

Review

Artificial intelligence transformations in geotechnics: progress, challenges and future enablers

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A B S T R A C T

Our reliance on the underground space to deliver critical civil engineering infrastructure is growing: to accommodate utility and transport infrastructure in urban environments, to provide innovative housing and commercial solutions, and to support proliferating renewable energy infrastructure, particularly offshore. Artificial intelligence (AI) is arguably the most promising enabler to transform geotechnical engineering by extracting knowledge from data to achieve step-change increases in efficiency, sustainability, reliability and safety. This paper seeks to develop a shared understanding of the state of the art of AI in geotechnics and to explore future developments. By way of example, specific popular use cases in geotechnics are considered to highlight current progress in AI applications including intelligent site investigation, predictive modelling for soil behaviour, and optimisation of design and construction processes. The paper then addresses key research challenges, such as data scarcity and interpretability, and discusses the opportunities that lie ahead in the integration of AI with geotechnical engineering. Finally, priority technological enablers are identified for future transformations.

1. Introduction

The integration of artificial intelligence (AI) is already spurring transformative advancements in a range of domains. In healthcare, AI-driven diagnostic tools and predictive models have enhanced disease

detection and treatment planning (Jiang et al. 2017). Applications in finance and economics have streamlined trading strategies, risk management, and fraud detection (Goodell et al. 2021). AI technologies have also been used in the digital twinning of large infrastructures e.g. railway bridge and rail tracks (Febrianto et al., 2022; Sun et al., 2023). With

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the recent rapid advancements in large language models (LLMs; e.g. ChatGPT; [Vaswani et al. 2017](#)), there has been a surge in motivation to explore the potential for AI to realise step-change increases in efficiency and innovation in geotechnics.

A key motivation for AI in geotechnical engineering stems from the pressing need to address the increasingly complex challenges faced in both underground infrastructure development (e.g. [Sheil et al. 2020a, 2020b](#)), and offshore energy infrastructure development (e.g., [Stuyts and Suryasentana, 2023](#)). Subsurface ground conditions can be both highly complex and uncertain. Accurate prediction of soil behaviour is also highly challenging. Traditional analytical methods often struggle to cope with the intricacies and paradoxes of geotechnical data, leading to potential inaccuracies and inefficiencies in design and construction processes ([Suryasentana and Sheil 2023](#)). There is potential to leverage advanced machine learning (ML) algorithms and data-driven techniques to gain deeper insights from growing datasets, enabling more holistic and accurate predictive models and efficient processes. Importantly, many ML approaches can also be extended to capture model uncertainty, enhancing reliability in scenarios with complex or incomplete data.

This position paper synthesises key opportunities, challenges, and research needs for the application of AI in geotechnical engineering. Rather than providing an exhaustive review of historical literature, we highlight selected illustrative use cases, namely intelligent site investigation, predictive modelling of soil behaviour, and optimisation of design and construction processes, to support our arguments. However, each emerging theme identified is grounded in current evidence.

2. The rise of AI

The field of AI aims to create intelligent machines that can mimic human-like intelligence. Its fundamental goal is to enable machines to perceive the environment, reason, learn from experience, and make informed decisions based on data and patterns ([Russell & Norvig 2010](#)). AI is a broad umbrella term that encompasses ML, computer vision and robotics. Subfields within ML include deep learning (DL), reinforcement learning (RL), Bayesian variants, and natural language processing (NLP), each addressing specific aspects of intelligence emulation (see

[Fig. 1](#)).

ML is a fundamental element of intelligent system development involving the development of algorithms and/or statistical models that allow machines to progressively improve their performance on a specific task, given training data. DL represents an additional subfield of ML that focuses on the design and training of artificial neural networks, inspired by the architecture and functioning of the human brain. DL leverages multiple layers (hence the term “deep”) of interconnected nodes or neurons to handle more complex tasks by using its hierarchical structure to automatically learn hierarchical representations of data, abstracting and extracting features at different levels of complexity. RL explores how ‘agents’ can learn to perform a task through repeated interactions with a given environment. The agent learns to optimise its behaviour over time by receiving feedback on decisions made, in the form of penalties or rewards. In contrast, NLP seeks to enable machines to understand, analyse, and generate human language. This can extend beyond simple language recognition to include tasks such as sentiment analysis, language translation, and question answering. Bayesian variants of ML are also popular for considering aleatoric and epistemic uncertainties in the analysis of the system of interest. In geotechnical applications, these might include model uncertainties, such as those related to the material (including spatial variability and uncertainties of material properties) and/or numerical model, along with uncertainties inherent to data quality and measurement systems ([MacKay, 2003, Kennedy and O’Hagan, 2001, Girolami et al., 2021](#)).

3. Recent progress in select popular AI applications in geotechnics

In this paper, we focus on recent progress in regression models and classifiers for (i) inversion (e.g. linking field data to geotechnical parameters), (ii) predicting material responses (e.g. pile installation, foundation movements, landslides), (iii) predicting structural responses (e.g. TBM control), and (iv) improving the efficiency of deterministic approaches (e.g. constitutive models).

Intelligent site investigation and ground modelling

ML has been widely applied in geotechnics for data-driven ground modelling, helping to inform foundation design and identify optimal

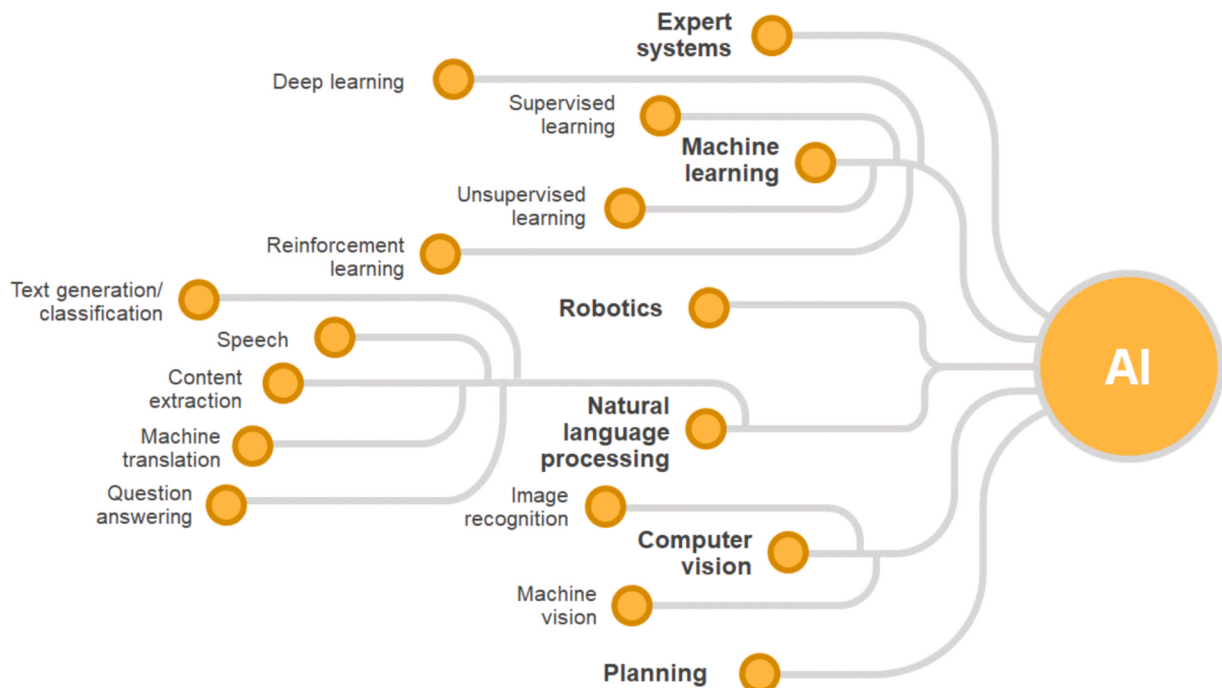


Fig. 1. Map of AI sub-fields.

sampling locations for site investigation campaigns (Hu et al., 2021; Zhao and Wang, 2019; Yoshida et al. 2022). Data-driven ground models are usually constructed from geotechnical data such as cone penetration test (CPT) data or dynamic penetration test (DPT) data. These models involve two main predictive tasks: soil stratigraphy/layering identification and spatial interpolation/prediction of geotechnical properties.

Various ML techniques have been employed for soil stratigraphy identification, such as Gaussian Process regression (GPR), which is mathematically equivalent to its predecessor, kriging (Li et al., 2016), Bayesian model class selection (Wang et al., 2013), changepoint detection (Houlsby and Houlsby, 2013; Ching et al., 2015; Suryasentana et al., 2023), Bayesian compressive sampling (Wang et al. 2020), random field approaches (Cao et al., 2019; Gong et al., 2020), lasso-based regression (Shuku et al. 2020), clustering (Hegazy and Mayne, 2002; Zhao and Wang, 2020) and more recently, deep learning (Zhou et al. 2024). Fig. 2 shows recent examples of the identification of soil layer boundaries using DPT and CPT data, respectively. Suryasentana et al. (2024) showed that univariate Bayesian change point detection (BCPD) methods outperform multivariate approaches in delineating soil strata from CPT data. In particular, the composite soil behaviour index I_c yields more reliable boundary predictions than the joint analysis of cone resistance Q_t and friction ratio F_r , likely due to the empirical calibration of I_c against established soil classification databases, which implicitly embed prior knowledge relevant to stratigraphic interpretation.

For spatial predictions of geotechnical properties, previous researchers have used kriging (Firouziandbandpey et al., 2015; Cai et al., 2019; Hu et al., 2020; Rahman et al., 2021), random field approaches (Cai et al., 2019), Bayesian compressive sampling (Wang and Zhao, 2017; Wang et al., 2020; Wang and Li, 2021; Zhao et al., 2020), multiple point statistics (Shi and Wang, 2021a), XGBoost (Shi and Wang, 2021b) and neural networks (Sauvin et al., 2019; Wu et al., 2021).

In addition, there has been recent increased interest in integrated ground modelling that combines multiple data sources, such as geophysical and geotechnical data. Fusing multiple types of data aims to produce more accurate and consistent ground models that leverage the strengths of each data source. Data fusion techniques have been used to learn the relationships between the different data sources and exploit them for sub-surface prediction. These techniques include co-kriging (Sauvin et al., 2019; Xie et al., 2022), random field approaches (Huang et al., 2018), multi-scale approaches (Ghose and Goudswaard 2004), Bayesian inference (Wellmann et al., 2018; Medina-Cetina et al., 2019), multi-source Bayesian compressive sampling (Xu et al., 2021,

2022), random forests (Christensen et al., 2021) and neural networks (Sauvin et al., 2019; Chen et al., 2021; Coelho and Karaoulis, 2022).

Predictive modelling for soil behaviour.

Soils are complicated particulate materials that exhibit complex mechanical behaviours including critical state (Roscoe et al., 1958; Schofield and Wroth, 1968), state-dependency (e.g., Been and Jefferies 1985), stress dilatancy (e.g., Reynolds, 1885; Taylor, 1948; Bolton 1986), anisotropy (e.g., Bishop, 1966, Amarasinghe and Parry, 1975), destructuration (e.g., Burland, 1990, Leroueil and Vaughan, 1990, Liu et al. 2013), stress-path dependency (e.g., Lade and Duncan, 1976), time-dependency (e.g., Suklje, 1957, Bjerrum, 1967), and non-coaxiality (e.g., Roscoe et al., 1967). Such behaviours have motivated the development of a range of constitutive models to capture time-dependency (e.g., Kim and Leroueil, 2001, Yin et al. 2011), state-dependency (e.g., Su and Yang, 2019, Kang et al., 2019a), stress dilatancy (e.g., Wan and Guo, 1988, Su et al., 2010), anisotropy (e.g., Dafalias, 1986, Yin et al., 2010, Kang et al., 2019b), stress-path dependency (e.g., Hu et al., 2018), non-coaxiality (e.g., Tian and Yao, 2017), and phase change (e.g., Zhou and Meschke, 2013).

In conventional constitutive modelling, a mathematical equation, with a set of parameters or variables, is hypothesised to capture the behaviour of the soil. However, the desire to capture advanced soil behaviours has led to increasingly complex constitutive models with greater numbers of material parameters. For example, SANISAND (Dafalias and Manzari, 2004) incorporates multiple fabric tensors and internal variables, which, although successfully capturing complex soil behaviours, increase model calibration complexity and limit interpretability.

With the increasing availability of AI resources in the early 90s, several researchers began exploring the application of AI methods, and particularly neural networks (NN), as an alternative for modelling material behaviour (e.g., Ghaboussi et al., 1990, 1991). Ellis et al. (1992) and Ghaboussi et al. (1990) pioneered NN constitutive models (NNCMs) for soils; a notable influx of AI-based constitutive models followed (e.g., Ellis et al., 1995; Ghaboussi and Sidarta, 1998; Penumadu and Zhao, 1999). This evolution in constitutive modelling extended beyond NNs to include other AI-based techniques such as evolutionary regression (Javadi and Rezania, 2009a). More recently, research in this area has moved towards numerical implementation of these 'intelligent' material models (e.g., Shin and Pande, 2000, Lefik and Schrefler, 2003; Hashash et al., 2004, Javadi and Rezania, 2009b). However, the performance of these early purely data-driven AI-based constitutive models was mixed,

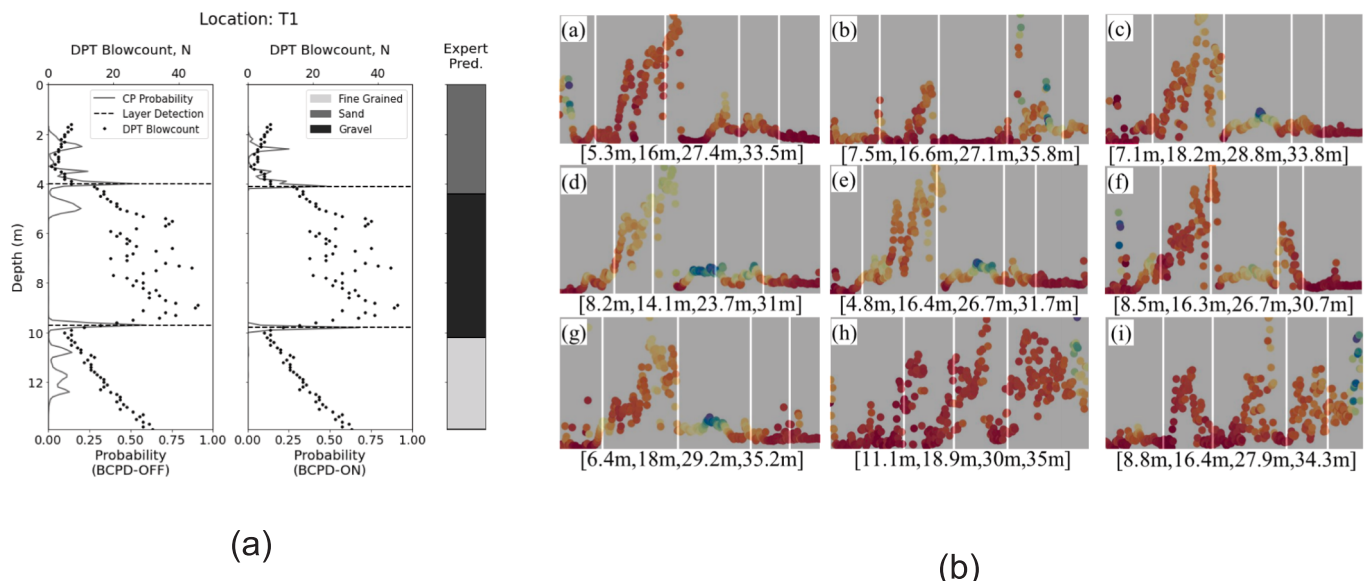


Fig. 2. Predictions of soil layer boundaries using (a) DPT data (Suryasentana et al. 2023), and (b) CPT data (Zhou et al. 2024).

owing to their lack of interpretability and requirements for big data for effective training. Importantly, these models exhibited poor generalisation (extrapolative capabilities) where predictive reliability deteriorated outside the feature space of the training data.

The recent resurgence of AI in geotechnics has renewed momentum in developing AI-based constitutive models, with physics-informed machine learning (PIML) methods (Raissi et al., 2019, Masi et al., 2021, Masi and Stefanou, 2022) emerging as a key trend in material modelling. Recent studies have explored combining prior knowledge, such as empirical expressions or physics-based laws, with ML to constrain predictions within reasonable bounds (e.g. Weinan and Yu, 2018, Liu and Wang, 2019, Sun et al., 2020, Cuomo et al., 2022, Vlassis and Sun, 2021, Flaschela et al., 2021). Whilst these advances have achieved significantly improved generalisation, such hybrid models still require large high-quality datasets to achieve predictive performance that is competitive with conventional constitutive models.

These challenges have inspired interpretable ML-based approaches which are suitable for training on sparse geotechnical datasets (Zhang et al., 2023a). For example, Zhang et al. (2022a) incorporated three different theoretical frameworks into a prior information based neural network ('PiNet'), including incremental nonlinearity, hyperelasticity and elastoplasticity (see example in Fig. 3). The three PiNet models were subsequently applied to simulate the behaviour of real soils in conjunction with a multi-fidelity framework to maximise the impact of (and therefore reduce the dependency on) sparse high-fidelity data. The adopted strategy provided an efficient, accurate and general method of modelling soil behaviour, hence demonstrating the potential of physics-informed AI methods for soil constitutive modelling.

Optimisation of geotechnical design, construction processes and risk assessment

The optimisation of geotechnical design and construction processes has become a focal point in contemporary geotechnical engineering, with a growing emphasis on leveraging AI technologies. Historically, geotechnical design relied heavily on manual analyses, empirical

methods, and simplified models (Das, 2021). While these approaches demonstrated efficacy in numerous scenarios, their limitations in addressing complex modern challenges have become increasingly evident.

In foundation engineering, a range of ML algorithms have been applied to the prediction of the capacity (e.g. Provenzano et al., 2004, Shahnazari and Tutunchian, 2012, Tsai et al., 2013, Lawal and Kwon, 2023) and settlement (e.g. Shahin et al., 2002, 2003, Rezaei and Javadi, 2007, Samui and Sitharam, 2008, Zhang et al., 2022b) of shallow footings. Similarly, researchers have leveraged AI techniques to refine various elements of pile design including: (a) pile driveability (e.g. Vergote and Raymackers, 2022, Buckley et al., 2023), (b) resistance to vertical loading (e.g. Pal and Deswal, 2010, Alkroosh and Nikraz, 2011, Kordjazi et al., 2014, Kardani et al., 2020, Alexander et al., 2024), (c) resistance to lateral loading (e.g. Suryasentana et al., 2020, Muduli et al., 2013, Taherkhani et al., 2023), (d) settlements and displacements (e.g. Nejad et al., 2009, Jebur et al., 2018, Ge et al., 2023), and (e) group effects (e.g. Khattai et al., 2023).

An example of the design method improvements that AI can facilitate is presented in Fig. 4, in this instance for the pile driveability problem (Buckley et al., 2023). The figure plots the error in pile driveability predictions using the industry-standard Alm and Hamre (2001) model and an ML-updated generalised model during driving of an offshore production pile in transitional soils. It is worth noting that the IMPACT wave-equation model serves as a key component of the ML framework, and its internal parameters are not updated during learning. The results show that the ML-updated generalised model achieves significantly improved performance over Alm and Hamre (2001). Such an approach is not limited to this problem and has also been successfully adopted for pipe-jacking predictions (Sheil et al., 2022).

Slope stability design is another popular use-case for AI (Deng et al., 2021; Xu et al., 2023). The literature has focused predominantly on the optimisation of slope failure mechanisms and factor of safety estimates (Luo et al., 2021, Mahmoodzadeh et al., 2022, Aminpour et al., 2023),

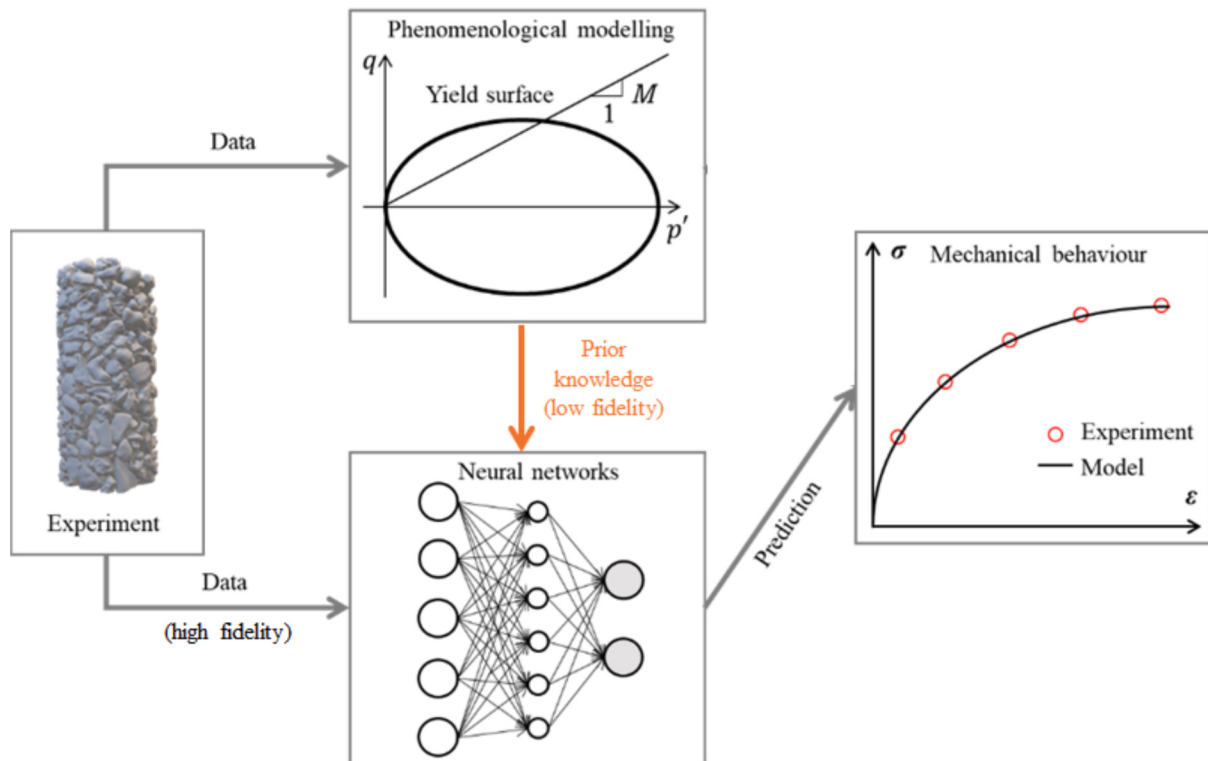


Fig. 3. Adopted multi-fidelity modelling workflow in Zhang et al. (2023a) involving the combination of a data-driven neural network and conventional phenomenological models.

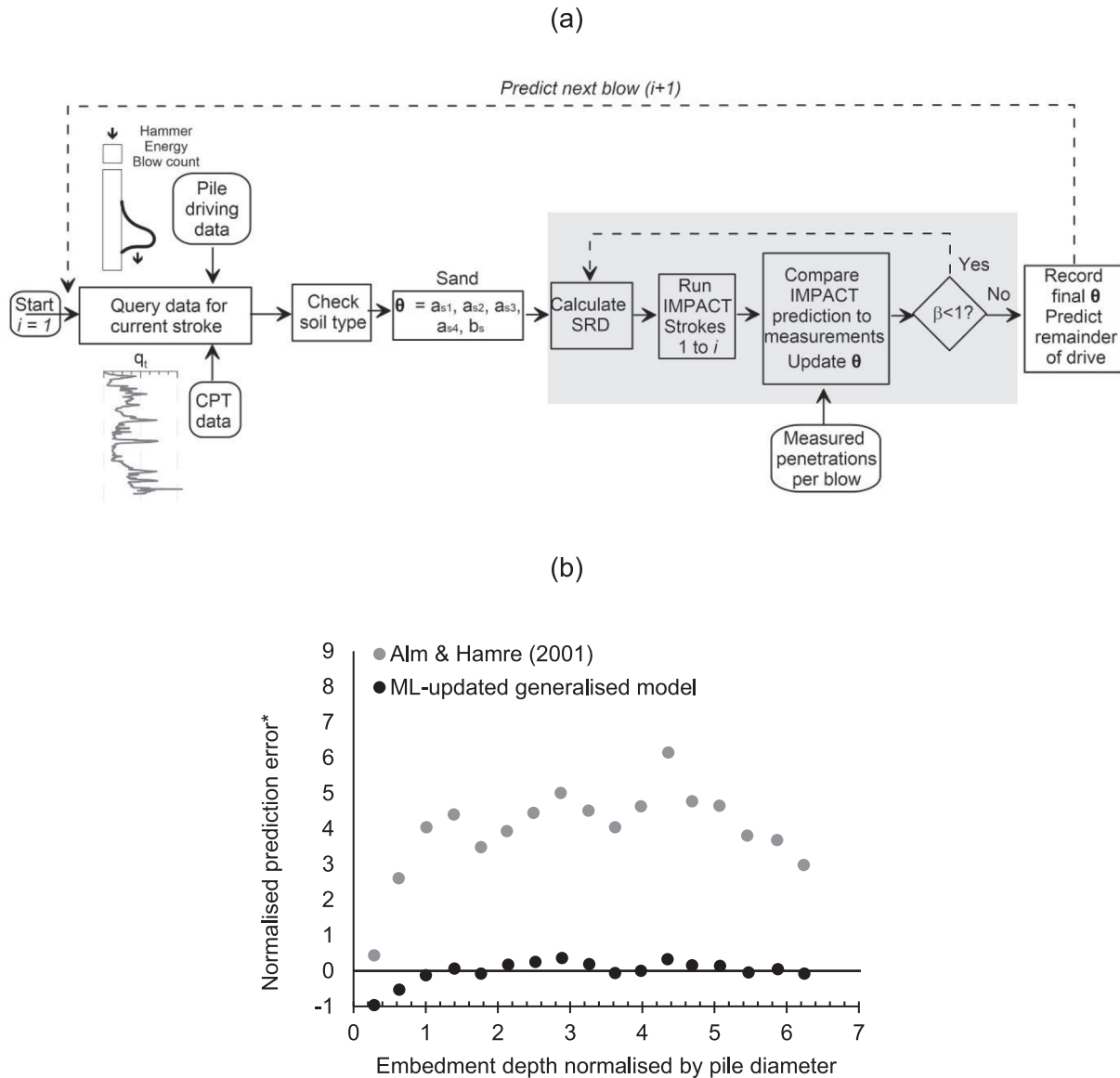


Fig. 4. (a) Workflow for an ML-updated generalised prediction model and (b) the corresponding pile driveability prediction error plotted during the driving of an unseen offshore pile compared to those obtained using the industry-standard [Alm and Hamre \(2001\)](#) model ([Buckley et al., 2023](#)). *relative error is defined as the difference between predicted and measured pile penetration normalised by the measured value.

prediction of failure times ([Zhang et al., 2022a](#)), spatio-temporal landslide hazard mapping ([Xiao et al., 2023](#)), and data-driven surrogate development ([Guardiani et al., 2022](#)). Recent work has also included the development of stochastic methods boosted by ML algorithms ([Lin et al., 2018](#), [He et al., 2020](#), [Zeng et al., 2022](#)). An emerging research area in this field relates to the combination of ML and remote sensing technologies, such as interferometric satellite synthetic aperture radar (InSAR), to forecast anomalous behaviours indicative of incipient collapse (e.g. [Novellino et al., 2021](#), [Bayarara et al., 2023](#)).

Popular applications to geotechnical construction processes primarily relate to tunnelling activities, with the most prevalent being (a) tunnel boring machine (TBM) performance prediction, (b) tunnel-induced settlement prediction, (c) geological forecasting and (d) cutterhead design optimisation. Other research areas have included tunnel-induced building damage prediction ([Cao et al., 2020](#); [Ninić et al., 2024](#)), TBM automation ([Mokhtari and Mooney, 2019](#)), tunnel condition assessment ([Chen et al., 2019](#); [Li et al., 2017](#); [Zhu et al., 2020](#)), anomaly detection (e.g. [Sheil et al., 2020c](#); [Yu et al., 2018](#)), tunnel profile measurement (e.g. [Xue and Zhang, 2019](#)), resilience assessment

(e.g. [Khetwal et al., 2019](#)), structural defect identification (e.g. [Ding et al., 2019](#)), tunnel face stability (e.g. [Hayashi et al., 2019](#)), rockburst prediction (e.g. [Liu and Hou, 2019](#)) and intelligent building information modelling (e.g. [Zhao et al., 2019](#)).

Finally, AI can be used to bridge different disciplines and allow the application of advanced numerical models to regional-scale planning procedures ([Charles et al., 2023](#)). This can be done by means of surrogate models (e.g. [Lambert et al., 2021](#); [Previtali et al., 2022](#)) that replicate the output of a more complex and computationally intensive model at a fraction of its cost. An example use-case is rockfall risk mitigation ([Fig. 5](#)), where regional-scale hazard assessment is carried out by geologists, using tools such as Geographic Information Systems (GIS), field investigations and remote sensing to inform rockfall propagation codes ([Lanfrancioni et al., 2020](#)). At this stage, measurement uncertainty and natural variability is addressed by means of stochastic analysis, resulting in hundreds of thousands of simulations, for which it would not be feasible to apply standard numerical procedures.

(a).

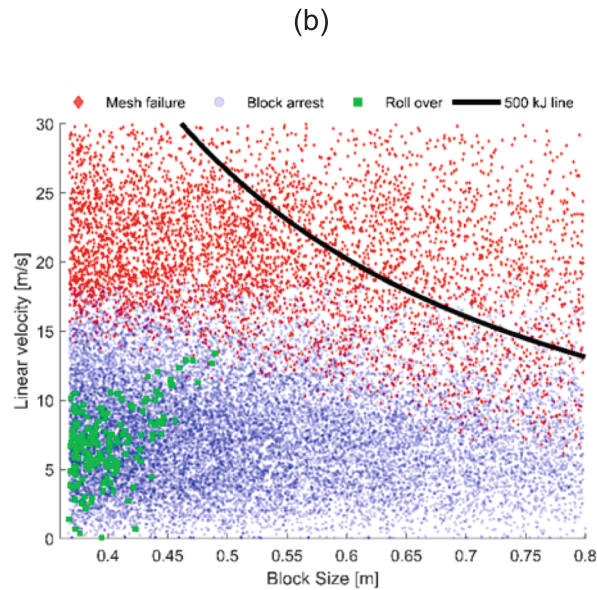
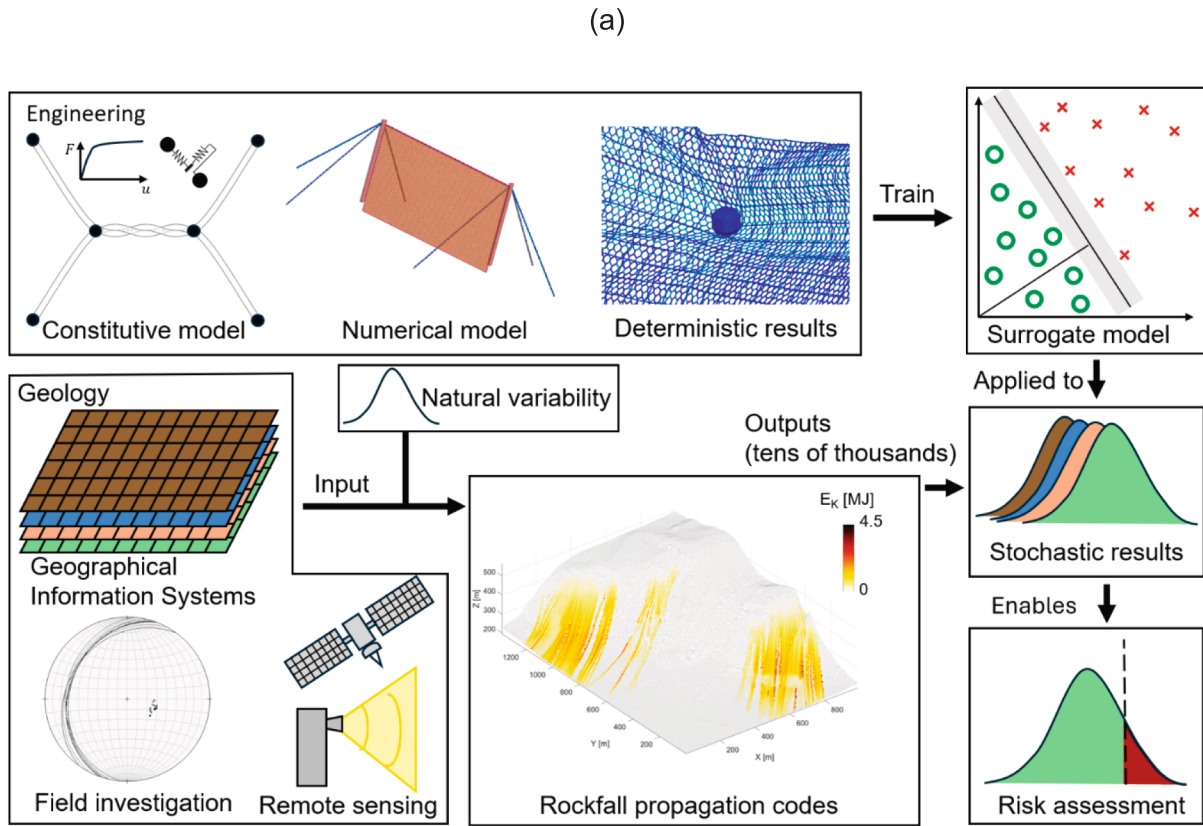


Fig. 5. (a) Flowchart for the use of AI-based surrogate models to bring the accuracy of advanced numerical models to the efficiency standards required by large-scale planning, (b) example results from a surrogate model against the standard 500 kJ energy threshold (Previtali et al. 2022).

4. Key challenges for AI in geotechnics

Fig. 6 identifies key challenges for the proliferation of AI in geotechnics. A cross-cutting challenge relates to how geotechnical AI applications fit into the wider context of ground engineering. Whilst there are opportunities to share data and models towards a more holistic perspective of the underground space, common ontologies and data interoperability are required to curate a standardised framework for data and model exchange. We elaborate below on these challenges and

offer viable solutions.

Challenge 1: Data scarcity and quality

All data-driven processes depend on the quantity and quality of training data. Thus, one significant obstacle to AI prosperity in geotechnics is scarcity of high-quality, annotated and diverse data. Geotechnical datasets require meticulous annotation, where domain experts label data points with accurate and detailed information about soil properties, geological features, and engineering parameters, and comment on test procedures. Limited data availability has been well-

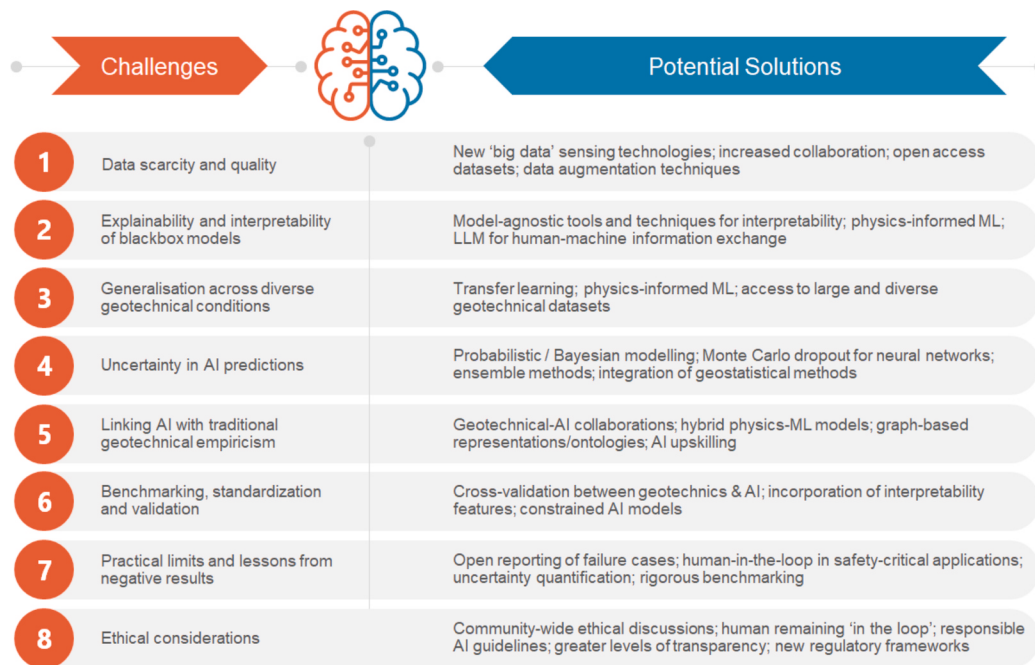


Fig. 6. Identified AI challenges for future applications of AI in geotechnical engineering and potential solutions.

documented to have a major influence on the training of ML algorithms (Bao et al. 2019) increasing the risk of inaccuracies, poor generalisation and, in extreme cases, spurious predictions arising from overfitting. There is a pressing need to establish unified standards for assessing geotechnical data quality, distinguishing between tests of varying reliability due to operator-dependence, testing procedures or instrumentation. Structured frameworks for assessing data quality in geotechnical monitoring have recently been proposed (e.g. Jeong et al. 2019), and data exchange standards such as AGS and DIGGS are gaining renewed relevance. In low-data regimes, model developers often rely on probabilistic surrogates (Suryasentana and Sheil, 2023), domain-informed augmentation, or transfer learning.

To address this challenge, opportunities lie in federating trained models owned by various stakeholders to overcome data-sharing concerns within the geotechnical community. This typically involves training a shared model across multiple decentralised datasets held by different stakeholders, where each data owner trains the model locally and only model updates (not raw data) are shared. A common set of parameters and hyperparameters is used to coordinate training across sites. This strategy also aligns with MLOps principles, which facilitate traceable, reproducible and scalable model management. State-of-the-art data collection methods will also help to alleviate data scarcity, such as advanced sensing technologies (e.g. distributed fibre optic sensing (Soga and Luo 2018), wireless mesh networks (Jeong et al. 2019)), and remote sensing (e.g. satellite InSAR (Bayarara et al. 2022)). Collaborative efforts to share anonymised datasets and establish standardised data formats can also enhance the availability of diverse data e.g. the 'DINGO' pile load test database (Voyagaki et al. 2022). Furthermore, data science techniques such as data augmentation, transfer learning, and synthetic data generation can be employed to amplify existing datasets, enabling AI models to generalise better in diverse geotechnical scenarios despite initial scarcity.

Challenge 2: Explainability and interpretability of blackbox models

AI (particularly DL) algorithms are commonly perceived as "black boxes" that offer little insight into the underlying decision-making process. In geotechnical engineering, where transparency and understanding of model predictions are crucial for informed decision-making, the lack of explainability is a significant obstacle; new techniques are required to extract meaningful insights from complex AI models. For

example, NLP can be used to learn geotechnical design codes for code compliance checking. Additional techniques could include model-agnostic interpretability tools, sensitivity analysis, and attention mechanisms to analyse model outputs and, in turn, identify influential factors in geotechnical predictions. PIML also has potential to integrate domain knowledge into AI models to leverage the relative strengths of physics-based models and data-driven techniques to enhance both interpretability and reliability of predictions (Vahab et al. 2023). Recent successes in physics-informed constitutive models (e.g. Zhang et al. 2023a; see Fig. 7) also demonstrate that data-driven modelling with physical constraints can lead to more robust predictions, as shown in Fig. 8. Dropout can act as a training-time regulariser as well as generate stochastic samples at inference using the Monte-Carlo dropout formulation. The resulting mean prediction and its variance respectively capture the best estimate and the epistemic uncertainty of the model output.

There have been concerted efforts aimed at improving model interpretability. Some of the proposed approaches include: (a) model decomposition (Ribeiro et al. 2016), where complex models are broken down into smaller, more understandable components; (b) rule extraction (Guidotti et al., 2018), where complex models are approximated by rule-based models comprising if-then rules; (c) feature importance (Lundberg and Lee, 2017), where technical frameworks such as SHAP (SHapley Additive exPlanations) can highlight which features most significantly impact model outputs, and (d) model cards reporting (Mitchell et al., 2019), where documentation detailing the model development, performance, and intended use cases are created including full model versioning and development history tracking, as enabled through MLOps pipelines.

Challenge 3: Generalisation across diverse geotechnical conditions

Generalising across a wide range of soil types, geological formations, and environmental factors is a complex task. The challenge lies in creating models that not only perform well on training data but also demonstrate robustness when applied to new unseen conditions. Transfer learning techniques are a promising solution to this challenge, where models trained on data from one set of geotechnical conditions are subsequently fine-tuned in a second stage to adapt to different scenarios. Zhou et al. (2024) already demonstrated the effectiveness of these approaches for soil boundary detection where a generic open access 'source database' was used for the first stage of model training with

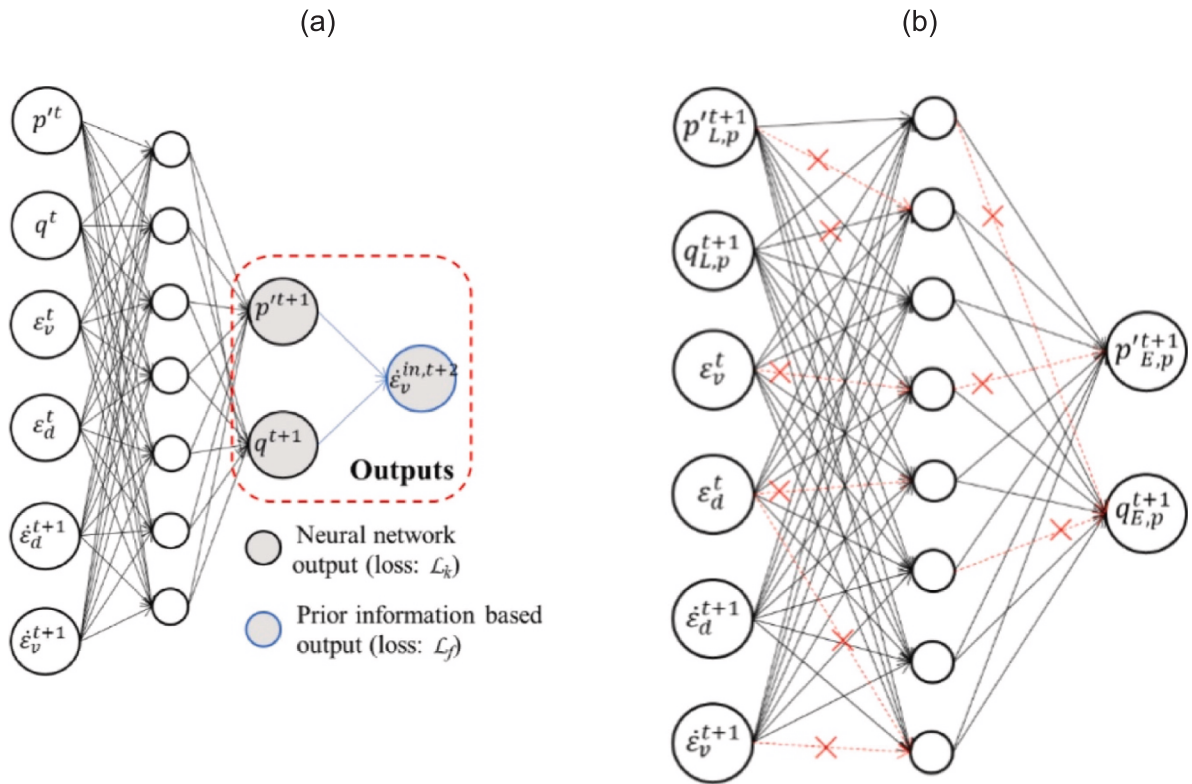


Fig. 7. Adopted modelling framework in Zhang et al. (2023b): (a) architecture showing model inputs and interaction between neural network outputs and physics constraints (circled in red; using incremental nonlinear modelling in this example), and (b) one instance of severed neural connections during a Monte Carlo dropout implementation of the neural network. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

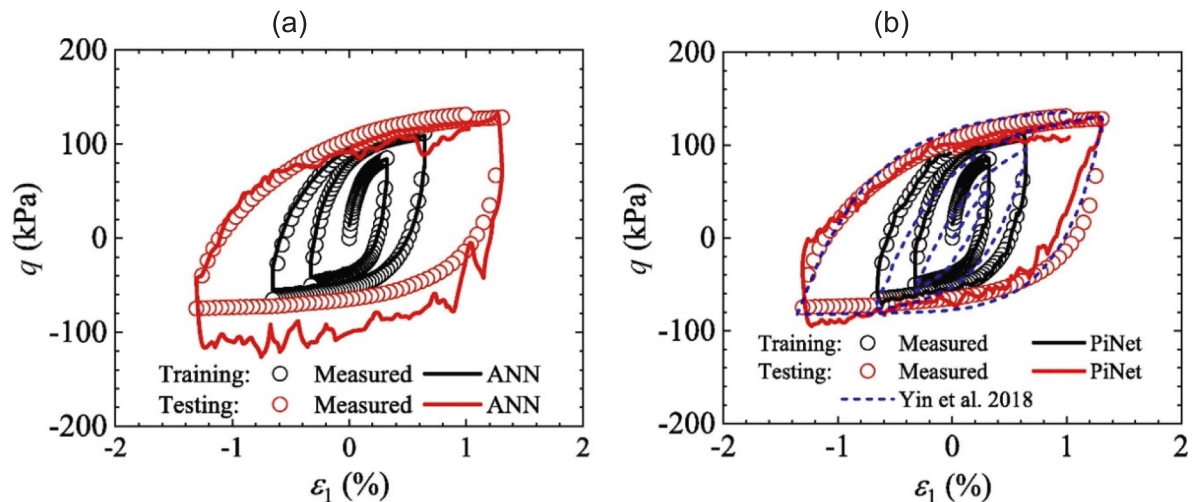


Fig. 8. Comparison between model predictions and laboratory measurements of the triaxial stress-strain response of Toyora sand using an (a) ANN and (b) prior information-based neural network ('PiNet') (Zhang et al. 2023b).

fine-tuning performed on the site-specific 'target database' (see framework in Fig. 9). PIML can also enable models to encode fundamental geotechnical mechanisms to reliably extrapolate to diverse conditions (e.g. see Zhang et al. (2023b)). Ensuring training datasets are both representative and sufficiently diverse is also crucial for improving generalisation. Overcoming this challenge will enable more versatile, reliable, and broadly applicable AI models for real-world geotechnical engineering.

Challenge 4: Uncertainty in AI predictions

Given the cost of mistakes, uncertainty estimates are highly desirable

in geotechnical engineering. However, achieving such estimates from AI models remains difficult. Probabilistic modelling, using Bayesian ML techniques, offer a robust and principled means of capturing uncertainty. In particular, GPR has already been shown to be highly adept at modelling geotechnical uncertainty intrinsically (e.g. Sheil et al. 2020a, Suryasentana and Sheil 2023; see Fig. 10). Even for deterministic AI models, techniques exist to obtain estimates of epistemic uncertainty. For example, in neural networks, Monte Carlo dropout is one of the most common methods to test the sensitivity of model outputs to the exact model architecture. Other popular options include ensemble methods,

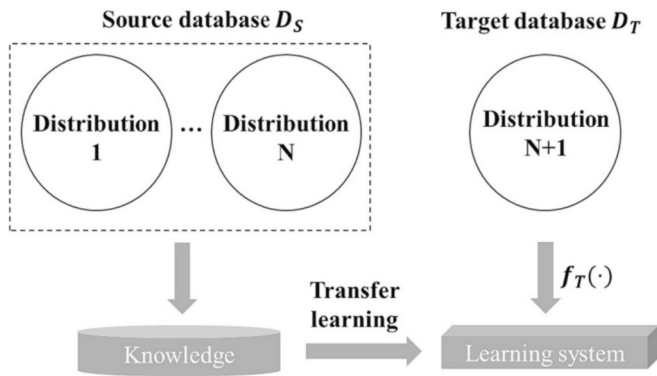


Fig. 9. Transfer learning framework for soil boundary detection adopted in Zhou et al. (2024).

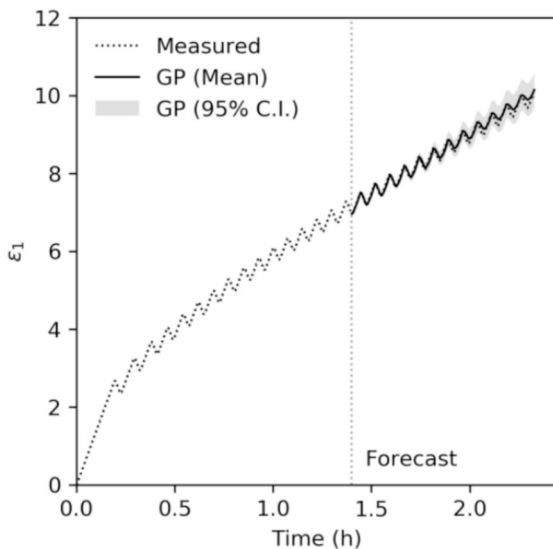


Fig. 10. Comparison of the measured axial strain for an undrained cyclic triaxial test on clay and the forecasted axial strain (shaded bounds are the 95 % confidence interval of the forecast) by the GP regression model predictions with an LE + SE*PER covariance function; Suryasentana and Sheil (2023); SE = squared exponential, LE = linear, PER = periodic.

such as bootstrapping.

Developing frameworks that integrate geostatistical methods with AI models will also allow for a more comprehensive understanding of spatial uncertainties. Recognising and accounting for uncertainty in AI predictions will not only build confidence in these geotechnical models but also provide engineers and decision-makers with valuable information to make informed choices given highly uncertain subsurface conditions.

Challenge 5: Linking AI with traditional geotechnical models and empiricism

While AI can analyse large high-dimensional geotechnical datasets, incorporation of domain expertise and contextual understanding is crucial to realise accurate and meaningful interpretations. Ensuring that AI models align with the community's established engineering principles, design codes, and geotechnical theories represents another important challenge. A promising future technique to address this issue is automated code-compliance checking of any data-driven geotechnical design e.g. Peng and Liu (2023). A multidisciplinary approach is also necessary, involving collaboration between AI researchers and geotechnical experts. Hybrid models that combine data-driven techniques with physics-based principles can leverage the strengths of both approaches, providing more interpretable and trustworthy results.

Additionally, knowledge graph-based representations and ontologies can be employed to explicitly encode and integrate domain-specific knowledge into AI models. Effectively overcoming this challenge in the longer term will likely require a degree of upskilling for the modern geotechnical engineer such that one no longer analyses only the data, but also the data-driven models fitted to the data. It is critical that AI solutions are developed in a way that aligns with the nuanced understanding and valuable expertise of geotechnical engineers.

Challenge 6: Benchmarking, standardisation and validation

The likelihood of encountering 'over-fitting', and thus generating spurious predictions, is substantially greater for AI algorithms compared to traditional design models owing to their highly nonlinear constituent expressions. Unlike traditional numerical models, where engineers cross-validate results with simplified analytical models to ensure reasonability, AI models may lack a similar mechanism for validation. Validation of AI models in geotechnics typically involves k-fold cross-validation or hold-out testing, with performance metrics such as RMSE, R2, MAE, and, increasingly, uncertainty bounds used to assess generalisation. However, domain-specific challenges (e.g. spatial autocorrelation in site data) require careful protocol design. Implementing AI in geotechnics requires balancing accuracy, training time, and computational resources which can also be significantly influenced by hyperparameter tuning. Common parameters (e.g. learning rate, regularisation terms, and architecture depth) require systematic tuning, often via grid or Bayesian search. Simple models (e.g. tree-based or linear) train quickly on standard laptops, while deep learning models (e.g. for 3D data or physics-informed tasks) may need hours or days on high-performance GPUs. Inference is usually fast, but training can be costly for smaller organisations without pre-trained models or cloud services.

Existing geotechnical models (e.g. modified Cam clay) are inherently deterministic, yielding consistent results irrespective of the specific training data used. Engineers can rely on the well-established principles and mathematical formulations within these models to anticipate the behaviour of geotechnical materials with a high degree of confidence. This predictability allows practitioners to understand the strengths, weaknesses, and applicable ranges of a given constitutive model, enabling effective validation through comparison with experimental or field data. In contrast, AI models, being data-driven and influenced by the diverse datasets used during training, may exhibit variations in their outputs, making it challenging to establish a universally reliable framework. The stability and consistency inherent in constitutive models are key factors contributing to their enduring value in geotechnics.

To address this, establishing a framework for cross-validation between AI outputs and traditional geotechnical approaches is essential. Such an approach may involve integrating AI as a complementary tool rather than a standalone solution, allowing for constant comparison with established engineering knowledge. Incorporating interpretability features into AI models, such as explainability algorithms, can further facilitate the identification of potential discrepancies and enhance trust in AI-generated insights within the context of geotechnical engineering practices. Another effective solution is to constrain the AI model with known and well-accepted theoretical/empirical concepts.

Challenge 7: Practical limits and lessons from negative results

Published geotechnical AI studies rarely label outcomes as 'failures' yet the broader literature documents recurring failure modes that warrant explicit recognition: overfitting to small or homogeneous datasets; performance collapse under domain shift (new soil types, stress paths, or instrumentation); data leakage during cross-validation; mis-labelled or weakly constrained training targets; hallucination or spurious reasoning in LLM assistants; and the omission of governing physics leading to non-physical extrapolation (Shahin et al., 2008; Baghbani et al., 2022; Febrianto et al., 2022; Latif et al., 2023; Kumar, 2024; Suryasentana & Sheil, 2023). The tendency to publish only positive results makes it difficult to form a complete and accurate picture of model performance

and highlights the importance of open and transparent reporting of negative outcomes.

Thus, it is prudent to highlight areas where conventional approaches may be preferable (today): (i) decision contexts governed by codes / closed-form design methods with proven margins of safety; (ii) projects with extremely sparse or heterogeneous data where rigorous model validation is impossible; (iii) regulatory submissions requiring full parameter traceability; (iv) extrapolation far outside the training envelope (new geology, loading) without embedded physics constraints; and (v) safety-critical real-time control decisions unless uncertainty bounds are available and monitored.

Challenge 8: Ethical and legal considerations

AI models that are purely data-driven are particularly susceptible to inadvertently perpetuating biases in the training data. It is also likely that the topic of “accountability” will become a focal point in future litigation and will play a crucial role in shaping the legal landscape surrounding AI in geotechnics. It seems imperative that the geotechnical community rapidly and proactively engages in ethical discussions surrounding the use of AI in our teaching, research, and industrial practice. Firstly, it is worth noting that the use of AI in geotechnics will involve a human “in the loop” in the foreseeable future such that AI is used as a tool rather than a fully autonomous agent. Nevertheless, guidelines will be required outlining responsible approaches to AI use. It is also likely that the use of AI will require significantly greater levels of transparency to ensure predictions are interpretable and there is satisfactory accountability. This evolving legal landscape will likely prompt the development of regulations and guidelines that balance technological advancements with ethical considerations.

5. Current technological enablers

Physics-constrained AI modelling

Physics-constrained AI modelling was identified as a promising solution to many of the aforementioned challenges and is thus considered a priority enabler. Fig. 11 summarises the various levels to which ML models can be constrained by physical concepts ranging from pure data-driven (no constraints) to pure model-driven (but with ML updating). For example, in levels three and four, physical constraints can be weakly or strongly enforced respectively, as shown in Fig. 12 for a neural network implementation. It is also worth noting that advances in data-

driven dynamics have recently been shown to be capable of solving complex physics with limited measurement data e.g. Erichson et al. (2020). Therefore, the degree to which a model should be constrained will depend on several factors including the size and quality of training data, the complexity of the problem to be modelled, the risk of spurious predictions, and the degree to which the physical laws are accepted within the geotechnical community. Recent work demonstrates the feasibility of physics-informed neural networks for core geotechnical tasks, e.g., 3-D Terzaghi consolidation (Yuan et al., 2025), drilled-shaft capacity prediction (Ouyang et al., 2024), and seepage assessment of cut-off walls (Chen et al., 2023). These studies report accuracy within $\pm 5\%$ of numerical benchmarks while offering orders-of-magnitude speed-ups.

Multi-fidelity modelling

The premise of multi-fidelity modelling is to leverage both (i) low-fidelity datasets, such as simplified expression or numerical analyses, which may lack some degree of accuracy but can cheaply generate large training datasets and (ii) high-fidelity datasets, such as field/laboratory measurements, which have the highest level of accuracy but are insufficient on their own for AI training due to the typically small and expensive datasets (see Table 1). It is also notable that further sub-classifications of fidelity exist within these broad classifications (e.g. fidelity level 1 subclassifications will depend on test and material type). Multi-fidelity models can take many forms but commonly involve training one model directly on the low-fidelity data and tasking a second model to learn the relationships between the low- and high-fidelity datasets, as illustrated in Fig. 13. While Fig. 13 presents a sequential two-stage process for clarity, contemporary multi-fidelity methods frequently employ richer interactions. Common enhancements include: (i) co-training or hierarchical residual learning, where the high-fidelity model learns corrections to the low-fidelity output recursively (e.g. Perdikaris et al., 2017); (ii) Bayesian fusion methods that propagate uncertainty from both fidelities into the combined prediction (e.g. Le Gratier and Garnier, 2014); (iii) deep-operator frameworks that learn mappings across fidelities in a single network (e.g. Xu et al., 2024); and (iv) iterative feedback loops that alternate training phases to improve consistency and calibrate uncertainty bounds (e.g. Lam et al., 2015). These advanced patterns enable more robust generalisation and quantification of predictive confidence in complex geotechnical settings. Future developments in this area may involve refining techniques for

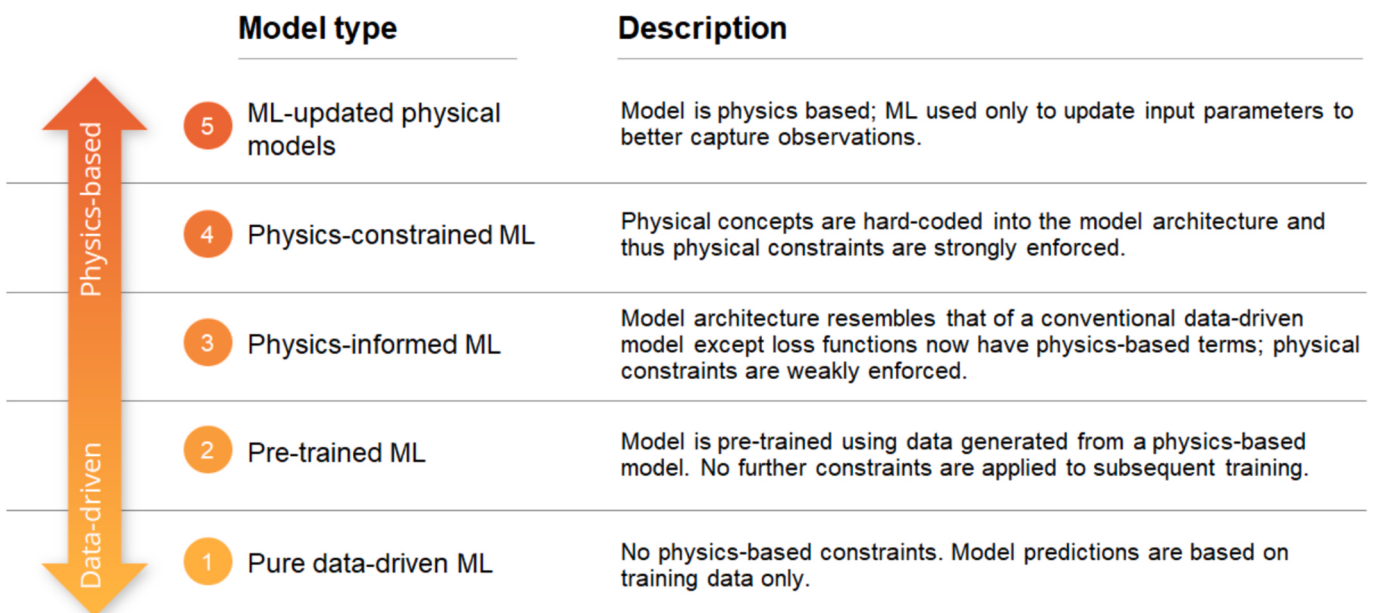


Fig. 11. Varying degrees to which ML models can be constrained with physical principles.

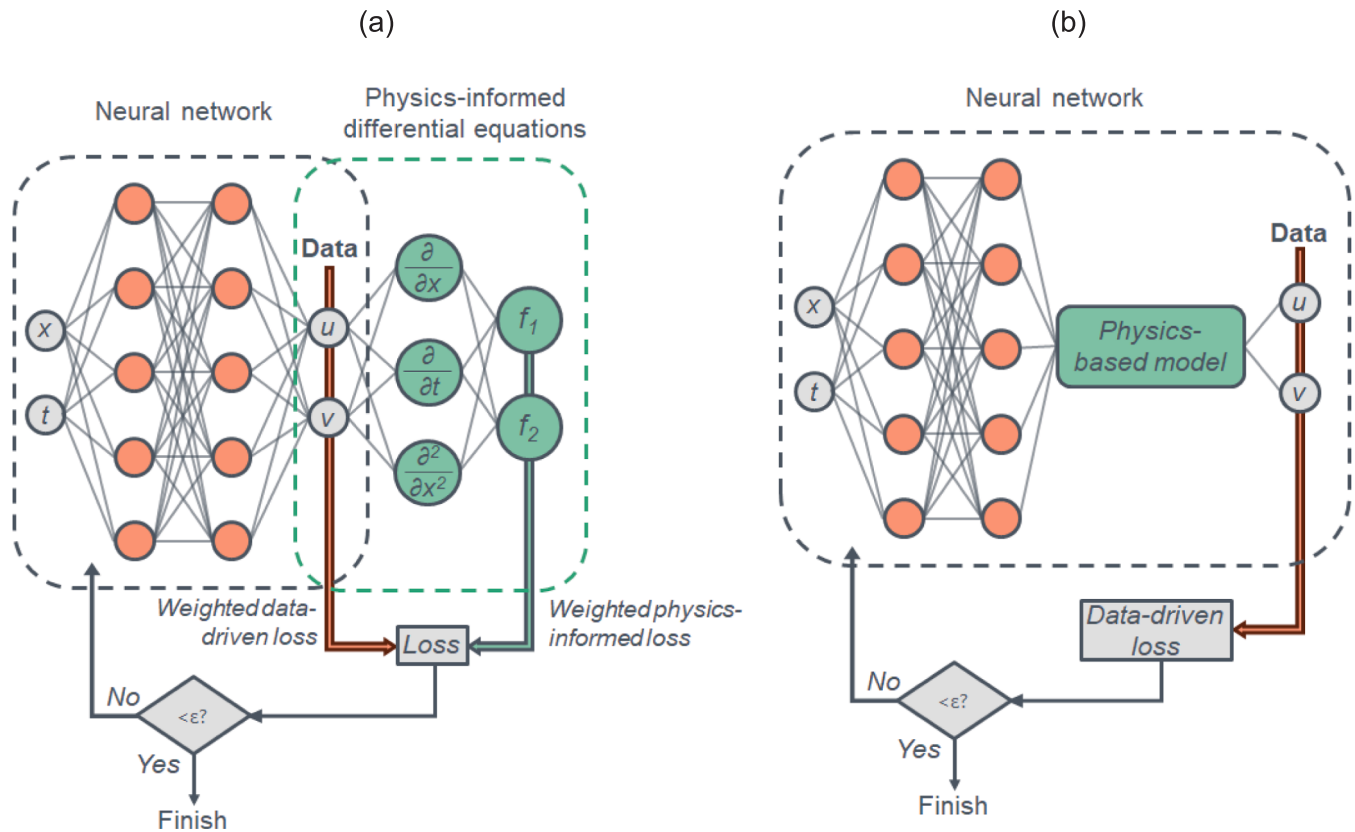


Fig. 12. Schematic illustration of (a) physics-informed (weakly constrained) ML model and (b) physics-constrained (strongly constrained) ML model.

Table 1
Exemplar fidelity levels for geotechnical engineering.

Fidelity level	Description
1 (highest)	High-quality field measurements
2	High-quality laboratory measurements
3	3D numerical analysis
4	2D numerical analysis
5	1D numerical analysis
6	Empirical 'rules of thumb'

seamlessly coupling different fidelity models, optimising their integration through ML algorithms, and developing adaptive strategies that dynamically allocate computational resources based on the specific requirements of a given problem.

Recent geotechnical demonstrations include a multi-fidelity DeepONet that fuses process-oriented FE simulations (low fidelity) with sparse field monitoring (high fidelity) for real-time settlement prediction in mechanised tunnelling (Xu et al., 2024); a multi-scale GAN that reconstructs subsurface profiles from blended low- and high-fidelity exploration datasets (Zhou and Shi, 2025); and physics-informed multi-fidelity residual networks that leverage mechanistic simulations plus limited laboratory data to model hydromechanical response and constitutive soil behaviour (Zhang et al., 2022c; He et al., 2023; Zhang et al., 2024).

Knowledge discovery

Data-driven knowledge discovery holds significant promise for transformative advancements in geotechnics. Two popular techniques in this area include data-driven dynamics (Brunton et al. 2016) and PIML. For example, Zhang et al. (2023c) recently demonstrated the ability of PIML to discover Terzaghi consolidation theory directly from consolidation measurements. Fig. 14 illustrates an inverse modelling workflow based on PiNet, in which a governing partial differential equation is first

recovered from data and then solved to infer unknown parameters (in this case, the coefficients of consolidation). This process is iterative and leverages the physics-informed loss function to minimise prediction error across the spatio-temporal domain. As access to geotechnical data continues to increase, there will be increasing opportunities to extract new insights, patterns, and mechanical laws from complex geotechnical processes which are currently only captured by empiricism.

Digital twinning

Digital twinning seamlessly integrates digital and physical systems, creating a real-time digital replica of a physical asset for simulation and scenario forecasting. Physical sensing keeps the digital twin updated, enabling health diagnostics and virtual control. ML supports autonomous updates and predictions, making twin systems central to future site robotics and automation. In geotechnics, this will evolve into federated digital twins, integrating models of ground, foundations, utilities, and structures, to enable holistic understanding of system interactions and dependencies (see Fig. 15).

Recent work is beginning to operationalise digital twins for underground and geotechnical systems. Related civil-infrastructure studies such as the statFEM twin of a self-sensing railway bridge (Febrianto et al., 2022) illustrate transferable, uncertainty-aware data-physics fusion relevant to geotechnical assets. Latif et al. (2023) streamed TBM operating data into an ML-enabled twin for real-time performance prediction and visualisation. Apoji et al. (2023) outlined AI-assisted decision layers for future mechanised tunnelling based on big data. Zhao et al. (2024) explored how digital-twin functions support construction, safety and lifecycle management for tunnels.

Human-machine interaction via large language models

LLMs (e.g. GPT-4) offer significant potential for advancing human-algorithm interaction in geotechnics. Building on earlier NLP models, they enable deeper insights from text and open new possibilities for expert-AI collaboration. LLM-driven interfaces promise more intuitive and dynamic deployments (e.g. Fig. 16). Generic LLMs often falter on

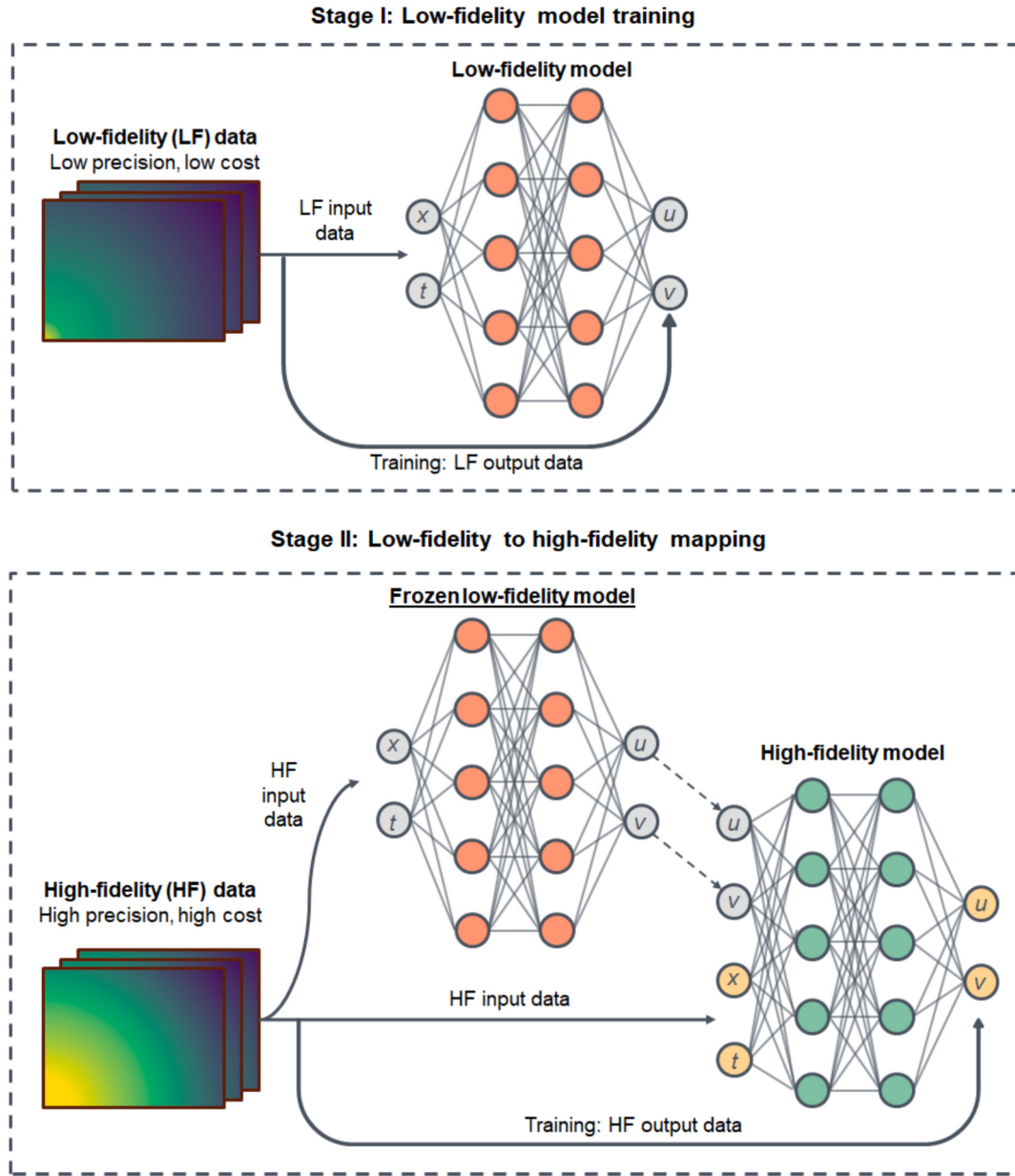


Fig. 13. Schematic illustration of one simplified instance of a sequential multi-fidelity modelling workflow.

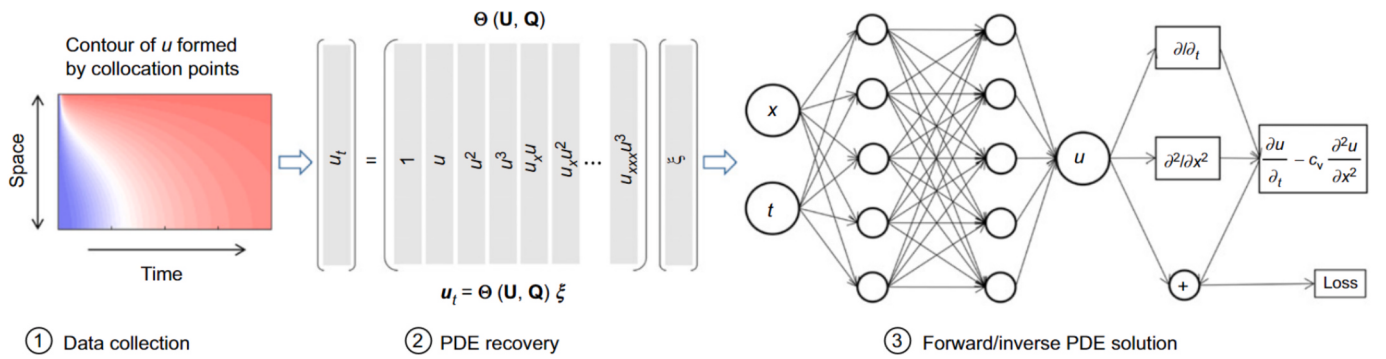


Fig. 14. Example data-driven discovery of Terzaghi consolidation theory using physics-informed neural networks (Zhang et al. 2023c).

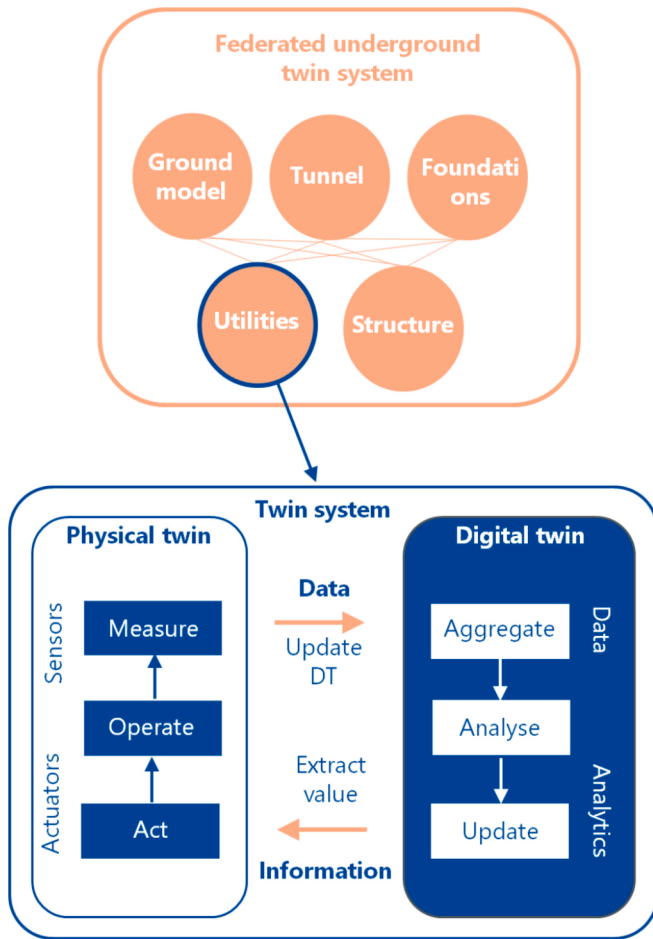


Fig. 15. Illustration of a federated underground twin system.

niche geotechnical queries that lie outside their pre-training data. This limitation can be mitigated via lightweight fine-tuning or retrieval-augmented generation (RAG) on an expert corpus curated and periodically reviewed by a specialist panel. Early feasibility studies show that GPT-4 can answer textbook-level geotechnical questions with ~70 % accuracy and draft ground-investigation specifications (Chen et al., 2024). Kumar (2024) demonstrated reliable geotechnical interpretation via carefully engineered prompts, while Xu et al. (2025a) introduced *GeoLLM*, a specialised LLM fine-tuned for intelligent geotechnical design automation. Recent studies have explored the application of LLM techniques such as RAG and few-shot learning in various geotechnical engineering tasks, including automated site planning (Qian and Shi, 2025), geological modelling (Li and Shi, 2025), and foundation design (Xu et al., 2025b). These studies confirm the practical potential of LLMs,

whilst also highlighting prompt-engineering and hallucination challenges to be managed.

Generative modelling

Generative AI, founded by generative adversarial networks (GANs; Goodfellow et al., 2014) and advanced by diffusion models (Song et al., 2020), offers three main opportunities for geotechnics. First, it can generate realistic synthetic datasets to enhance multi-fidelity modelling and simulation. Second, it enables automated, constraint-driven design workflows that rapidly explore and evaluate geotechnical layouts, shortening iteration cycles and revealing novel solutions. Third, by learning from historical and site-specific data, generative models can anticipate failure modes and inform proactive risk-mitigation strategies. Together, these capabilities promise faster, more innovative, and safer geotechnical engineering practice.

Recent domain-specific adaptations include *SchemaGAN* (Montero et al. 2025) which produces realistic geotechnical subsurface schematisations directly from sparse CPT data and outperforms kriging-based interpolation. Zhou and Shi (2025) employed a multi-scale GAN to fuse multi-fidelity exploration data for 2-D profile reconstruction with a significant reduction in mean-squared error versus classical inversion benchmarks. For time-series problems, Ge et al. (2024) introduced *RGAN-LS*, a recurrent GAN that augments scarce displacement records and improves landslide-displacement prediction accuracy by up to 18 % in blind tests.

Operator learning and graph-based simulators

Neural-operator frameworks, such as the Wavelet Neural Operator and the Physics-Informed Geometry-Aware Neural Operator, have recently been adapted for computational mechanics, achieving mesh-independent speed-ups of 50–100 times over the finite element method (FEM) while retaining physics consistency (Tripura & Chakraborty 2023; Zhong and Meidani, 2025). Parallel advances in graph neural network (GNN) simulators enable computationally efficient particle-scale representations of granular flows. Jiang et al. (2024) showed that GNN simulators can accurately predict granular collapse dynamics and efficiently optimise DEM parameters. In more recent work, a differentiable GNN surrogate replicated multi-layered slope run-out dynamics with $145 \times$ speed-up over the material point method whilst also supporting inverse parameter identification (Choi et al., 2025). These operator-learning and graph-based approaches open a pathway to real-time, differentiable multi-scale geomechanical simulations.

6. Closure

This paper has described the potential of integrating AI into geotechnical engineering, driven by the need to address intricate challenges in various complex interactions between soils, groundwater, structures and the environment. Highlighted recent advancements in popular geotechnical applications for AI including intelligent site investigation, soil behaviour modelling, and optimisation of

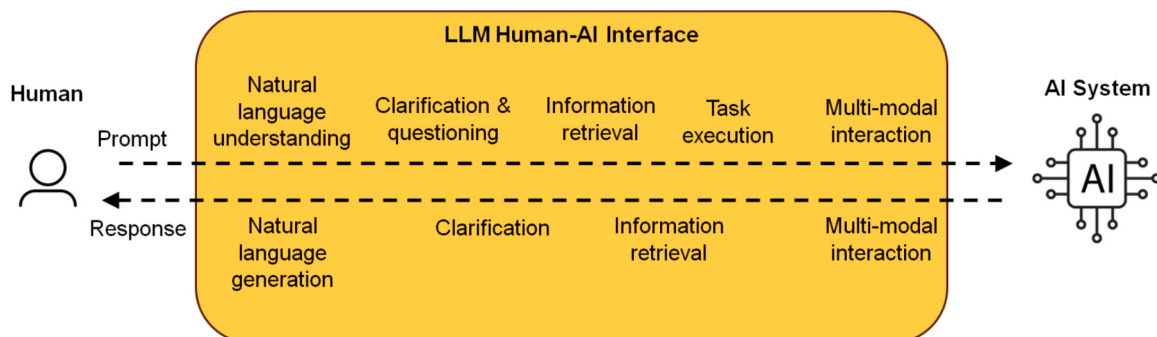


Fig. 16. Conceptualisation of an LLM-based interface between human and AI system.

geotechnical design processes, demonstrated how AI is already facilitating more accurate predictive models and streamlined operations. These selected use cases provide tangible evidence of how AI can deliver benefits today.

However, to fully realise the future potential AI, several key challenges specific to geotechnics were identified. Data scarcity remains a key challenge and risks hampering ML training due to the complex interactions in any geotechnical project. The complexity of applying AI to geotechnics rigorously was also linked to model interpretability, generalisation across diverse conditions, and uncertainty integration. Bridging AI with traditional geotechnical models and establishing benchmarks becomes crucial for ensuring the alignment of AI models with established engineering knowledge, overcoming potential biases and enhancing trust within the geotechnical community.

Finally, the paper also explored priority technological developments in geotechnical AI, including human-machine interaction through large language models, multi-fidelity modelling, knowledge discovery, digital twinning, generative modelling, operator learning and graph-based simulators. To achieve advancements in this area which align with established engineering principles, this paper considered it necessary to pursue a multidisciplinary approach involving collaboration between AI researchers and geotechnical experts. The ethical dimensions, particularly addressing bias and accountability, highlight the importance of responsible AI use within legal frameworks.

CRedit authorship contribution statement

Brian Sheil: Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Christos Anagnostopoulos:** Writing – review & editing, Conceptualization. **Róisín Buckley:** Writing – review & editing, Investigation, Conceptualization. **Matteo Oryem Ciantia:** Writing – original draft, Investigation, Conceptualization. **Elky Febrianto:** Writing – review & editing, Conceptualization. **Jinlong Fu:** Writing – review & editing. **Zhiwei Gao:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Xueyu Geng:** Writing – review & editing. **Bin Gong:** Writing – review & editing. **Kevin Hanley:** Writing – review & editing. **Pengpeng He:** Writing – review & editing. **Kostas Kolomvatsos:** Writing – review & editing. **Bruna de C.F.L. Lopes:** Writing – review & editing. **Jelena Ninic:** Writing – review & editing. **Marco Previtali:** Writing – original draft, Data curation. **Mohammad Rezania:** Writing – review & editing. **Agustin Ruiz-Lopez:** Writing – review & editing. **Jin Sun:** Writing – review & editing. **Stephen Suryasentana:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **David Taborda:** Writing – review & editing. **Stefano Utlili:** Writing – review & editing. **Scott Whyte:** Writing – review & editing. **Pin Zhang:** Writing – original draft, Conceptualization.

Declaration of competing interest

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Data availability

No data was used for the research described in the article.

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