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A Systematic Review of Physical Artificial Intelligence (Physical AI): Concepts, Applications, Challenges, and Future Directions

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Abstract

Physical AI represents a significant evolution from digital AI , interacting directly with the physical world and mimicking human functions to a greater extent. PAI is a multidisciplinary field divided into Integrated PAI (IPAI) and Distributed Physical AI (DPAI). This systematic literature review analyzes the concept of PAIs, their implementation in various domains such as IoT, automotive, agriculture, healthcare, and logistics, and highlights their transformative potential. Nonetheless, PAIs face significant challenges such as general AI concerns (privacy, bias) and specific challenges (presence in unregulated spaces, information organization, social acceptance, Cannikin law). The integration of PAIs into Cyber-Physical Systems (CPS) also presents challenges related to uncertainty, limited resources, and adversarial attacks. PAIs are supported by advanced technologies from materials science, mechanical engineering, computer science, chemistry, and biology, including deep learning, multimodal processing, domain randomization, zero-shot learning, and large language objects (LLOs). This research provides comprehensive insights to drive the development of reliable and transformative PAIs in the future.

Keywords: *Physical Artificial Intelligence (PAI), Robotics, Cyber-Physical Systems (CPS), AI Applications, Challenges, Technologies*

1. Introduction

The main driver behind the emergence of innovation and social development in many industries is artificial intelligence. Initially, AI peaked through the initial idea of building a training machine from Wiliams neurons by MC Culloch and Pitts in 1943. However, the advent of computational hardware, such as GPU cards, which accelerated computational power in 2012, has transformed AI. Nevertheless, AI machine learning systems, like most industrial applications to date, remain single-purpose and data-driven in signal processing industries, entirely reliant on data from specialized sensors for results. Complex business rules and limitations in handling simple details in digital AI, which often function as a “black box” behind its success in solving problems, are reasons why researchers do not fully understand it. These limitations restrict most AI applications today to specific tasks, such as CNN in image and text classification, where CNN is effective, or RNN in machine translation and voice recognition, where it is also effective.[1]

In overcoming limitations and advancing the theoretical foundations of AI, researchers will propose combining digital AI with Physical AI to significantly advance the theoretical foundations of AI. Nature-inspired robots and intelligence-driven robots are multidisciplinary fields that integrate autonomous robots, materials, structures, and perception, referring to Physical AI. Software and hardware are required to balance Physical AI. It can be seen as an extension of the distributed computing continuum in the field of AI, which is necessary for continuous signal processing whose sources are distributed at the edge, fog, and Internet of Things (IoT). With this, Physical AI is expected to mimic the entire human body, not just the cognitive abilities of the brain, thereby greatly expanding the applications of AI across various academic and industrial fields.[1]

Various application domains for physical AI have been extensively explored. For infrastructure construction and maintenance, collaborative robots based on “open-source design” are proposed to adapt flexibly to diverse environments, such as disaster sites or lunar base construction. In the healthcare sector, AI-powered humanoid assistant robots could offer personalized services and enhance effectiveness for individuals with disabilities, while also reducing the workload of healthcare workers. In the manufacturing industry, the emergence of Physical AI through physical reservoir computing with monostable stochastic resonance units (MSRU) promises lower power consumption and comparable learning performance for handwriting recognition. A hybrid physical-AI approach is used for non-destructive diagnosis of aeroengine rotor blade connections, addressing the issue of labeled data scarcity by generating training data from randomly generated physical models and adapting them to real-world data. FireDrone is a thermal-agnostic aerial robot designed using super-insulation materials and a specialized cooling system for operation in extreme temperature environments, enhancing aerial robotics capabilities in hazardous situations. The emergence of large language objects (LLOs) can extend the capabilities of large language models into the physical world through generative interfaces and interactions, offering new ways to listen to music, tell stories, and play.[1]

In transforming various sectors, Physical AI has the potential to address socio-economic issues such as aging populations and natural disasters. This systematic literature review aims to comprehensively analyze the Physical AI landscape, identify current advances, and highlight areas for future research. To achieve this goal, this study will answer the following key questions:

1. How is Physical AI defined, categorized, and fundamentally distinguished from Digital Artificial Intelligence , and how is Physical AI implemented in various application domains?
2. What are the main challenges and essential supporting technologies in the development, implementation, and management of Physical AI systems in the real world?

2. Method

This research article presents a systematic literature review to identify and classify existing literature on the transformative potential of Physical AI in addressing socio-economic issues such as aging populations and natural disasters. In addition, this article aims to analyze topics that have potential for further research in the future. The rigorous selection of literature review as a methodology is based on two main reasons. First, it is a transparent, systematic, and replicable way to investigate, evaluate, and interpret the available literature [2]. Second, it is an appropriate approach to generating knowledge because synthesizing existing studies is sometimes more relevant and significant than conducting new research

The literature review approach in this study is based on five processes and analyzes the problem based on database selection, article selection, classification, and article analysis. This methodology has proven to be a reliable and applicable method in published literature review studies.

2.1. Time horizon for selection of papers

For the purposes of review and evaluation, the publication dates of journal articles cover the period from 2020 to 2025. Based on this, the review analysis covers a period of five years. The year 2025 marks the peak of physical AI potential.

2.2. Selection of databases

In this study, online databases were used as research tools to identify relevant articles or publications. The Scopus database was chosen as the main source for the literature review because of its consistent standards in indexing articles. Scopus is an indexing database linked to leading international journals. This search method has been widely recognized and used in previous literature reviews [3]. Ultimately, the decision to use the Scopus database was driven by its broad coverage and precise search capabilities [4].

2.3. Article selection

First, title, abstract, and keywords are determined as filtering criteria for searching articles in reputable international journals in online databases. Utilizing the search criteria TITLE-ABS-KEY ("Physical AI" OR "Physical Artificial Intelligence") on the title/abstract/keywords contained in the journal article in the online database mentioned above and included in the entire text. Then, every document from to 2025 was taken into account. Based on a total of 12 documents found. The presentation of the article selection process flow can be seen in Figure 1. Next, the abstracts were reviewed to assess the relevance of the documents related to Physical AI. In order to ensure consistent focus and reduce bias, articles that were deemed inappropriate were removed. In addition, to prevent double counting in our analysis, duplicate articles were removed[5]. In the filter menu, the type of article was selected to limit the findings to publications classified as articles, not conference papers. Based on the description, a total of 10 articles were analyzed and selected based on their original purpose and relevance.[6]

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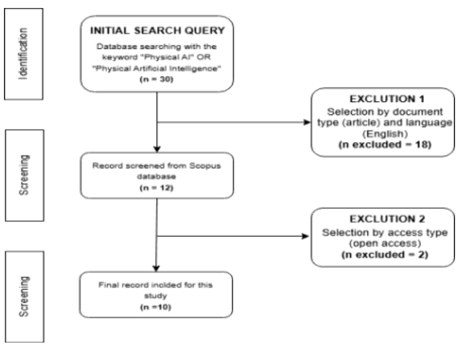

Fig. 1: Summary of article selection process

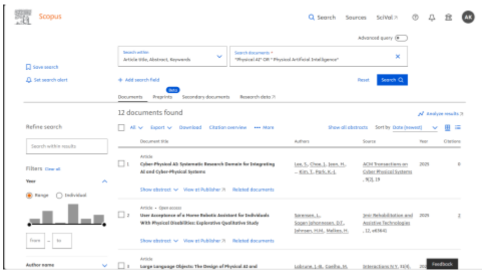

Fig. 2: Number of documents in the Scopus database

Based on Figure 2, the number of documents is shown in detail. Only a few research articles were considered for Physical AI, and the number of records was limited. Considering many previous research recommendations, we consider this topic to be important. The acceptance of literature review articles was carried out with the aim of ensuring high standards and accuracy of this manuscript. The next phase involved the classification of articles.

2.5. Article classifications

The final article consists of 10 journal articles, which were then analyzed in depth and categorized individually based on the characteristics described in the following section. The selected journal publications were reviewed, analyzed, and synthesized across various research domains. As mentioned earlier, a comprehensive review was conducted of previous works by various authors that have explored issues related to the potential of physical AI at the present time. More specifically, the classification process was guided by the 10 articles identified to identify physical AI in various sectors. Therefore, the findings of the current review shape the direction of future research. A brief summary of the important findings obtained from analyzing the 10 selected articles can be seen in Table 1.

Table 1: Key review of selected journal articles

Author	Review
[7]	• Method: Qualitative (observation + interview). • Data: 9 participants with physical disabilities (27-78 years old). • Focus: User acceptance of AI-based home assistant robots. • Findings: Robots were perceived as helpful for practical tasks, but not suitable for personal care; acceptance was influenced by social norms, perceived control, and privacy issues.
[5]	• Method: Descriptive-conceptual, design study at MIT. • Data: 4 Large Language Objects (LLO). • Focus: Design of natural language-based physical AI. • Findings: LLOs enable adaptive and personalized human-machine interaction, supporting collaborative creative processes between AI and humans.
[8]	• Method: Hybrid physical-AI (physical model + deep learning). • Data: Simulation + real data of aeroengine rotor. • Focus: Rotor bolt condition diagnosis without labeled fault data (zero-shot). • Findings: Model accuracy reached 94.27% with domain randomization and transfer learning; effective for real-time engine monitoring without disassembly.
[9]	• Methods: MATLAB/SIMULINK-based RC circuit simulation. • Data: STM benchmark, parity check, MNIST digit recognition. • Focus: Optimization of reservoir computing with high power efficiency. • Findings: MSRU reduces power consumption compared to BSRU, with learning performance remaining competitive.
[2]	• Methods: Descriptive study of a Japanese national project (Moonshot). • Data: Collaborative robot system for construction. • Focus: Adaptation of open design-based robots for extreme infrastructure environments. • Findings: Generating adaptive and collaborative robots through physical AI integration, suitable for solving labor and aging infrastructure problems.
[3]	• Methods: Experimental design and validation of Physical AI-based drones. • Data: Thermal-agnostic drone prototype with aerogel material. • Focus: Development of drones that can withstand extreme temperatures (hot/cold). • - Findings: Drone with polyimide aerogel structure and PCM cooling system proved to be capable of functioning in extreme environments; design inspired by natural thermoregulation mechanisms.
[10]	• Method: Hybrid physical-AI (dynamic model + unsupervised machine learning). • Data: Simulation and real tests on broken gear spur gears. • Focus: Estimation of gear damage severity without broken data training (zero-shot learning). • - Findings: A “traffic-light” approach to damage classification; able to accurately detect and classify damage severity using physics-based features and AI models.
[4]	• Methods: Systematic study of Cyber-Physical AI (CPAI) domains. • Data: Analysis of 104 studies on the integration of AI and CPS. • Focus: Developing a research framework for efficient and secure integration of AI in cyber-physical systems. • Findings: Developed a 3D classification scheme (Constraint-Purpose-Approach) and 9 key challenges in AI-CPS integration.
[1]	• Methods: Conceptual review and classification of PAI (Physical AI). • Data: Theoretical literature and early applications of PAIs. • Focus: Describing a new domain “Physical AI” that combines digital AI and physical AI. • Findings: PAI is divided into two: integrated and distributed PAI; high potential for development of physical sensor-based AI and sustainable edge computing.

[6]	• Methods: Quantitative (online survey, n=325), analysis with AMOS & SPSS PROCESS macros. • Data: Retail consumers in India, users of AI anthropomorphic assistants. • Focus: The role of product usage barriers, psychological distance, and trust on consumer-brand relationships. • - Findings: AI anthropomorphic assistants enhance brand relationships; trust amplifies this effect even in the presence of barriers or psychological distance.

2.6. Analysis of classification

In the final stage, the categorized journal articles underwent a rigorous process of appeal, distinction and assessment. To facilitate the organization and understanding of the findings of the available scientific materials, we directed our attention to making significant groupings of potential physical AI. Then, during critical examination and discussion, we identified potential areas for future work. It should be emphasized that this paper, being descriptive in nature, aims to assess and categorize the extant literature on physical AI. Therefore, statistical methods for categorizing articles were not used.

3. Result and Discussion

In this study, analysis of the distribution of theories used in the reviewed articles shows a clear dominance of Physical Artificial Intelligence (PAI), accounting for 36.4% of the total. This proportion indicates that most of the research or studies in the collection of articles focused on the physical implementation of artificial intelligence. Furthermore, Bioinspiration ranked second with a contribution of 27.3%, indicating that nature-inspired principles play an important role in many articles. Meanwhile, Reservoir Computing and Neural Networks & Machine Learning each accounted for 18.2% of the overall theory used. This similarity in percentage highlights the relevance of both fields, albeit with a more specific scope compared to PAIs and Bioinspiration. Cumulatively, this data exposes a diverse theoretical landscape in the articles analyzed, with PAIs and Bioinspiration as the main pillars shaping the research direction. as can be seen in Figure 3.

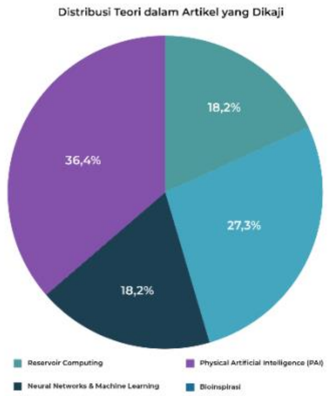

Fig. 3: literature review article theory distribution

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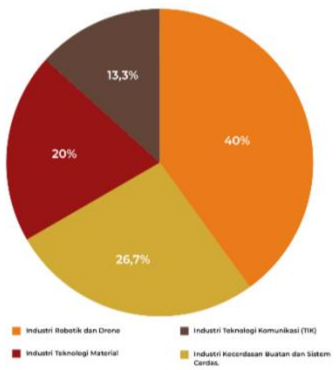

Fig. 4: literature review article theory distribution

This pie chart showing the "Distribution of Recent Investment Trends in Renewable Energy" presents a clear picture of capital allocation across the various sectors supporting renewable energy development. It can be seen that the Robotics and Drones Industry leads the way with the largest share of 40%, signaling that automation and unmanned technologies are increasingly vital in green energy innovation. Following close behind, the Artificial Intelligence and Intelligent Systems Industry accounted for 26.7% of the total investment, underscoring the importance of AI in optimizing the efficiency and management of renewable energy systems. Meanwhile, the Materials

Technology Industry took up 20% of the investment pie, showing a focus on the development of advanced materials to improve the performance and sustainability of these technologies. Finally, the Communication Technology (ICT) Industry, although with the smallest share of 13.3%, still plays an important role in providing connectivity infrastructure that supports the operation and monitoring of the renewable energy sector. Overall, these investment trends reflect a shift towards more automated, intelligent and innovative material-based solutions to drive renewable energy growth.

3.1. Conceptualization of PAI and its Difference from DIAI

Artificial Intelligence (AI) has undergone significant evolution from its primary focus on signal and data processing to a concept that is more integrated with the physical world. Digital AI (DIAI), as defined in the literature, refers to data-driven AI and data processing that is popular today. However, most DIAI applications are limited to specific tasks such as natural language processing (NLP), speech recognition, face detection, and image classification, and still face difficulties in handling trivial details and complex business rules. In addition, DIAI often functions as a poorly explained “black box”, prompting the emergence of the field of Explainable Artificial Intelligence (XAI).[4]

As a response to the limitations of DIAI, the concept of Physical AI (PAI) has been proposed, referring to robots inspired by nature and driven by intelligence. PAI is seen as a multidisciplinary field that integrates autonomous robots, materials, structures, and perception. PAI requires a balance between software (intelligent systems) and hardware (materials, mechanics, etc.). Unlike DIAI that mimics the brain's logical thinking ability, PAI seeks to mimic the entire human body, drastically expanding AI applications.[7]

The concept of PAI was expanded into two main sub-domains:

1. Integrated PAI (IPAI):Refers to systems that mimic individuals and integrate the perception of the physical world through various sensors (e.g., material sensors, temperature, vision, sound), induction of various indices, and physical responses in the physical world.Robots are a typical example of IPAI.
2. Distributed PAI (DPAI):Distributes perception, computation, and response modules across a wide space, similar to human society.Industrial IoT systems are a good illustration of DPAI.DPAI will grow in popularity as edge computing matures and every device is connected to the network.

The importance of PAI also lies in its role as an extension of the distributed computing continuum system in the field of AI, as PAI requires continuous signal processing from distributed sources at the edge, fog, and Internet of Things (IoT).

3.2. Application Domain Physical AI

The application of Physical AI (PAI) covers a wide range of industrial sectors and daily life, demonstrating its ability to directly interact with the physical environment and solve real-world problems.

- Internet of Things (IoT): IoT is a mixed application of cloud, sensors, software, and data analysis, which is a typical application domain for PAI. AI can be used to improve the stability of each IoT node, such as sensors or central data analysis and prediction. IoT nodes for sensing and control require support from various sciences and technologies, including materials, chemistry, mechanics, computer science, and even biology[1].
- Automotive: Self-driving cars can be thought of as a variant of intelligent robotic systems. Self-driving cars have the same essential features as regular robots: sensors, embedded computing modules, mechanical systems, new materials, and so on. These cars are often connected to the Internet for navigation, which gives them the features of a distributed system[8].
- Agriculture: Agriculture is one of the most successful application domains of PAI. Sensors, including cameras, temperature gauges, and hygrometers, are used to monitor the progress of crop growth and predict the best harvest time. Defect detection is also often performed to warn of potential risks that require intervention.
- Healthcare: PAIs have important applications in healthcare, especially for prevention. Biological and chemical sensors are used to monitor the elderly and patients to predict potential risks, such as falls or unstable situations. A central server will be notified by edge devices when a risk occurs, with computing taking place on both the edge side and the central server. AI-powered robotics in healthcare can offer precision and consistency in tasks, often beyond human capabilities. These systems also facilitate telemedicine, extending medical services to underserved areas. Individuals with disabilities are generally positive towards robotic assistance as it can increase independence and reduce the need for human caregivers, although there are some current drawbacks. Users are likely to accept robotic physical assistants if they can perform most tasks autonomously[10].
- Logistics: PAIs have been used extensively in various aspects of logistics. The “last mile” problem in parcel and food delivery, which is expensive and difficult, has been addressed with the use of delivery robots and drones to replace humans. Automated sorting robots have also been used in logistics sorting centers[7].
- Infrastructure Construction and Maintenance: The construction industry in Japan is facing socio-economic issues such as the COVID-19 pandemic, aging population, aging infrastructure, and severe natural disasters. Projects are using “collaborative robots for diverse environmental adaptation and infrastructure construction innovation” based on an “open design” approach to robotics. The goal is to develop robots that can respond to unexpected situations and perform tasks in hazardous environments, such as natural disaster recovery or lunar base construction, while addressing the issue of labor shortages due to an aging population[6].
- Manufacturing and Cyber-Physical Systems (CPS): PAI can contribute to fault diagnosis and severity estimation in manufacturing systems, such as gears. A hybrid physical-AI strategy is proposed for fault severity estimation of broken teeth in spur gears using zero-shot learning. The method involves dynamic modeling, experimental characterization, feature extraction, and unsupervised machine learning algorithms, overcoming the lack of labeled fault data by generating training datasets through randomized physical models and adapting them to real data. In addition, physical reservoir computing with a monostable stochastic resonance unit (MSRU) is proposed as a novel activation unit for RC systems to achieve lower power consumption and comparable learning performance, for example in MNIST handwriting recognition[1].
- Robotics in Extreme Environments: Thermal-agnostic aerial robots such as FireDrone have been developed to operate in extreme temperature environments such as fire disasters or polar regions. These drones utilize structural thermal insulation materials (polyimide aerogels) and phase change material cooling systems, inspired by natural thermal regulation principles. This approach enables the creation of a physiologically adaptive system, overcoming drone payload limitations for conventional thermal management systems.

- Human-AI Interaction and Large Language Objects (LLOs): PAI also evolved into the concept of large language objects (LLOs), which are physical artifacts that extend the capabilities of large language models (LLMs) to the physical world. LLOs serve as physical interfaces to LLMs, providing multimodal input, end effectors, user feedback, and most importantly, real-time world and context knowledge. LLOs can revise and challenge classical definitions of form and function, marking physical AI design as a new frontier for design. Examples of LLOs include generative board games (Memeopoly), puppet shadow storytelling devices (Narratron), language-based music navigation radios (VBox), and LLM-based prayer devices (AIncense). LLOs deliver more flexible and adaptive functionality, and interactions that can progressively evolve from simple to complex. The consumer-brand relationship with physical AI anthropomorphic assistants is also affected by product usage barriers, psychological distance, and trust.

3.3. Physical AI Challenge

The development and implementation of Physical AI (PAI) faces various challenges, both technical and non-technical, that require special attention to realize its full potential.

Although AI has advanced rapidly, there are some fundamental challenges that are also relevant to DIAI and PAI. Data security is crucial as AI models require large volumes of data, requiring hardware and software protection. Deepfake technology that can alter human faces in videos to look realistic raises social and legal issues, challenging the concept of “seeing is believing”. Social privacy aspects are also a major focus, as AI enables behavioral tracking and inference of a person's profile from online data, which has triggered bans on facial recognition in public spaces in many countries. In addition, AI training data often comes from web sources, which naturally contain societal biases, such as those found in hiring screening AI systems[1].

Physical AI faces more complex governance issues due to its highly complex and ubiquitous characteristics compared to DIAI. Key challenges include presence issues, where the installation of more extensive sensors in unregulated spaces can raise privacy and social concerns. Information organization issues arise from the high complexity of organizing different types and layers of data and information. Cannikin's law is a barrier as the development of PAIs relies on the simultaneous progress of five disciplines (materials science, mechanical engineering, chemistry, computer science and biology), where slower progress of one discipline can hinder the progress of the whole. Finally, social acceptance remains a concern as the ubiquitous application of Physical AI may raise societal concerns regarding unemployment and privacy[8].

Integrating AI into Cyber-Physical Systems (CPS) presents significant challenges due to the fundamental differences between the operational principles of AI and CPS. AI operates on the principle that "good things happen probabilistically," while CPS adheres to the principle that "bad things must not happen," requiring a strong awareness of uncertainty. Uncertainty in CPS can be categorized into model, data, network, and physical uncertainty. Even minor errors can have serious consequences, such as system failures or physical hazards, especially given the complexity of interactions among CPS components.

Moreover, AI often assumes that resources are always available and dedicated solely to AI tasks. In contrast, CPS treats resources as limited shared commodities. This creates a major challenge for CPS-AI integration, as mainstream AI research tends to prioritize accuracy over resource efficiency. The resources in question include computing power, networks, sensors, and human involvement.

AI also faces computational limitations due to complex model architectures and high processing demands, as well as network limitations due to large data volumes and real-time transmission constraints. Adversarial attacks, which involve manipulating input data to cause incorrect AI decisions, pose a serious threat to Physical AI (PAI), and can be considered a form of data drift. Other challenges include data-related issues such as data imbalance, data scarcity, and insufficient labeling, along with drift phenomena (i.e., changes in data distribution or input-output relationships over time). Furthermore, data loss caused by network or hardware failures and unreliable inference results are also major concerns.

3.4. Physical AI Supporting Technology

The development of Physical AI (PAI) is highly dependent on the convergence and advancement of various disciplines and technologies that support the interaction of AI with the physical world.

- Material Science and Mechanical Engineering: Materials play a crucial role in enabling Physical AI functions. For example, heat-resistant drones like FireDrone use super-insulating materials like polyimide aerogel to protect internal components from extreme temperatures. Polyimide aerogels have very low thermal conductivity and a high strength-weight ratio, making them ideal thermal insulators where space and weight are limited. Mechanical engineering also plays a role in the design of robots' mechanical structures and systems that enable movement and physical interaction.
- Computer Science and AI: Neural networks (NNs) and deep learning algorithms (such as CNN, RNN, and LSTM) are the foundation for the computational power of PAIs, enabling learning from sensory data and decision-making. PAIs utilize feature extraction, classification, and prediction to process data. Multimodal processing is essential for understanding information from various sensors (material, temperature, vision, sound) and making better decisions. To overcome the scarcity of labeled data, domain randomization is used to generate robust training datasets on the physical model, and transfer functions are applied to reduce the discrepancy between simulated and actual data. The zero-shot learning method enables fault diagnosis without training on real labeled fault data. In the context of physical reservoir computing, a monostable stochastic resonance unit (MSRU) has been proposed as an alternative to a bistable stochastic resonance unit (BSRU) for lower power consumption and comparable learning performance.
- Chemistry and Biology: These disciplines provide foundational inspiration and materials for Physical AI (PAI). Natural thermal regulation in animals such as penguins, spittlebugs, and Arctic foxes inspires the design of robots capable of withstanding extreme environments. Chemistry plays a crucial role in developing new materials with desired properties, while biology aids in understanding and mimicking the adaptive systems of living organisms[9].
- Hybrid Physical-AI Approach: The convergence of physical models and AI algorithms is becoming increasingly important. This hybrid approach combines in-depth understanding of physical phenomena from dynamic models with the learning capabilities of AI to improve the accuracy of diagnostics and predictions. For example, estimating the severity of gear faults can be enhanced through a combination of physical simulations and unsupervised learning. This approach also enables the use of synthetic data to train algorithms, which is particularly useful when labeled real-world data is scarce.

- Cyber-Physical Systems (CPS): PAI represents an interdisciplinary research domain in the integration of AI and CPS. Cyber-Physical AI (CPAI) addresses the challenges that arise during CPS-AI integration, with a focus on the constraints of uncertainty and resource limitations. CPAI aims to unify fragmented studies and provide guidance for reliable and resource-efficient AI integration as a component of CPS[4].
- Large Language Objects (LLOs): As a new class of artifacts, LLOs extend the capabilities of large language models (LLMs) into the physical world, serving as physical interfaces for LLMs. LLOs provide multimodal inputs and user feedback, and most importantly, real-time context and world knowledge. They challenge and revise classical definitions of form and function, marking physical AI design as a new frontier. This enables generative experiences where object behavior is designed on demand through user interaction, rather than being permanently encoded. Examples of LLOs include the generative board game Memeopoly, shadow puppet storytelling devices (Narratron), language-based music navigation radios (VBox), and LLM-powered prayer devices (AIncense). LLOs offer more flexible and adaptive functionality, and interactions that can progressively evolve from simple to complex. Consumer-brand relationships with anthropomorphic physical AI assistants are also influenced by product usability barriers, psychological distance, and trust[5].

4. Conclusion

This systematic literature review has outlined the rapidly evolving landscape of Physical Artificial Intelligence (PAI), highlighting its significance as the next evolution of Digital AI (DIAI). PAI, defined as intelligence that is nature-inspired and physically embodied, moves beyond pure signal and data processing to emulate human physical interaction with the world, thereby drastically expanding the application domain of AI. The conceptualization of PAI as a multidisciplinary system encompassing Integrated PAI (IPAI) and Distributed PAI (DPAI) demonstrates its capacity to operate both at the individual and societal levels by leveraging distributed computing continuum systems.

This study identifies various transformative application domains of PAI. PAI has shown tangible potential in enhancing the stability and functionality of IoT, revolutionizing agriculture, automating logistics, and improving autonomous vehicle operations. In the healthcare sector, AI-powered physical assistive robotics promise greater independence for individuals with disabilities and a reduced workload for healthcare providers—especially with high-autonomy solutions receiving positive user acceptance. PAI is also crucial in construction and infrastructure maintenance through adaptive collaborative robots. Furthermore, PAI paves the way for innovations in manufacturing, such as zero-shot fault diagnosis and low-power physical reservoir computing, as well as extreme-environment robotics like FireDrone, which utilizes super-insulating materials. The concept of Large Language Objects (LLOs) further expands AI interaction into the realm of physical generative experiences, challenging classical definitions of form and function.

Despite PAI's vast potential, this review also highlights significant challenges. PAI faces common AI issues such as data security, deepfakes, privacy, and bias, along with additional complexity due to operation in unregulated physical spaces, complex information organization, and the "Cannikin Law," which underscores the dependency on simultaneous advancements across multiple disciplines. Social acceptance remains a critical concern. The integration of PAI into Cyber-Physical Systems (CPS) poses major challenges related to uncertainty (model, data, network, physical) and resource constraints (computing, network, sensors, human). Issues such as adversarial attacks, data problems (imbalance, scarcity, insufficient labels, drift, loss), and unreliable inference also present significant barriers.

To address these challenges, PAI is supported by advanced technologies from various disciplines. Materials science and mechanical engineering contribute adaptive materials and robust robotic designs. Computer science and AI provide the foundation for deep learning algorithms, multimodal processing, domain randomization, transfer functions, and zero-shot learning. Chemistry and biology offer inspiration from natural systems and functional materials. The hybrid physical-AI approach, which integrates physical models with machine learning, has proven effective. Finally, the concept of LLOs demonstrates the synergy between LLMs and physical interaction, paving the way for richer generative experiences.

In conclusion, PAI is a transformative field with the promise of bridging the gap between the digital and physical worlds. By continuing focused research on existing challenges and leveraging multidisciplinary strengths, PAI holds immense potential to reshape the future of technology and human interaction.

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