs, reports, and monitoring data within a unified reasoning framework.

(7) Real-time digital twins have only one demonstration in the entire GHE literature, despite being essential for continuous monitoring, state estimation, and system-level optimization.

This methodological gap implies that the next generation of GHE research requires a shift from isolated prediction tasks toward integrated, physics-aware, uncertainty-quantified, and real-time adaptive frameworks capable of supporting design, monitoring, control, and long-term performance assessment.

4.2. Consolidated research roadmap

The combined insights from Fig. 26 and Table 9 reveal two parallel but complementary gaps: (i) the uneven maturity of AI research across GHE types, and (ii) the near-complete absence of modern physics-aware, uncertainty-quantified, and real-time AI methodologies. Integrating these perspectives provides a coherent roadmap for next-generation GHE research. Future progress requires a shift toward advanced and emerging AI methods such as physics-integrated learning, uncertainty-aware modeling, operator-learning surrogates, reinforcement-learning controllers, generative data-augmentation, LLM-assisted workflows, and real-time digital-twin infrastructures. These advancements enable a move beyond isolated prediction tasks toward continuously updated, physically consistent, and operationally adaptive frameworks that support design, monitoring, and long-term system optimization. This roadmap marks a clear transition from conventional predictive models to next-generation intelligent geothermal systems that can learn from sparse data, quantify uncertainty, embed physics, and adapt in real time to field conditions.

5. Conclusions

This review presents a comprehensive and structured evaluation of AI applications in GHEs, including BHEs, HGHEs, energy piles, energy tunnels, energy walls, and geothermal pavements. A total of 59 peer-reviewed studies were critically analyzed and categorized by GHE type, AI algorithm, application domain, and research objectives. The review also covers the integration of AI in the interpretation of TRTs, which, while not GHE systems themselves, are essential for characterizing subsurface thermal properties and optimizing GHE performance. Key findings are summarized as follows: (i) Most studies focus on thermal performance prediction, particularly for BHEs, using traditional ML and widely adopted DL models (ANN, CNN, DNN, and hybrid DL); (ii) AI applications in HGHEs, energy tunnels, walls, and pavements remain limited and are often restricted to COP prediction or basic thermal parameter estimation; (iii) Critical physical processes, such as soil–structure interaction, groundwater flow, soil heterogeneity, cyclic thermal loading, and multiphysics coupling are rarely addressed in current AI frameworks; (iv) Advanced AI technologies– including physics-integrated learning, uncertainty-aware models, operator-learning surrogates, reinforcement learning, generative models, LLMs, and real-time digital twins, are

Table 9
Summary of AI maturity levels across GHE systems.

GHE type	(a) Mature AI applications	(b) Exploratory domains	(c) Untapped areas & Future opportunities
BHEs	Outlet temperature prediction (ANN/CNN)	Pipe configuration & grout/backfill effects	PINNs/XPINNs for conduction–convection physics
	g-function estimation	Seasonal/dynamic performance	FNO/DeepONet for fast parametric sweeps
	Heating/cooling capacity	Groundwater–thermal interaction	RL for real-time operational control
	Heat extraction forecasting	Coaxial BHE modelling	BNNs for TRT uncertainty quantification
		Very limited digital-twin use	Diffusion/GAN models for synthetic g-function augmentation
			LLMs for automated design interpretation & QC
HGHEs	COP prediction (ANN)	Soil-moisture dependency	Spatial DL for 2D/3D subsurface variability
	Basic thermal response inference	Trench geometry & spacing	PINNs for moisture–thermal coupling
		Spatial heterogeneity learning	Digital twins for shallow trench monitoring
			RL for adaptive operation under moisture fluctuations
			Diffusion models for synthetic soil-moisture fields
Energy piles	Outlet temperature prediction	Soil–structure interaction under cyclic loading	PINNs/VPINNs for fully coupled thermo-mechanical PDEs
	COP prediction	Coupled thermo-mechanical behaviour	Operator learning for pile–soil interaction
	Thermomechanical deformation (ANN)	Partial SHM integration	RL for thermal cycling optimization
			BNNs for deformation uncertainty
			Digital twins for real-time SHM-based safety evaluation
			Generative AI for synthetic thermo-mechanical datasets
Energy tunnels	Heat flux prediction	Simplified steady-state thermal models	PINNs for coupled airflow–ground exchange
	Outlet temperature (very limited)	Basic geometry-dependent studies	RL for ventilation–thermal co-optimization
			Digital twins for large tunnel networks
			FNO/DeepONet for transient coupled airflow thermal PDEs
			Generative models for missing sensor data
			LLM-assisted multi-sensor interpretation
Energy walls	Basic thermal and deformation prediction	Groundwater interaction	PGNNs for wall–soil–water coupling
		Thermoelastic cycling	PINNs for cyclic thermomechanical processes
		Limited SHM involvement	RL for performance optimization
			Digital twins for retaining + geothermal hybrid systems
			BNNs for long-term deformation risk
Geothermal pavements	Material deformation prediction	Limited thermal-performance analysis	Physics-integrated ML for cyclic traffic + heat transfer
	Resilient modulus	No dynamic-loading coupling	Diffusion models for long-term degradation synthesis
			RL for adaptive surface thermal management
			FNO/DeepONet for large-scale pavement heat-harvesting modelling
			Digital twins for geothermal smart-road systems

almost entirely absent from the current GHE literature, despite their established relevance in other areas of geoscience and engineering. AI-enhanced analysis of TRTs demonstrates promising improvements in estimating thermal conductivity, volumetric heat capacity, and groundwater effects, especially through ANN, ensemble models, and DNN; (v) A detailed classification table and an alluvial diagram were developed to visualize the distribution of AI applications by GHE type, field of interest, and research focus, offering a clear roadmap for future research.

Collectively, these findings indicate that next-generation geothermal research must move beyond isolated prediction tasks toward integrated frameworks that combine physics-based constraints, real-world monitoring data, and uncertainty quantification. Future studies should prioritize developing adaptive, physics-consistent, and data-efficient AI systems that remain robust across diverse geological and operational conditions. By identifying both system-specific gaps (across different GHE types) and methodological gaps (across AI technologies), this review defines a dual-layered roadmap for advancing shallow-geothermal engineering. This roadmap highlights the need for interdisciplinary strategies that integrate AI with geoscience, geotechnical engineering, and thermo-hydro-mechanical modeling, enabling the design of intelligent, resilient, and sustainable geothermal infrastructures.

CRediT authorship contribution statement

Danial Sheini Dashtgoli: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Methodology, Investigation, Data curation, Conceptualization. **Guillermo A. Narsilio:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Qusi I. Alqawasmeh:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Michela Giustiniani:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition. **Martina Busetti:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation. **Claudia Cherubini:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation.

Declaration of competing interest

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

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References

Abdalla, R., Hollstein, W., Carvajal, C.P., Jaeger, P., 2023. Actor-critic reinforcement learning leads decision-making in energy systems optimization—steam

injection optimization. Neural Comput. Appl. 35, 16633–16647.
Adebiyi, T.A., Ajenifuja, N.A., Zhang, R., 2024. Digital twins and civil engineering phases: reorienting adoption strategies. J. Comput. Inf. Sci. Eng. 24, 100801.
Ahmad, Z., Jaffri, Z.U.A., Chen, M., Bao, S., 2024. Understanding GANs: fundamentals, variants, training challenges, applications, and open problems. Multimed. Tool. Appl. 84, 10347–10423.
Ahmed, N., Assadi, M., Ahmed, A.A., Banihabib, R., 2023a. Optimal design, operational controls, and data-driven machine learning in sustainable borehole heat exchanger coupled heat pumps: key implementation challenges and advancement opportunities. Energy Sustain. Dev. 74, 231–257.
Ahmed, N., Assadi, M., Zhang, Q., 2023b. Investigating the impact of borehole field data's input parameters on the forecasting accuracy of multivariate hybrid deep learning models for heating and cooling. Energy Build. 301, 113706.
Ahmed, N., Assadi, M., Ahmed, A.A., Banihabib, R., Zhang, Q., 2024a. Assessing the impact of borehole field data on AI-based deep learning models for heating and cooling prediction. Geothermics 117, 102867.
Ahmed, N., Assadi, M., Zhang, Q., Sliwa, T., 2024b. Data-driven insights for improved heating and cooling predictions: impact of input parameters on multivariate deep learning algorithms using geothermal borehole field data. Appl. Therm. Eng. 245, 122870.
Akkem, Y., Biswas, S.K., Varanasi, A., 2024. A comprehensive review of synthetic data generation in smart farming by using variational autoencoder and generative adversarial network. Eng. Appl. Artif. Intell. 131, 107881.
Akram, M.W., Chen, Q., Nortz, G., Nortz, P., 2024. Experimental investigation and numerical modeling of an innovative horizontal coaxial ground heat exchanger (HCGHE) for geothermal heat pump applications. Appl. Therm. Eng. 257, 124492.
Akteruzzaman, M., 2025. Implementation of the developed solar photovoltaic system performance model in real-world applications for sustainable energy optimization. J. Sustain. Dev. Policy 1 (1), 365–394.
Al-Qadami, E.H.H., Mustaffa, Z., Al-Atroush, M.E., 2022. Evaluation of pavement geothermal energy harvesting technologies towards sustainability and renewable energy. Energies 15, 1201.
Alexis Sazon, T., Zhang, Q., Nikpey, H., 2024. Comparison of different strategies for operating a solar-assisted ground-source CO2 heat pump system for space and water heating. Energy Convers. Manag. X 22, 100604.
Ali, H., Safdar, R., Liu, J., et al., 2025. Hybrid fusion paradigm in advanced process monitoring: a panoramic review and future perspectives. Ind. Eng. Chem. Res. 64 (47), 22465–22514.
Alqahtani, H., Kavakli-Thorne, M., Kumar, G., 2021. Applications of generative adversarial networks (GANs): an updated review. Arch. Comput. Methods Eng. 28, 525–552.
Alqarafi, A., Batool, H., Abbas, T., Janjua, J.I., Ramay, S.A., Ahmed, M., 2024. Estimating uncertainty in deep learning methods and applications. In: Proc. 2024 Int. Conf. Comput. Appl. (ICCA), pp. 1–6. Cairo, Egypt.
Alqawasmeh, Q.I., Narsilio, G.A., Makasis, N., Kreitmair, M.J., 2024. The impact of soil layering and groundwater flow on energy pile thermal performance. Geomech. Energy Environ. 38, 100538.
Alqawasmeh, Q.I., Kreitmair, M.J., Narsilio, G.A., 2025. The role of ground hydrothermal spatial variability on energy pile group thermal performance. Comput. Geotech. 179, 106983.
Alves, E., Gurupadayya, B.M., Prabhakaran, P., 2025. Artificial intelligence in HPLC method development: a critical review of technological integration, limitations, and future directions. Crit. Rev. Anal. Chem. 1–43.
Aresti, L., Christodoulides, P., Florides, G., 2018. A review of the design aspects of ground heat exchangers. Renew. Sustain. Energy Rev. 92, 757–773.
Arif Ali, Z., Abduljabbar, Z.H., Tahir, H., Bibo Sallow, A., Almufti, S.M., 2023. eXtreme gradient boosting algorithm with machine learning: a review. Acad. J. Nawroz Univ. 12, 320–334.
Arulrajah, A., Ghorbani, B., Narsilio, G., Horpibulsuk, S., Leong, M., 2021. Thermal performance of geothermal pavements constructed with demolition wastes. Geomech. Energy Environ. 28, 100253.
Azizzadenesheli, K., Kovachki, N., Li, Z., Liu-Schiaffini, M., Kossaifi, J., Anandkumar, A., 2024. Neural operators for accelerating scientific simulations and design. Nat. Rev. Phys. 6, 320–328.
Bacsa, K., Liu, W., Abdallah, I., Chatzi, E., 2025. Structural dynamics feature learning using a supervised variational autoencoder. J. Eng. Mech. 151, 04024106.
Baharuddin, S., John, C.M., 2025. Using generative adversarial networks to translate microresistivity image logs of carbonates into synthetic core images with accurate Dunham textures. J. Geophys. Res. Mach. Learn. Comput. 2 e2024JH000533.
Bandeira Neto, L., Narsilio, G., Makasis, N., Choudhary, R., Carden, Y., 2023. Experimental and numerical data of thermal response tests executed in groups of energy piles connected in series. Data Brief 48, 109256.
Bandeira Neto, L.A., Fei, W., Narsilio, G.A., 2024. Improving thermal performance of groups of energy screw piles with phase change materials. Appl. Therm. Eng. 236, 121874.
Bao, J., Lee, J., Yoon, H., 2024. Enhanced geothermal site characterization using generative adversarial network and ensemble method. In: Proc. 58th U.S. Rock Mech./Geomech. Symp.. Golden, CO, USA, paper D022S021R005.
Barla, M., Di Donna, A., Perino, A., 2016. Application of energy tunnels to an urban environment. Geothermics 61, 104–113.
Barla, M., Di Donna, A., Insana, A., 2019. A novel real-scale experimental prototype of energy tunnel. Tunn. Undergr. Space Technol. 87, 1–14.
Barsha, F.L., Eberle, W., 2025. An in-depth review and analysis of mode collapse in generative adversarial networks. Mach. Learn. 114, 141.
Batini, N., Rotta Loria, A.F., Conti, P., Testi, D., Grassi, W., Laloui, L., 2015. Energy and geotechnical behaviour of energy piles for different design solutions. Appl. Therm. Eng. 86, 199–213.
Baumgärtel, S., Schweighofer, J.A.V., Rohn, J., Luo, J., 2021. The performance of geothermal passive heating and cooling for asphalt and concrete pavement. Dev. Built Environ. 7, 100051.
Bidarmaghz, A., Narsilio, G.A., 2018. Heat exchange mechanisms in energy tunnel systems. Geomech. Energy Environ. 16, 83–95.
Bourhis, P., Cousin, B., Loria, A.F.R., Laloui, L., 2021. Machine learning enhancement of thermal response tests for geothermal potential evaluations at site and regional scales. Geothermics 95, 102132.
Bramm, A.M., Matrenin, P.V., Khalyasmaa, A.I., 2025. A review of XAI methods applications in forecasting runoff and water level hydrological tasks. Mathematics 13, 2830.
Cai, S., Mao, Z., Wang, Z., Yin, M., Karniadakis, G.E., 2021. Physics-informed neural networks (PINNs) for fluid mechanics: a review. Acta Mech. Sin. 37, 1727–1738.
Chaoran, W., Chanjuan, H., 2024. Prediction and optimization of heat extraction in ground source heat pump system using surrogate model. IOP Conf. Ser. Earth Environ. Sci. 1335, 012017.
Chen, T., Guestrin, C., 2016. XGBoost: a scalable tree boosting system. In: Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min, pp. 785–794.
Chen, S., Mao, J., Chen, F., Hou, P., Li, Y., 2018. Development of ANN model for depth prediction of vertical ground heat exchanger. Int. J. Heat Mass Transf. 117, 617–626.
Chen, G., Luo, X., Jiao, J.J., Jiang, C., 2023a. Fracture network characterization with deep generative model based stochastic inversion. Energy 273, 127302.
Chen, G., Luo, X., Jiao, J.J., Jiang, C., 2023b. Fracture network characterization with deep generative model based stochastic inversion. Energy 273, 127302.
Chen, W., Ding, J., Wang, T., Connolly, D.P., Wan, X., 2023c. Soil property recovery from incomplete in-situ geotechnical test data using a hybrid deep generative framework. Eng. Geol. 326, 107332.
Chen, L., Tophel, A., Hettiyadura, U., Kodikara, J., 2024a. An investigation into the utility of large language models in geotechnical education and problem solving. Geotechnics 4, 470–498.
Chen, M., Mei, S., Fan, J., Wang, M., 2024b. An Overview of Diffusion Models: Applications, Guided Generation, Statistical Rates and Optimization arXiv: 2404.07771.
Cimmino, M., Cook, J.C., Isiordia Farrera, J.A., 2024. Optimal discretization of geothermal boreholes for the calculation of g -functions. Sci. Technol. Built Environ. 30, 234–249.
Clifton, J., Laber, E., 2020. Q-learning: theory and applications. Annu. Rev. Stat. Appl. 7, 279–301.
Cobbinah, M., Nunoo-Mensah, H., Ebenezer Adjei, P., Adoma Acheampong, F., Acquah, I., Tutu Tchao, E., Selasi Agbemenu, A., John Kponyo, J., Abaidoo, E., 2025. Diversity in stable GANs: a systematic review of mode collapse mitigation strategies. Eng. Rep. 7, e70209.
Congedo, P.M., Colangelo, G., Starace, G., 2012. CFD simulations of horizontal ground heat exchangers: a comparison among different configurations. Appl. Therm. Eng. 33–34, 24–32.
Cotoarbă, D., Straub, D., Smith, I.F.C., 2025. Probabilistic digital twins for geotechnical design and construction. Data-Centric Eng. 6, e30.
Cui, L., Li, H., Chen, K., Shou, L., Chen, G., 2024a. Tabular Data Augmentation for Machine Learning: Progress and Prospects of Embracing Generative AI, 21523 arXiv:2407.
Cui, P., Yang, W., Zhang, W., Zhu, K., Spitler, J.D., Yu, M., 2024b. Advances in ground heat exchangers for space heating and cooling: review and perspectives. Energy Built. Environ. 5, 255–269.
Dai, X., Bidarmaghz, A., Narsilio, G.A., 2023a. Energy tunnels: a review of the state of the art and knowledge gaps to harness renewable energy from underground infrastructure. Tunn. Undergr. Space Technol. 142, 105431.
Dai, X., Bidarmaghz, A., Narsilio, G.A., 2023b. Numerical investigation on the thermal performance of energy tunnels under groundwater flow and tunnel airflow. In: Proc. Symp. Energy Geotech. 2023, pp. 1–2.
Das, S., Tariq, A., Santos, T., Kantareddy, S.S., Banerjee, I., 2023. Recurrent neural networks (RNNs): architectures, training tricks, and introduction to influential research. In: Colliot, O. (Ed.), Machine Learning for Brain Disorders, pp. 117–138. Neuromethods.
Demiss, B.A., Elsaigh, W.A., 2024. Application of novel hybrid deep learning architectures combining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN): construction duration estimates prediction considering preconstruction uncertainties. Eng. Res. Express 6, 032102.
Deng, Y., Kang, X., Ma, H., Qian, J., Ma, L., Luo, Q., 2024. Characterization of discrete fracture networks with deep-learning based hydrogeophysical inversion. J. Hydrol. 631, 130819.
Dike, H.U., Zhou, Y., Deveerasetty, K.K., Wu, Q., 2018. Unsupervised learning based on artificial neural networks: a review. In: 2018 IEEE Int. Conf. Cyborg Bionic Syst. CBS), pp. 322–327.
Dong, J., Li, X., Han, B., Tian, R., Yu, H., 2022. A regional study of in-situ thermal conductivity of soil based on artificial neural network model. Energy Build. 257, 111785.
Dong, J., Wang, H., Huang, S., Jiang, Y., Liu, J., 2024. Advances in the effects of multiple factors on the thermal performance of deep borehole heat exchangers: a systematic review. J. Build. Eng. 96, 110488.
Duan, M., Xiao, X., 2024. Enhancing soil pile-bearing capacity prediction in

geotechnical engineering using optimized decision tree fusion. Multiscale and Multidiscip. Model. Exp. Des. 7, 2861–2876.

Düber, S., Fuentes, R., Narsilio, G., 2023. Effect of horizontal connection pipes on operation of borehole heat exchangers under different climatic conditions. Geothermics 110, 102679.

Dudukcu, H.V., Taskiran, M., Cam Taskiran, Z.G., Yildirim, T., 2023. Temporal Convolutional Networks with RNN approach for chaotic time series prediction. Appl. Soft Comput. 133, 109945.

Esen, H., Inalli, M., 2010. ANN and ANFIS models for performance evaluation of a vertical ground source heat pump system. Expert Syst. Appl. 37, 8134–8147.

Esen, H., Inalli, M., Sengur, A., Esen, M., 2008a. Forecasting of a ground-coupled heat pump performance using neural networks with statistical data weighting pre-processing. Int. J. Therm. Sci. 47, 431–441.

Esen, H., Inalli, M., Sengur, A., Esen, M., 2008b. Modelling a ground-coupled heat pump system using adaptive neuro-fuzzy inference systems. Int. J. Refrig. 31, 65–74.

Esen, H., Esen, M., Ozsolak, O., 2017. Modelling and experimental performance analysis of solar-assisted ground source heat pump system. J. Exp. Theor. Artif. Intell. 29, 1–17.

Fadejev, J., Simson, R., Kurnitski, J., Haghighat, F., 2017. A review on energy piles design, sizing and modelling. Energy 122, 390–407.

Fan, J., Zhang, K., Huang, Y., Zhu, Y., Chen, B., 2023. Parallel spatio-temporal attention-based TCN for multivariate time series prediction. Neural Comput. Appl. 35, 13109–13118.

Fan, L., Liu, F., Chen, C., 2025. Domain Adaptation of Large Language Models for Geotechnical Applications arXiv:2507.05613.

Fannou, J.-L.C., Rousseau, C., Lamarche, L., Kajl, S., 2014. Modeling of a direct expansion geothermal heat pump using artificial neural networks. Energy Build.

Faroughi, S.A., Pawar, N.M., Fernandes, C., et al., 2024. Physics-guided, physics-informed, and physics-encoded neural networks and operators in scientific computing: fluid and solid mechanics. J. Comput. Inf. Sci. Eng. 24, 040802.

Florides, G., Kalogirou, S., 2007. Ground heat exchangers—A review of systems, models and applications. Renew. Energy 32, 2461–2478.

Fu, B., Guo, Z., Yan, J., Sun, L., Zhang, S., Nie, L., 2023. Research on the heat extraction performance optimization of spiral fin coaxial borehole heat exchanger based on GA–BPNN–QLMPA. Processes 11, 2989.

Fujii, H., Nishi, K., Komaniwa, Y., Chou, N., 2012. Numerical modeling of slinky-coil horizontal ground heat exchangers. Geothermics 41, 55–62.

Gang, W., Wang, J., 2013. Predictive ANN models of ground heat exchanger for the control of hybrid ground source heat pump systems. Appl. Energy 112, 1146–1153.

Gang, W., Wang, J., Wang, S., 2014. Performance analysis of hybrid ground source heat pump systems based on ANN predictive control. Appl. Energy 136, 1138–1144.

García, L.C.H., Valencia, J.V., Colorado, L., Henry, A., 2025. Modeling an artificial neural network to estimate cement consumption in clayey waste-cement mixtures based on curing temperature, mechanical strength, and resilient modulus. Constr. Build. Mater. 467, 140376.

Ge, Q., Li, J., Wang, X., Deng, Y., Zhang, K., Sun, H., 2024. LiteTransNet: an interpretable approach for landslide displacement prediction using transformer model with attention mechanism. Eng. Geol. 331, 107446.

Ghalandari, T., Hernando, D., Hasheminejad, N., Moenielal, M., Vuye, C., 2023. Lessons learnt from thermo-mechanical feasibility assessment of pavement solar collectors using a FE-ANN approach. Case Stud. Constr. Mater. 19, e02582.

Ghorbani Bam, P., Rezaei, N., Roubanis, A., et al., 2025. Digital twin applications in the water sector: a review. Water 17, 2957.

Ghorbani, B., Arulrajah, A., Narsilio, G., Horpibulsuk, S., Leong, M., 2021a. Resilient moduli of demolition wastes in geothermal pavements: experimental testing and ANFIS modelling. Transp. Geotechn. 29, 100592.

Ghorbani, B., Arulrajah, A., Narsilio, G., Horpibulsuk, S., Win Bo, M., 2021b. Thermal and mechanical properties of demolition wastes in geothermal pavements by experimental and machine learning techniques. Constr. Build. Mater. 280, 122499.

Gonon, L., Jentzen, A., Kuckuck, B., Liang, S., Riekert, A., von Wurstemberger, P., 2024. An Overview on Machine Learning Methods for Partial Differential Equations: from physics-informed Neural Networks to Deep Operator Learning arXiv:2408.13222.

Gu, X., Makasis, N., Motamedi, Y., Narsilio, G.A., Arulrajah, A., Horpibulsuk, S., 2022. Geothermal pavements: field observations, numerical modelling and long-term performance. Geotechnique 72, 832–846.

Guan, Z., Wang, Y., 2024. Fusion of three-dimensional geotechnical and geophysical data for developing digital twin of underground space. Soils Found. 64, 101528.

Gupta, J., Pathak, S., Kumar, G., 2022. Deep learning (CNN) and transfer learning: a review. J. Phys., Conf. Ser. 2273, 012029.

Gutiérrez-Oribio, D., Stathas, A., Stefanou, I., 2025. AI-driven approach for sustainable extraction of Earth's subsurface renewable energy while minimizing seismic activity. Int. J. Numer. Analyt. Method. Geomech. 49, 1126–1138.

Han, J., Hong, J., Chen, X., et al., 2024. Integrating convolutional attention and encoder–decoder long short-term memory for enhanced soil moisture prediction. Water 16, 3481.

Hanif, M.F., Ahmad, R., Farooq, A.B., et al., 2025. The solar AI nexus: reinforcement learning shaping the future of energy management. WIREs Energy Environ. 14, e70012.

Harris, B.E., Lightstone, M.F., Reitsma, S., Cotton, J.S., 2022. Analysis of the transient performance of coaxial and u-tube borehole heat exchangers. Geothermics 101, 102319.

Harsuko, R., Bi, Z., Nakata, N., 2025. GAIA: Geothermal Analytics and Intelligent Agent arXiv:2511.03852.

He, F., Tan, R., Jiang, S., Qian, C., Bu, C., Wang, B., 2025. Deep learning-based investigation of multiphase flow and heat transfer in CO2–water enhanced geothermal systems. Fluid Dynam. Mater. Process. 21, 2557–2577.

Hemmatabady, H., Welsch, B., Formhals, J., Sass, I., 2022. AI-based enviro-economic optimization of solar-coupled and standalone geothermal systems for heating and cooling. Appl. Energy 311, 118652.

Hou, G., Taherian, H., Song, Y., Jiang, W., Chen, D., 2022. A systematic review on optimal analysis of horizontal heat exchangers in ground source heat pump systems. Renew. Sustain. Energy Rev. 154, 111830.

Hu, S., Kong, G., 2024. Data-driven prediction model for the heat performance of energy tunnels. Tunn. Undergr. Space Technol. 154, 106127.

Hu, S., Kong, G., Yu, D., Yang, Q., 2023. Thermomechanical performance of energy retaining pile influenced by surrounding utility tunnel via the regression tree model. Comput. Geotech. 162, 105679.

Hu, K., Li, M., Song, Z., et al., 2024a. A review of research on reinforcement learning algorithms for multi-agents. Neurocomputing 599, 128068.

Hu, S., Kong, G., Hong, Y., Li, C., 2024b. Evaluation and machine learning prediction on thermal performance of energy walls in underground spaces as part of ground source heat pump systems. Tunn. Undergr. Space Technol. 148, 105750.

Imtiyaz, P.A., Khalad, A., Muqtadir, S.A., 2023. Prediction of thermal conduction of energy piles using various machine learning models. Int. J. Geotech. Eng. 17, 668–680.

Insana, A., Barla, M., 2020. Experimental and numerical investigations on the energy performance of a thermo-active tunnel. Renew. Energy 152, 781–792.

Iranzad, R., Liu, X., 2025. A review of random forest-based feature selection methods for data science education and applications. Int. J. Data Sci. Anal. 20, 197–211.

Islam, S., Aziz, MdT., Nabil, H.R., et al., 2024. Generative adversarial networks (GANs) in medical imaging: advancements, applications, and challenges. IEEE Access 12, 35728–35753.

Jabeen, N., Naseem, A., Sarfraz, M., et al., 2025. Cross-disciplinary research gaps in physical, chemical, and environmental sciences: an integrative review from nanotechnology to wastewater treatment, renewable energy, artificial intelligence, and biomedical engineering. Sch. J. Phys. Math. Stat. 12, 369–388.

Jacques, L., Pasquier, P., 2023. Obtaining the hydraulic and thermal properties of the main hydrostratigraphic units surrounding a standing column well using a thermal response test. J. Hydrol. 623, 129823.

Jahan, N., Ali, M.H., Miyara, A., 2024. Numerical analysis of thermal performance of various types of horizontal ground heat exchangers. AIP Adv. 14, 095107.

Javadi, H., Ajarostaghi, S.S.M., Mousavi, S.S., Pourfallah, M., 2019. Thermal analysis of a triple helix ground heat exchanger using numerical simulation and multiple linear regression. Geothermics 81, 53–73.

Jensen-Page, L., Narsilio, G.A., Bidarmaghz, A., Johnston, I.W., 2018. Investigation of the effect of seasonal variation in ground temperature on thermal response tests. Renew. Energy 125, 609–619.

Jensen-Page, L., Loveridge, F., Narsilio, G.A., 2019. Thermal response testing of large diameter energy piles. Energies 12, 2700.

Jeon, J.-S., Lee, S.-R., Kim, M.-J., Yoon, S., 2018. Suggestion of a scale factor to design spiral-coil-type horizontal ground heat exchangers. Energies 11, 2736.

Jiang, B., Gong, H., Qin, H., Zhu, M., 2022a. Attention-LSTM architecture combined with Bayesian hyperparameter optimization for indoor temperature prediction. Build. Environ. 224, 109536.

Jiang, J., Wang, F., Yang, X., et al., 2022b. Evaluation of the long-term performance of the deep U-type borehole heat exchanger on different geological parameters using the Taguchi method. J. Build. Eng. 59, 105122.

Karrari, S.S., Heidari, M., Khaleghi-Esfahani, M., 2025. New rock toughness index based on drilling and tensile strength by using entropy of decision tree and geotechnical analysis. Q. J. Eng. Geol. Hydrogeol. 58 qjegh2024-q2168.

Khan, A.A., Chaudhari, O., Chandra, R., 2024. A review of ensemble learning and data augmentation models for class imbalanced problems: combination, implementation and evaluation. Expert Syst. Appl. 244, 122778.

Kharseh, M., Koujok, M.E., Wallbaum, H., 2020. Estimating the ground temperature around energy piles using artificial neural networks. In: Arai, K., Bhatia, R., Kapoor, S. (Eds.), Proceedings of the Future Technologies Conference (FTC) 2019, Adv. Intell. Syst. Comput. Springer International Publishing, Cham, pp. 223–229.

King, M., Yune, C.-Y., 2024. Advanced machine learning techniques: forecasting thermal resistance in borehole heat exchanger system through RSM and hybrid DFNN-GA approaches. Geothermics 120, 103004.

King, M., Woo, S.I., Yune, C.-Y., 2024. Utilizing a CNN-RNN machine learning approach for forecasting time-series outlet fluid temperature monitoring by long-term operation of BHEs system. Geothermics 122, 103082.

Koh, E., Kim, N., 2025. Recent progress in scientific machine learning for numerical solutions of partial differential equations. JMST Adv. 7, 39–47.

Kong, Z., Cui, Y., Xia, Z., Lv, H., 2019. Convolution and long short-term memory hybrid deep neural networks for remaining useful life prognostics. Appl. Sci. 9, 4156.

Kong, G., Chen, Y., Wang, L., Meng, Y., Yang, Q., 2024. Seasonal performance of an energy pile heat pump system and prediction of building thermal load. Appl. Therm. Eng. 241, 122359.

Kose, A., Petlenkov, E., 2016. System identification models and using neural networks for ground source heat pump with ground temperature modeling. In: 2016 International Joint Conference on Neural Networks (IJCNN). Presented at the 2016 International Joint Conference on Neural Networks (IJCNN). IEEE, Vancouver, BC, Canada, pp. 2850–2855.

Kovachki, N.B., Lanthaler, S., Stuart, A.M., 2024. Chapter 9 - operator learning: algorithms and analysis. In: Mishra, S., Townsend, A. (Eds.), Numerical Analysis Meets Machine Learning, Handb. Numer. Anal. Elsevier, pp. 419–467.

Kreuzer, T., Papapetrou, P., Zdravkovic, J., 2024. Artificial intelligence in digital twins—A systematic literature review. Data Knowl. Eng. 151, 102304.

Kumar, K., 2024. Geotechnical parrot tales (GPT): harnessing large language models in geotechnical engineering. J. Geotech. Geoenviron. Eng. 150, 02523001.

Kumar, P., Samui, P., 2022. Design of an energy pile based on CPT data using soft computing techniques. Infrastructures 7, 169.

Kumar, P., Samui, P., 2024. Reliability-based load and resistance factor design of an energy pile with CPT data using machine learning techniques. Arabian J. Sci. Eng. 49, 4831–4860.

Kupiec, K., Larwa, B., Gwadera, M., 2015. Heat transfer in horizontal ground heat exchangers. Appl. Therm. Eng. 75, 270–276.

Laloui, L., Sutman, M., 2021. Experimental investigation of energy piles: from laboratory to field testing. Geomech. Energy Environ. 27, 100214.

Lee, D., Ooka, R., Ikeda, S., Choi, W., 2019. Artificial neural network prediction models of stratified thermal energy storage system and borehole heat exchanger for model predictive control. Sci. Technol. Built Environ. 25, 534–548.

Lee, S., Kim, D., Park, H., Choi, H., Park, S., 2025. Data-driven prediction of long-term thermal performance for steel pipe heat exchanger (SPHX) energy piles. Geothermics 129, 103292. Geothermics.

Leng, J., Su, X., Liu, Z., et al., 2025. Diffusion model-driven smart design and manufacturing: prospects and challenges. J. Manuf. Syst. 82, 561–577.

León, O., Rivera, V., Vázquez-Patiño, A., Ulloa, J., Samaniego, E., 2025. Exploring energy minimization to model strain localization as a strong discontinuity using Physics Informed Neural Networks. Comput. Meth. Appl. Mech. Eng. 436, 117724.

Li, M., Peng, H., 2025. Stepwise multi-objective framework for decoupling multi-parameter estimation of ground heat exchangers. Geothermics 127, 103249.

Li, Z., Liu, F., Yang, W., Peng, S., Zhou, J., 2022. A survey of convolutional neural networks: analysis, applications, and prospects. IEEE Trans. Neural Netw. Learn. Syst. 33, 6999–7019.

Li, B., Qi, P., Liu, B., et al., 2023. Trustworthy AI: from principles to practices. ACM Comput. Surv. 55, 1–46.

Li, X., Gong, M., Dong, J., Zhou, Z., Han, B., Yu, H., 2024. Forecasting regional in-situ thermal conductivity of soil based on tree-based ensemble learning. Int. Commun. Heat Mass Transf. 159, 107996.

Li, Z., Huang, Q., Yang, L., et al., 2025. Diffusion Models for Tabular Data: Challenges, Current Progress, and Future Directions arXiv preprint arXiv: 2502.17119.

Liu, Y., Mei, X., Zhang, G., Cao, Z., 2023. Long-term performance prediction of ground source heat pump system based on co-simulation and artificial neural network. J. Build. Eng. 79, 107949.

Liu, H., Su, H., Sun, L., Dias-da-Costa, D., 2024. State-of-the-art review on the use of AI-enhanced computational mechanics in geotechnical engineering. Artif. Intell. Rev. 57, 196.

Lotfollahi, M., Naghipourfar, M., Theis, F.J., Wolf, F.A., 2020. Conditional out-of-distribution generation for unpaired data using transfer VAE. Bioinformatics 36, i610–i617.

Loveridge, F., McCartney, J.S., Narsilio, G.A., Sanchez, M., 2020. Energy geostructures: a review of analysis approaches, in situ testing and model scale experiments. Geomech. Energy Environ. 22, 100173.

Luo, K., Zhao, J., Wang, Y., et al., 2025. Physics-informed neural networks for PDE problems: a comprehensive review. Artif. Intell. Rev. 58, 323.

Lyu, C., Xu, W., Wang, K., et al., 2025. A digital twin system for long-term slope deformation prediction based on an adaptive updating surrogate model. Eng. Geol. 357, 108325.

Ma, Q., Tian, S., Wei, J., Wang, J., Ng, W.W.Y., 2019. Attention-based spatio-temporal dependence learning network. Inf. Sci. 503, 92–108.

Ma, C., Donna, A.D., Dias, D., Zhang, J., 2021. Numerical investigations of the tunnel environment effect on the performance of energy tunnels. Renew. Energy 172, 1279–1292.

Ma, C., An, L., Di Donna, A., Dias, D., 2024. Application of machine learning technique to predict the energy performance of energy tunnels. Comput. Geotech. 166, 106010.

Magdic, L., Zakula, T., Boban, L., 2023. Improved Analysis of borehole heat exchanger performance. Energies 16, 6116.

Mahmoud, M., Semeraro, C., Ramadan, M., Abdelkareem, M.A., Olabi, A.G., 2025. Building a digital twin for a ground heat exchanger. Chem. Eng. Technol. 48, e202300492.

Makasis, N., Narsilio, G.A., 2022. Investigating the thermal performance of energy soldier pile walls. Geomech. Energy Environ. 30, 100242.

Makasis, N., Narsilio, G.A., Bidarmaghz, A., 2018. A machine learning approach to energy pile design. Comput. Geotech. 97, 189–203.

Makasis, N., Narsilio, G.A., Bidarmaghz, A., Johnston, I.W., Zhong, Y., 2020. The importance of boundary conditions on the modelling of energy retaining walls. Comput. Geotech. 120, 103399.

Mao, Y., Li, Y., Teng, F., Nanehkaran, Y.A., Azarafza, M., Zhang, M., 2024. Predicting the elasticity modulus of sedimentary rocks using Deep Random Forest Optimization (DRFO) algorithm. Environ. Earth Sci. 83, 487.

Maslej, N., Fattorini, L., Perrault, R., et al., 2024. Artificial Intelligence Index Report 2024 arXiv preprint arXiv:2405.19522.

Mazzotti Pallard, W., Lazzarotto, A., 2021. Thermal response tests: a biased parameter estimation procedure? Geothermics 97, 102221.

Michailidis, P., Michailidis, I., Kosmatopoulos, E., 2025a. Reinforcement learning for optimizing renewable energy utilization in buildings: a Review on applications and iInnovations. Energies 18, 1724.

Michailidis, P., Michailidis, I., Minelli, F., Coban, H.H., Kosmatopoulos, E., 2025b. Model predictive control for smart buildings: applications and innovations in energy management. Buildings 15, 3298.

Mimouni, T., Laloui, L., 2015. Behaviour of a group of energy piles. Can. Geotech. J. 52, 1913–1929.

Moayedi, H., Mosallanezhad, M., Rashid, A.S.A., Jusoh, W.A.W., Muazu, M.A., 2020. A systematic review and meta-analysis of artificial neural network application in geotechnical engineering: theory and applications. Neural Comput. Appl. 32, 495–518.

Mohamad, Z., Fardoun, F., Meftah, F., 2021. A review on energy piles design, evaluation, and optimization. J. Clean. Prod. 292, 125802.

Mojtahedi, F.F., Yousefpour, N., Chow, S.H., Cassidy, M., 2025. Deep learning for time Series forecasting: review and applications in geotechnics and geosciences. Arch. Comput. Methods Eng. 32, 3415–3445.

Motamedi, Y., Makasis, N., Gu, X., Narsilio, G.A., Arulrajah, A., Horpibulsuk, S., 2021. Investigating the thermal behaviour of geothermal pavements using Thermal Response Test (TRT). Transp. Geotechn. 29, 100576.

Nakata, R., Nakata, N., Ren, P., Bi, Z., Lacour, M., Erichson, B., Mahoney, M.W., 2025. Simulating seismic wavefields using generative artificial intelligence. Lead. Edge 44, 123–132.

Nazmabadi, R., Asgari, B., Hakkaki-Fard, A., 2022. On the thermal performance enhancement of spiral-coil energy piles with a thermal recovery system. Energy Build. 269, 112240.

Ostertagová, E., 2012. Modelling using Polynomial Regression. Procedia Eng. 48, 500–506.

Ouko, E., Lujan, E., Edelman, A., Metcalfe, R., 2025. Decision-support and modeling withlarge language models for geothermal well arrays. In: Proceedings of the 50th Workshop on Geothermal Reservoir Engineering. Stanford University, Stanford, CA, USA.

Pan, Z., Yu, W., Yi, X., Khan, A., Yuan, F., Zheng, Y., 2019. Recent progress on generative adversarial networks (GANs): a Survey. IEEE Access 7, 36322–36333.

Pang, Y., He, T., Liu, S., Zhu, X., Lee, C., 2024. Triboelectric nanogenerator-enabled digital twins in civil engineering infrastructure 4.0: a Comprehensive review. Adv. Sci. 11, 2306574.

Parsa-Pajouh, A., 2025. Application of generative AI to automate numerical analysis and synthetic data generation in geotechnical engineering. Mach. Learn. Data Sci. Geotech. 1, 46–55.

Pasquier, P., Marcotte, D., 2020. Robust identification of volumetric heat capacity and analysis of thermal response tests by Bayesian inference with correlated residuals. Appl. Energy 261, 114394.

Pasquier, P., Zarrella, A., Labib, R., 2018. Application of artificial neural networks to near-instant construction of short-term g-functions. Appl. Therm. Eng. 143, 910–921.

Pei, H., Song, H., Meng, F., Liu, W., 2022. Long-term thermomechanical displacement prediction of energy piles using machine learning techniques. Renew. Energy 195, 620–636.

Phoon, K.-K., 2024. Trustworthy data-centric geotechnics. Geodata AI 1, 100008.

Piere Canilandi, M., Sutopo, Ashat, A., Dominicus Sinurat, P., 2025. The application of physics-informed neural networks (PINNS) for geothermal well thermal recovery post-injection. IOP Conf. Ser. Earth Environ. Sci. 1456, 012006.

Piotrowska-Woroniak, J., Nęcka, K., Szul, T., Lis, S., 2024. Comparative analysis of methods for predicting brine temperature in vertical ground heat exchanger—A case study. Energies 17, 1465.

Popov, R.K., Georgiev, A.G., Dzhonova-Atanasova, D.B., 2016. Parameter estimation of borehole thermal properties using artificial intelligence methods. Bulg. Chem. Commun. 48, 88–95.

Previati, A., Crosta, G., 2024. On groundwater flow and shallow geothermal potential: a surrogate model for regional scale analyses. Sci. Total Environ. 912, 169046.

Prudencio, R.F., Maximo, M.R., Colombini, E.L., 2023. A survey on offline reinforcement learning: taxonomy, review, and open problems. IEEE Trans. Neural Netw. Learn. Syst. 35, 10237–10257.

Pu, L., Xu, L., Qi, D., Li, Y., 2018. Structure optimization for horizontal ground heat exchanger. Appl. Therm. Eng. 136, 131–140.

Puttige, A.R., Andersson, S., Östin, R., Olofsson, T., 2020. A novel analytical-ANN hybrid model for borehole heat exchanger. Energies 13, 6213.

Puttige, A.R., Andersson, S., Östin, R., Olofsson, T., 2022. Modeling and optimization of hybrid ground source heat pump with district heating and cooling. Energy Build. 264, 112065.

Rao, C., Zhang, Y., Wen, J., Xiao, X., Goh, M., 2023. Energy demand forecasting in China: a support vector regression-compositional data second exponential smoothing model. Energy 263, 125955.

Ray, P.P., 2025. Physical AI: bridging the sim-to-real divide toward embodied. In: Ethical, and Autonomous Intelligence. Preprint, TechRxiv.

Raymond, J., Therrien, R., Gosselin, L., Lefebvre, R., 2011. A review of thermal response test analysis using pumping test concepts. Groundwater 49, 932–945.

Richter, S., Lubashevsky, K., Randow, J., Henker, S., Buchwald, J., Bucher, A., 2024. Global sensitivity analysis and uncertainty quantification for design parameters of shallow geothermal systems. Geotherm. Energy 12, 8.
Rojas, S., Maczuga, P., Muñoz-Matute, J., Pardo, D., Paszyński, M., 2024. Robust variational physics-informed neural networks. Comput. Meth. Appl. Mech. Eng. 425, 116904.
Saxena, D., Cao, J., 2022. Generative adversarial networks (GANs): challenges, solutions, and future directions. ACM Comput. Surv. 54, 1–42.
Selamat, S., Miyara, A., Kariya, K., 2016. Numerical study of horizontal ground heat exchangers for design optimization. Renew. Energy 95, 561–573.
Semeraro, C., Aljaghoub, H., Al-Ali, H.K.M.H., Abdelkareem, M.A., Olabi, A.G., 2025. Harnessing the future: exploring digital twin applications and implications in renewable energy. Energy Nexus 18, 100415.
Sepúlveda-Oviedo, E.H., Travé-Massuyès, L., Subias, A., Pavlov, M., Alonso, C., 2025. Artificial intelligence in photovoltaic fault diagnosis: a natural language-based topic-tSNE fusion analysis. Energy AI 21, 100558.
Sheini Dashtgoli, D., Giustiniani, M., Busetti, M., Cherubini, C., 2024a. Artificial intelligence applications for accurate geothermal temperature prediction in the lower Friulian Plain (north-eastern Italy). J. Clean. Prod. 460, 142452.
Sheini Dashtgoli, D., Dehnad, M.H., Mobinipour, S.A., Giustiniani, M., 2024b. Performance comparison of machine learning algorithms for maximum displacement prediction in soldier pile wall excavation. Undergr. Space 16, 301–313.
Sheini Dashtgoli, D., Sadeghian, R., Reza Mahboubi Ardakani, A., Mohammadnezhad, H., Giustiniani, M., Busetti, M., Cherubini, C., 2024c. Predictive modeling of shallow tunnel behavior: leveraging machine learning for maximum convergence displacement estimation. Transp. Geotechn., 101284
Sheini Dashtgoli, D., Giustiniani, M., Busetti, M., Cherubini, C., Alessandrini, G., Narsilio, G.A., 2026a. Artificial intelligence in deep geothermal energy: trends, insights, and future perspectives. Renew. Energy Focus 56, 100781.
Sheini Dashtgoli, D., Giustiniani, M., Busetti, M., Cherubini, C., Narsilio, G., 2026b. Learning with constraints: a physics-guided bayesian framework for reliable geothermal temperature mapping in Northeastern Italy. SSRN.
Shi, R., Wang, Y., Du, M., Shen, X., Chang, Y., Wang, X., 2025. A Comprehensive Survey of Synthetic Tabular Data Generation arXiv preprint arXiv:2504.16506.
Shih, Y.-C., Tamilarasan, S., Chen, C.-S., Zargar, O.A., Kuan, Y.-D., 2024. Attention-based integrated deep neural network architecture for predicting the effectiveness of data center power usage. Int. J. Thermofluids 24, 100866.
Shima, A., Ishitsuka, K., Lin, W., Bjarkason, E.K., Suzuki, A., 2024. Modeling unobserved geothermal structures using a physics-informed neural network with transfer learning of prior knowledge. Geotherm. Energy 12, 38.
Shoji, Y., Katsura, T., Nagano, K., 2022. MICS-ANN model: an artificial neural network model for fast computation of G-function in moving infinite cylindrical source model. Geothermics 100, 102315.
Siddique, T., Mahmud, M., Keesee, A., Ngwira, C., Connor, H., 2022. A survey of uncertainty quantification in machine learning for space weather prediction. Geosciences 12, 27.
Song, G., Geiger, S., Abels, H., et al., 2024. Towards a subsurface geothermal digital twin: efficient construction of geological scenarios for modelling fluvial geothermal reservoirs. In: Fifth EAGE Global Energy Transition Conference & Exhibition (GET 2024). Presented at the Fifth EAGE Global Energy Transition Conference & Exhibition (GET 2024). European Association of Geoscientists & Engineers, Rotterdam, Netherlands, pp. 1–5.
Stavrev, S., Ginchev, D., 2024. Reinforcement learning techniques in optimizing energy systems. Electronics 13, 1459.
Stemmle, R., Menberg, K., Rybach, L., Blum, P., 2022. Tunnel geothermics – a review. Geomech. Tunn. 15, 104–111.
Su, X., Yan, X., Tsai, C., 2012. Linear regression. WIREs Comput. Stat. 4, 275–294.
Su, C., Cai, Z., Tian, Y., Chang, Z., Zheng, Z., Song, Y., 2025. Diffusion Models for Time Series Forecasting: a Survey arXiv preprint arXiv:2507.14507.
Taheri Hosseinkhani, N., 2025. Artificial intelligence and large language models in energy systems and climate strategies: economic pathways to cost-effective emissions reduction and sustainable growth. SSRN J.
Tang, F., Nowamooz, H., Wang, D., Luo, J., Wang, W., Sun, X., 2022. Heat exchange capacity prediction of borehole heat exchanger (BHE) from infrastructure based on machine learning (ML) methods. IEEE Trans. Intell. Transport. Syst. 23, 22409–22420.
Tao, F., Zhang, H., Zhang, C., 2024. Advancements and challenges of digital twins in industry. Nat. Comput. Sci. 4, 169–177.
Thuraisingham, B., 2022. Trustworthy machine learning. IEEE Intell. Syst. 37, 21–24.
Tong, C., Li, X., Ju, H., Duanmu, L., Huang, C., 2024. A hybrid numerical model for horizontal ground heat exchanger. Renew. Energy 230, 120825.
Toscano, J.D., Oommen, V., Varghese, A.J., Zou, Z., Ahmadi Daryakenari, N., Wu, C., Karniadakis, G.E., 2025. From PINNs to PIKANs: recent advances in physics-informed machine learning. Mach. Learn. Comput. Sci. Eng. 1, 15.
Tyralis, H., Papacharalampous, G., 2024. A review of predictive uncertainty estimation with machine learning. Artif. Intell. Rev. 57, 94.
Wang, A.X., Chukova, S.S., Simpson, C.R., Nguyen, B.P., 2024a. Challenges and opportunities of generative models on tabular data. Appl. Soft Comput. 166, 112223.
Wang, L., Wang, Lin, Zhang, W., Meng, X., Liu, S., Zhu, C., 2024b. Time series prediction of reservoir bank landslide failure probability considering the spatial variability of soil properties. J. Rock Mech. Geotech. Eng. 16, 3951–3960.
Wang, Y., Ma, T., Shen, L., Wang, X., Luo, R., 2025. Prediction of thermal conductivity of natural rock materials using LLE-transformer-lightGBM model for geothermal energy applications. Energy Rep. 13, 2516–2530.
Wei, W., Liu, L., 2025. Trustworthy distributed AI systems: robustness, privacy, and governance. ACM Comput. Surv. 57, 1–42.
Wei, R., Garcia, C., El-Sayed, A., Peterson, V., Mahmood, A., 2020. Variations in variational autoencoders - a comparative evaluation. IEEE Access 8, 153651–153670.
Xu, Z., Wang, Z., Li, S., Zhang, X., Lin, P., 2024. GeoPredict-LLM: intelligent tunnel advanced geological prediction by reprogramming large language models. Intell.Geoeng. 1, 49–57.
Xu, H.-R., Zhang, N., Yin, Z.-Y., Njock, P.G.A., 2025. Multimodal framework integrating multiple large language model agents for intelligent geotechnical design. Autom. ConStruct. 176, 106257.
Yang, Y., Xiong, Q., Wu, C., et al., 2021. A study on water quality prediction by a hybrid CNN-LSTM model with attention mechanism. Environ. Sci. Pollut. Res. 28, 55129–55139.
Yang, Y., Zhang, Y., Cheng, Y., et al., 2023. Using one-dimensional convolutional neural networks and data augmentation to predict thermal production in geothermal fields. J. Clean. Prod. 387, 135879.
Yang, Y., Gao, Y., Ding, Z., et al., 2024. Advancements in q-learning meta-heuristic optimization algorithms: a survey. WIREs Data Min. Knowl. Discovery 14, e1548.
Youwai, S., Thongnoo, C., 2025. Load-deformation prediction of bored piles using sequential soil profile encoding with transformer architecture: a study of Bangkok subsoil. Expert Syst. Appl. 275, 127085.
Yu, P., Zhang, H., Song, Y., Wang, Z., Dong, H., Ji, L., 2025. Safe reinforcement learning for power system control: a review. Renew. Sustain. Energy Rev. 223, 116022.
Zanchini, E., Lazzari, S., Priarone, A., 2010. Improving the thermal performance of coaxial borehole heat exchangers. Energy 35, 657–666.
Zhang, R., Li, Y., Goh, A.T.C., Zhang, W., Chen, Z., 2021a. Analysis of ground surface settlement in anisotropic clays using extreme gradient boosting and random forest regression models. J. Rock Mech. Geotech. Eng. 13, 1478–1484.
Zhang, X.H., Wu, F., Li, Z., 2021b. Application of convolutional neural network to traditional data. Expert Syst. Appl. 168, 114185.
Zhang, D.Z., Zhao, P., Li, X.Z., et al., 2022. Heat transfer analysis of a borehole heat exchanger array in a layered subsurface. Appl. Therm. Eng. 216, 119076.
Zhang, X., Han, Z., Li, G., Li, X., 2022. Effect of temperature measurement error on parameters estimation accuracy for thermal response tests. Renew. Energy 185, 230–240.
Zhang, W., Zhou, H., Bao, X., Cui, H., 2023. Outlet water temperature prediction of energy pile based on spatial-temporal feature extraction through CNN–LSTM hybrid model. Energy 264, 126190.
Zhang, X., Han, Z., Li, X., 2024. Accurate identification of soil thermal parameters and groundwater flow from thermal response tests. Renew. Energy 236, 121393.
Zhong, Y., Narsilio, G.A., Makasis, N., Scott, C., 2022. Experimental and numerical studies on an energy piled wall: the effect of thermally activated pile spacing. Geomech. Energy Environ. 29, 100276.
Zhong, Y., Bidarmaghz, A., Narsilio, G.A., Makasis, N., 2023. Thermo-hydraulic analysis in geothermal energy walls. Tunn. Undergr. Space Technol. 132, 104862.
Zhong, Y., Narsilio, G.A., Makasis, N., Villegas, L., 2024. Field investigation on a pilot energy piled retaining wall. Can. Geotech. J. 61, 1311–1330.
Zhou, Y., Narsilio, G., Makasis, N., Soga, K., Chen, P., Aye, L., 2024. Artificial neural networks for predicting the performance of heat pumps with horizontal ground heat exchangers. Front. Energy Res. 12, 1423695.
Zhu, Y., Brettin, T., Xia, F., et al., 2021. Converting tabular data into images for deep learning with convolutional neural networks. Sci. Rep. 11, 11325.
Zhuang, Z., Ben, X., Yan, R., Pang, J., Li, Y., 2017. Accurately predicting heat transfer performance of ground heat exchanger for ground-coupled heat pump systems using data mining methods. Neural Comput. Appl. 28, 3993–4010.

Dr. Danial Sheini Dashtgoli received his PhD in Geoscience, Fluid Dynamics, and Mathematics from the University of Trieste in collaboration with the National Institute of Oceanography and Applied Geophysics, Italy. His research focuses on artificial intelligence and deep learning methods for subsurface energy systems, with particular emphasis on predictive modeling, data reconstruction in sparse and heterogeneous datasets, uncertainty-aware and physics-guided learning, and surrogate modeling. His work covers both shallow and deep geothermal applications, integrating data-driven approaches with physics-based numerical models for performance prediction and decision support. His background in geotechnical engineering, combined with professional experience in infrastructure and subsurface engineering projects, supports the development of physically consistent and industry-relevant AI frameworks.