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Topical Review

Finite element analysis, machine learning, and digital twins for soft robots: state-of-arts and perspectives

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Abstract

The current boom in soft robotics development has spurred extensive research into these flexible, deformable, and adaptive robotic systems. However, the unique characteristics of soft materials, such as non-linearity and hysteresis, present challenges in modeling, calibration, and control, laying the foundation for a compelling exploration based on finite element analysis (FEA), machine learning (ML), and digital twins (DT). Therefore, in this review paper, we present a comprehensive exploration of the evolving field of soft robots, tracing their historical origins and current status. We explore the transformative potential of FEA and ML in the field of soft robotics, covering material selection, structural design, sensing, control, and actuation. In addition, we introduce the concept of DT for soft robots and discuss its technical approaches and integration in remote operation, training, predictive maintenance, and health monitoring. We address the challenges facing the field, map out future directions, and finally conclude the important role that FEA, ML, and DT play in shaping the future of soft robots.

Keywords: soft robots, finite element analysis, machine learning, digital twins, data-driven design, robotics

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Contents

1. Introduction

Soft robot (SR) is an attractive and rapidly emerging field that focuses on the development of robots with flexible and deformable structures [1–5]. These soft robots are designed to mimic the characteristics and capabilities of soft-bodied organisms found in nature [6], such as worms [7–12], octopuses [13–17], caterpillars [18–21], and fish [22–28]. Their unique features include flexibility [29–32], compliance [33–36], safe interaction [37–40], adaptability [41–45], and versatility [46–49]. Soft robots are made from materials like elastomers [50–58], polymers [59–65], and hydrogels [66–71], allowing them to deform and change shape and making them well-suited for tasks that involve navigating through complex and confined spaces [72]. Soft robots have broad applications in different area, including medical devices [73–75], search and rescue operations [76–79], assistive devices and wearable robotics [80–82], space missions [83–85], agriculture [86–89], and underwater exploration [90–94].

Recent advancements in big data, finite elements analysis (FEA), machine learning (ML), and digital twin (DT) technologies have significantly contributed to the development and potential of SRs [95–102]. The integration of these cutting-edge technologies has revolutionized the way soft robots are designed, controlled, and optimized, unleashing unprecedented levels of performance and intelligence. The use of big data analytics in SRs provides valuable insights into robot behavior and performance, supporting data-driven decision-making and enhancing their capabilities. ML empowers soft robots to learn from experience, adapt to changing conditions, and autonomously optimize their actions, enabling them to process complex sensory data and continuously improve their performance through iterative learning [103–113]. DT technology plays a pivotal role in the development and operation of soft robots by creating virtual replicas of physical systems. This technology facilitates real-time monitoring, predictive analysis, and scenario simulations, enabling remote diagnostics, predictive maintenance, and performance optimization for soft robots [114–116]. The goal of applying big data, FEA, ML, and DT technologies to soft robots is to optimize their performance, enhance their adaptability, and revolutionize their capabilities in various applications.

There has been a lot of research focusing on the application of these technologies in the field of soft robots, and there are also some review articles related to these topics. (1) For FEA and ML, Pinskier and Howard [117] reviewed the state of autonomous SR design, spanning from parametric optimizations to evolutionary algorithms (EAs). They highlighted the need for advanced simulators and manufacturing processes to explore the intricate landscape of soft robot design, combining simulation and experimental data. Wang and Sun [118] conducted a review focusing on the integration of ML in SRs. The review highlighted the challenges posed by the elastomeric nature of soft robots in perception, control, and signal processing. They explored the use of hydrogels and ML as promising solutions. The review assessed hydrogel-based sensing and actuation methods and outlined mechanisms of perception. Additionally, they evaluated recent achievements in ML for processing soft robots' sensing data and optimizing their performance, listing strategies for implementing ML models. Yang and Wu [119] conducted a review focusing on ML applications in soft robot sensors. The study emphasized the use of compliant and soft sensors for closed-loop feedback control in soft robots. The review highlighted advancements in strain sensor-integrated SR design, including sensor materials optimization, signal analysis, and in-sensor computing, all driven by ML techniques. Wang *et al* [120] conducted a review focusing on ML applications in the control of soft continuum robots. They discussed the trade-off between flexibility and controllability and emphasized the use of data-driven modeling strategies with ML algorithms. The review covered current kinematic/dynamic model-free

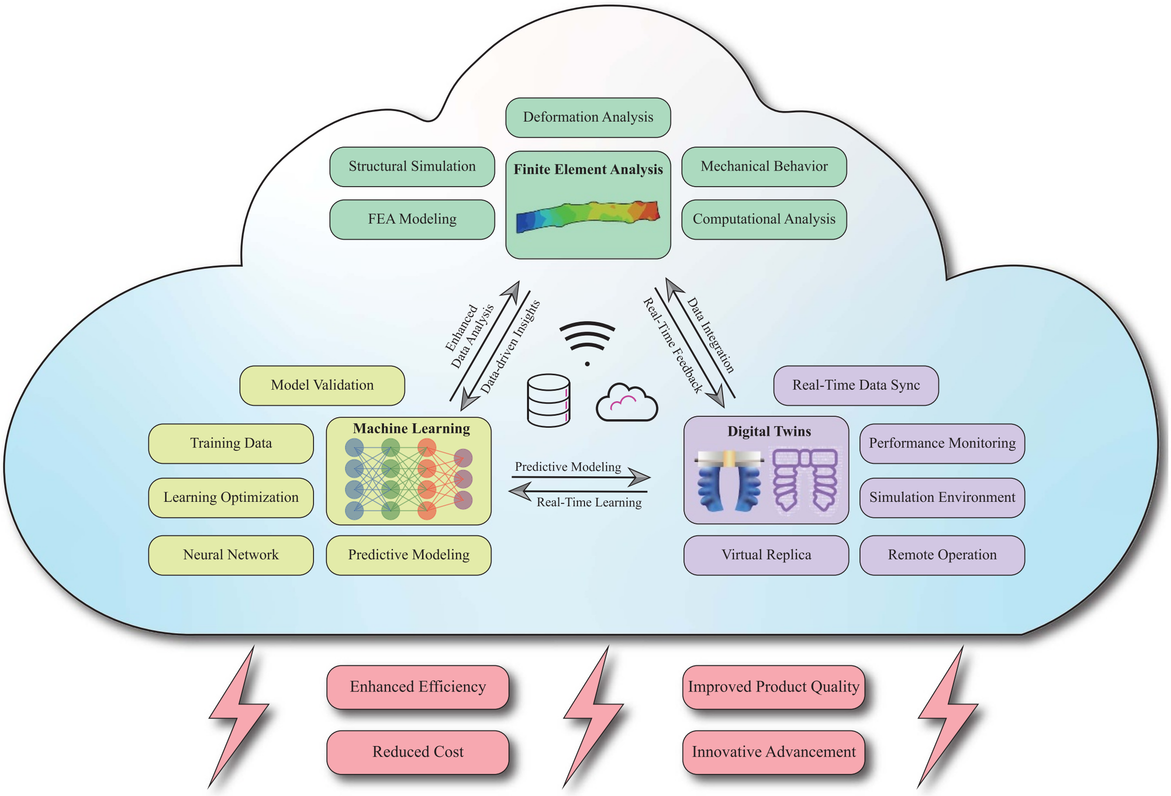

Figure 1. Interconnected landscape: finite element analysis, machine learning, and digital twin for soft robots.

control schemes, highlighting learning-based approaches, and explored their similarities and differences. Kim *et al* [121] reviewed ML techniques in SRs, categorized their applications in soft sensors, actuators, and wearable robots, and analyzed trends in different ML approaches for various soft robots. It also identified research limitations and summarized existing machine-learning methods for soft robots. Bhagat *et al* [103] reviewed the fusion of deep reinforcement learning (RL) with soft bio-inspired robots, emphasizing different kinds of deep reinforcement algorithms. (2) For DTs, Mazumder *et al* [122] reviewed trends of DT-incorporated robotics in both high and low research-saturated robotic domains. Zhang *et al* [123] reviewed the sensing technology for the DT of soft robots. These are the only two reviews that include the DTs for soft robots. However, most review papers focus on a sub-topic, some only discuss ML for soft robots, and some only study DTs for soft robots, but these three technologies are interconnected and promote each other, which is demonstrated in figure 1. Therefore, in our review paper, we will explore the application of these technologies in the field of soft robots and underscore their interplay and significance.

This paper aims to provide an overview of the recent advances and potential prospects in the field of SRs, with a particular focus on the transformative impact of big data, FEA, ML, and DT technologies. By analyzing various optimization methods, we aim to show how these techniques can improve the performance, efficiency, and adaptability of soft robots in different application areas.

The remainder of this essay is organized as follows. In section 2, we will lay the groundwork by exploring the basic concepts that are foundational to the fields of big data, FEA, ML, and DTs, which collectively contribute to the evolving landscape of SRs. Additionally, we will delve into the current research status within the realm of soft robots to provide a comprehensive understanding of ongoing developments. In section 4, we will focus on the integration of FEA and ML in the context of soft robots. This section will provide an overview of both FEA and ML and their relevance to the research domain of SRs. We will explore how these technologies are leveraged in material selection and characterization, structural design and analysis, and the critical aspects of sensing, control, and actuation in SR systems. Each subsection within this section will shed light on the current research status in its respective domain, providing insights into the cutting-edge advancements. Moving forward to section 5, we will turn our attention to DTs and their application in the realm of SRs. We will delve into the technical approaches employed in designing, prototyping, behavior modeling, simulation, performance optimization, remote operation, training, predictive maintenance, and health monitoring of soft robots through the lens of DTs. Additionally, we will offer a glimpse into the current research status within this domain. In section 6, we will confront the challenges that persist in the field of SRs and chart potential future directions. Finally, in section 7, we will draw conclusions based on the insights gained in the previous sections and present a comprehensive overview of the current status and bright prospects of SRs in the era of advanced technology.

2. Basic concepts and current status

In this section, we will explore the basic concepts in the field of FEA, ML, and DTs for SRs and delve into the current research status. Subsequently, we will survey the current research status of SRs and examine the latest developments and trends in this dynamic field.

2.1. Basic concepts

2.1.1. Big data. In the digital age, the sheer volume, speed, and diversity of data have given rise to a phenomenon known as big data. At its core, big data comprises vast and intricate datasets that defy traditional data processing tools and techniques [124]. It's a multifaceted concept characterized by three defining attributes:

- Volume: big data is synonymous with vast quantities of information, often measured in terabytes, petabytes, or more. This staggering volume dwarfs conventional data repositories.
- Velocity: in the age of real-time information, data streams into systems at breakneck speeds. The velocity of big data is marked by the rapid generation, transmission, and processing of data.
- Variety: big data is a diverse ecosystem of information. It encompasses structured data found in databases and spreadsheets, as well as unstructured data like text, images, and videos. The variety of data types and sources adds complexity to the big data landscape [125].

However, big data is more than just numbers and bytes—it represents a transformative force that touches various facets of our digital world. It encompasses social phenomena, information assets, data sets, analytical techniques, storage technologies, processes, and infrastructures. Microsoft aptly describes it as the application of 'serious computing power' to the colossal ocean of information, while the National Institute of Standards and Technology (NIST) underscores the need for a 'scalable architecture for efficient storage, manipulation, and analysis' [126].

Key aspects of big data include:

- Volume, velocity, and variety: these dimensions encapsulate the essence of big data. They emphasize the massive scale, rapid flow, and diverse nature of the data involved.
- Specialized technology and analytical methods: effectively harnessing big data necessitates unique technologies and analytical methods tailored to its intricacies and challenges.
- Transformation into insights and economic value: the true power of big data lies in its capacity to extract valuable insights, fueling innovation, and creating economic value. By applying advanced analytics, organizations can uncover meaningful patterns and trends within the data, empowering informed decision-making.

In essence, big data represents a paradigm shift in the world of data. It calls for scalable technologies, advanced analytics, and the potential to unlock valuable insights and economic benefits. As we navigate the big data landscape, we find ourselves in an era where data is not just abundant—it is transformative.

2.1.2. ML. ML is a specialized domain dedicated to developing and understanding methods that enable machines to enhance their performance on specific tasks through data-driven learning [127, 128]. As a subfield of artificial intelligence, it focuses on creating algorithms and models capable of learning, predicting, and making decisions autonomously, without explicit programming [129–131]. ML involves building computer systems that can analyze vast amounts of data, identify patterns, and extract meaningful insights to continuously improve their performance over time [132–134]. Different ML tasks are categorized based on learning approaches (supervised/unsupervised), learning models (classification, regression, clustering, dimensionality reduction), or specific algorithms utilized for a particular task.

ML models come in various types (figure 2), depending on their learning algorithms, objectives, and underlying mathematical techniques. Some commonly used ML models include:

- Supervised learning models: linear regression, logistic regression, support vector machines, random forest, decision trees, neural networks (NNs) (e.g. Multi-layer Perceptron), gradient boosting models (e.g. XGBoost, LightGBM).
- Unsupervised learning models: K-means algorithm, hierarchical clustering, self-organizing maps (SOM), principal component analysis (PCA), Gaussian mixture models (GMM), autoencoders.
- Deep learning models: convolutional NNs (CNN), recurrent NNs (RNN), generative adversarial networks (GAN), long short-term memory (LSTM), transformers.
- RL models: deep Q-networks (DQN), Q-learning, Monte Carlo tree search (MCTS), policy gradient methods, actor-critic methods.
- Bayesian models: Bayesian networks, naive Bayes, Gaussian processes, hidden Markov models (HMM).
- Dimensionality reduction models: t-distributed stochastic neighbor embedding (t-SNE), principal component analysis (PCA), linear discriminant analysis (LDA).
- Ensemble learning models: boosting (e.g. AdaBoost, Gradient Boosting), bagging (Bootstrap Aggregating), stacking, voting.
- Recommender systems models: content-based filtering, collaborative filtering, hybrid approaches.

These models represent a diverse range of techniques used in ML, each possessing unique strengths and applications. Researchers and practitioners select the most appropriate models based on the specific problem they are addressing and the characteristics of their data.

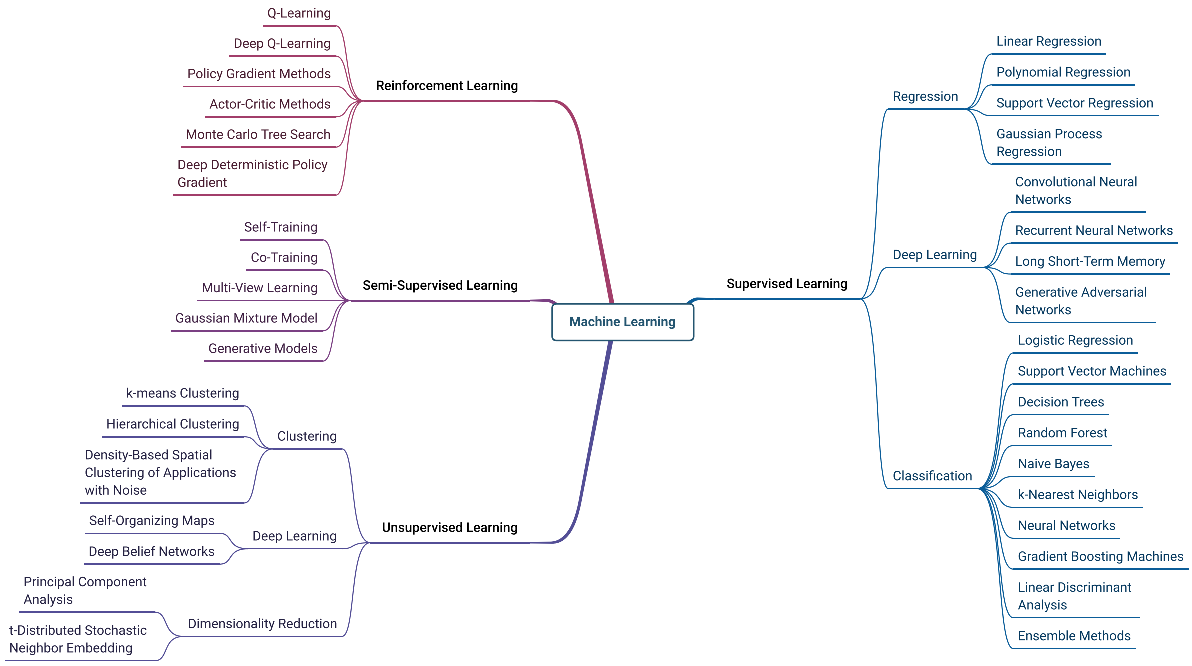

Figure 2. Machine learning methods used for soft robots.

2.1.3. DTs. A DT is a virtual representation of a physical object or system that spans its entire lifecycle. What sets DTs apart is their dynamic nature—they are continuously updated with real-time data and enriched through simulations, ML, and reasoning processes. This fusion of real-world data and digital modeling enables organizations to make informed decisions and gain unparalleled insights.

The roots of the DT concept delve deep into the annals of technological evolution, tracing back to pivotal moments that have shaped its trajectory. The recognition of the DT concept materialized in the year 2002, catalyzed by a presentation hosted by Challenge Advisory at the University of Michigan [135]. This presentation featured Michael Grieves and centered around the development of a product lifecycle management center. Within this pioneering presentation lay the foundational elements that would define DTs—an amalgamation of real and virtual spaces, along with the seamless flow of data and information between these domains. Although terminologies may have evolved over time, the core essence of uniting digital and physical counterparts into a singular entity has remained consistent since its inception.

Yet, the narrative of DTs extends beyond the early 2000s. Remarkably, the concept's origins can be traced back to the 1960s [136], a period when NASA employed rudimentary twinning ideas for space programming. During this era, physical duplicates of systems were painstakingly recreated on the ground to mirror those operating in the far reaches of space. This methodology found its pinnacle during the ill-fated Apollo 13 mission in April 1970 [137]. As unforeseen technical challenges emerged 200 000 miles away from Earth, NASA's DT model of the spacecraft became instrumental in devising life-saving solutions. This landmark event highlighted the critical role that DT technology could play, ultimately sowing the seeds for the DTs that dominate modern innovation.

Interestingly, the term 'digital twin' itself appeared in an unconventional context. In 1998, a digital replica of actor Alan Alda's voice was used to refer to the term in 'Alan Alda meets Alan Alda 2.0 [138].' However, the true convergence of the historical roots and its contemporary significance of DT occurred in the early 2000s, when it became recognized as a key strategic technology trend. The convergence was driven by the emergence of the Internet of Things (IoT), which rendered DTs more accessible and cost-effective. With the sensors and connectivity of IoT, the symbiotic relationship between physical systems and their digital counterparts became key to innovation.

2.2. Research status of soft robots

The current status of research in soft robots reflects the advancements and growing interest across various fields of robotics and engineering. Significant advances have been made in materials science [139–141], robot control [142–144], and computer technology [145], leading to breakthroughs in soft robot design [146–149], sensing [150–154], and actuation [155–161]. The integration of sensor technologies and control algorithms has enhanced the adaptability and versatility of soft robots. In addition, the development of novel soft materials and manufacturing techniques has expanded the capabilities of these robots. Soft robots have found applications in various fields, including healthcare [162–165], human-robot interaction [166–168], biomedical applications [169–173], extreme environments [174–179], and more. The integration of artificial intelligence and autonomy into soft robots holds promising potential for their operation in unstructured and dynamic environments. This section will explore the history and current status of research in soft robots in more detail, highlighting their design, sensing, control, material science, human–robot interaction, biomedical applications, autonomy, and extreme environment capabilities.

- Design and morphology: researchers are actively exploring novel design approaches and morphologies for soft robots [180]. These include bio-inspired designs [181–183], origami-based structures [31, 184], and soft actuators that mimic natural movements [185–189]. The goal is to create robots capable of complex and versatile motions, leading to applications in exploration, medical devices, and human–robot interactions.
- Sensing and perception: soft robots often require advanced sensing and perception capabilities to effectively interact with their surroundings. Researchers are integrating innovative sensor technologies, such as stretchable and flexible sensors [190–194], to provide real-time feedback and enable soft robots to autonomously adapt to changes in their environment.
- Control and actuation: achieving precise and efficient control of soft robots is a challenging yet crucial aspect of research. Advancements in actuation techniques, such as pneumatics [78, 195–197], hydraulics [198–201], and shape memory materials [202], are being combined with sophisticated control algorithms, including model-based [203–206] and learning-based [120, 207, 208] methods, to enable precise manipulation and locomotion of soft robots.
- Material science and manufacturing: the development of new soft materials, such as elastomers [54, 56, 209–211] and hydrogels [68–71, 212–214], is expanding the capabilities of soft robots. Manufacturing techniques, such as 3D printing and soft lithography [215–222], are also evolving to create intricate and customized soft robot structures, enabling rapid prototyping and cost-effective production.
- Human–robot interaction: soft robots offer the potential for safe and seamless interactions with humans. Research in this area focuses on creating SR prosthetics [223–229], exoskeletons [230–235], and wearable devices [236–239] that enhance human capabilities and support rehabilitation and assistance for people with disabilities.
- SRs in biomedical applications: soft robots are increasingly being explored for biomedical applications, including surgery [240–245], drug delivery [246–251], and wearable health monitoring devices [252–255]. The inherent compliance and biocompatibility of soft materials make them well-suited for integrating with biological systems.
- Autonomy and artificial intelligence: integrating autonomy and artificial intelligence into soft robots enables them to perform tasks in unstructured and dynamic environments. ML algorithms and DT technologies play a crucial role in enhancing the adaptability and decision-making capabilities of soft robots [100, 115, 121, 122, 256, 257].
- Soft robots in extreme environments: soft robots have the potential to operate in challenging environments where traditional rigid robots may be limited [258]. Research is being conducted to explore applications in space exploration [259–261], underwater exploration [27, 262–264], and disaster response scenarios [265–269].

In this subsection, we have explored the history and current research status of soft robots. The current research status of soft robots reveals remarkable progress and increasing interest in the field of robotics and engineering. Soft robots have emerged as a prominent branch of robotics, attracting significant attention and extensive research efforts.

3. FEA enabled soft robots

FEA has emerged as a powerful numerical tool for modeling and simulating the mechanical behavior of soft robots. FEA enables researchers to accurately predict the deformation and stress distribution of soft robot structures under various loading conditions [270–272]. It allows for the analysis of complex geometries and nonlinear material properties, essential for capturing the intricate behavior of soft robots [95, 273–275]. FEA-based simulations aid in virtual prototyping, enabling researchers to explore and refine multiple soft robot designs without the need for costly physical prototypes [276]. By providing detailed insights into structural integrity and performance, FEA facilitates the optimization of soft robot configurations to achieve better functionalities and adaptability in real-world applications.

In material selection and characterization, FEA is a powerful tool used to virtually test and simulate the behavior of soft materials under different conditions, helping researchers identify materials that offer the required elasticity, compliance, and viscoelasticity. Structural design and analysis also rely on FEA to model and analyze the mechanical behavior of soft robot structures under various loads and deformations. FEA plays a crucial role in modeling kinematics and control optimization as well, where understanding the kinematic behavior of soft robot actuators and components is crucial for developing sophisticated control strategies.

The design process of soft robots demands meticulous consideration of material selection. FEA provides a numerical technique to simulate the mechanical behavior of soft robots under different loading conditions, helping in the assessment of material suitability and guiding design improvements [277]. For sensing and actuation optimization, integrating sensors within soft robot structures requires careful consideration, and FEA plays a vital role in evaluating sensor placement and performance.

FEA has established itself as a reliable tool in modeling linear systems and solving multiphysics problems, thanks to its detailed, physics-based approach. Its application in SRs has enabled researchers to simulate the deformation and stress distribution of complex geometries with nonlinear materials, which are crucial to capturing the intricate behavior of soft robots. However, when applied to nonlinear elastic materials, FEA can encounter convergence issues, where the computational schemes must be adapted to stabilize the solution [278]. In these cases, problem-specific modifications to the

FEA model may be necessary, or alternative numerical methods, such as finite difference approaches, might be preferred to achieve stable and accurate results. The performance of FEA in nonlinear contexts is often influenced by the specific material properties and structural dynamics of the soft robots, and overcoming convergence issues remains a primary challenge when working with highly flexible, elastic structures. Moreover, SR structures frequently experience mechanical instabilities such as wrinkling, snap-through, and limit-point instabilities. These phenomena, while critical to the design and functionality of soft robots, present additional difficulties for FEA, requiring specialized mathematical adjustments or even entirely different modeling approaches to accurately capture these behaviors and to design against unwanted deformations.

While FEA is a core method in the classical continuum approach, it is only one among various numerical techniques available for addressing the complexities of SRs. Other methods—finite difference, finite volume, and smoothed particle hydrodynamics (SPH), for example—provide alternative frameworks that can complement or substitute for FEA, especially in scenarios where FEA is less effective. For instance, finite volume and SPH methods are often more suitable for fluid dynamics, which is crucial when modeling fluidic actuators frequently used in soft robots. FEA, while highly capable in solid mechanics, is generally less adaptable to fluidic behaviors, making computational fluid dynamics (CFD) methods more applicable for fluid-based actuators. In this way, the continuum approach to SRs modeling incorporates a suite of methods beyond FEA, allowing researchers to select the most effective tools based on the specific mechanical or fluidic behavior in question, ultimately enhancing the accuracy and reliability of SR simulations.

4. ML powered soft robots

The application of ML in the field of SRs holds immense promise and is rapidly advancing the capabilities and understanding of these highly deformable and adaptive systems [279–284]. Soft robots, with their flexible and compliant structures, offer unique advantages in various applications, including human–robot interaction, biomedical devices, and exploration in complex environments. FEA and ML complement each other, providing valuable insights and solutions to the challenges faced in soft robot design, analysis, control, and optimization.

The integration of FEA and ML in SRs opens up new possibilities to create more capable and autonomous systems. Combining FEA-based simulations with ML algorithms can automatically optimize SR designs. This approach leads to the discovery of innovative and efficient soft robot architectures that can adapt to different tasks and environments. Using ML techniques, soft robots become more environment-aware, self-correcting, and capable of learning from experience, making them highly adaptive and versatile in real-world scenarios.

4.1. Overview

The application of ML to soft robots encompasses four fundamental domains that play a crucial role in the advancement of this field: material selection and characterization, structural design and analysis, kinematics and control optimization, and sensing and drive optimization, which are illustrated in figure 3. ML offers powerful capabilities that complement traditional FEA methods, particularly in enabling soft robots to adapt to changing environments and learn from data [285–287]. With RL, soft robots can autonomously learn optimal control strategies for locomotion and manipulation, considering their inherently complex and nonlinear kinematics [103, 288–290]. Supervised and unsupervised ML techniques further enhance sensing and perception capabilities, supporting tasks like environment perception, object recognition, and human–robot interaction, crucial for advanced SR applications.

In material selection, ML techniques support material characterization by enabling the optimization of material properties for specific applications, such as elasticity or compliance, which expands the possibilities for soft robots [291]. By leveraging large datasets, ML can also uncover novel material combinations and configurations, accelerating the material discovery process.

For structural design, ML algorithms enhance the generation of optimized soft robot morphologies by learning from data and simulations. This approach enables the creation of structures that better meet performance and adaptability requirements, often leading to innovative robot architectures that can self-correct and adapt in dynamic environments.

In kinematics and control, ML-driven approaches provide adaptive control by optimizing parameters based on real-time data, enhancing precision and stability in soft robot motion [292]. This is especially valuable in dynamic and unpredictable settings, where robots must adjust to new conditions on the fly.

Lastly, in sensing and actuation, ML-based techniques, particularly sensor fusion, help soft robots process and interpret sensory data efficiently, enabling advanced perception and adaptability in challenging environments. By leveraging ML to interpret sensor data, soft robots gain a higher level of autonomy, further contributing to their effectiveness in real-world scenarios.

4.2. Material selection and characterization

The selection of materials is one of the keys to designing soft robots. The materials should be soft, have good plasticity and high elasticity [293]. These material properties enable soft robots to deform under the action of external forces, facilitating adaptation to complex environments and diverse task requirements.

The selection of materials is one of the keys to designing soft robots. The materials must be soft, have good plasticity and high elasticity. These material properties enable soft robots to deform under the action of external forces,

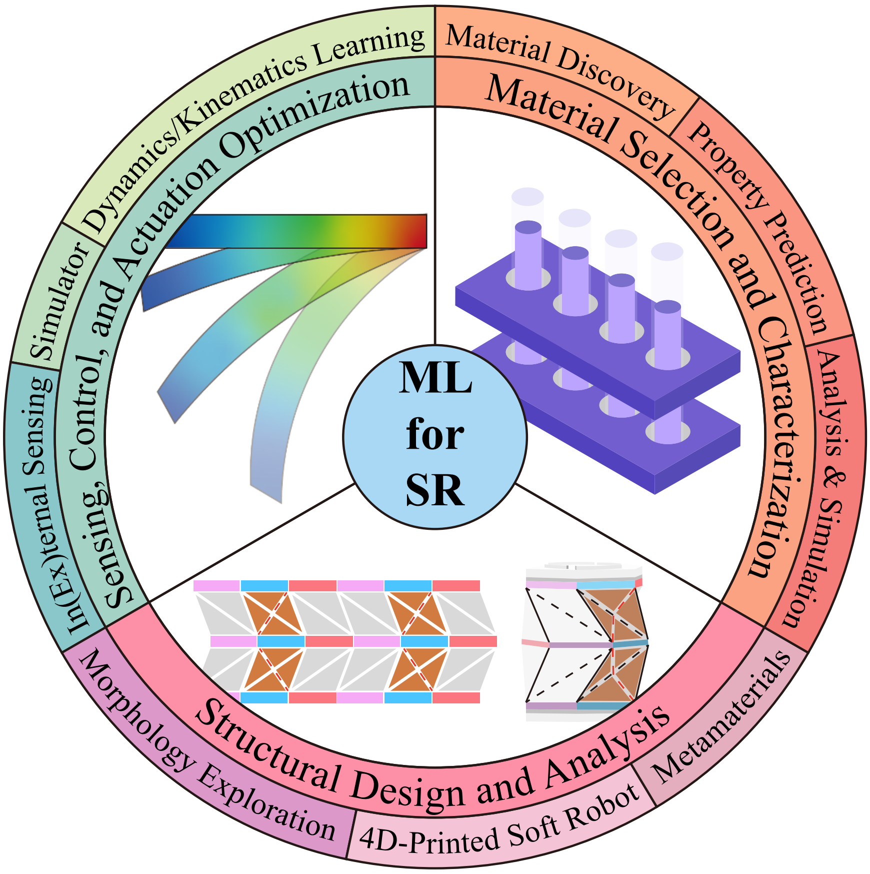

Figure 3. Research domain of machine learning powered soft robots.

thereby adapting to complex environments and diverse task requirements.

Recently, the concept of AI scientists has gained popularity, leading to the development of a robotic chemist that embodies intelligent chemistry. Traditional chemical research faces challenges with complex and high-dimensional objects, relying on exhaustive trial and error methods that often get stuck in local optima. In response to this, Zhu *et al* [294] created a machine chemist platform that performs the entire chemical synthesis, characterization, and testing process under the influence of big data and intelligent models. This platform surpasses similar devices in Europe and the United States both in software and hardware capabilities, boasting stronger chemical intelligence and extensive development capabilities. These techniques of data-driven material discovery and ML can also be applied to the material selection and characterization of soft robots.

In the current landscape of SRs, several materials have garnered attention for their suitability in constructing these robots. Silicone elastomers [295–310], urethanes [311–320], hydrogels [321–328], braided fabrics [329–344], hydraulic fluids [198, 345–354], and gasses [355–358] have emerged as the primary choices for manufacturing soft robots. The selection of these materials allows for the creation of robots that are inherently compliant, allowing them to interact safely with humans and adapt to dynamic surroundings. The design process of soft robots demands meticulous consideration of material selection. Elastomers, gels, and other flexible materials offer a wide range of properties that directly influence the performance and capabilities of the robot. For instance, certain materials like hydrogels and elastomers excel in high compliance, granting enhanced flexibility, but might exhibit lower strength. In contrast, other materials including shape memory polymers (SMP) and alloys possess remarkable strength while compromising compliance. This trade-off in material properties necessitates a thoughtful approach to selecting the optimal material based on the specific application requirements of the robot.

The application of FEA and ML is an effective way to address the complexity involved in material selection and design optimization. FEA provides a powerful numerical technique to simulate the mechanical behavior of soft robots under different loading conditions. By using FEA, how soft robots composed of different materials respond to external forces can be analyzed, helping in the assessment of material suitability and guiding design improvements [277]. In addition, ML algorithms have been utilized to assist in the selection of suitable materials for soft robots. These algorithms can analyze datasets containing material properties, environmental conditions, and performance criteria to identify patterns and correlations [359]. By applying ML, more informed decisions about material choices can be made, the design process can be optimized, and the overall performance of soft robots can be improved.

In this subsection, we will delve into the fields of applying FEA and ML to material selection and characterization for soft robots. Our exploration will focus on two crucial aspects: material discovery and material property prediction, as well as material analysis and simulation.

4.2.1. Material discovery and property prediction.

4.2.1.1. Material discovery. The application of ML to material discovery for soft robots has revolutionized the design process, especially when dealing with the complexities inherent in soft materials. Data-driven material discovery methods, based on advanced ML algorithms, have emerged as a promising approach for both material and morphological structure discovery in the soft materials [360–364].

Data-driven material discovery using ML is a powerful approach that leverages existing materials data to identify and propose new materials with specific properties suited for soft robot applications [365]. Traditionally, material discovery involved time-consuming and expensive trial-and-error methods, where researchers would synthesize and test numerous materials to find the desired properties [366]. However, with the advent of ML, data-driven approaches have become increasingly popular due to their ability to expedite the discovery process and enhance the efficiency of materials research [367].

In data-driven material discovery for soft robots, the first step is to compile a comprehensive database of materials and their associated properties. The database can include experimental data from material testing, simulation results, and literature data. The collected information covers material properties that are relevant to soft robot performance, such as mechanical properties, thermal behavior, and more. Once the data is prepared, ML algorithms are trained on the dataset to learn the relationships between material composition, designed structure, and overall properties. ML algorithms can use the patterns and correlations present in the data to generate predictive models that can estimate the properties of materials based on their characteristics. After the models are trained and validated, they can be applied to explore the more space of potential materials for soft robots. By inputting specific requirements and constraints for the soft robot's intended application, the ML models can output candidate materials with the desired properties. The ML-enabled process can significantly reduce the time and resources required to identify promising materials [368].

Moreover, ML can explore unconventional and novel materials that traditional methods may overlook. By analyzing the data holistically, ML models can identify previously undiscovered correlations and patterns, suggesting innovative materials with unique combinations of properties. Data-driven material discovery cannot only accelerate the search for suitable materials but also enable a more informed decision-making process. The ML models can provide insights into the relationships between different material properties, making it possible to weigh trade-offs and optimize materials for specific SR applications [369]. Although data-driven material discovery is effective, it is important to note that the quality and size of the initial materials dataset play a crucial role in the accuracy and reliability of the predictions [359]. Efforts are ongoing to expand and improve materials databases and integrate data from various sources to enhance the performance of ML models further.

In this subsection, we will explore four kinds of ML-integrated methods for the material discovery of soft robots: virtual screening, variational autoencoders (VAEs), generative adversarial networks, and RL techniques.

In the context of soft robots, ML-driven material discovery has enabled researchers to identify and optimize high-performance soft materials with specific functionalities. One notable application is the use of high-throughput virtual screening [370–372], where ML algorithms are employed to rapidly analyze vast databases of potential materials and identify promising candidates for specific SR applications. This approach has significantly accelerated the process of discovering materials with desired properties, leading to the development of soft robots that are more efficient and effective. Pinskier and Howard [117] reviewed existing manual and automated designs, highlighting the need for novel high-fidelity simulators and high-throughput manufacturing and testing processes to explore the complex soft material, morphology, and control landscape. Omar *et al* [373] conducted a review focusing on high-throughput virtual screening for organic electronics materials. The analysis of high-throughput virtual screening extended beyond identifying top candidates, often revealing new patterns and structure-property relations. The field is dynamic, continuously adapting to match the evolving landscape of applications, methodologies, and datasets. Dhasmana *et al* [374] focused on reviewing high-throughput virtual screening methods for material discovery of soft robots. They discussed widely used techniques, tools, and databases for the virtual screening of natural compounds and computational methods for absorption, distribution, metabolism, excretion, and toxicity prediction.

VAEs have also played a crucial role in the material discovery process for soft robots [375–377]. By converting discrete molecular representations into continuous latent spaces, VAEs allow for efficient exploration and optimization of material properties. This has opened up new avenues for designing soft materials with tailored functionalities, such as self-healing, shape memory, and adaptive behavior. Anantharanga *et al* [378] linked the material structure to its thermal, dielectric, and mechanical properties through semi-supervised learning of structure-property links in the VAE network. They used physically meaningful microstructural descriptors as design parameters and trained the ML model on a generated dataset of descriptors and property quantities. In-silico Design of the Experiment was performed using the Sobol sequence to sample the design space and generate a comprehensive dataset of 3D microstructure realizations. The VAE encoder acted as a surrogate for numerical solvers of multifunctional homogenizations, and its decoder was used for material design. Milazzo and Buehler [379] developed a method using VAE for material discovery in SRs inspired by fire. They used fire interactions to sonify flames, creating audible representations and generating novel flame images. The VAEs were utilized to generate continuous 3D geometries from image stacks, which were then 3D printed to create nature-inspired materials derived from fire.

Moreover, generative adversarial networks have been utilized to guide the structural evolution of organic compounds, enabling the creation of soft materials optimized for specific SR applications [380]. Zhao *et al* [381] developed CubicGAN, a generative adversarial network-based deep NN model, for the large-scale generative design of novel cubic materials in high-throughput screening. Trained on 375 749 ternary materials from the open quantum materials database, the model effectively rediscovered known cubic materials and generated hypothetical materials with new structure prototypes. Matsuda *et al* [382] developed an alternative approach for discovering porous materials using a conditional generative adversarial network (CGAN). They configured a materials discovery design space based on key porous materials and hybridized them structurally using the CGAN. The CGAN was controlled by a vector design variable that represented the intensity of each key porous material. By varying the vector latent variable input, multiple similar hybrid porous materials could be generated.

RL also greatly enhances the development of material discovery for soft robots by guiding the search process toward materials with desired characteristics. Volk *et al* [383] developed AlphaFlow, a self-driven fluidic lab that utilizes RL for autonomous material discovery in complex, multistep chemistries. AlphaFlow integrates a modular microdroplet reactor capable of performing various reaction steps with in-situ spectral monitoring. The system was applied to discover and optimize synthetic routes for shell growth of core–shell semiconductor nanoparticles. Sui *et al* [384] employed deep RL (DRL) to automate the design process of digital materials without prior designer knowledge. The DRL scheme utilized a collaborative deep Q network architecture with two cooperative agents for element-level modification operations.

To further advance generative design in SRs, challenges related to graph isomorphism and generation need to be addressed [385]. By effectively combining emerging graph-based feature representations with generative algorithms, researchers can unlock even more possibilities for creating novel soft materials with unique properties.

In the domain of soft matter applications, designing condensed-phase and multi-material properties, like self-assembly and self-healing, presents both challenges and opportunities [386]. ML predictions, combined with genetic algorithms, have shown promise in designing new polymeric repeat units with desired properties for soft robots [387]. Additionally, the creation of databases containing computed and experimental polymer properties facilitates the future design of polymeric materials with specific functionalities.

In summary, the application of ML to material discovery for soft robots, especially through generative design methods, has transformed the field by expediting the identification and optimization of soft materials with tailored properties.

4.2.1.2. Material property prediction. The application of ML to material property prediction for soft robots has revolutionized the field of soft materials modeling, particularly in the context of predicting physical observables based solely on a material's chemical structure. Three approaches have been explored: the first-principles method, the empirical method, and the semi-empirical method. Although all approaches have been adopted in the soft material community, they face limitations related to accuracy and computational cost.

Recent breakthroughs in featurization approaches and ML algorithms have shown great promise in enabling the statistical learning of first-principles-derived physical properties at a significantly reduced computational cost. To achieve successful material property predictions, effective representation of material as inputs to ML algorithms is crucial. Cartesian coordinates alone are inadequate due to their lack of appropriate invariances to translation, rotation, and permutation of like atoms. Therefore, various featurization approaches, such as density functional theory [388–391], quantum Monte Carlo [392–397], and *ab initio* molecular dynamics [398–401], are employed to encode structural and chemical properties. Jha *et al* [402] utilized density functional theory in combination with deep transfer learning to build a highly accurate predictive model for material property prediction of soft robots. Conradie [403] developed a methodology that combined generative design approaches, accurate finite element modeling, and quantum Monte Carlo simulations to design SR actuators. The approach involved exploring a 2D design space using pattern-generating methods and generative design algorithms. Finite element modeling was used to simulate unit properties and behaviors, and the results showed the validity of the design methodology, with physical models closely matching the simulated results.

Empirical methods play a significant role in predicting material properties for soft robots, offering practical and computationally efficient approaches [404]. One common empirical method used is the Lennard–Jones potential [405–408], which describes van der Waals interactions between atoms or molecules, making it suitable for modeling interactions in soft materials. For instance, in molecular dynamics simulations, the Lennard–Jones potential can be applied to study the behavior of SR materials at the atomic level, such as the interaction between soft polymer chains. Another empirical approach widely utilized is the ReaxFF (Reactive Force Field) [409–412], which enables the study of chemical reactions in condensed-phase systems. For soft robots, this method could be used to investigate the reaction mechanisms involved in the synthesis of soft and flexible materials used in their construction. Overall, empirical methods offer valuable tools for material property prediction in SRs, enhancing the understanding and design of innovative soft robot components and materials. Marechal *et al* [413] compiled a unified database of material constitutive models and experimental characterizations for seventeen elastomers commonly used in SRs. Using nonlinear least-squares methods, they derived parameters for hyperelastic material models from the tensile test data. The resulting material properties were shared on the SRs Materials Database GitHub repository, providing valuable information for the SRs community to optimize the design and simulation of soft-bodied robots.

Semi-empirical methods also play a important role in predicting material properties and understanding the behavior of complex molecules. Three notable examples of semi-empirical methods are PM3, MNDO, and AM1. PM3 approximates the electronic structure of molecules using parameterized Hamiltonians, making it computationally efficient for calculations of molecular properties [414–416]. MNDO, on the other hand, is particularly suitable for studying large molecular systems, making it valuable for molecular structure optimizations and electronic structure calculations in soft robot materials [417–419]. AM1, an enhancement of MNDO with improved atomic parameters, is well-suited for investigating larger molecules and transition states of chemical reactions relevant to soft robot material design. By leveraging these semi-empirical methods, researchers in SRs can efficiently predict material properties, optimize molecular structures, and gain valuable insights into the behavior of materials used in soft robot components [420–422].

Therefore, the application of ML to material property prediction for soft robots has opened up exciting opportunities for predicting and optimizing soft materials' physical properties. As the field continues to grow, advancements in featurization techniques, algorithm development, and access to high-quality data will undoubtedly drive further progress, leading to the design of novel soft materials that are critical for constructing advanced and efficient SR systems.

4.2.2. Material analysis and simulation. The simulation of soft matter is a challenging problem in materials science and computational physics. The difficulty to simulate properties and behaviors of soft matter arise from the complex and often nonlinear interactions between its constituent particles or components [423]. One of the main challenges in simulating soft matter is the large number of degrees of freedom and the highly dynamic nature of soft matter systems [424, 425]. Soft matter materials can undergo conformational changes, phase transitions, and self-assembly, which require accurate and efficient simulation techniques to capture internal behavior. Traditional simulation methods, such as molecular dynamics and Monte Carlo simulations, may struggle to handle the large length and board time scales associated with soft matter phenomena. Another challenge is the accurate representation of the interactions between particles or molecules in soft matter systems [426]. Empirical force fields, which rely on analytical functions to describe particle interactions, cannot be able to capture the full complexity of soft matter behavior. Developing accurate and transferable force fields for soft matter materials remains an active area of research. Some research about the material analysis and simulation using ML are illustrated in figure 4.

The combination of ML and finite element methods is of utmost importance for advancing material analysis and simulating soft robots. Accurately representing the intricate energetic interactions within soft materials is crucial for predictive modeling and successful design efforts. Traditional particle-based simulations, relying on specific analytical functions from electronic-structure calculations, have limitations in accuracy and transferability. In this context, machine-learning force fields (MLFFs) offer a promising alternative, accurately predicting material properties with reduced computational cost [429–433]. MLFFs have proven effective across various systems, encompassing small molecules to electrolyte solutions. They enable a comprehensive description of complex effects, including reactivity and polarizability [434], making them versatile tools for soft matter research. Challenges persist, especially with systems of rich chemical complexity, but researchers are addressing these issues by devising novel feature descriptors and incorporating long-range physics in MLFFs, leading to improved efficiency and accuracy [435]. In soft matter research, coarse-grained modeling is fundamental, and ML can significantly enhance its accuracy, efficiency, and transferability [436]. However, developing MLFFs for coarse-grained simulation may require more data, which is addressed by exploring hierarchical system representations and leveraging symmetries to reduce data requirements.

Enhanced sampling techniques, when combined with ML, offer powerful tools to overcome the limitations of traditional simulation methods in exploring the conformational space and free energy landscapes of soft matter materials [437]. Soft matter systems often exhibit complex and rare events, such as phase transitions, conformational changes, and self-assembly, which occur on long timescales and are challenging to capture using standard simulation methods. One of the main advantages of enhanced sampling techniques is their ability to accelerate the exploration of rare events [438]. These methods use biasing potentials or reweighting schemes to encourage the system to visit states that are energetically unfavorable or occur with low probability in unbiased simulations. By effectively enhancing the sampling of these rare events, researchers can obtain more comprehensive and accurate representations of the soft matter system's behavior. ML models play a crucial role in enhanced sampling techniques by learning from the biased simulation data and providing an unbiased estimate of the system's free energy landscape. The ML models can correct for the introduced biases and extract essential information about the system's thermodynamics and kinetics. This allows researchers to obtain more accurate estimates of free energy differences between different states, such as transition states and metastable states, which are crucial for understanding the underlying mechanisms of soft matter behavior. Moreover, enhanced sampling techniques combined with ML enable the exploration of multiple collective variables that characterize the soft matter system's complex behavior [439]. Collective variables are quantities that describe the system's macroscopic properties and can provide insights into the underlying physics and mechanisms of soft matter materials. ML models can efficiently identify and track these collective variables, making it possible to study the correlations and transitions between different states in the conformational space. These enhanced sampling techniques are particularly valuable for studying phase transitions and critical phenomena in soft matter materials. For example, in the study of liquid-to-crystal transitions or protein folding, enhanced sampling

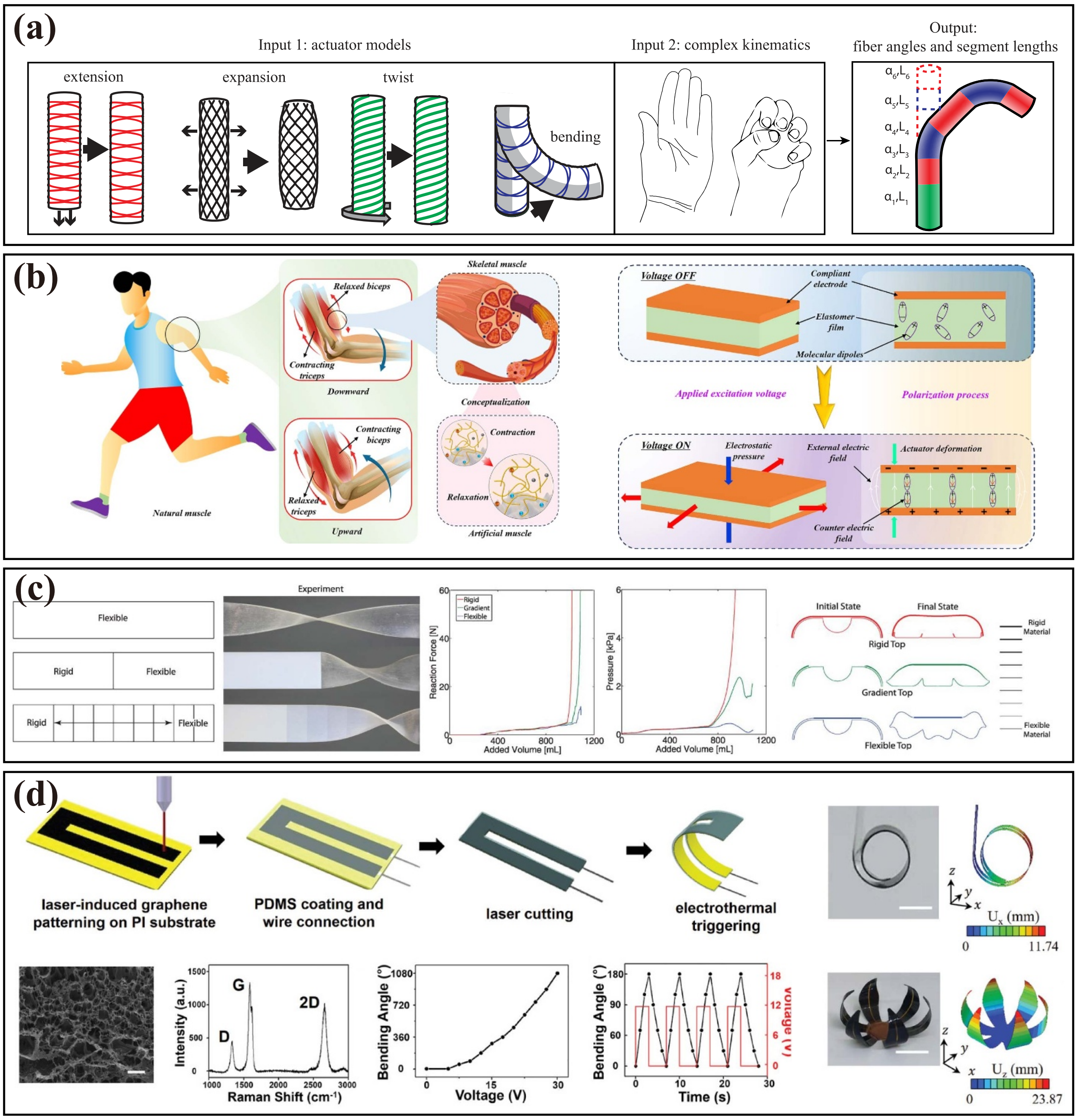

Figure 4. Research status for material selection and characterization of soft robots using finite element analysis and machine learning. (a) Automatic design of fiber-reinforced soft actuators for trajectory matching. Reproduced from [427]. CC BY 4.0. (b) High-performance electrically responsive artificial muscle materials for soft robot actuation. Reprinted from [161], Copyright (2024), with permission from Elsevier. (c) Material optimization for the gradient distribution. From [355]. Reprinted with permission from AAAS. (d) Transformation of the common plastic substrate into graphene material with excellent electrical properties using laser-induced graphite technology. [428] John Wiley & Sons. © 2020 WILEY-VCH Verlag GmbH & Co. KGaA, Weinheim

methods can efficiently sample the high-dimensional energy landscapes, leading to a more accurate characterization of the thermodynamic properties and transition pathways [440].

4.2.3. Current research status. The current research status of the application of FEA and ML in material selection and characterization of soft robots is promising, with a strong focus on self-healing materials, graphene-based materials, dielectric elastomers, liquid-crystalline elastomers (LCEs), ionic polymer-metal composites, and ferromagnetic materials. The integration of these methodologies holds significant potential for creating more robust, resilient, and functional soft robots that can adapt to complex and unpredictable environments. As research progresses, the continuous exploration of these advanced materials and techniques is expected to push the boundaries of what soft robots can achieve in various real-world applications.

Soft robots, with their unique ability to undergo free-form changes and operate in complex and harsh environments, necessitate materials with self-healing capabilities to ensure sustained functionality and resilience. The study of self-healing materials has emerged as a hot area of research, addressing the critical need to enhance the durability and longevity of flexible robots. Researchers are exploring innovative approaches to embed self-healing mechanisms into flexible robot components, such as microcapsules of healing agents or reversible chemical bonds, enabling autonomous repair of damage sustained during operation. Finite element modeling has played a crucial role in designing and characterizing self-healing soft materials for SRs. Terryn *et al* [441] demonstrated the impressive healing capabilities of self-healing elastomers in soft pneumatic actuators (SPAs) like grippers, hands, and artificial muscles through mild heat treatment. FEA enhanced the practical application of these materials, ensuring robustness in uncertain and dynamic environments. Similarly, Markvicka *et al* [442] developed a self-healing liquid metal-elastomer composite using Galinstan, which repairs itself when subjected to mechanical shear, exhibiting high toughness and elasticity, making it suitable for flexible electronic devices.

Graphene has also proven to be an excellent material for fabricating soft actuators and robots. Ling *et al* [428] utilized laser-induced graphite technology to transform common plastic substrate into graphene material with excellent electrical properties, reducing production costs and improving efficiency. The team employed FEA to quantitatively optimize laser power and irradiation time, resulting in better graphene quality and higher electrical conductivity. This approach facilitated the fabrication of three-dimensional assemblies with electrothermal control and mechanical guidance, allowing for the design of a flexible human actuator with fast response characteristics, high tensile performance, and repeatability. Stacked graphene has shown promise as an elastic-plastic material with excellent mechanical properties and deformation ability, making it valuable for soft robot applications. Wang *et al* [443] designed and prepared soft robots by adjusting the stacking of graphene layers to achieve asymmetry in different parts to expand their morphology and functionality. By applying genetic algorithms, they optimized soft robots capable of achieving desired deformations with enhanced performance and adaptability.

Dielectric elastomers are an attractive actuator technology for SRs due to their flexibility, pliability, and low energy consumption. Li *et al* [444] proposed a dielectric elastomer actuator with optimized shape and dimensions through FEA simulations. They explored the effects of different shapes, sizes, and material parameters on performance metrics, resulting in an actuator with higher mechanical flexibility and electrical capacity for improved functionality.

LCEs represent another promising material for soft actuators and robotics due to their unique combination of elasticity and anisotropic properties, which enable them to undergo large, reversible deformations in response to various stimuli, such as heat, light, or electrical fields [445–447]. The liquid-crystalline phase within the elastomer matrix allows for programmable shape changes, making LCEs highly adaptable for complex tasks in SRs. He *et al* [448–451] demonstrated the use of LCEs in creating soft actuators capable of precise, controlled movements by harnessing the alignment of liquid-crystal molecules under thermal activation. Their research employed FEA to optimize the material's structural properties, resulting in enhanced actuation performance and faster response times.

Soft ionic polymer-metal composites have also been investigated for soft actuator design. Carrico *et al* [452] used 3D printing to fabricate custom actuators with integrated control circuits and electrodes, simplifying production and increasing productivity. The introduction of a machine-learning algorithm optimized the control of the actuator, achieving accurate motion control, essential for precise application scenarios. The least square proximal algorithm, based on optimization theory, effectively improved the control accuracy and stability of the actuator motion.

Furthermore, ferromagnetic soft body robots, designed using the level-set multiphysics field topology optimization principle, can deform autonomously and be controlled by an external magnetic field. Tian *et al* [453] utilized the level-set method to optimize the robot's shape parametrically, achieving superior flexibility and efficiency. The combination of FEA simulation and topology optimization automatically adjusted the robot's shape and internal structure for optimal kinematic performance and adaptability.

4.2.4. Section conclusion.

The material selection and characterization for soft robots is a critical aspect that directly influences the performance, adaptability, and safety of these robots. Selecting appropriate materials with softness, plasticity, and high elasticity allows soft robots to effectively deform and interact with their surroundings. The field of soft robots has made significant progress with the integration of FEA and ML in material discovery, property prediction, analysis, and simulation. Overall, the application of FEA and ML in material selection and characterization for soft robots has revolutionized the field of soft robots. It has facilitated the discovery of novel soft materials, accurate prediction material properties, and improvement for the simulation and analysis of soft matter behavior.

4.3. Structural design and analysis

Structural design and analysis play an important role in optimizing the performances and functionality of soft robots. The combination of FEA and ML techniques opens up exciting possibilities for exploring innovative shapes, optimizing material distribution, and improving overall structural integrity. This section highlights three key areas where FEA and ML are making significant contributions to the structural design and analysis of soft robots, including shape exploration for soft robot morphology, 4D-printed soft robots, and the development of metamaterials.

4.3.1. Shape exploration for soft robot morphology.

Shape exploration is a fundamental aspect of soft robot design, as the morphology of a robot directly influences its capabilities and adaptability. FEA, combined with ML algorithms, can explore a wide range of potential SR shapes and configurations. By iteratively modifying the robot's geometry and boundary using geometric primitives or parametric curves, the robot's deformation and functionality can be optimized. This approach can discover novel soft robot designs to maximize performance metrics and adapt to specific tasks and environments.

Moreover, shape exploration enables the design of soft robots for diverse applications, such as medical devices, search and rescue operations, or exploration in challenging terrains. ML algorithms can be trained on a dataset of performance metric datasets to identify correlations between shape parameters and desired outcomes, leading to data-driven shape optimization. In this section, we will explore four methods of shape exploration: nature-inspired design, model-based design optimization, geometric optimization, and generative and evolutionary design. Figure 5 lists some studies on shape exploration of SR morphology.

4.3.1.1. Nature-inspired design. Nature-inspired design of soft robots draws inspiration from biological systems to create innovative and efficient robotic solutions. These designs mimic the remarkable capabilities of living organisms, resulting in soft robots that can navigate complex environments, adapt to various tasks, and interact delicately with their surroundings.

Biomimicry is a core concept in nature-inspired design [457–459]. Soft robots can replicate the movements, structures, and behaviors of animals, plants, and even microorganisms. Nature's solutions have evolved over millions of years, making them efficient and adaptable. By harnessing nature-exist principles, the nature-inspired designs of soft robots can enhance their functionality, efficiency, and versatility, contributing to advancements in fields such as healthcare, exploration, and disaster relief. For example, soft robot tentacles can replicate the flexibility and dexterity of an octopus arm [460], allowing them to manipulate objects in confined spaces. Bird-inspired wing-like structures can enable soft robots to achieve efficient aerial locomotion [461, 462]. This approach also integrates bio-inspired materials that replicate the compliance and elasticity of natural tissues. Soft robots equipped with these materials can achieve better interaction with the environment, providing safer human–robot interactions, enhanced adaptability, and resilience. In addition, sensing systems inspired by biological counterparts enable soft robots to sense and respond to their surroundings like animals, which can give soft robots enhanced perception capabilities, making them more flexible in a variety of applications.

4.3.1.2. Model-based design optimization. Design optimization of soft robots, particularly in a model-based approach, involves several key components that collectively drive the process towards finding the best-performing designs [463]. These components, including design parameters, dynamics of the system, objective function, constraints, and lower and upper boundaries, work together to shape the optimization process and achieve optimal soft robot designs.

1. Design parameters: design parameters encompass the variables that define the structural and behavioral characteristics of a soft robot, which can include material properties (such as elasticity, stiffness, and density), geometric dimensions (lengths, diameters, angles), actuation mechanisms (pneumatic chambers, cables), and other relevant parameters. These parameters are manipulated during optimization to explore a wide design space and find configurations that fulfill performance requirements.
2. Dynamics of the system: understanding the dynamic behavior of a soft robot is fundamental for optimization. This involves comprehending how the robot's shape, motion, and interaction with its environment change over time. Dynamic models, often based on physics principles and mathematical equations, describe the robot's responses to different inputs. FEA plays a crucial role in simulating these dynamics and predicting how design parameter variations impact the robot's behavior.
3. Objective function: the objective function quantifies the goal of the design optimization. It encapsulates the desired performance criteria that the soft robot should achieve. These criteria could be diverse, ranging from maximizing bending capabilities, achieving specific locomotion patterns, to minimizing energy consumption. The objective function serves as a metric to evaluate and compare different design iterations, allowing the optimization algorithm to search for designs that optimize the functionality.
4. Constraints: constraints are the limitations or conditions that a design need to adhere to. They can be physical, engineering, or safety-related. For instance, constraints might include ensuring that stresses and strains within the soft robot's materials remain within acceptable limits, or that certain motion trajectories are achieved without violating mechanical limitations. Constraints guide the optimization process towards feasible solutions.
5. Lower and upper boundaries: design parameters often have limits beyond which they might lead to impractical or non-functional designs. Lower and upper boundaries define these limits. For example, the length of a pneumatic chamber will have a lower boundary to ensure it is not too short to function effectively, and an upper boundary to prevent it from becoming too bulky. Boundaries constrain the optimization process to physically meaningful solutions.

The integration of these components in a model-based design optimization process for soft robots results in a systematic approach to creating robots that meet specific performance objectives. FEA simulations, complemented by ML techniques, facilitate efficient exploration of the design space. The dynamics of the system, defined by mathematical models, guide the optimization process to ensure that solutions align with the desired robot behavior. Objective functions, constraints, and boundaries collectively shape the optimization process, enabling the discovery of soft robot designs that excel in their intended tasks while adhering to practical limitations and requirements.

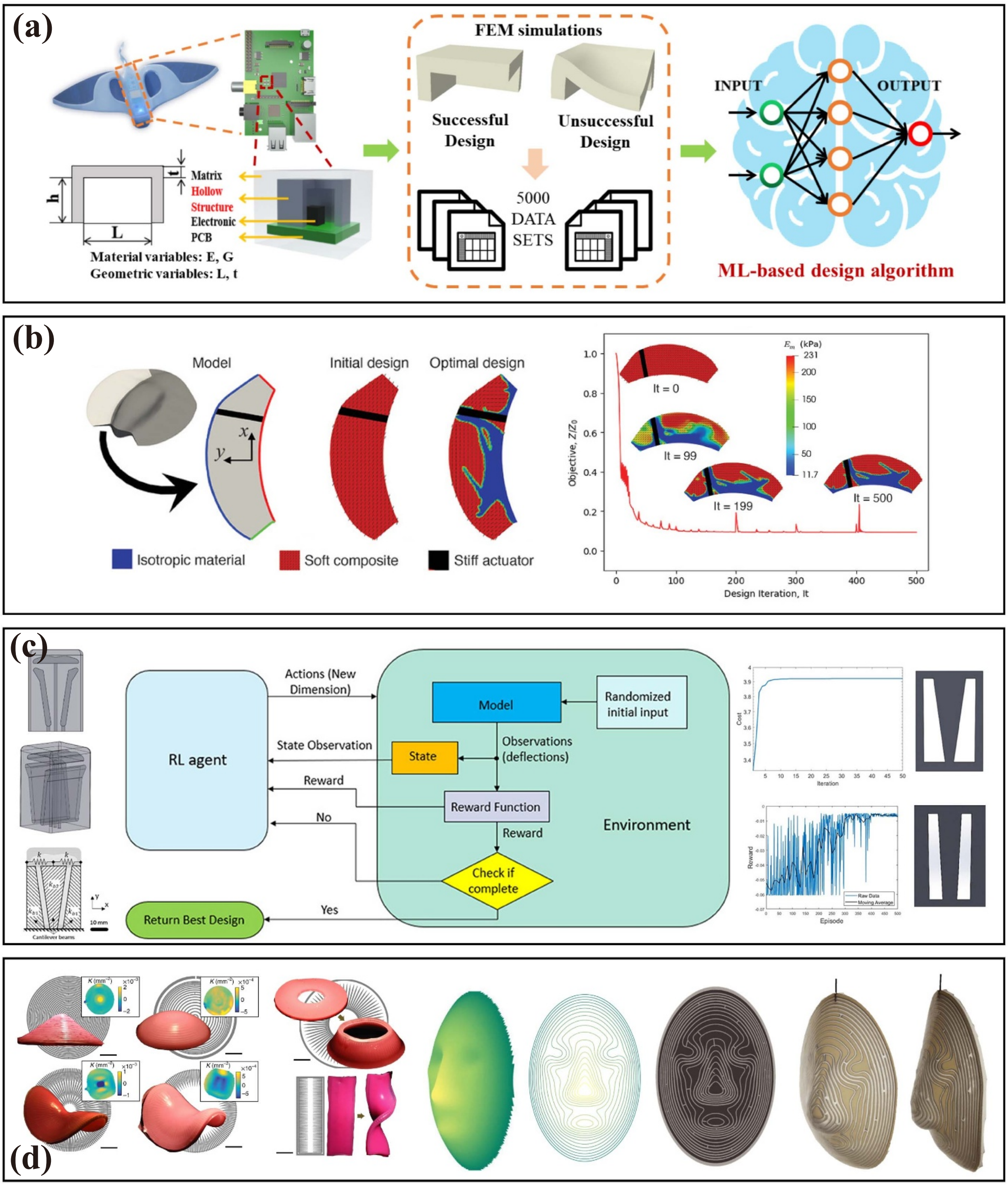

Figure 5. Shape exploration for soft robot morphology. (a) Machine-learning-accelerated design of functional structural components in deep-sea soft robots. Reprinted from [111], Copyright (2022), with permission from Elsevier. (b) Optimal soft composites for under-actuated soft robots. [454] John Wiley & Sons. © 2021 The Authors. Advanced Materials Technologies published by Wiley-VCH GmbH. (c) Design optimization of a pneumatic SR actuator using model-based optimization and deep reinforcement learning. Reproduced from [455]. CC BY 4.0. (d) The surface topography of inflated baromorph structures for bio-inspired pneumatic shape-morphing elastomers. Reproduced from [456], with permission from Springer Nature.

Researchers are exploring various techniques and methodologies to optimize the design of soft robots using models, simulations, and computational tools. For example, Nikolov *et al* [464] presented an analytical model for soft fiber-reinforced bending actuators featuring an elastomeric air chamber with inextensible fiber reinforcement. This model connected input pressure to the bending angle and contact force. The outcomes indicated that optimized actuators demanded around 48% less input pressure for a given bending angle, in comparison to non-optimized actuators. Additionally, the optimized actuators produced about 18% stronger contact force with external obstacles compared to uniform wall thickness actuators. Raeisinezhad *et al* [455] presented two frameworks for optimizing the mechanical performance of a multi-chamber pneumatic-driven soft actuator. The optimization involved shaping and arranging air chambers using the firefly algorithm and deep RL. FEA and model-based formulations were integrated into the optimization process. The optimized design, achieved through the deep RL approach, effectively decoupled motions while meeting the intended application's displacement requirements. Yang *et al* [465] focused on optimizing the design of SPAs for enhanced grasping force in soft grippers. The researchers introduced an efficient design methodology by approximating the complex SPA structure with a cantilever beam. The relationship between input pressure and output torque was established through mechanical analysis. This model-based optimization approach was used to determine optimal design parameters.

4.3.1.3. Geometric optimization. Geometric optimization plays an important role for soft robots and covers three aspects: size, shape, and topology optimization. Size optimization involves the careful adjustment of specific parameters like length, width, and height, which directly influence the overall behavior of soft robots. Shape optimization focuses on the complex manipulation of contours and shapes to achieve desired movements and functionalities. The iterative process often results in complex and customized shape designs tailored to specific tasks. Topology optimization, meanwhile, addresses the fundamental arrangement and connectivity of SR components [466, 467]. Topology optimization aims to discover the optimal distribution of material within the design space, often yielding complex structures that might challenge traditional manufacturing methods. Topology optimization involves minimizing weight, maximizing stiffness or toughness, and reducing stress concentrations under defined constraints. Although the concept of optimizing structures for optimal performance dates back centuries, formal topology optimization emerged in the 1980s [468] and 1990s [469]. This multidimensional approach to geometric optimization empowers soft robots to achieve enhanced adaptability, complex functionalities, and even entirely novel forms in diverse applications.

FEA and ML play pivotal roles in advancing the geometric optimization of soft robots, amplifying their design capabilities and ensuring practical feasibility. FEA enables accurate simulations of complex mechanical behaviors in soft materials, providing insights into deformation, stress distribution, and overall performance. This aids in fine-tuning geometric parameters during size and shape optimization, resulting in designs that are both functional and structurally sound. ML, on the other hand, brings efficiency and innovation to this optimization process. By learning from vast datasets of simulations and designs, ML algorithms can quickly identify patterns and correlations, enabling the prediction of optimal design configurations. This not only expedites the optimization process but also opens avenues for unconventional and novel shapes that might otherwise be overlooked. Additionally, ML can assist in multi-objective optimization, where soft robots need to fulfill diverse performance criteria. The fusion of FEA and ML thus transforms geometric optimization from a time-intensive and intuition-driven endeavor to a data-guided, efficient, and creative process. This synergy ultimately propels the frontier of soft robot design, leading to more adaptable, functional, and diverse robotic systems. Zolfagharian *et al* [470] leveraged the synergy between topology optimization, 3D bioprinting, FEA, and ML to enhance the performance of soft actuators. These soft structures, constructed using stimuli-responsive polymers, exhibited improved flexibility and shape recovery. By employing multi-material topology optimization and electrolytic stimulation, the bending performance of bioprinted soft actuators was enhanced and controlled. Yuhn *et al* [471] extended density-based topology optimization into the realm of dynamic soft robots, a field previously dominated by static structures. This innovation, termed '4D topology optimization,' harnessed finite element simulations and ML. It enabled simultaneous optimization of SR structure and self-actuation over time, addressing challenges related to deformations and intricate interactions. The approach employed multi-indexed density variables, efficiently optimized through gradient-based methods. By leveraging forward and backward simulations using the material point method, the team successfully designed self-actuating soft bodies for locomotion, posture control, and rotation tasks. By treating the mechanical design of a soft cable-driven gripper as a topology optimization problem, Chen *et al* [472] applied FEA to synthesize the gripper's structure. They improved on previous compliant mechanism optimization by incorporating practical interactions involving pressure loadings and friction tractions with objects. The effects of interaction uncertainties were also examined by varying contact locations and areas.

4.3.1.4. Generative and evolutionary design. The application of FEA and ML in the generative and evolutionary design of soft robots has transformed the field. Generative design leverages ML algorithms to analyze existing designs and simulations, extracting patterns for informed creation. FEA simulates soft robot behaviors under different conditions, guiding design choices for optimal performance and safety. Integrating ML and FEA, EAs refine designs iteratively. These algorithms learn from FEA simulations, suggesting design changes that enhance performance. This synergy accelerates design cycles, fosters innovation, and facilitates the creation of complex soft robots. The approach enables the emergence of EAs that consider both structure and functionality, driving the development of soft robots capable of intricate and biomimetic movements. Venter *et al* [473] employed a generative and evolutionary design approach to tackle the challenges of SRs. Utilizing FEA and ML, they devised a practical process that combined various techniques to streamline design. By integrating reduced-order models, L-systems, MCMC, curve matching, and optimization, they achieved rapid creation of functional 2D articulating soft robot designs in under 1 s. This marked a significant time reduction compared to traditional methods. Moreover, the approach was extended to develop intricate 3D robots like an articulating tentacle with multiple grippers, highlighting its potential for complex designs.

Various simulators have been explored for the generative and evolutionary designs of soft robots. VoxCAD [474–476], a widely used simulator, employs a mass-spring-based particle approach to model the nonlinear dynamics of soft bodies efficiently. While it sacrifices some accuracy compared to FEA, it can handle contact, gravity, and friction modeling. However, its limitations in bridging the gap between simulation and physical reality are evident, as physical behaviors often do not match simulated results. Alternative simulators include formal grammars for robot growth [477] or the use of gene regulatory networks (GRNs) for evolving cell-by-cell soft robots [478, 479]. Another simulator, SOFA [480–482], integrates finite element modeling to simulate deformable objects and has potential in soft robot optimization. One notable research made by Schegg *et al* [483] presented SofaGym, an open-source software to create OpenAI Gym interfaces. These simulators, along with VoxCAD, provide platforms for exploring the complexities of soft robot design, incorporating elements of evolutionary and generative design techniques.

4.3.2. 4D printed soft robots. In recent years, the emergence of 4D printed soft robots has promoted the development of the field of robotics [484–489]. Unlike rigid robots, 4D printed soft robots not only have the extraordinary ability to deform and morph into various shapes when external stimuli are applied [222], but also can do so autonomously over time. The 4D printing effect is achieved by combining advanced additive manufacturing technology and the integration of responsive materials [490–492].

The term ‘4D printing’ adds an extra dimension to the concept of 3D printing, introducing the temporal aspect that underscores the dynamic behavior of soft robots. The fourth dimension refers to time, indicating that the printed structures can undergo programmed changes in shape, structure, or functionality over a certain period of time [493–496]. This paradigm shift opens up new horizons in soft robots, enabling the creation of robots that can adapt, camouflage, grasp, or perform specific tasks based on their interactions with the environment.

The fabrication process of 4D-printed soft robots involves the use of materials that can respond to environmental cues such as temperature variations [497–500], humidity levels [501, 502], light exposure [503–505], and electric [506, 507]/magnetic [508–514] fields. Through precise design and material selection, these robots can self-transform or adapt in predefined ways, offering a new level of versatility in their potential applications. Such applications span a wide spectrum, including microelectronics [515], biomedical [516–518], tissue engineering [519, 520], and automotive [521].

The burgeoning field of 4D-printed soft robots not only underscores the impressive strides made in materials science and manufacturing technologies but also presents interdisciplinary opportunities at the intersection of robotics, engineering, and materials research. Researchers are actively exploring novel design strategies, material innovations, and computational modeling techniques to unlock the full potential of these dynamic robots.

Therefore, it is crucial to develop accurate models for predicting the behavior of 4D printed soft robots. Such models will not only help in the design and optimization of 4D printed soft robots, but also elucidate the underlying principles that govern their dynamic responses.

4.3.2.1. Modeling. Modeling 4D printed soft robots is challenging due to the complex and dynamic nature of their behavior, that is, 4D printed soft robots are designed to undergo controlled shape changes over time in response to environmental stimuli like temperature, light, or moisture. To accurately predict shape morphing, advanced modeling techniques are essential to guide the design, optimize performance, and provide better control of 4D printed soft robots.

One of the primary challenges in modeling 4D printed soft robots is accurately capturing the behavior of their materials. These robots are often composed of elastic materials with nonlinear, time-dependent mechanical properties. These properties can change based on factors such as strain rate, temperature, or process parameters in 3D printing. Therefore, it is critical to develop constitutive models—mathematical descriptions of material behavior—based on experimental data to ensure accurate predictions.

FEA plays a crucial role in simulating the behavior of these robots. By discretizing their geometries and material properties, FEA allows for precise predictions of how soft robots will deform and interact with their environment. However, modeling 4D printed soft robots introduces additional complexity. Their behavior is influenced by a complex interplay between material characteristics, structural geometry, and external stimuli, all of which need to be accounted for in the simulation.

Another critical aspect of 4D printed soft robot modeling is incorporating the time-dependent response. The ‘4D’ aspect of 4D printed soft robots refers to their ability to change shape in response to specific stimuli over time. Thus, modeling must account not only for the initial configuration of soft robots but also for how its shape evolves as it reacts to stimuli. This requires integrating time-dependent material properties and environmental factors into the simulation.

To address these complexities, several modeling approaches are utilized. Hyperelastic material models can be used to accurately represent the deformation behavior of the material. Hyperelastic models can handle the large strains common in soft robots, providing a more accurate description of the material’s behavior under deformation.

Data-driven approaches have gained importance in SRs modeling, especially for time-dependent response. ML techniques are being used to predict soft robot behavior from experimental data, enabling more efficient and precise forward prediction. These approaches can capture complex behaviors that may be difficult to describe using traditional methods alone, offering a complementary tool for improving model efficiency.

Successfully modeling 4D printed soft robots requires integrating advanced material models, computational methods like FEA, and ML based data-driven approaches. These models provide crucial insights into the behavior of 4D printed soft robot, helping refine designs and improve their performance in practical applications. This section will explore both analytical and FEM-based approaches to modeling 4D printed soft robots, highlighting the challenges and solutions in this emerging field.

4.3.2.1.1. Analytical model of soft robots. An analytical model for 4D-printed soft robots can be conceptualized by integrating principles of material behavior, structural mechanics, and dynamic response. The model aims to predict the intricate shape-changing mechanisms of these robots in response to external stimuli. The analytical approach proposed by Alici *et al* [522] served as a means to predict the bending angle of an actuator based on specific input parameters. This method was rooted in the concept that a disparity between the center of pressure within the actuator and the centroid of its cross-sectional area induces bending towards the lower part of the section. The application of pressure generates tensile forces, initiating a bending moment that results in deflection. However, it is important to acknowledge that this method employs a constant modulus of elasticity for the sake of generality, although in reality, this modulus varies, thereby introducing a certain degree of result inaccuracy. To address this limitation, Alici *et al* [522] introduced an effective modulus, calculated using empirical stress–strain data. The resultant analytical expression, which describes the steady-state bending angle of the actuator, becomes the pivotal tool for quantifying the extent of actuator bending in response to given conditions. An analytical expression for the steady-state bending angle of the actuator is

$$\theta(P) = \underbrace{\frac{L_i A^2 e}{A_w E^2 I}}_{C} P^2 + \underbrace{\frac{L_i A e}{EI}}_{D} P = CP^2 + DP \tag{1}$$

where I is the moment of inertia, the center of pressure, denoted as P, is positioned at the centroid of the air chamber's cross-section. The variable e represents the distance from the actuator cross-section's centroid to the center of pressure. L_i signifies the initial length, A stands for the cross-sectional area of the chamber, and A_w represents the cross-sectional area of the actuator.

4.3.2.1.2. FEM modeling of soft robot for large deformation. Modeling the complex behavior of 4D-printed soft robots under large deformations is a fundamental challenge. The finite element method has emerged as a powerful tool to simulate and analyze the mechanical responses of soft robots. In this context, the Neo–Hookean and Mooney–Rivlin models, which are formulated in terms of the invariants of the right Cauchy–Green tensor [523–525], play pivotal roles in capturing the complex material behavior of elastomeric structures.

The Neo–Hookean model, a foundational hyperelastic material model, forms the cornerstone of FEM simulations for soft robots [526]. Rooted in the strain energy density function, this model assumes isotropic behavior and offers a quadratic relationship between stress and strain. Its simplicity and computational efficiency make it suitable for small to moderate deformations. The Neo–Hookean model requires only one material parameter—the shear modulus—simplifying the material characterization process [527]. While effective in many scenarios, its accuracy diminishes as deformations become more pronounced. The strain energy density function for an incompressible Neo–Hookean material in a three-dimensional description is

$$W = C_1 (I_1 - 3) \tag{2}$$

where C_1 is a material constant. I_1 symbolizes the first strain invariant, which is a measure of the volumetric strain in the material. It is calculated based on the deformation gradient tensor and is often used in the formulation of hyperelastic material models to describe the strain energy density function. The calculation of strain invariants is shown in equation (3).

$$\begin{aligned} I_1 &= \lambda_1^2 + \lambda_2^2 + \lambda_3^2 \\ I_2 &= \lambda_1^2\lambda_2^2 + \lambda_2^2\lambda_3^2 + \lambda_1^2\lambda_3^2 \\ I_3 &= \det(\ldots) = \lambda_1^2\lambda_2^2\lambda_3^2 = \left(\frac{V_F}{V_o}\right)^2 = J^2. \end{aligned} \tag{3}$$

For incompressible material, $\lambda_1\lambda_2\lambda_3 = 1$. Therefore,

$$\begin{aligned} I_1 &= \lambda_1^2 + \lambda_2^2 + \lambda_3^2 \\ I_2 &= \frac{1}{\lambda_1^2} + \frac{1}{\lambda_2^2} + \frac{1}{\lambda_3^2} \\ I_3 &= (\lambda_1\lambda_2\lambda_3)^2 = 1. \end{aligned} \tag{4}$$

For a compressible Neo–Hookean material the strain energy density function is given by

$$W = C_1 (I_1 - 3 - 2\ln J) + D_1 (J - 1)^2. \tag{5}$$

The Neo–Hookean material model does not anticipate a rise in modulus under significant strains and usually holds accuracy solely for strains below 20% [528]. Moreover, this model is insufficient for biaxial stress conditions and has been replaced by the Mooney–Rivlin model.

For soft robots undergoing large deformations, the Mooney–Rivlin model emerges as a valuable alternative within the FEM framework [529, 530]. As an extension of the Neo–Hookean model, the Mooney–Rivlin model introduces additional material parameters to capture higher-order deformation effects. This enhanced complexity allows the Mooney–Rivlin model to better represent the nonlinear behavior of elastomeric materials under significant strains. Consequently, it provides a more accurate depiction of the intricate mechanics governing soft robots subjected to substantial deformation. The Mooney–Rivlin class of models expresses the mechanical strain energy as a sum of the invariants as follows [529, 530].

$$W = \sum_i \sum_j C_{ij} (I_1 - 3)^i (I_2 - 3)^j + D (J - 1)^2. \tag{6}$$

Note that the series is not a function of I_3 since it remains a constant value, 1. The coefficients, C_{ij} and D, are derived by fitting actual stress–strain curves to the equation's derivative. The quantity of terms in the series expansion is determined by the precision demands of the specific application. For instance, the initial terms of the sequence are as follows:

$$W = C_{10}(I_1 - 3) + C_{01}(I_2 - 3) + C_{11}(I_1 - 3)(I_2 - 3) + C_{20}(I_1 - 3)^2 + \cdots + D(J - 1)^2. \tag{7}$$

Each principal Cauchy stress is related to the derivative of the above equation with respect to the corresponding λ. For example, the 1st principal Cauchy stress corresponds to derivatives of W with respect to the first stretch ratio, λ_1.

$$\sigma_1 = \lambda_1 \frac{\partial W}{\partial \lambda_1} = \lambda_1 \left(\frac{\partial W}{\partial I_1}\frac{\partial I_1}{\partial \lambda_1} + \frac{\partial W}{\partial I_2}\frac{\partial I_2}{\partial \lambda_1} + \frac{\partial W}{\partial J}\frac{\partial J}{\partial \lambda_1} \right). \tag{8}$$

The derivatives of the strain energy with respect to the invariants, and J, are

$$\frac{\partial W}{\partial I_1} = C_{10} + C_{11}(I_2 - 3) + 2C_{20}(I_1 - 3) + \cdots$$

$$\frac{\partial W}{\partial I_2} = C_{01} + C_{11}(I_1 - 3) + \cdots \tag{9}$$

$$\frac{\partial W}{\partial J} = 2D(J - 1). \tag{10}$$

And the derivatives of the invariants, and J, with respect to λ_1 are

$$\frac{\partial I_1}{\partial \lambda_1} = 2\lambda_1 \qquad \frac{\partial I_2}{\partial \lambda_1} = -\frac{2}{\lambda_1^3} \qquad \frac{\partial J}{\partial \lambda_1} = \lambda_2 \lambda_3. \tag{11}$$

All of these terms can be combined to give polynomials relating stretch ratios to principal stresses, with coefficients such as C_{10}, C_{01}, C_{11}, and C_{20} that are determined from curve-fitting these equations to experimental data.

4.3.2.2. ML enabled inverse design of 4D printed soft robots. The convergence of additive manufacturing's remarkable progress and the breakthroughs in active materials has ushered in a new frontier in material science—the realm of active composites [531–534]. These ingenious combinations involve smart materials that can undergo tailored transformations in response to specific stimuli, paired with inert counterparts. From SMPs [535–540] and shape memory alloys [541–545] to liquid crystal elastomers [546–554] and hydrogels [555–568], this class of materials has ignited a revolution in design possibilities and functionalities. The interaction of these active and passive components gives rise to an exciting array of potential applications, particularly when harnessed within the context of 4D printing.

4D printing's fusion of additive manufacturing with responsive materials has fueled an explosion of research interest [572–579]. It's a domain where digital design interfaces with physical reality, offering the ability to craft structures that can dynamically change shape and properties over time in response to environmental cues. A cornerstone of this innovation lies in the concept of topology optimization, which guides the spatial distribution of materials within these 4D-printed structures.

At its core, topology optimization is about optimizing material distribution to achieve desired structural behavior [580–583]. Different from topology optimization for single-material soft robots that only deals with the distribution of one material, topology optimization for the 4D-printed soft robots focuses on the material distributions of at least two materials. By strategically embedding smart materials within passive materials, complex shape changes can be dictated by stimuli. This dynamic interplay between materials unlocks design potential that was previously unattainable. The topology optimization for 4D-printed soft robots can create highly customized soft robots with hierarchical architectures to meet the needs of specific applications. 4D-printed soft robots advance the frontiers of SRs, allowing for the development of soft robots with unprecedented functionalities and adaptability.

The incorporation of ML into the topology optimization of 4D-printed soft robots holds immense significance, offering a transformative approach to addressing the complex design challenges posed by active composites. In the design of active composites, the challenge lies in orchestrating precise shape changes that respond predictably to external stimuli. This intricate design process involves a demanding inverse problem: determining the optimal spatial distribution of materials to achieve a desired displacement field or shape change. Conventional approaches, including topology optimization methods, have been limited by the multiphysics nature of active materials, which introduce nonlinearities that hinder gradient-based optimization strategies. Moreover, the discrete nature of voxel-based 3D printing methods complicates traditional optimization methods. ML is a powerful solution to these challenges, providing a data-driven approach that complements the complexity of active composites and 4D printing. ML algorithms can learn from historical data to create accurate predictive models for the responses of active materials. ML has the potential to navigate the multifaceted design space of active composites due to its ability to quickly process large amounts of data and predict the deformation performance of 4D-printed soft robots. This approach helps predict material behavior under different stimuli and helps determine the optimal material distribution for desired shape changes. Importantly, ML's ability to handle diverse and nonlinear multi-physics interactions is well aligned with the behavior of active materials. By leveraging the strengths of ML, the design of 4D-printed soft robots can move beyond traditional limitations and explore complex designs that achieve new actuation responses.

Several research works have been devoted to integrating ML and finite element-based topology optimization techniques to enhance the performance of 4D printed active composites. Hamel *et al* [584] enhanced active composite development using multi-material 4D printing. To achieve desired shape changes, they employed a ML approach, combining FEA with an EA. By optimizing the distribution of passive and active materials in voxel units, they successfully designed active composite structures that realized specific shape-shifting responses. Similarly, Athinarayanarao *et al* [569] focused on advancing 4D printing through smart material arrangement and energy stimulus as shown in figure 6(a). Their innovative approach combined FEA and an EA to optimize material properties distribution within voxelized structures. This approach effectively addressed the inverse design challenge of achieving desired shape changes in 4D-printed active composites by incorporating void voxels. Sun *et al* [570] employed a ML and evolutionary algorithm (EA) framework, anchored in a RNN model trained on finite element simulations for forward shape-change predictions as shown in figure 6(b). They harnessed ML-empowered EA to tackle the inverse problem of optimal design. Demonstrating efficacy across diverse target shapes, this ML-EA approach showcased remarkable efficiency. Moreover, coupling ML-EA with computer vision introduced a streamlined paradigm, exemplified by transforming active beams from hand-drawn lines to 4D-printed profiles. Compared with Hamel *et al* [584]'s work, Sun *et al* [570]'s method can accomplish the same task in thousands of times less time. Jin *et al* [571, 585] developed the residual NN-based-forward prediction method and evolutionary algorithm-based inverse optimization method for inverse design of 4D printed hierarchical architecture with non-rectangular shape. The proposed method can be applied to inverse design the soft gripper as shown in figure 6(e).

4.3.3. Development of metamaterials. The development of metamaterials for soft robots has gained significant attention in recent years, offering new insights into the design of SR systems [586, 587]. Metamaterials are materials designed at microscopic or mesoscopic scales to exhibit unique physical properties not commonly found in natural materials. These properties are derived not only from the base material but also from the featured structures at the microscopic scale, including shape, orientation, and arrangement. In the context of soft robots, metamaterials offer unprecedented opportunities for enhancing structural performance and achieving unconventional behaviors as shown in figure 7.

The use of metamaterials in soft robots offers a multitude of significant advantages, rendering them highly attractive for various applications at the forefront of modern robotics and engineering. (1) One key advantage lies in their ability to exhibit unconventional mechanical properties that are rarely found in natural materials. Metamaterials can be engineered to possess characteristics such as negative Poisson's ratio (auxetic behavior), extreme flexibility, high stretchability, tunable stiffness, and directional deformation. These extraordinary properties empower soft robots to achieve complex and adaptive motions, elevating their capabilities beyond what is attainable with conventional materials [31, 590–597]. (2) Another compelling advantage of employing metamaterials in soft robots is the opportunity for tailored functionality. These materials can be meticulously designed and constructed at the microscopic or mesoscopic scale, allowing for the precise encoding of specific functionalities within the robot's structure. By controlling the microstructure and composition with precision, soft robots can be equipped with highly customized behaviors, such as shape memory, self-healing, self-adaptation, or even programmable responses to external stimuli. This level of customization opens up new avenues for innovative applications across industries and research domains [117, 598–605]. (3) Metamaterials also offer the advantage of being lightweight and compact, a crucial factor in SRs. The materials' ability to achieve remarkable mechanical performance while maintaining a compact form factor is particularly advantageous for soft robots that need to interact delicately with humans or operate in confined spaces. Their reduced weight and size make them less cumbersome and more portable, facilitating smoother and safer human–robot interactions, as well as enhancing the robot's mobility in constrained environments [589, 593, 604, 606–618]. (4) Furthermore, metamaterials significantly enhance the load-bearing capabilities of soft robots, a crucial advantage with vast implications. By integrating metamaterials into their design, soft robots gain the ability to carry or manipulate objects of substantial weight relative to their own size. This newfound strength and robustness open up a myriad of possibilities for applications in industrial automation, logistics, healthcare, and beyond [619]. Soft robots with enhanced load-bearing capacities can perform tasks that were previously deemed challenging or impossible, revolutionizing industries where precision and strength are essential [589, 593, 603, 620–623].

4.3.3.1. Metamaterial categories. Metamaterials have emerged as a promising avenue for enhancing soft robots with unique mechanical properties and functionalities, enabling them to perform tasks otherwise unattainable with conventional materials. The wide variety of metamaterial options offers designers an array of choices to tailor soft robots for specific applications. The common used metamaterials for soft robots can be divided into five categories: anisotropic textile fabrics, origami and kirigami structures, auxetic structures, elastic beam elements, and active magneto-mechanical metamaterials [624].

Anisotropic textile fabrics represent one of the intriguing metamaterial choices for soft robots. By carefully designing patterns within the fabric, anisotropic properties are achieved, allowing soft robots to execute programmed motions in multiple directions. This capability finds applications in wearable robotic devices for hand, ankle, and foot rehabilitation, where the fabric's anisotropy contributes to conformable monolithic systems [625–630]. Connolly *et al* [631] fabricated and mechanically characterized a new type of bending textile actuator using a lamination and layering process, eliminating the need for complex cut-and-sew procedures. Films were used to create air-impermeable textile composites, allowing for complex deformation patterns. Bhat *et al* [632] explored the use of anisotropic textile fabrics in SRs, specifically for developing bending and torsional actuators. They combined silicone polymer-based bladders with reconfigurable fabric skins to create actuators with unique mechanical properties. The fabric skin acted as a constraint, allowing for complex

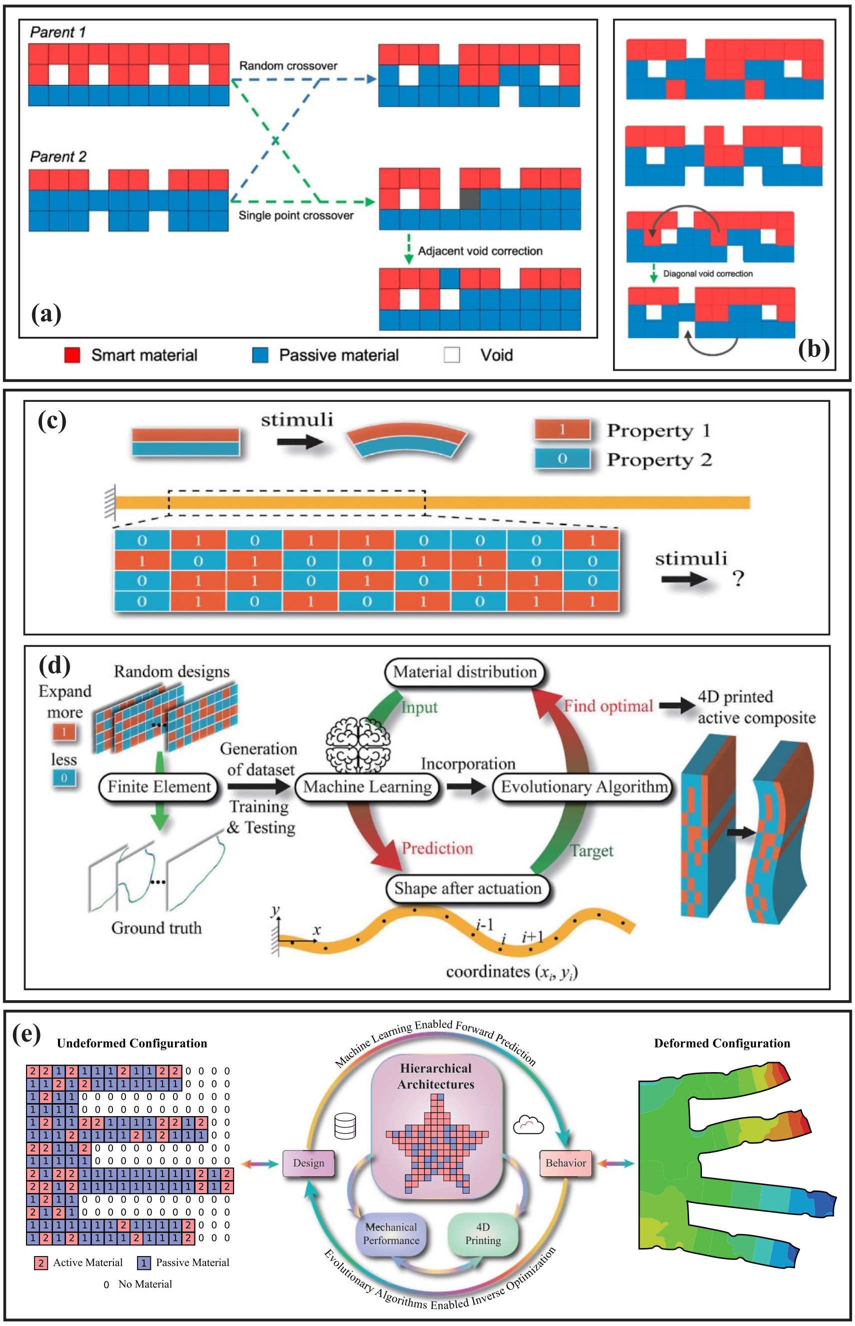

Figure 6. Topology optimization of 4D printed active composite structure. (a), (b) Computational design for 4D printing of topology optimized multi-material active composites. Reproduced from [569]. CC BY 4.0. (a) Schematic illustration of the random crossover. Every voxel has a 50–50 chance of inheriting the properties from either parent, and single point crossover where two children are produced from two parents with genome splicing at one point (represented by the grey voxel here). (b) The mutations are applied to the genome created from random crossover in (a). (c), (d) Schematic illustration of the proposed solution for the design of a 4D-printed active composite beam. [570] John Wiley & Sons. © 2021 Wiley-VCH GmbH. (c). Actuation of the active composite due to property mismatches, which can involve bilayer structures or more complex property distributions. Properties are represented as '1' and '0'. (d) The complete design process includes generating a dataset through finite element simulations, predicting shape changes using machine learning, and designing material distributions using machine learning-integrated EAs. The volumetric expansion mismatch simulates a general eigenstrain mismatch caused by various mechanisms. The initial undeformed cantilever composite beam has a voxel-based material/property distribution digitally encoded as a 2D number array, serving as input for the machine learning model. The resulting actuated beam shape is parameterized as coordinate data for sampling points and is the output of the machine learning model. (e) Machine learning-enabled inverse design of 4D-printed soft gripper. Reprinted from [571], Copyright (2024), with permission from Elsevier.

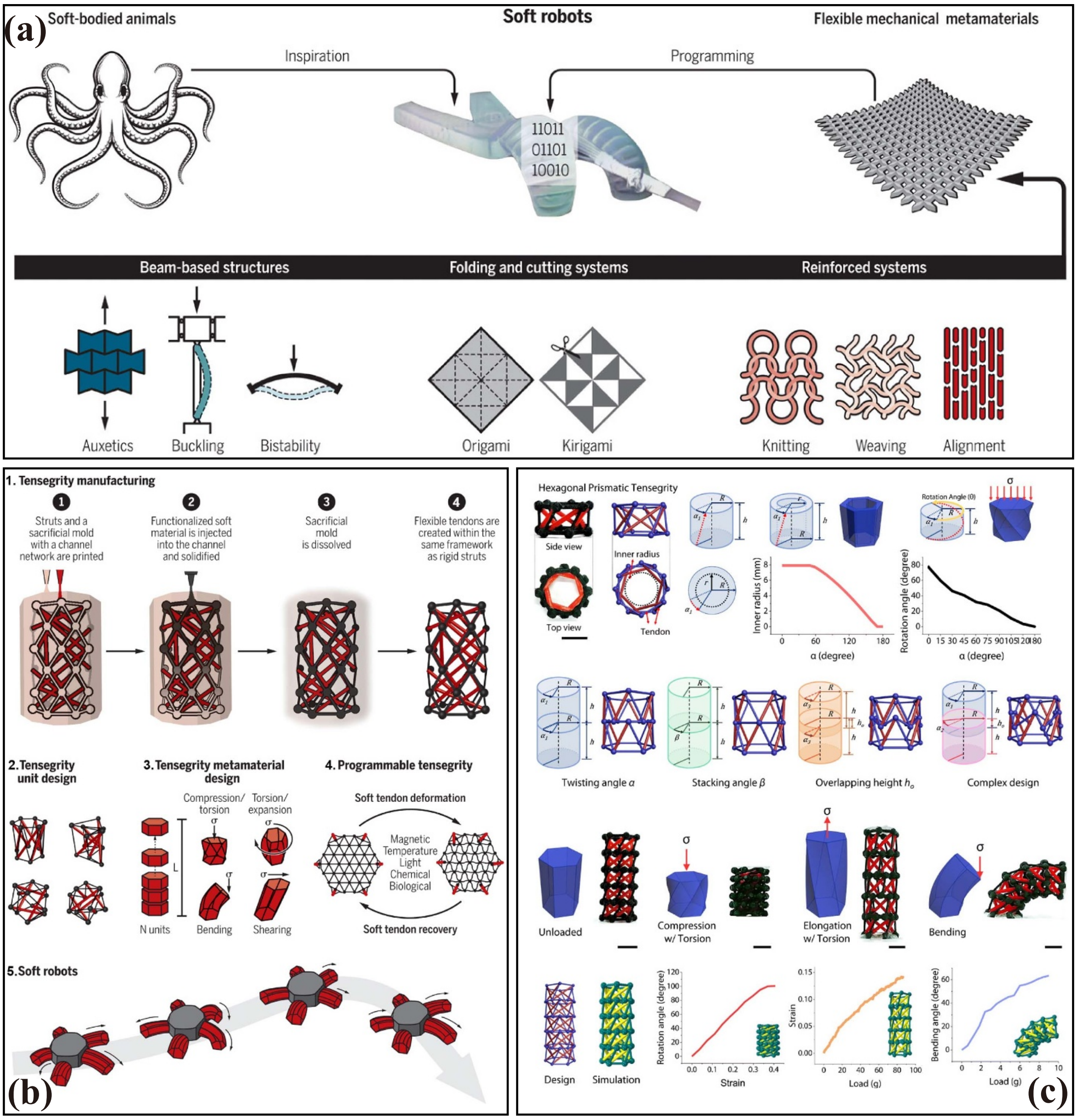

Figure 7. Metamaterials for soft robots. (a) Programming soft robots with flexible mechanical metamaterials. From [31]. Reprinted with permission from AAAS. (b) Tensegrity metamaterials for soft robotics. From [588]. Reprinted with permission from AAAS. (c) 3D-printed programmable tensegrity for soft robots. From [589]. Reprinted with permission from AAAS.

motions and achieving large twists in torsional actuators. The absence of inextensible fabrics reduced actuator stiffness and lowered actuation pressures. Multilayer designs demonstrated high-force capabilities suitable for wearable assistive devices. Ge *et al* [633] designed, modeled and evaluated soft fabric-based pneumatic actuators (SFPAs) for soft wearable assistive gloves. They explored various woven and rib-weft-knitted fabric structures to create SFPAs that could assist thumb abduction and finger flexion and extension motions. Mathematical models were developed to analyze the influence of geometric parameters on the actuators' performance, which was verified through experiments. Hu *et al* [634] devised helical-artificial fibrous muscle structured tubular soft actuators (HAFMS-TSAs) using anisotropic textile fabrics. These actuators could be endowed with 11 different morphing modes through programmable regulation of their 3D helical fibrous architectures. The HAFMS-TSAs demonstrated diverse photoresponsive behaviors, enabling adaptive omnidirectional reorientation, resembling morphing intelligence of living plants.

Origami and kirigami structures provide soft robots with programmable morphing and folding abilities. These metamaterials, inspired by the art of paper folding, impart flexibility and versatility to soft robots, enabling them to manipulate objects delicately and navigate complex environments with ease [635–647]. Zhang *et al* [648] created and precisely controlled a pneumatic-driven, origami-based deformation unit for soft robots. This unit offered all-purpose deformation modes, including three basic motion types and their combinations, resulting in seven distinct motion modes in total. The origami modules could be assembled as needed, enabling plug-and-play characteristics and providing unprecedented opportunities for soft robots to perform complex tasks. Ze *et al* [649] developed a magnetically actuated small-scale origami crawler for SRs. The origami assembly allowed in-plane contraction and crawling motions, facilitated by magnetic actuation. The crawler demonstrated untethered movement, steering capabilities, and the ability to navigate confined spaces. Kaufmann *et al* [650] employed Kresling origami modules for a biology-inspired approach to SR arm design. The origami modules exhibited predictable bistability, allowing the robotic arm to switch between flexible joints and stiff links without continuous power. Guo *et al* [651] introduced a novel SPA inspired by Kirigami techniques for versatile SR applications. Kirigami-inspired cuts in the actuator design enabled multiple deformation modes, including bending, stretching, contraction, and combinations thereof. He *et al* [652] presented an electronics-free approach using Kirigami techniques to achieve autonomous control in soft robots. Responsive materials, like liquid crystal elastomers, regulated modular control units, enabling the robot to autonomously sense and respond to external stimuli (light, heat, solvents), resulting in trajectory changes.

For simplifying the locomotion of soft robots, auxetic structures are employed. Metamaterials with negative Poisson's ratio, known as auxetic behavior, demonstrate the capacity to undergo unique deformations when subjected to external forces. Soft robots equipped with such metamaterials can achieve locomotion with just one actuator, streamlining their design and enhancing efficiency [653–659]. Alapan *et al* [660] developed a high-throughput magnetic programming method for soft robots, focusing on auxetic structures. By heating magnetic soft materials above the Curie temperature of ferromagnetic particles and applying magnetic fields during cooling, they achieved reprogrammable, discrete, and three-dimensional magnetization with high spatial resolution. This approach enabled various applications, including reconfigurable mechanical behavior in auxetic structures, tunable locomotion of soft robots, and adaptive grasping with a soft gripper. Kaarthik *et al* [661] employed 3D printing to create motorized SR actuators using cylindrical handed shearing auxetics (HSAs) made from polyurethane resins. Mechanical tests confirmed the auxetic behavior of individual HSAs, and assembled HSA pairs formed multi-degree-of-freedom legs for untethered quadrupeds.

Elastic beam elements present yet another metamaterial option for soft robots. When subjected to axial compressions, these elements buckle and produce reversible pattern transformations. This simple yet powerful mechanism enables soft robots to perform various motions with a single negative pressure, improving structural stiffness and enhancing grasping force [662–664]. Yang *et al* [665] investigated the use of elastomeric beams in SRs, specifically focusing on a buckling actuator design. The actuator utilized negative pressure (vacuum) for actuation, which induced buckling and torsional motion in the elastomeric structure. By assembling multiple units, they achieved parallel and sequential actuation. Chen *et al* [666] developed an untethered soft swimming robot using elastic beams that exploit temperature-triggered bistable elements for propulsion. SMP muscles power the bistable elements to actuate the robot's fins, enabling preprogrammed directional movement without the need for a battery or onboard electronics. Zhang *et al* [667] proposed a systemic framework for designing and fabricating multimaterial soft robots with integrated soft actuators and a rigid body. The framework utilized topology optimization to simultaneously determine structure and material distribution. They focused on a pneumatic soft finger as a compliant mechanism, optimizing it for maximum bending deflection and adapting it for applications in grippers, rehabilitation, and artificial hands.

Active magneto-mechanical metamaterials leverage magneto-mechanical actuation to achieve untethered, fast, and reversible shape configurations. Soft robots incorporating these metamaterials benefit from their dynamic shape-changing capabilities, allowing them to adapt rapidly to changing environmental conditions and perform tasks efficiently [668–671]. Zou *et al* [672] successfully developed a magneto-thermomechanical method for creating active magneto-mechanical metamaterials. This approach enabled untethered, reversible, low-powered reprogrammable deformations and shape locking using a single material system. By combining magnetic control and thermomechanical behavior of shape-memory polymers, they achieved versatile and efficient transformations without the need for new materials or high-energy methods. Zhao and Zhang [673] demonstrated an optimization-based approach to design active magneto-mechanical metamaterials and structures that can be reprogrammed by toggling external magnetic fields. This innovation allowed for versatile behaviors, including multi-functional actuation, adaptable snap-buckling, switchable deformation, and tunable bistability. Han *et al* [674] designed and fabricated magneto-mechanical metamaterial unit cells using 3D printing technology. These metamaterials demonstrated unique deformations under external magnetic fields, achieving substantial reversible deformations of up to 85% and rapid shape recovery upon magnetic field removal. They also showcased the application potential of these metamaterials in a biomimetic blood vessel, demonstrating remote controllable particle transport.

4.3.3.2. Research directions of metamaterial development. The integration of FEA and ML in the development of metamaterials for soft robots is a crucial and powerful approach, bringing about numerous benefits that contribute to the advancement of SRs and metamaterial engineering.

One of the primary challenges in working with metamaterials is their complex mechanical behavior, which often defies simple analytical prediction. Here, FEA steps in as a valuable tool, providing a robust numerical simulation method to study the mechanical response of these materials under various loading conditions. Through FEA, researchers gain valuable insights into how metamaterials deform, bend, twist, and interact with their environment, thus facilitating the optimization of their design and ensuring they fulfill their intended functionalities [675, 676]. Vanneste *et al* [677] proposed the use of new 3D-printed mesostructured materials to build soft robots, targeting specific mechanical properties like heterogeneous stiffness and anisotropic behavior. To support the design and control of soft robots with these mesostructured materials, they developed a modeling method based on numerical homogenization and the FEM to capture anisotropic deformations. The method was tested on a 3-axis parallel soft robot initially made of silicone, showing the change in kinematics when built with mesostructured materials and comparing the behavior with modeling results. Tao *et al* [678] investigated a shape-reconfigurable, mechanically adjustable, and reusable intelligent multi-stable metamaterial for soft robots. The metamaterial demonstrated reconfigurable and self-expandable properties, and the FEM helped analyze its behavior during compression tests. Wang *et al* [679] developed a design framework combining experiments, hierarchical theoretical models, and finite element simulations to program the mechanical behaviors of fractal metamaterials for soft robots. They used a digital design tool for 3D printing and achieved large stretchability (approximately 360%), bionic stress–strain curve matching, and imperfection insensitivity by tuning the geometric parameters.

Metamaterials offer an expansive and intricate design space, encompassing a wide array of possibilities for microstructures and compositions. However, physically testing each design iteration is impractical in terms of time and cost. FEA efficiently fills this void by allowing virtual simulations and evaluations of an extensive range of metamaterial designs. This capability expedites the exploration of different configurations, enabling researchers to identify and select those with desired properties, significantly accelerating the metamaterial development process [680, 681]. Mao *et al* [682] developed an experience-free and systematic approach using generative adversarial networks for designing complex architectured materials for soft robots. They trained the networks with simulation data from millions of randomly generated architectures and demonstrated modeling and experimental results of over 400 two-dimensional architectures that approached the Hashin–Shtrikman upper bounds on isotropic elastic stiffness. Khajehtourian and Kochmann [683] explored the design of soft robots using FEA to investigate substrate-free reconfigurable structures composed of multistable unit cells. The study focused on utilizing structural instabilities and bistable actuators to achieve locomotion and morphing surfaces. They provided general guidelines for unit cell selection and predicted the behavior of the resulting structure for various geometric and material properties using a continuum description. Zhong *et al* [684] developed phase-transforming mechanical metamaterials (PMMs) for applications in SRs and flexible electronics. They utilized a theoretical model and finite element simulations to guide the design process and created various PMMs suitable for different applications, such as reconfigurable antennas, soft lenses, biomimetic hands, and self-contained soft grippers.

ML plays a pivotal role in predicting the mechanical properties of metamaterials and inverse design tasks based on their design characteristics. By leveraging existing data and training ML models, accurate estimations of the mechanical properties of new metamaterial designs become achievable. This integration of ML expedites the material development process further, reducing the reliance on laborious simulations or physical testing. Consequently, researchers can make informed decisions about the viability of specific metamaterial designs for SR applications [685, 686]. On the other hand, inverse design involves defining desired material behaviors, and ML models efficiently identify the corresponding metamaterial designs that can bring those behaviors to life [687, 688]. This synergy between FEA and ML empowers researchers with powerful tools to drive innovation and discovery in metamaterial engineering for soft robots. Tian *et al* [689] utilized efficient and prior knowledge-free ML algorithms to predict the dynamic characteristics of Poisson's ratio in 2D metamaterials. They employed molecular dynamics simulations to generate a large dataset for training/validation and used CNN and Cycle-GAN ML algorithms for prediction and inverse design. Ma *et al* [690] developed an inverse design framework using a deep residual network to predict the mechanical properties of magneto-mechanical metamaterials. This approach allowed them to create metamaterials with predetermined global strains under magnetic actuations. The framework was validated through direct-ink-writing printing of magnetic soft materials to fabricate the designed complex metamaterials. Deng *et al* [691] used mechanical metamaterials based on hinged quadrilaterals to achieve target nonlinear mechanical responses. They introduced a NN to establish a computationally inexpensive relationship between geometry parameters and stress–strain response. By combining the NN with an evolution strategy, they efficiently identified geometries resulting in various target nonlinear mechanical responses, enabling the design of optimized energy-absorbing systems, soft robots, and morphing structures.

Moreover, the combination of FEA and ML opens up exciting opportunities for optimization. Researchers can employ optimization algorithms to search for the optimal combination of microstructures and composition, achieving specific mechanical properties tailored to the needs of soft robots [692]. Dong and Wang [693] developed a digital design and optimization method for lattice metamaterials in flexible electronics and SRs. They used ML to accurately predict mechanical behaviors based on finite-element simulations. The method considered both material distributions and structural design, allowing the researchers to quickly find optimal designs that match multiple targets. Fernández *et al* [694] presented a ML-based constitutive model for optimizing parametric metamaterials, specifically elastic beam lattices with cubic anisotropy. They used microstructure simulations to determine relevant material and topology parameters, generating training data with homogenized stress-deformation responses. The artificial NN constitutive model was calibrated with the simulation data and proved to represent and predict the effective behavior of parametric lattices accurately. Garland *et al* [695] demonstrated how ML was used to optimize metamaterials for soft robots. They employed the AI approach to discover new unit cells that were Pareto optimal for multiple objectives, such as maximizing elastic stiffness and minimizing wave speed during an impact event.

In summary, the combination of FEA and ML in the development of metamaterials for SRs offers a powerful and innovative approach to address key challenges in this field. FEA provides a way to study the mechanical behavior of metamaterials, helping to optimize design and achieve functionality. The combination of FEA and ML can accelerate metamaterial development by virtually simulating various designs, effectively identifying the best configuration and making informed decisions. The combination of FEA and ML can also enable predictive modeling and reverse design, helping to accurately estimate mechanical properties and achieve desired behavior.

4.4. Sensing, control, and actuation optimization

In this subsection, we will explore the key aspects of optimizing sensing, control, and actuation in SRs. These elements are critical in enhancing the overall performance and capabilities of SR systems. We will also address the role of ML in advancing soft robot sensing, kinematics, and control, with a focus on both internal and external sensing mechanisms and control optimization. Figure 8 shows some related research.

4.4.1. ML driven soft robot sensing. In the domain of soft robot sensing, ML serves a pivotal role in processing and interpreting the data garnered from sensors to extract critical information about the soft robot's characteristics, including its pose [699, 700]. This application of ML entails the analysis of sensor data streams, often containing complex and dynamic information due to the inherent flexibility of soft robots. By employing advanced ML algorithms, these data streams are scrutinized, and patterns are extracted to deduce the soft robot's configuration and pose in real-time or near real-time. This analytical process enables the soft robot to perceive its own state and spatial orientation within its environment, even amidst intricate deformations. ML algorithms, through continuous learning and adaptation, improve their accuracy in estimating the soft robot's information from sensor data, enhancing the robot's awareness and enabling it to make informed decisions based on its surroundings. This synergy between ML and sensor data has substantially elevated the perceptual capabilities of soft robots, enabling them to navigate and interact more intelligently and effectively [701, 702].

This capability of ML can be classified into two different categories based on the source of data: embedded sensor data (internal sensing) and external sensor data (external sensing). In this section, we will delve into the role of ML in these two kinds of sensing for soft robots.

4.4.1.1. Internal sensing. In internal sensing, soft robots are equipped with built-in sensors that can capture various physical quantities, such as strain, pressure, or deformation. These sensors are strategically integrated into the structure of the soft robot, allowing them to sense internal changes caused by movements or interactions. The captured data is then fed into ML to learn the relationship between sensory data and soft robot state, and a ML model can be built that can interpret these sensor readings and infer the current state of the robot. This approach provides soft robots with a level of self-awareness, enabling them to navigate and respond to its environment without relying on external sensory inputs.

4.4.1.1.1. Mechanism. ML significantly augments the internal sensing capabilities of soft robots by harnessing data generated by embedded sensors strategically placed throughout the robot's structure. These sensors encompass a range of technologies, including strain gauges, pressure sensors, capacitive sensors, and more, each chosen for its suitability in capturing specific deformations and interactions [698, 703, 704]. The real innovation lies in the synergy between these sensors and ML algorithms.

To enable a soft robot to sense itself and its environment, ML models are employed to decipher the complex sensor data [705]. These models are meticulously designed and trained to decipher patterns, correlations, and relationships in the data. During the training phase, the model learns to associate sensor readings with corresponding physical states and parameters of the robot. This process involves a comprehensive dataset of sensor inputs and corresponding ground truth values, usually generated through controlled experiments or simulations.

The trained ML model becomes a versatile interpreter that can convert raw sensor data into meaningful information. For example, strain gauges embedded within the soft robot structure can convey information about deformation patterns, and pressure sensors can provide data on the contact forces between the soft robot and the external environment. The predictions of the ML model can cove various critical information such as deformation magnitude, shape change, and applied force. The fusion of sensor data readings and ML-based analysis enables the soft robot to dynamically understand its own state and better interact with the environment.

4.4.1.1.2. Data acquisition and preprocessing. The foundation for effective internal sensing in soft robots depends on the data acquisition strategy. Sensor data acquisition involves collecting information about the soft robot's morphological changes, deformations, and interactions in real-time. These dynamic changes are continuously monitored and fed into a machine-learning framework for accurate predictive modeling. However, data acquired from sensors is often affected by external noise and artifacts, resulting in fluctuations, inconsistencies, and anomalies in the collected raw sensor data that can distort the final predictions if not addressed. This requires a preprocessing step to ensure the reliability and accuracy of subsequent ML analysis. Therefore, noise reduction is a crucial initial step in preprocessing, which involves filtering out irrelevant signals and minimizing random fluctuations in the data. Noise reduction can be achieved through techniques such as low-pass filtering, which attenuates high-frequency noise while retaining essential information. However, filtering alone may not be sufficient for optimal analysis. Therefore, the subsequent step involves normalization, which is scaling the sensor readings to a common range or unit. This process

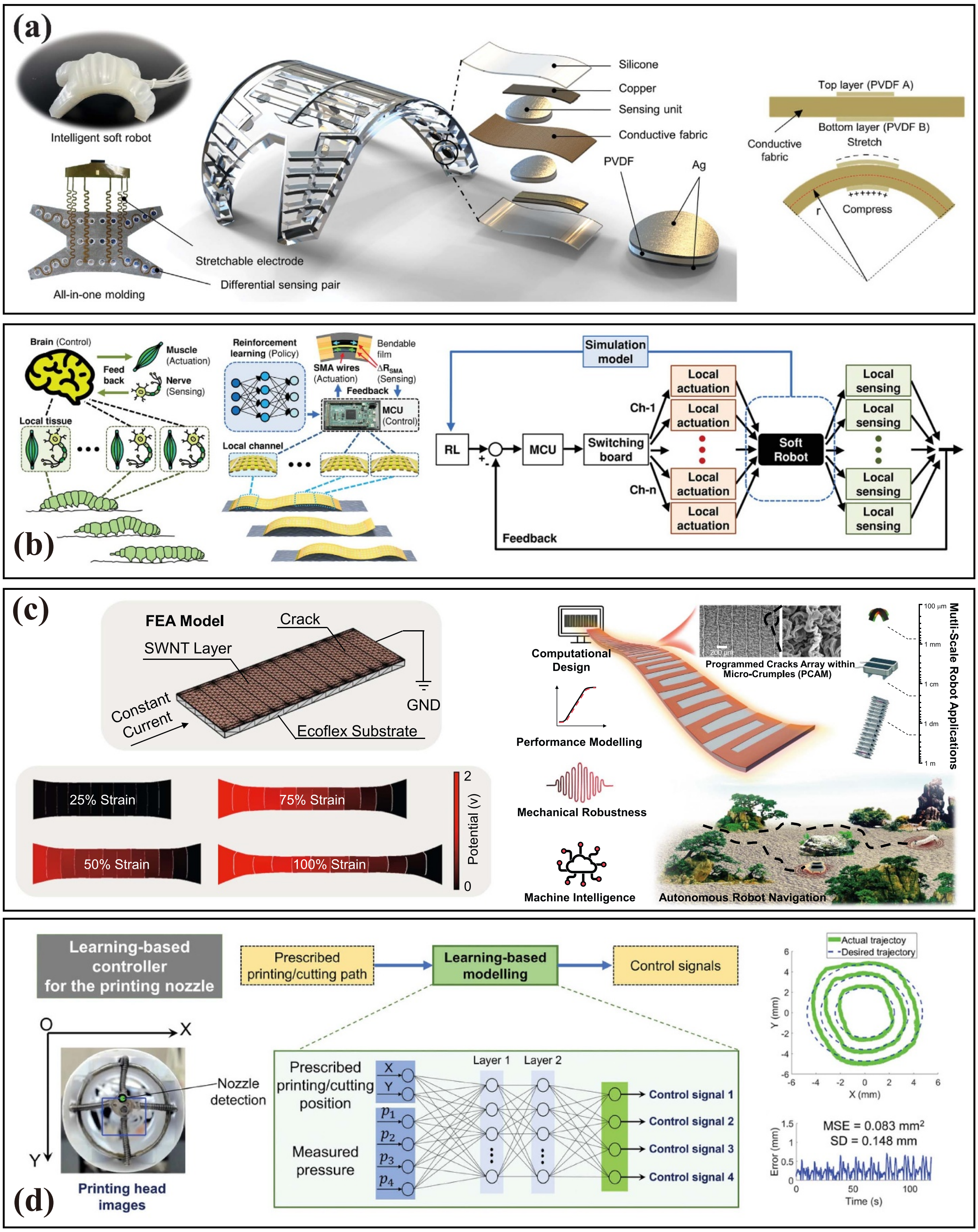

Figure 8. Machine learning assisted sensing, control, and actuation of soft robots. (a) Machine-learning assisted electronic skins capable of proprioception and exteroception in soft robotics. [696] John Wiley & Sons. © 2023 Wiley-VCH GmbH. (b) Closed-loop soft robot control frameworks with coordinated policies based on reinforcement learning and proprioceptive self-sensing. [697] John Wiley & Sons. © 2023 Wiley-VCH GmbH. (c) Computational design of ultra-robust strain sensors for soft robot perception and autonomy. Reproduced from [698]. CC BY 4.0. (d) Machine learning-based controller for an advanced soft robotic system for in-situ 3D bioprinting and endoscopic surgery. Reproduced from [241]. CC BY 4.0.

ensures that the ML model is not biased by sensors with inherently different measurement scales. Normalization is followed by feature extraction, which extracts relevant features from the data. These features are the basis for the predictions of the ML model. For example, in the case of a pressure sensor, the spatial distribution of pressure may be a key feature for understanding the interaction of the robot with its surroundings. Therefore, data acquisition and preprocessing ensure that ML models operate on clean, meaningful data, thereby improving the accuracy and reliability of subsequent internal sensing mechanisms.

There has been a significant amount of research focused on the application of ML techniques to enhance the internal-sensing capabilities of soft robots. These research can be categorized as follows:

1. Internal-sensor embedding: Buso *et al* [706] introduced a SR module designed to sense and control contact forces. Optical sensors and a pneumatic bellow encapsulating a foam spring were integrated into the module. The shape changes in the module were captured through variations in light reflectivity. These shape measurements, along with air pressure data, were used in a ML model to predict contact forces. This module was suited for pressure distribution control in support devices. Jin *et al* [257] presented a smart SR gripper utilizing triboelectric nanogenerator sensors. The gripper captured continuous motion and tactile information, allowing accurate identification of diverse objects through a ML-based approach. The gripper's real-time operation was mirrored in a virtual environment for applications like assembly lines and unmanned warehouses. Loo *et al* [707] addressed the challenge of sensor integration into soft robots. An indirect sensing approach was proposed using an estimation scheme based on robot dynamics and available measurements. A RNN-based adaptive unscented Kalman filter (RNN-AUKF) architecture was presented for indirect sensing in soft robots. Pang *et al* [252] presented a textile-based tactile sensor that mimics human skin capabilities for perceiving various stimuli. The sensor employed triboelectric and piezoresistive sensing layers to achieve multifunctional sensing. The sensor can recognize voice, monitor physiological signals, perceive surface textures, and control SR movements. Schaff *et al* [708] focused on real-time proprioception for soft robots. The proposed method integrated multiple low-cost sensors into pneumatic actuators and used ML to predict 3D deformation. The framework enabled accurate reconstruction of soft robot shape and can be applied to various SR designs. Truby *et al* [110] presented a framework for predicting the 3D configuration of soft robots using a proprioceptive sensor skin and deep learning. The methodology involved rapid sensorization using kirigami, kinematic descriptions, and NN designs.
2. Integrated guiding and multimodal cognition: Ang and Yeow [702] explored the integration of self-sensing capabilities into soft actuators using 3D printing techniques. ML was used to characterize nonlinear behavior in soft sensors. The proposed approach eliminated the need for implanting sensing elements, ensuring consistent sensing performance. The methodology estimated bending curvature and external forces applied to soft actuators in real time, showing potential for multimodal sensing applications. Ding *et al* [105] focused on addressing uncertainty in soft robot sensing due to mechanical compliance. A framework based on deep learning was presented to estimate predictive uncertainty in soft robot multimodal sensing. The framework quantified uncertainty to enhance the confidence associated with predictions during inference, contributing to safe learning and model interpretability in SRs. Shi *et al* [709] introduced an intelligent SR gripper integrating ultrasonic and triboelectric sensors. The gripper combined noncontact ultrasonic distance sensing with tactile sensing for object manipulation. A deep-learning NN analyzed multimodal information to achieve high accuracy in classifying objects. Shi *et al* [710] also presented a SR perception system integrating ultrasonic and triboelectric sensors. The ultrasonic sensor detected object shape and distance, aiding robotic positioning. Multimodal sensory information, including object properties, was fused using a deep-learning framework, enabling effective object identification and manipulation.
3. Nonlinear behavior prediction: Chin *et al* [100] outlined the progress of ML methods in SRs for sensing and control. Data-driven methods addressed complex dynamics and nonlinearity, offering solutions for contemporary SRs challenges. Supervised and RL showed promising results for various SR systems. Wang *et al* [286] developed a bioinspired approach, mirroring human proprioception. Unlike traditional smart material sensors, a synthetic analog using soft pneumatic chambers as receptors was created. Redundant receptors were employed, and deep learning generated kinematic models from pressure data. This enabled proprioception in a three-degree-of-freedom continuum joint. Failure responses and solutions were explored. This innovative method offers proprioception for closed-loop control, enhancing soft robot interaction.
4. Soft sensor layout optimization: Wall *et al* [711] proposed a method for sensorizing soft actuators using an iterative process to find an effective sensor layout. The approach involved using off-the-shelf materials, a kinematic description, and ML to predict actuator deformation.

4.4.1.2. External sensing. Soft robots can also utilize external sensors, like cameras, to gather information about themselves and their surroundings. Visual data captured by cameras can be processed using ML techniques such as computer vision. These algorithms analyze the images or videos to identify landmarks, objects, or markers that can help determine the soft robot's pose and spatial orientation. This method allows the robot to interact with the environment based on real-time visual feedback. The integration of ML with camera data provides soft robots with enhanced perception capabilities, enabling them to respond intelligently to dynamic and complex scenarios.

External sensors offer a multitude of advantages, prominently starting with their unparalleled versatility and adaptability. Particularly exemplified by cameras and other external vision systems, these sensors establish themselves as an all-encompassing solution for the intricate task of sensing within the realm of SRs. Their ability to seamlessly function across diverse environments and scenarios eliminates the necessity for tailored modifications to the robot's physical structure.

This adaptability renders external sensors indispensable tools in domains where soft robots are expected to navigate and perform across a spectrum of settings, from structured laboratories to complex and unstructured real-world environments.

One of the paramount merits of external sensing lies in its non-intrusive nature. Unlike internal sensors, which demand integration within the very fabric of the soft robot, external sensors are observers from a distance. This unique attribute circumvents any need for structural alterations or modifications that internal sensors might necessitate. Consequently, the fundamental design and functional integrity of the soft robot remain intact. Avoiding invasive interventions not only simplifies the robot development process, but also improves the overall durability and performance of the robot, marking a key advancement in the field of SRs.

Moreover, external sensing offers the remarkable potential for multi-modal perception. It presents a complex sensor fusion structure where external sensors can be seamlessly integrated with multiple sensing modalities. For example, cameras, as primary external sensors, can synergistically collaborate with depth sensors, lidar technology, and even thermal sensors to form a robust sensory network. This complex interplay of sensor types gives the robot a comprehensive understanding of its surroundings. The integration of multiple sensing modalities caters to a higher level of perception, enabling the soft robot to interpret complex environmental cues and make well-informed decisions in real-time.

The research conducted by the team led by Charlie C L Wang, particularly highlighted in the articles [712, 713], significantly advances the field of external sensing for soft robots. Scharff *et al* [712] introduced an ingenious approach for sensing bending deformations in soft robots by leveraging multicolor 3D printing. By utilizing compact color sensors, they detected deformation which is visualized through changes in color ratios. The researchers presented two novel designs, termed external and internal signal generators, to produce color signals on 3D-printed objects. They also developed signal processing and calibration methods to transform raw RGB data into meaningful deformation metrics. Scharff *et al* [713] also proposed an innovative proprioception method for soft actuators during real-time interactions with previously unknown objects. Their approach involves a two-step process. Firstly, they designed a color-based sensing structure that translated the inflation of a bellow into changes in color. This color change was subsequently detected by a miniaturized color sensor. This sensor could be easily integrated into SPAs to capture local deformations. Secondly, the team utilized a feedforward NN to reconstruct a multivariate global shape deformation based on these local color signals. Their experimental results demonstrated that this method accurately reconstructs deformations during interactions, including complex sigmoid-like shapes. This advancement in accurate shape sensing represented a significant stride towards enabling closed-loop control of soft robots in unstructured environments.

Thuruthel *et al* [404, 714] also did some research on the external sensing of soft robots. Thuruthel *et al* [404] developed a synthetic system inspired by human perception of soft robots. By combining a vision-based motion capture system and a general ML approach, they successfully modeled previously unknown soft-actuated systems in real-time. The approach was robust against sensor nonlinearities and drift. Notably, this system estimated applied forces during interactions with external objects. This innovative approach enabled the creation of force and deformation models for SRs, with potential applications in human–robot interaction, soft orthotics, and wearable robotics. By combining diverse sensorimotor data, Thuruthel and Iida [714] also employed end-to-end deep learning, bypassing the need for intermediary sensor processing. The approach was demonstrated on a soft anthropomorphic finger embedded with soft sensors. The research also highlighted its extension to advanced cognitive functions, including recognizing the self, the environment, and mastering object manipulation.

4.4.2. Kinematics and control optimization. SRs have been extensively researched due to their flexibility, compliance, and adaptability to the surrounding environments. To unleash their full potential across various research fields, how to efficiently design a control system for the soft robot to achieve satisfactory performance becomes another critical issue. However, due to the continuum nature and increasing complexity of functions of soft robots, it is indeed a complex endeavor to model the kinematics and design the required manipulation acting on these robots. Conventional control schemes used for rigid-bodied robots are not possible due to the assumption that discrete joints are positioned along a chain of rigid links. Recently, learning-based techniques could have addressed different levels of the control pipeline in the lack of existing analytical or numerical models for the underlying dynamics [100, 120, 144, 715–719]. There are three common tactics used to handle soft robot control in the field: NN modeling, data-driven order reduction, and RL as demonstrated in figure 9.

ML plays an increasingly prominent role in SRs, particularly for modeling nonlinear systems where traditional analytical methods often fall short. By harnessing data-driven approaches, ML enables the creation of adaptive control and sensing models that are highly responsive to the unique challenges posed by soft robots. These robots often operate in dynamic, unpredictable environments, with complex deformation behaviors that make traditional methods cumbersome and insufficiently flexible [603, 720]. ML's adaptability to non-linearities allows for real-time adjustments, giving soft robots a level of responsiveness and adaptability that classical methods struggle to match. This is particularly valuable in tasks requiring precise, flexible movement and sensing capabilities, such as navigating complex terrains, human–robot interaction, or biomedical applications.

However, ML also faces inherent limitations that can hinder its effectiveness in SRs. One primary constraint is the need for large, high-quality datasets to train models

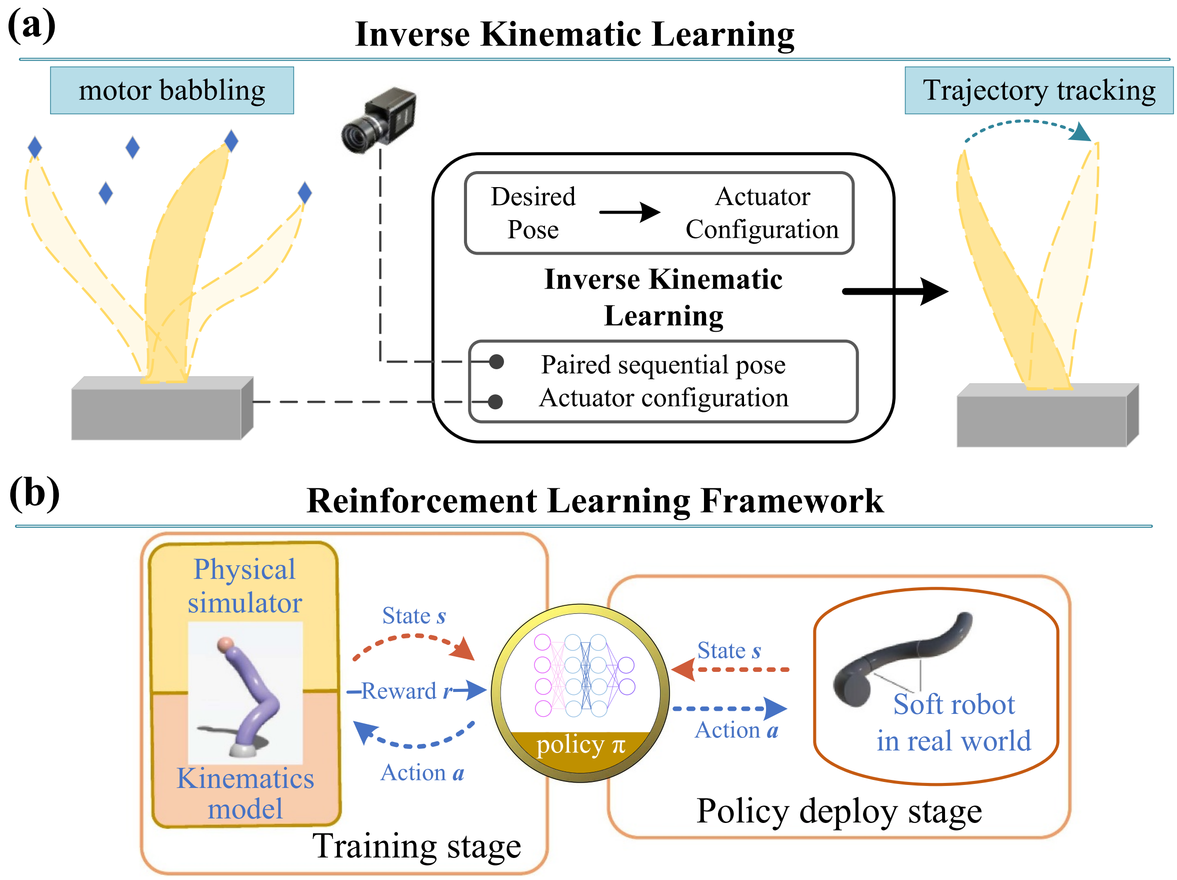

Figure 9. (a) Learning inverse kinematics requires training data composed of matched pairs of robot sequential pose and actuator configuration caused the transition. A neural network model encodes the relationship between sampled data to generalize to an arbitrary desired pose. (b) Reinforcement learning framework by iteratively evaluating the performance of the resultant trajectory with respect to some cost function and updating parameters to increase that performance during the optimization.

effectively. Without robust datasets that capture the full range of environmental and operational variability, ML models risk overfitting, where they may perform well in specific contexts but fail to generalize across different conditions. This issue poses a significant challenge for soft robots, which often need to adapt to entirely new tasks and settings. Furthermore, ML-based models lack the interpretability of classical analytical and numerical approaches, making it difficult to predict exactly how a model will respond to unseen conditions or to troubleshoot unexpected behavior. This opacity stands in contrast to deterministic methods like FEA, where the mechanics of each calculation are well-defined and transparent.

In practice, ML and classical methods often complement each other in SRs applications. While ML excels in managing the complexities and inherent variability of nonlinear systems, deterministic approaches provide a stable, robust framework with greater interpretability. Classical methods, such as FEA, offer insights into underlying mechanical principles and allow for validation through first-principle analysis, which ML lacks. This dual approach, combining ML's adaptability with the rigorous, structured insights of analytical and numerical methods, creates a more holistic framework for tackling the unique challenges in SRs, balancing predictive adaptability with model reliability and interpretability.

4.4.2.1. NNs modeling. As the most commonly used regression model to approximate the mapping between the task space and actuation, NNs have demonstrated their effectiveness in solving various nonlinear problems across the soft robot field. Artificial neurons, inspired by the NNs found in biological systems, play a vital role as the foundational units of artificial NNs. Similar to their biological counterparts, artificial neurons transmit numerical signals to other neurons and each neuron computes its output by applying a non-linear combination of its inputs. In the context of SRs applications, the input and output layers of NNs typically correspond to actuation variables and robot outputs, respectively. The learning process involves optimizing the network weights using back-propagation, which leverages the chain rule. This process includes performing a forward pass through the network, followed by a backward pass to compute the network Jacobian and adjust the model's weights accordingly. The weight metrics associated with these connections are updated to improve the performance via optimization. A high dimensional set of nested functions of a NN is represented as:

$$y = f_N\left(W_N, \ldots, f_2\left(W_2, f_1\left(W_1, x\right)\right)\ldots\right) \tag{12}$$

where the values of the input node states are denoted as x, while the network's edge weights are represented by W_i. f_i denote the activation functions, and y represent the values of the output nodes.

4.4.2.1.1. Inverse kinematics (IKs) learning. As the kinematics of soft robots are usually highly nonlinear, the NNs have offered a promising alternative in approximating the kinematic and dynamic characteristics. Soft robot modeling can be viewed as a function that relates actuation and sensing signals as independent variables to robot outputs as dependent variables. Conversely, soft robot control represents the inverse process, with desired robot outputs and sensing signals acting as the independent variables, and actuation serving as the dependent variable.

The first work of implementation of NNs in the soft robot field was presented by Braganza *et al* [721]. This work proposed a controller for continuum robots utilizing a feed-forward NN (FNN) component to compensate for the dynamic uncertainties of the system, in an attempt to reduce the uncertainty bound. In one other paper with the same FNN approach, an experimental validation was done by Giorelli *et al* [722] for learning the IK of the cable-driven soft manipulator moving in 3D space. For the 2D control of a multi-segment extensible soft arm, a two-level approach that combines gradient descent with a NN is employed for solving the IKs [723]. Recently, Khoshkho *et al* proposed a nonlinear optimal control technique presented based on the state-dependent Riccati equation and the consideration of the dynamics of the continuum robot [724]. The present work uses a distilled neural technique to implement the controller and optimally control the challenging dynamics of a continuum robot. Almanzor *et al* [725] proposed IKs formulation in the image space with deep convolutional NN for accurate shape control that is robust to feedback noise and mechanical changes in the continuum arm. There are several key issues to consider in NN applications:

1. Training data collection: when training offline models, the collection and selection of training data are paramount for achieving high accuracy. To achieve this objective, the samples should fulfill two requirements: cover the entire workspace of the robot end-effector and be evenly distributed in the task space to ensure consistent estimation performance across all areas. An efficient exploration algorithm for generating training data samples to learn the IK formulation is performing a random walk within the actuation space on the physical hardware. This approach, known as continuous motor babbling, has been employed to learn directly the mapping from the task space to actuator space in various types of manipulators, including cable-driven continuum manipulators [203], pneumatic continuum manipulators [726], as well as simulated manipulators [271]. To tackle the significant challenges associated with IK modeling of a bionic trunk, such as high dimensionality and nonstationary system behavior, online goal babbling has been implemented with bootstrapping and adapting the IKs on the fly [727]. The inverse model is tasked with estimating the appropriate posture necessary to move the effector to each vertex, and the training process continues until the distance between the target and actual positions for each vertex is minimized. To fully unleash the advantage of the learning-based method, filtering and normalizations were usually required to conduct for obtaining abstract high-quality samples. Besides, filtering and regularization are also required operations to obtain high-quality samples before feeding into the network.
2. Redundant mapping: in IK learning control, redundancy is another issue that can lead to generating inconsistent samples even when the robot pose remains the same, but the actuation commands differ. The existence of this multiple-to-single mapping will deteriorate the performance of the learning-based controller. To solve the problem of redundant mapping, two particular methods are outlined for careful elaboration on pre-training data: (1) For single-segment manipulator control, the approach is the manual adjustment of original training data distribution in a uniform pattern within the workspace, such as using sample pair filtering in [728]. (2) For kinematically redundant manipulators, the alternative method is to introduce a reward/cost function to draw the system to a desired solution, such as constrained optimization in [729].

4.4.2.1.2. Fusion of analytical model and learning-based component. Systems do not need to be purely data-driven for ML to be helpful. The fusion of the analytical model and learning-based component allows the leveraging of existing knowledge so only the most intractable system components need to be learned. The strengths of the analytical dynamics/kinematics model and learning-based approaches can reinforce each other to accomplish robust control performance. Hybrid approaches allow the leveraging of existing knowledge so only the most intractable system components need to be learned. Learning the parameters of an analytical dynamics model, similar to traditional adaptive control methods, has been shown to be fast and effective if such a model can be constructed with enough fidelity.

Tang *et al* [204] proposed a control architecture integrating model predictive control (MPC) and iterative learning control (ILC) that simultaneously achieves model learning and reference trajectory-tracking of a wearable SR glove. The integration of the kinematic model and the ML-trained model was also validated, and most of the learning-based parts acted as error compensators of the analytical model. It is also possible to decompose control of multiactuator systems into analytic kinematic targets, where each actuator achieves the final shape through a system-level controller or individual actuator-level controllers [726]. Utilizing the fused pose feedback from the visual information and FBGs helically wrapped on the soft manipulator, Wang *et al* [730] proposed a hybrid controller incorporating kinematics and data-driven algorithms for reliable closed-loop control. In particular, even under full occlusion of the tracked features or complete darkness, an improved extreme learning machine algorithm with selective training data updates is implemented to solve pose estimation failures.

4.4.2.2. Data-driven order reduction. Some modeling tools employ different forms of data-driven order reduction to efficiently approximate the physical model. The Koopman operator linearizes the nonlinear dynamics of soft robots for modeling and simulation. The Koopman operator theory provides a data-driven approach that avoids physical simplifying assumptions but also yields explicit control-oriented models. By leveraging the linear structure of the Koopman operator, this approach can construct linear models of nonlinear controlled dynamical systems from input-output data and control them using established linear control methods. Wang *et al* [730] represented a dynamic system as $\dot{x}(t) = F(x(t))$ in an infinite-dimensional function space F, which is composed of all continuous real-valued functions with the compact domain. The flow of the system is characterized by the set of Koopman operators U_t, which define the transformation of the observables $f \in F$ along the trajectories of the system according to the following definition:

$$U_t f = f \circ T_t \tag{13}$$

where $\circ$ indicates the composition operation, while T_t is the flow (or dynamic) map of the system. In this way, the Koopman operator lifts the dynamics of the system from the state space to the space of the observables.

4.4.2.3. RL architecture. RL refers to a family of learning-based algorithms where the agent autonomously learns to deal with new tasks during the interaction with its environment. Compared to supervised learning where the model learns from the 'answer key' in training data, RL enables the model to discover the optimal behavior policy from experience. Nowadays, RL applied in the control of soft robots has been attracting lots of interest and developing fast since it could avoid prior knowledge of robot configuration.

Learning kinematic or dynamic models for a soft robot means that, while part of the control pipeline relies on empirically learnt models, the controller itself is still engineered. RL is a ML strategy that allows the controller itself to be created through learning from sequential environmental interactions, rather than from previously collected exogenous data. RL is regarded as a Markov decision process (MDP), represented using a tuple. In the agent's interaction with the environment, S is the set of the agent's possible states, where s is the current state and s' is the next state after the agent transition. A presents the set of the agent's actions, where a is the action. $p(s'|s,a)$ is the state transition probability of the agent transiting from the current state s to the future states' after the implementation of action a. $r(s,a)$ represents the immediate reward of one transition and R is the accumulated reward or expected return of the whole trajectory. $R(\tau) = \sum_{t=0}^{\infty} | \gamma^t \cdot r(s_t,a_t)$. Policy $\pi(a|s)$ is the mapping from the states to the action a, namely, given the current state, it could suggest the next step to obtain an optimal reward. The value function could evaluate the quality of the policy, offering the quantitative metric for the behavior decision maker, which can be divided as state–value function $V^{\pi}(s)$ and action–value function:

$$\begin{aligned} V^{\pi}(s) &= E_{a\sim\pi}\left[R(\tau)\,|s_t = s\right] \\ Q^{\pi}(s) &= E_{a\sim\pi}\left[R(\tau)\,|s_t = s, a_t = a\right]. \end{aligned} \tag{14}$$

When considering in robot control, the goal of RL is to figure out a control strategy that could generate optimal instruction for robot action in order to accomplish the specified task effectively. The reward function is manually designed to train the robot with certain features, for example, penalizing the times of transition to enable the robot to reach the target in as few movements as possible. Xu *et al* [731] explored the development of an innovative robotic motion control technique that employs a broad learning system (BLS). This approach streamlined the design of the controller and the process of parameter adjustment, providing a more effective means of managing robotic motion. The control strategy revolved around a BLS for point-reaching motion, and its implementation was examined through the convergence of the artificial magnetic fish movement towards the target area while successfully circumventing obstacles.

To navigate the soft robots under a dynamic environment, Cai *et al* [732] presented a deep RL framework-based approach for controlling the flow rate rejection of soft magnetic miniature robots. This research presented the development and implementation of the deep RL framework, which aims to improve the performance and adaptability of these robots in various fluid environments.

Policy gradient-based RL converges to a locally optimal controller without an analytical model of the robot dynamics but requires much more time and data for training than supervised learning. This is due to the need to evaluate the full trajectory produced by following a controller from a specific state before making updates to the model at a given optimization step. A common robotics solution is learning in simulation for many trials, and several physical simulators have good prediction and optimization results for robot control and planning algorithms:

1. To address the shortcomings of soft-body simulation methods in solving inverse problems such as optimal control and motion planning, Hu *et al* [733] designed ChainQueen, a real-time microphysical simulator based on the moving least squares material point method. The simulator is able to predict the motion and shape of soft structures and their response to external forces at the millisecond level.
2. At the same time, ChainQueen provides a differentiable interface that can be integrated with deep learning controllers for more efficient and intelligent control. For optimization, they used an SDG (stochastic gradient descent) based optimization algorithm to train the deep NN controller to make the most of ChainQueen's physical model. They used

a loss function to measure the difference between the predicted output and the target state and a backpropagation algorithm to compute the gradient. Then, they used SGD to update the controller's parameters to minimize the loss function. They also introduced a new regularization technique called 'balanced regularization,' which helps control overfitting and improves generalization performance. In addition, applications of other optimization methods, such as model-based predictive control and gradient descent optimization, are also explored in their paper. All these methods aim to improve the control accuracy and real-time performance of ChainQueen. Finally, they also validated the performance and accuracy of ChainQueen through a series of experiments.

3. Naughton *et al* [36] discussed the development of a computational framework called Elastica, which was designed to simulate and control SR systems. This framework aims to address the challenges faced in SRs, such as the complex interactions between the robot body and its surroundings, and the nonlinear and highly deformable nature of soft materials. Elastica provides a platform to develop and test new control strategies for soft robots, thereby exploring of their capabilities and potential applications. The framework is designed to be flexible and modular, allowing for the integration of various models and algorithms to improve the performance of SR systems.
4. Bhatia *et al* [734] from Massachusetts Institute of Technology introduced a benchmarking platform called Evolution Gym, which was designed to facilitate the optimization and evolution of SR systems. The platform consists of a simulation environment, a set of predefined tasks, and a suite of optimization algorithms, which aims to address challenges in SRs by providing a modular and extensible framework to evaluate and compare various soft robot designs, optimization techniques, and control strategies. They presented benchmark tasks that covered locomotion and manipulation challenges, discussed the optimization algorithms included in the platform, and shared experimental results that demonstrated the effectiveness of Evolution Gym in optimizing soft robot designs and control strategies.

5. DTs enabled soft robots

In the realm of technological innovation, the convergence of virtual and physical realities has birthed a concept that bridges the gap between the tangible and the digital with remarkable potential: the DT. A DT refers to a virtual counterpart that replicates the behavior, characteristics, and interactions of a physical entity, offering a real-time simulation that enables analysis, optimization, and enhanced understanding [735]. Simultaneously, the domain of robotics has seen a remarkable evolution with the advent of soft robots—dynamic machines constructed from flexible materials that replicate the adaptability and grace of natural organisms. This section embarks on an exploration of the dynamic synergy between these two groundbreaking concepts, investigating the manifold applications of DTs in the realm of SRs. With the convergence of DTs and soft robots, a new horizon of possibilities emerges, promising to revolutionize design, performance optimization, remote operation, and more as shown in figure 10.

It is within the dynamic domain of SRs that DTs find their contemporary and transformative vocation. The attributes of soft robots, characterized by their malleability, adaptability, and emulation of biological paradigms, instigate an amalgamation of innovation and intricacy. Within this context, DTs offer a salient proposition by facilitating the creation of virtual surrogates that faithfully replicate the intricate dynamics of their tangible counterparts. This emulation forms the linchpin of an emergent epoch in SRs—a paradigm distinguished by expeditious developmental trajectories, iterative experimentation, and heightened exploratory veracity.

This section is organized as follows. First, we begin by exploring the transformative applications of DTs in the field of SRs. This exploration of the uncharted territory of innovation reveals the potential to redefine the boundaries of SRs through the DTs. Next, we delve into the complex techniques employed in the development of DTs for soft robots. This segment serves as a backstage pass into the art of translating physical dynamics into virtual simulations, highlighting the foundational methods for the fusion of reality and virtuality. Finally, we will examine the current research landscape of DTs for soft robots.

5.1. Technical approach

In this section, we will embark on an exploration of the profound implications that the integration of DTs holds for the evolution of SRs. This exploration will encompass a comprehensive exploration through five pivotal aspects: design and prototyping, behavior modeling and simulation, performance optimization, remote operation and training, and predictive maintenance and health monitoring, each contributing to the overarching narrative of the transformative power of DTs in reshaping the landscape of soft robot development.

5.1.1. Design and prototyping. For soft robot, the transition from concept to functional physical prototype is often a complex and iterative process. Traditional design approaches require the creation of multiple physical iterations, which increases time costs and leads to material waste. However, DTs revolutionize this process by acting as virtual laboratories, enabling the exploration of a wide range of design possibilities in a virtual environment [736]. By accurately replicating the behavior and characteristics of soft robots, DTs can be meticulously simulated and tested before any physical construction begins. This virtual experimentation capability makes it possible to identify potential defects, optimize designs, and fine-tune performance parameters while avoiding

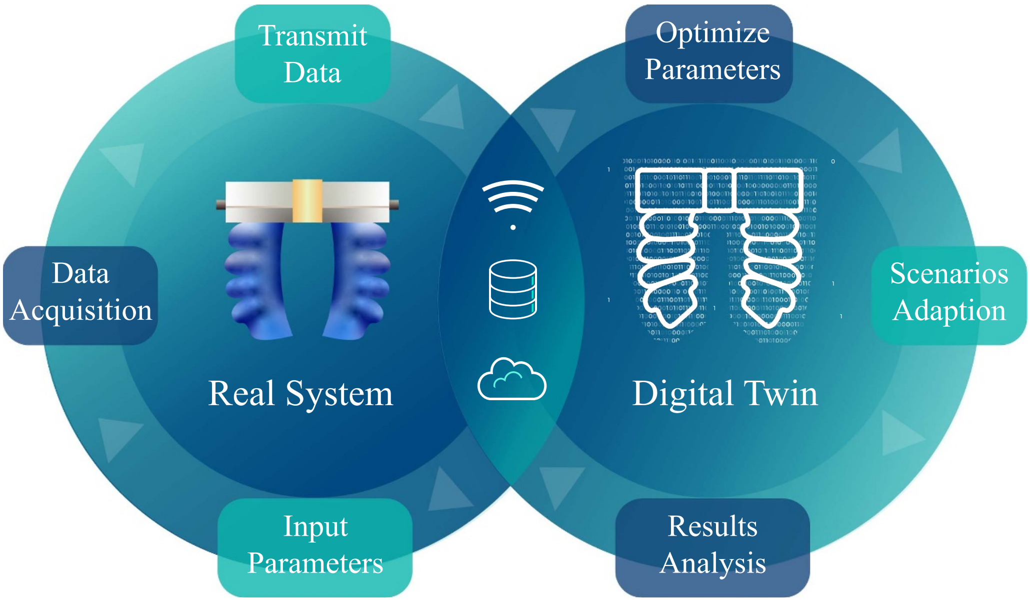

Figure 10. Components and principles of digital twins for soft robots.

the time-consuming and resource-intensive physical prototyping phase.

One of the pivotal advantages of utilizing DTs in the design and prototyping of soft robots is the acceleration of the design iteration process [737]. The virtual realm allows for rapid modifications and refinements to be seamlessly applied, fostering a dynamic design process that expedites the creation of more sophisticated and efficient prototypes. This iterative approach not only enhances the quality of the final product but also significantly reduces the time required for development.

Moreover, the cost-effectiveness inherent in DT-based design cannot be overstated [738]. Traditional prototyping involves the fabrication of numerous physical models, each with associated expenses in terms of materials, labor, and equipment. In contrast, DTs drastically cut down on these costs by allowing for multiple design variations to be tested virtually, without the need for physical materials. This results in substantial financial savings, making innovative design experimentation feasible for a broader range of researchers and designers.

To construct the geometric model of the soft robot, various pathways are available. One option is to employ user-friendly 3D tools such as 3DMAX, Maya, Unity3D, and unreal engine (UE) [739], which seamlessly integrate modeling, animation, and rendering capabilities. Alternatively, 3D design software like UG (Siemens NX), AutoCAD, Revit, Bentley Systems, and building information modeling (BIM) software can ensure precision, collaboration, and seamless integration through geometry engines and constraint solvers.

For highly accurate modeling, laser point cloud models generated through laser scanning can be processed using tools like RapidForm and Geomatics software [740]. Additionally, the conversion of physical objects into 3D models can be achieved through photo-to-3D modeling using software like 3DSOM Pro and Autodesk 123D Catch. To create semantically meaningful DTs, data fusion, segmentation, and recognition from diverse sources, including point clouds, images, satellite imagery, and drone data, can be performed with tools such as Google.

Key technologies in this domain include model lightweighting through compression, multiple instances, hierarchical detailing (Level of Detail or LOD), and parametrization. Cloud rendering engines further enhance the visualization of DTs. To bring the DT to life, various simulation and visualization engines can be utilized. Game engines like Unity 3D and UE provide immersive simulation capabilities, while specialized 3D tools and engines, such as Uniview and 51world, focus on rendering and presentation to ensure a realistic and informative representation of the soft robot's DT. These design and prototyping techniques collectively enable the creation of a robust and accurate DT for SR systems.

In the development of DT models, the concept of model lightweighting emerges as a pivotal and noteworthy research domain [741–746]. DTs, serving as virtual replicas of physical assets, systems, or processes, often necessitate intricate and comprehensive models to faithfully replicate their real-world counterparts. However, handling highly detailed models can be computationally demanding and resource-intensive, particularly when dealing with extensive systems and simulations. Model lightweighting is designed to address this challenge, employing techniques aimed at crafting simplified yet efficient DT models. These streamlined models preserve vital features and essential data required for accurate simulations and analysis, while concurrently reducing memory and computational requirements. By optimizing the DT's model, it becomes more manageable to work with extensive datasets, process real-time data, and achieve enhanced performance during simulations. Several common techniques for model lightweighting are outlined here:

- LOD models [747–750]: these entail creating various versions of the model, each offering varying levels of detail. For example, a high-level LOD model may encompass only the core features, while a low-level LOD model contains fewer intricacies, enabling faster processing.
- Decimation [751–753]: this technique involves selectively removing certain elements or vertices from the 3D model, thereby diminishing its polygon count while preserving its overall shape.
- Feature suppression [754–756]: in this approach, specific features, annotations, or metadata that are deemed non-essential for the current analysis or simulation are temporarily hidden or simplified.
- Subdivision surfaces [752, 757, 758]: complex surfaces are represented using a reduced number of control points, resulting in a more lightweight model.
- Parameterization [759–761]: mathematical parameterization techniques are employed to represent complex shapes with simpler equations, enhancing model simplicity.
- Simplified physics models [762]: reduced or approximated physics models are utilized for simulations, albeit at the cost of some accuracy, in exchange for quicker computations.
- Data aggregation [763–765]: data points are grouped based on similarity, or statistical methods are applied to decrease the overall data volume.

The advantages of model lightweighting in DT development are multifaceted. First, it enables real-time or near real-time simulation, facilitating agile and responsive monitoring and control of physical assets and processes. Accurate and fast simulations are essential for optimizing design and production processes. In addition, model lightweighting simplifies the integration of DTs with other systems and technologies, streamlining data exchange and facilitating collaboration. Research efforts in model lightweighting focus on improving advanced algorithms, compression techniques, and data reduction methods, with the overall goal of efficiently representing complex physical systems without compromising accuracy.

In essence, integrating DTs during the design and prototyping phases of soft robots marks a paradigm shift in traditional engineering approaches. It provides unprecedented flexibility to fine-tune designs, troubleshoot potential issues, and optimize performance attributes with remarkable efficiency.

5.1.2. Behavior modeling and simulation. Soft robots have flexible and adaptable structures that exhibit rich and complex nonlinear behaviors that distinguish them from rigid robots [766]. These behaviors are often characterized by complex interactions with the environment, presenting unique challenges and opportunities. The inherent flexibility of SR materials makes their behaviors challenging to predict and control by traditional means [122]. However, entering the field of DTs, the combination of virtual replication and real-time simulation reveals a transformative approach to understand, model, and ultimately master the behaviors of soft robots. DTs provide a valuable way to accurately model and simulate these behaviors. By carefully replicating the physical properties, material responses, and environmental interactions of soft robots, DTs provide a virtual testing ground to explore a variety of scenarios without the constraints of the physical domain. This level of fidelity enables in-depth studies of the precise simulation of soft robot behaviors, revealing the interactions between shape changes, forces, and external stimuli.

Behavioral modeling and simulation capabilities are a typical direction that reflects the DT empowerment of soft robots. Soft robots mimic the graceful undulations of aquatic organisms or the sinuous movements of snakes, and their gaits are often challenging to predict using traditional analytical methods alone. DTs can simulate these gaits in detail by adjusting parameters in real time to observe the resulting behavior. This dynamic exploration not only enhances the understanding of the principles of motion, but also provides insights into how different environments affect the robot's performance. In addition, the ability to simulate behavior helps develop advanced control strategies. By observing how the soft robot responds to various inputs and stimuli in the digital domain, control algorithms can be fine-tuned for optimal performance. For example, the manipulation of SR arms in delicate surgeries can be improved by considering simulations of human tissue interactions, the mechanical properties of the soft robot, and surgeon input [245].

There are several techniques for behavior modeling and simulation. Some of them are listed below:

1. Simulation of diverse physical phenomena: to accurately replicate physical phenomena such as vibrations, collisions, noise, and explosions, a suite of simulation tools is available. Notably, industry leaders like Siemens, ANSYS, and ZWSOFT offer comprehensive solutions. Siemens provides a robust platform that excels in simulating complex physical interactions, making it suitable for scenarios involving vibrations, collisions, and even explosive events. ANSYS, renowned for its versatility, empowers to model various physical phenomena, including vibrations and explosions, enabling precise simulation. ZWSOFT specializes in simulation software designed to effectively replicate physical events like collisions and vibrations, providing valuable insights into the dynamic behavior of soft robots.
2. Material mechanics, elasticity, and dynamics simulation: understanding material behavior, elasticity, and dynamics is critical for simulating soft robot motion and predicting fatigue. In this domain, Comsol offers a versatile platform for material mechanics, elasticity, and dynamic simulations, enabling in-depth analyses of how soft robot materials respond to various forces and loads. This capability is crucial for designing soft robots to obtain optimal performance and durability.
3. Simulation of manufacturing processes: the development of soft robots requires consideration of their manufacturing processes, such as molding, casting, bending, and printing. Dassault Systèmes, through its comprehensive simulation solutions, assists in simulating these processes. Dassault's software ensures that soft robot components are designed

with the specific manufacturing processes in mind, reducing potential defects and optimizing production efficiency.
4. Simulation of production lines, factory layout, logistics, and human factors: beyond the behavior of the soft robot itself, a holistic approach to DT development necessitates the simulation of the broader production environment, encompassing equipment layout, logistics, and human factors. Factory IO specializes in this aspect, offering tools to simulate production lines, factory layouts, and logistics. Furthermore, it allows for the consideration of human factors in the production process. This comprehensive view facilitates the seamless integration of soft robots within manufacturing environments, optimizing efficiency and safety.

In summary, DTs advance the field of SRs by providing a high-fidelity, low-risk arena for exploring complex behaviors. These digital replicas provide a path for experimentation, analysis, and control beyond what the physical world can offer. As soft robots enter the virtual realm, the complexity of soft robot behavior can be unraveled, opening up a new realm of possibilities, from improving locomotion to redefining our approach to automation in complex environments.

5.1.3. Performance optimization. DTs can be used in the field of soft robot performance optimization. The combination of virtual replication and real-time simulation can enhance the performance of soft robots in a range of tasks and environments, bringing benefits that go beyond the limitations of traditional methods. At the core of soft robot performance optimization is the meticulous testing and improvement of control algorithms and strategies. In the field of robotics, the interaction between flexible and dynamic soft robots and their environment can be complex, so predicting and optimizing performance is a daunting challenge. However, DTs provide a valuable platform for exploring the consequences of various control inputs and strategies, ensuring that the robot's behavior is consistent with the expected results.

The key advantage of utilizing DTs in performance optimization lies in the availability of real-time data feedback [767]. Sensors embedded in the physical robot collect information about its interactions, forces, and responses. This data is seamlessly integrated into the DT, providing a dynamic feedback loop that refines the accuracy of simulations and enhances the predictability of outcomes. This real-time alignment between the virtual and physical realms enables researchers to iteratively fine-tune control strategies based on actual, rather than theoretical, performance.

Beyond controlled laboratory environments, the integration of DTs in real-world environments is where they can really advance the development of SRs. When soft robots are used in unstructured and unpredictable environments, such as disaster response or space exploration, virtual testing and tuning of soft robots before deployment can help optimize their performance in challenging scenarios [768]. DTs can minimize risk, increase mission success, and ensure that the robot's behavior adapts to the complexity of the target environment.

Performance optimization techniques are instrumental in enhancing the capabilities of a DT for a soft robot. These techniques encompass a range of strategies aimed at refining the robot's behavior and efficiency. Simulation-based optimization stands as a cornerstone, leveraging advanced tools for iterative simulations and analysis to fine-tune the robot's design and control algorithms [769–771]. Multi-objective optimization takes a holistic approach, considering multiple performance criteria, such as speed, accuracy, energy efficiency, and safety, to achieve a balanced solution [772–777].

Parameter tuning involves adjusting the DT model, including control algorithms, material properties, and mechanical parameters, to optimize its response to various inputs and scenarios [778]. ML and artificial intelligence enable the DT to adjust its behavior based on real-world data and sensor feedback, thereby promoting continuous performance improvements.

Efficiency analysis can reduce energy waste and improve mechanical efficiency, driving design changes and control enhancements. Real-time monitoring and adaptive control continuously evaluate performance and dynamically adjust as conditions change. Sensitivity analysis evaluates how changes affect performance, enhancing robustness and reliability. Collaborative optimization considers the interactions between multiple soft robots or components to optimize system performance, while cost-benefit analysis guides decisions by weighing the optimization costs against the expected performance gains. Together, these different techniques improve the performance of soft robots and ensure efficiency, reliability, and adaptability for a variety of applications.

In conclusion, the convergence of DTs and soft robots transforms the landscape of performance optimization. It empowers to navigate the intricate interplay of control strategies and environmental factors within a dynamic virtual environment. As real-time data feeds into simulations, the chasm between theory and practice narrows, leading to enhanced soft robot performance that is finely tuned, adaptable, and aligned with real-world demands.

5.1.4. Remote operation and training. The integration of DTs with soft robots extends its transformative influence beyond the realm of design and optimization, delving into the domain of remote operation and training [779]. The convergence of virtual replication and real-time simulation opens up avenues for remote control, operation, and training, revolutionizing the way soft robots are deployed and harnessed in challenging, hazardous, or intricate environments.

Robotic systems, especially those with complex and adaptive behaviors such as soft robots, often require a high level of human involvement to control their behavior. DTs break geographical barriers and enable remote control of soft robots from a distance. This is particularly important in scenarios that are dangerous or challenging for human presence, such as disaster-stricken areas or confined spaces, where direct human intervention may be impractical or risky. Furthermore, DTs can provide virtual training to improve skills without physical proximity to the robot. The DT can interact, familiarize itself with the robot's behavior, test different control strategies, and train its decision-making capabilities in a controlled and risk-free environment. This virtual training not only accelerates the learning process but also enables the exploration of innovative technologies and approaches without endangering the physical robot. Furthermore, the integration of DTs in teleoperation promotes a seamless human–robot interaction paradigm. The actions and responses of the soft robot can be perceived through the simulation of the DT, effectively bridging the gap between physical distance and operational understanding. This enhanced interaction not only improves the quality of remote control but also enhances the potential for collaboration between human and robotic agents.

Augmented reality (AR) and virtual reality (VR) stand out as transformative tools for remote operation and training techniques of DTs for soft robots [780–793]. AR seamlessly merges digital information with the real world, making it possible to wear an AR headset or use an AR-equipped device to interact with the DT of a soft robot in its physical environment. This facilitates precise control, real-time feedback, and enhanced teleoperation capabilities while reducing the risk of collisions [123, 794, 795]. Conversely, VR takes training and simulation to a whole new level. It immerses trainees in a virtual environment that mirrors the behavior of the DT, allowing them to practice interactions with the soft robot safely. VR training encompasses a wide range of scenarios, from basic operations to complex maintenance tasks, enabling users to become proficient without physical access to the robot [796–798]. Interactive 3D modeling tools, often integrated with AR and VR, empower remote teams to collaboratively design, test, and optimize soft robots within the DT environment, fostering innovation and speeding up development. Specialized teleoperation interfaces facilitate intuitive and immersive control of soft robots through AR or VR systems.

These technologies are also adept at simulating a variety of real-world scenarios, from navigating tight spaces to handling delicate objects and dealing with unexpected obstacles, allowing for effective responses to a variety of situations. In addition, AR and VR provide real-time data visualization and sensor feedback that can make informed decisions during remote operations and training. These technologies facilitate remote collaboration by allowing multiple users to interact with DTs simultaneously. This is valuable for remote troubleshooting and expert guidance, as real-time assistance can be provided, improving efficiency and minimizing downtime. AR and VR technologies integrated into soft robot DTs span physical distances, providing an immersive, interactive experience that can significantly improve remote operation capabilities, simplify training, and ensure effective collaboration between geographically dispersed teams.

In summary, the fusion of DTs and soft robots transcends the boundaries of physical presence, paving the way for remote operations and training with far-reaching implications. DT technology enables remote control in hazardous environments and virtual training to improve the skills of the system, revolutionizing the landscape of human–robot interaction. As we move toward a future where robots explore unknown territory, the virtual companionship provided by DTs will become an indispensable tool for opening up new frontiers.

5.1.5. Predictive maintenance and health monitoring. The convergence of virtual replication and real-time data utilization introduces a proactive approach to maintaining and monitoring the health of soft robots, elevating their reliability, minimizing downtime, and contributing to significant cost savings. In the world of robotics, where mechanical wear, environmental factors, and external interactions can lead to gradual degradation, the concept of predictive maintenance emerges as a game-changer [799]. By modeling the physical robot's behavior and comparing it with the expected norms stored in the DT, researchers can anticipate deviations, anomalies, or signs of wear that might signal the need for maintenance or repairs.

The synergy between real-time data from sensors on the physical robot and the virtual counterpart enhances the precision of predictive maintenance. As the soft robot operates in its real-world environment, sensors capture data on factors such as temperature, force, strain, and movement [800]. This data is then fed back into the DT, updating its condition in real time. This dynamic feedback loop enables to observe any disparities between the virtual and physical behaviors, thereby fine-tuning the DT's predictive capabilities and ensuring that maintenance decisions are based on accurate information [801].

The implications of predictive maintenance are profound, particularly in industries where downtime can translate to substantial financial losses or compromised safety [802]. Consider a soft robot deployed in an industrial setting, performing critical tasks in intricate machinery. A failure or malfunction in such an environment could lead to production halts and substantial economic repercussions. Predictive maintenance, facilitated by the DT's real-time monitoring, has the potential to preemptively detect anomalies, allowing to intervene before a catastrophic failure occurs.

In addition to reducing costs, predictive maintenance can also help improve reliability and operational continuity. For soft robots operating in fields such as healthcare, accuracy and reliability are critical, and DTs can predict possible defects and perform proactive maintenance [803]. The seamless integration of DTs enables a more systematic and data-driven approach to ensure that these robots always meet performance expectations. Therefore, the combination of DTs and soft robots ushers in an era of predictive maintenance and health monitoring, going beyond traditional passive approaches. By closely monitoring behavior, leveraging real-time data, and pre-determining maintenance needs, the reliability and cost-effectiveness of soft robot deployments are improved. As the field of robotics develops, the concept of predictive maintenance demonstrates the transformative potential that DTs bring to the field of SRs.

5.2. Research status

The current landscape of DT research in the realm of SRs is in its nascent stages. While DT concepts have gained traction in robotics at large—encompassing domains like space, medical, rehabilitation, human–robot interaction, and industrial applications—the exploration of DTs specifically for soft robots remains relatively limited. Among the existing literature, only a couple of review papers have incorporated DT discussions within this context. Notably, Mazumder *et al* [122] delved into trends of DT-integrated robotics across diverse research-saturated domains, while Zhang *et al* [123] undertook an exploration of sensing technology for DT implementation in soft robots.

In terms of specific research endeavors, a pivotal contribution comes from Jin *et al* [257], who developed a smart soft-robotic gripper system. This innovation harnessed triboelectric nanogenerator sensors to capture motion and tactile data, leveraging distributed electrodes for contact position and area perception. Complementing this, a gear-based length sensor detected elongation, and ML achieved a 98.1% accuracy in object classification. Notably, this system's triboelectric data breathed life into a DT, facilitating virtual object identification and manipulation mirroring real-time soft-robotic gripper actions. This virtual emulation found its applications in scenarios like virtual assembly lines and unmanned warehouses.

Another notable study by Schegg *et al* [483] focused on DT simulation. The integration of OpenAI Gym and the physics-based SOFA engine led to the creation of SofaGym—a platform generating RL environments from DTs of soft robots. This amalgamation addressed the intricate challenges at the intersection of RL and SRs, paving the way for policy transfer and the exploration of complex interactions. The study showcased 11 diverse environments, encapsulating a range of soft robots and applications. This convergence not only enriched traditional control strategies but also introduced RL and planning solutions, thereby fostering a collaborative platform ripe for further research inquiries.

Sun *et al* [115]'s work ventured into DT applications for soft robots, designing a smart SR manipulator. This creation incorporated triboelectric nanogenerator tactile and length sensors, alongside a pyroelectric temperature sensor. By utilizing ML, sensor data fusion achieved a 97.143% accuracy in the automatic recognition of objects with varying shapes. The integration of IoT and AI analytics propelled the establishment of a digital-twin-based virtual shop—an immersive platform that enhanced user experiences. This innovative system showcased its prowess as an advanced human-machine interface, particularly within unmanned working spaces.

Although the prospect of DTs of soft robots is promising, there is still plenty of room for exploration. There are only a few pioneering studies in this field, and further research and innovation are needed, indicating that the future is full of untapped potential.

6. Challenges and future directions

In this section, we explore the challenges encountered when applying FEA, ML, and DTs in the field of soft robots and draw insights from our previous explorations. We also outline potential directions for future developments in this area.

Although artificial intelligence is now very mature, especially large language models such as ChatGPT. However, both in the field of ML and DTs, they currently face many challenges when applied to the field of soft robots.

The first challenge is modeling the complex behaviors of soft robots. Soft robots exhibit nonlinearities and are difficult to predict. Besides, the behaviors of soft robots can be affected by material properties, environmental conditions, and external stimuli. Accurately capturing and modeling complex behaviors of soft robots is a key requirement for achieving the desired performance, which needs to address some issues, including how soft robots respond to different levels of loading force, how soft robots adapt to different environmental conditions, and how they interact with other objects around them. It is challenging to develop mathematical models, simulations, or ML algorithms that can encompass these complexities and provide actionable solutions. In addition, soft robots are often designed for use in dynamic and real-world applications, such as healthcare, where precise and adaptable motion is critical. Models must not only accurately represent the behavior of soft robots, but must also facilitate real-time decision making and control. This interconnection between modeling and real-time performance presents a complex challenge,

The requirement for data-intensive training in the context of SRs is another significant challenge. ML algorithms require large amounts of data to train and learn the relationship between the input and output. Gathering the required amount of high-quality data is a time-consuming and resource-intensive endeavor. First, soft robots integrate a wide variety of sensors, including tactile sensors, force sensors, and cameras. These sensors generate vast datasets, and effectively integrating and synchronizing data from these various sources is a non-trivial task. Furthermore, labeling this data for supervised learning, which is often necessary for ML algorithms, adds an additional layer of complexity, as manual labeling can be labor-intensive and error-prone. For example, for topology optimization of active composite structures, Hamel *et al* [584], Athinarayanarao *et al* [569], and Sun *et al* [570] all used FEM-generated data as train data. If they want to make their algorithms more precise and use printed parts as train data, a lot of labor needs to be involved. Additionally, the collection of data for soft robots operating in real-world scenarios presents challenges. Environmental conditions may vary, and unforeseen circumstances can lead to unpredictable data patterns. Ensuring that the training data is representative of the full spectrum of potential scenarios and conditions is essential for robust model performance.

Real-time processing is a primary requirement in many soft robot applications, such as teleoperation, autonomous control, and human–robot interaction. Achieving low-latency performance while dealing with the computational demands of complex models is a central challenge. ML algorithms and DT models need to operate efficiently and swiftly to facilitate responsive control and decision-making. This entails optimizing algorithms, hardware, and software architectures to minimize processing delays. Balancing the need for high computational accuracy with real-time responsiveness is a delicate trade-off that researchers must navigate. Moreover, real-time processing in SRs is not solely about speed; it also involves ensuring the safety and reliability of the robot's actions. Developing mechanisms for graceful degradation and fault tolerance is critical to handle unexpected scenarios and ensure user safety.

Besides, because the development of DTs in SRs is not quite mature, there is a long way to go in this direction. The future directions for DT-assisted SRs encompass a multifaceted approach aimed at harnessing advancements across various domains to maximize their potential impact on the field. To fully unlock the capabilities of DTs in SRs, several critical areas need concerted attention and research focus:

1. Behavior modeling enhancement: the future of DTs in SRs hinges on refining behavior modeling. Advancements are needed to deepen the integration of surrogate modeling techniques within the DT hierarchy. This entails improving multi-physics validation and enhancing the performance of surrogate models through the utilization of larger datasets and emerging machine-learning methods. Moreover, the integration of sensing and actuation systems plays a pivotal role in advancing soft touch capabilities within DTs of soft robots. By enabling real-time, human-like tactile feedback, soft touch allows these systems to perceive and respond to delicate objects and varying environments. Such an integration enhances the DT's ability to simulate and predict accurate behaviors, supporting real-time decision-making and control. These enhancements will enable DTs to provide more accurate insights into soft robot behaviors and responses.
2. Unified ontology development: the SRs field requires standardized frameworks for DT development. Bridging the gap between low-level digital design and the high demand for DT technology is vital. This involves creating mathematical and simulation models that facilitate the seamless construction and integration of DTs across various stakeholders. Additionally, blockchain technology can be leveraged to ensure secure data access while safeguarding intellectual property.
3. Comprehensive data integration: building effective DTs for soft robots demands the integration of diverse manufacturing data from various sources. This includes capturing and processing 5M1E data, encompassing factors such as Manpower, Machine, Material, Method, Measurement, and Environment. A comprehensive understanding of SR systems necessitates considering complex manufacturing system phenomena, including external influences like orders and supply chains, as well as internal factors such as machine health and workers' skills.
4. Lifecycle integration: DTs for soft robots should be seamlessly integrated across the entire product lifecycle. This entails connecting DTs with physical counterparts and accommodating the decentralized nature of SR products. Data integration from different stakeholders and various lifecycle phases will be instrumental in realizing predictive maintenance, fault detection, and comprehensive diagnostics for soft robots.
5. Global collaboration and roadmap: to expedite the adoption of DTs in the realm of SRs, international collaboration and partnership formation are suggested. Such collaborations can address key challenges, including software and hardware complexities in multiscale-multiphysics modeling, standardization efforts, uncertainty quantification, verification and validation protocols, and the utilization of ML for creating surrogate models that enable real-time queries by DTs. Establishing a high-level roadmap for these endeavors will facilitate systematic progress in the field.

In conclusion, these challenges—complex behavior modeling, data-intensive training, real-time processing, and immaturity of DTs—are at the forefront of the endeavors to advance the capabilities of soft robots. Addressing these challenges requires multidisciplinary collaboration, innovative research, and the development of cutting-edge technologies to unlock the full potential of SRs in various practical applications.

7. Conclusion

In this paper, we have reviewed the interaction between FEA, ML, and DTs and explored how their synergy drives advancements for soft robots. We examined the impact of ML and FEA on material discovery and property prediction, structural design optimization, inverse optimization of 4D printed soft robots, and development of metamaterials. Besides, we discussed the importance of ML in enhancing sensing, control, and actuation performance. In addition, we have also explored the role of DTs in enhancing real-time monitoring, predictive maintenance, and remote operation of soft robots. We can conclude that the integration of FEA, ML, and DTs is critical to shaping the future of soft robots and expanding their capabilities across various applications.

Data availability statement

All data that support the findings of this study are included within the article.

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