Human–AI Collaborative Intelligence for Thermal-Fluid Systems from Numerical Simulation to Engineering Decision Support

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Abstract: Thermal-fluid engineering has traditionally relied on experimental investigations and numerical techniques such as the Finite Difference Method (FDM), Finite Element Method (FEM), Finite Volume Method (FVM), and Computational Fluid Dynamics (CFD) for the analysis of heat transfer and fluid flow phenomena. While these approaches provide physically consistent and reliable solutions, increasing system complexity and computational demands have motivated the integration of Artificial Intelligence (AI) technologies into engineering workflows. Recent advances in machine learning, deep learning, Physics-Informed Neural Networks (PINNs), Explainable Artificial Intelligence (XAI), and Digital Twins have significantly enhanced predictive capabilities, optimization efficiency, and real-time decision support. However, fully autonomous AI systems often face challenges related to interpretability, physical consistency, and engineering trustworthiness. This review examines the emerging paradigm of Human–AI collaborative intelligence for thermal-fluid systems, where human expertise and artificial intelligence operate synergistically to improve modeling, prediction, optimization, and engineering decision-making. The evolution of thermal-fluid modeling approaches, major computational frameworks, AI technologies, and representative engineering applications are comprehensively discussed. Furthermore, a Human–AI collaborative intelligence framework is presented to highlight the complementary roles of engineering knowledge and computational intelligence. Challenges associated with data availability, model reliability, explainability, Digital Twin integration, and human–AI interaction are critically analyzed, and future research opportunities are identified. The review demonstrates that Human–AI collaborative intelligence has the potential to establish a new generation of transparent, efficient, and trustworthy thermal-fluid engineering systems capable of supporting advanced industrial and scientific applications.

Keywords: *Human–AI Collaborative Intelligence; Thermal-Fluid Engineering; Computational Fluid Dynamics; Physics-Informed Neural Networks; Explainable Artificial Intelligence; Digital Twins; Machine Learning; Engineering Decision Support.*

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I. INTRODUCTION

Thermal-fluid systems constitute the backbone of numerous engineering applications, including heat exchangers, energy conversion systems, aerospace technologies, manufacturing processes, heating, ventilation and air-conditioning (HVAC) systems, microfluidic devices, and thermal management technologies. Accurate prediction of heat transfer and fluid flow behavior is essential for improving system performance, reliability, energy efficiency, and operational sustainability [1], [5]. Consequently, thermal-fluid engineering has witnessed continuous advancements in mathematical modeling, numerical simulation, and computational analysis over the past several decades.

The development of computational methods has significantly transformed the analysis of complex transport phenomena. Classical numerical techniques such as the Finite Difference Method (FDM), Finite Element Method (FEM), Finite Volume Method (FVM), and Computational Fluid Dynamics (CFD) have enabled detailed investigation of momentum transport, thermal behavior, turbulence, multiphase flows, and coupled multiphysics systems [5], [6]. These approaches have become indispensable tools for solving governing conservation equations and predicting engineering system performance. Recent investigations have further demonstrated the effectiveness of numerical simulations in analyzing magnetohydrodynamic flows, porous media transport, slip-flow phenomena, and nanofluid heat transfer applications [30]–[35].

Despite their predictive capability, conventional numerical simulations often require substantial computational resources, long execution times, mesh generation procedures, convergence analysis, and expert interpretation of results. The increasing complexity of modern engineering systems has therefore stimulated interest in intelligent computational techniques capable of accelerating simulations while preserving predictive accuracy [1], [6].

In recent years, Artificial Intelligence (AI) has emerged as a transformative technology in scientific computing and engineering analysis. Machine learning, deep learning, explainable artificial intelligence, and data-driven surrogate modeling techniques have demonstrated remarkable success in pattern recognition, prediction, optimization, and decision support across a wide range of engineering applications [1]–[4]. In thermal-fluid engineering, AI-driven methods have been employed for turbulence modeling, heat transfer prediction, flow reconstruction, fault diagnosis, performance optimization, and uncertainty quantification [2], [7], [8]. Furthermore, the development of Physics-Informed Neural Networks (PINNs) has established a new paradigm that integrates governing physical laws directly into machine learning frameworks, thereby improving physical consistency and reducing dependence on large training datasets [9]–[14].

Although AI-based approaches offer significant computational advantages, they are not intended to completely replace traditional engineering expertise. The successful development of thermal-fluid models continues to rely on human understanding of physical principles, governing equations, boundary conditions, numerical stability, validation procedures, and engineering constraints. In many practical situations, the interpretation of simulation outcomes and the selection of appropriate modeling strategies require substantial domain knowledge and engineering judgment. Consequently, the future of thermal-fluid engineering is increasingly expected to depend on collaborative intelligence, where human expertise and artificial intelligence operate synergistically rather than independently [15]–[18].

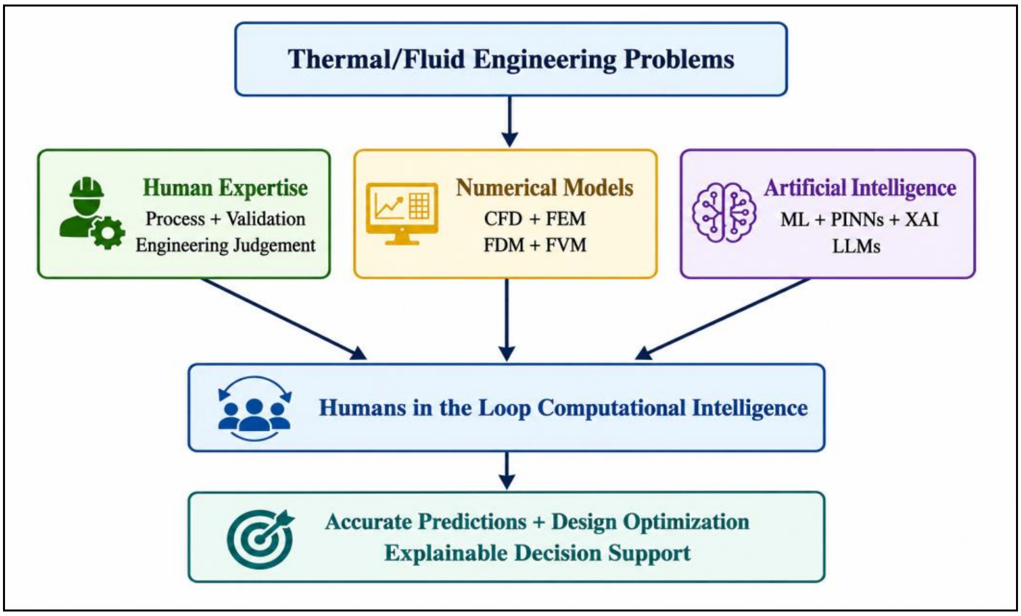

Fig 1 Human–AI Collaborative Intelligence for Thermal-Fluid Systems.

Figure 1 illustrates the proposed Human–AI collaborative intelligence paradigm in which human expertise, numerical modeling, and artificial intelligence collectively contribute to prediction, optimization, and engineering decision support within thermal-fluid systems.

The growing interest in explainable and trustworthy AI further reinforces the importance of human involvement in engineering decision-making. Explainable Artificial Intelligence (XAI) techniques provide transparency regarding model predictions, enabling engineers to understand the influence of governing parameters and establish confidence in AI-assisted solutions [19], [20]. Similarly, emerging technologies such as Digital Twins, human-in-the-loop learning systems, and engineering copilots highlight a transition from fully automated systems toward collaborative frameworks that combine computational intelligence with human oversight [21]–[25].

Despite substantial progress in both numerical modeling and artificial intelligence, existing studies predominantly focus on either conventional simulation methodologies or autonomous AI-driven prediction frameworks. Limited attention has been devoted to Human–AI Collaborative Intelligence paradigms that systematically integrate physical understanding, numerical simulations, artificial intelligence, explainability, and engineering decision support within a unified thermal-fluid framework. Furthermore, the role of collaborative intelligence in enhancing model reliability, interpretability, and practical engineering applicability remains insufficiently explored.

Motivated by these observations, this review investigates the emerging concept of Human–AI Collaborative Intelligence for thermal-fluid systems. The study aims to bridge the gap between traditional numerical modeling and

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modern artificial intelligence by examining how human expertise and computational intelligence can jointly contribute to modeling, prediction, optimization, and engineering decision-making. Figure 1 illustrates the proposed Human–AI collaborative intelligence framework that integrates human expertise, numerical modeling, and artificial intelligence for thermal-fluid applications.

The primary objectives of this review are: (i) to examine the computational foundations of thermal-fluid modeling; (ii) to analyze recent advances in machine learning, deep learning, explainable AI, and Physics-Informed Neural Networks; (iii) to propose a Human–AI collaborative intelligence framework for thermal-fluid systems; (iv) to discuss representative engineering applications; and (v) to identify key challenges and future research directions. By providing a comprehensive synthesis of these developments, the review seeks to establish a foundation for next-generation thermal-fluid systems characterized by intelligent prediction, explainable decision support, and effective collaboration between human expertise and artificial intelligence.

II. THERMAL-FLUID MODELING AND COMPUTATIONAL FOUNDATIONS

➢ *Governing Transport Equations*

The conservation of mass for incompressible flow is represented by the continuity equation.

$$\nabla \cdot V = 0 \qquad (1)$$

The momentum equation describing fluid motion is expressed as

$$\rho\left(\frac{\partial V}{\partial t} + \mathrm{V} \cdot \nabla \mathrm{V}\right) = -\nabla p + \mu \nabla^2 V + F \qquad (2)$$

The conservation of thermal energy is given by

$$\rho c_p\left(\frac{\partial T}{\partial t} + \mathrm{V} \cdot \nabla \mathrm{T}\right) = k \nabla^2 T + Q \qquad (3)$$

Where (ρ) denotes fluid density, (p) is pressure, (μ) represents dynamic viscosity, (c_p) is the specific heat capacity, (k) denotes thermal conductivity, and (Q) represents internal heat generation. To generalize transport phenomena, dimensionless variables are introduced as.

$$X = \frac{x}{L}, Y = \frac{y}{L}, U = \frac{u}{U_\infty}, V = \frac{v}{U_\infty} \qquad (4)$$

Several dimensionless parameters play a fundamental role in thermal-fluid analysis.

The Reynolds number is defined as

$$Re = \frac{\rho U L}{\mu} \qquad (5)$$

The Prandtl number is expressed as

$$Pr = \frac{\nu}{\alpha} \qquad (6)$$

The Nusselt number is given by

$$Nu = \frac{hL}{k} \qquad (7)$$

The Grashof number is defined as

$$Gr = \frac{g\beta(T_w - T_\infty)L^3}{\nu^2} \qquad (8)$$

The Richardson number is expressed as

$$Ri = \frac{Gr}{Re^2} \qquad (9)$$

These parameters characterize the relative significance of inertial, viscous, thermal diffusion, and buoyancy effects in thermal-fluid systems and are extensively employed in numerical and experimental investigations [26]–[29].

➢ *Computational Modelling Approaches*

The increasing complexity of thermal-fluid engineering problems has stimulated the development of advanced numerical methodologies capable of solving the governing transport equations efficiently.

- *Finite Difference Method*

The Finite Difference Method (FDM) approximates differential equations using finite difference expressions on structured computational grids. The method is simple to implement and computationally efficient for one-dimensional and boundary-layer transport problems [27].

- *Finite Element Method*

The Finite Element Method (FEM) subdivides the computational domain into discrete elements and employs weighted residual formulations to obtain approximate solutions. FEM provides excellent flexibility for handling complex geometries, coupled transport processes, and multiphysics systems. Recent investigations have successfully applied numerical techniques to magnetohydrodynamic flows, porous media transport, slip-flow systems, stretching surfaces, and inclined channel configurations [30]–[35].

- *Finite Volume Method*

The Finite Volume Method (FVM) is based on the conservation of fluxes across control volumes. Owing to its

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strong conservation properties, FVM forms the computational foundation of many commercial CFD platforms and is widely used in heat transfer and fluid flow simulations.

- *Computational Fluid Dynamics*

Computational Fluid Dynamics integrates numerical discretization methods with high-performance computing algorithms to solve complex transport phenomena. CFD enables detailed visualization of velocity fields, temperature distributions, pressure variations, and turbulence structures, making it one of the most powerful tools in modern thermal-fluid engineering [5], [6].

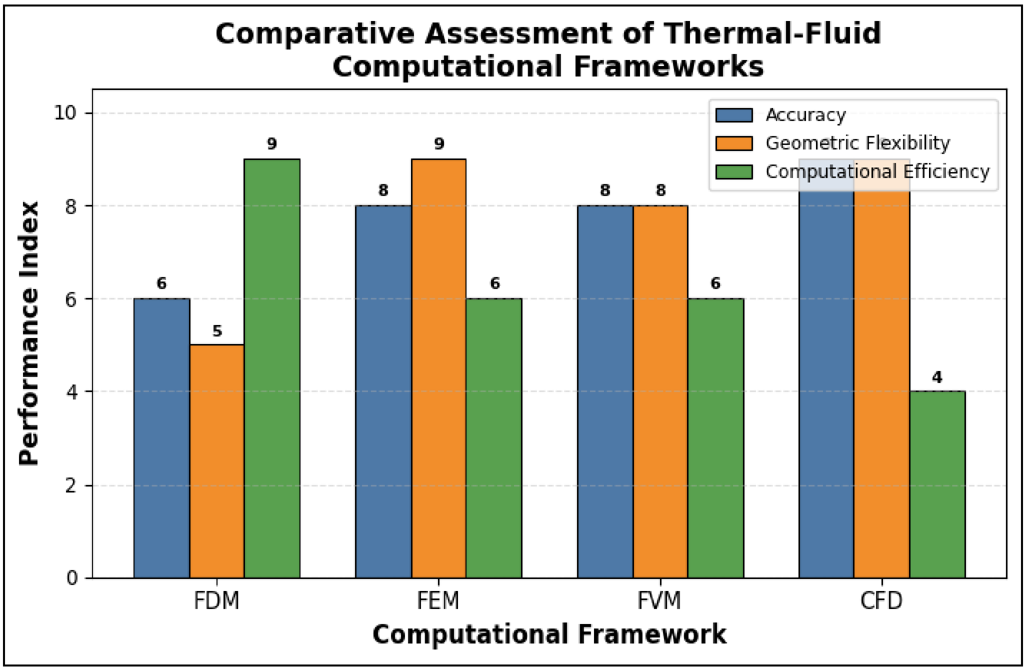

Fig 2 Comparison of Traditional Computational Frameworks for Thermal-Fluid Modeling.

As illustrated in Figure 2, CFD demonstrates the highest predictive capability for complex thermal-fluid systems, whereas FEM offers superior geometric flexibility for handling irregular domains and coupled multiphysics problems. FDM remains computationally efficient for structured computational grids, while FVM provides robust conservation characteristics for transport-dominated heat transfer and fluid flow simulations.

- *Limitations of Conventional Computational Frameworks*

Although conventional numerical methods have significantly advanced thermal-fluid engineering, several limitations remain. High-fidelity CFD simulations often require substantial computational resources, long execution times, mesh generation procedures, and expert intervention. Furthermore, model selection, boundary-condition specification, convergence assessment, and interpretation of results continue to depend heavily on engineering experience and physical understanding.

These limitations have motivated the integration of Artificial Intelligence techniques with conventional numerical simulations, leading to the emergence of Human–AI collaborative intelligence frameworks capable of improving prediction accuracy, computational efficiency, and engineering decision support.

III. HUMAN–AI COLLABORATIVE INTELLIGENCE FRAMEWORK FOR THERMAL-FLUID SYSTEMS

The growing complexity of thermal-fluid engineering problems has revealed the limitations of both purely physics-based numerical simulations and fully data-driven artificial intelligence models. Conventional computational approaches provide physically consistent solutions but often require significant computational resources and expert intervention. In contrast, artificial intelligence techniques offer rapid prediction and optimization capabilities but may lack interpretability and physical consistency. Consequently, a collaborative framework integrating human expertise and artificial intelligence has emerged as a promising paradigm for next-generation thermal-fluid systems.

Human expertise remains essential for defining governing assumptions, selecting numerical methodologies, specifying boundary conditions, validating simulation outcomes, and interpreting engineering results. Engineers contribute physical insight, domain knowledge, and practical experience that ensure model reliability and compliance with operational constraints [15]–[18]. Simultaneously, artificial intelligence techniques provide powerful capabilities for pattern recognition, surrogate modeling, optimization, uncertainty quantification, and real-time prediction [1]–[4].

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Recent advances in Physics-Informed Neural Networks (PINNs) have further strengthened the integration between physics-based modeling and machine learning by embedding governing equations directly into neural network architectures [9]–[14]. Similarly, explainable artificial intelligence techniques improve transparency and facilitate trust in AI-assisted engineering systems [19], [20].

The proposed Human–AI collaborative intelligence framework combines the complementary strengths of human expertise, numerical modeling, and artificial intelligence. Within this paradigm, engineers provide physical understanding, validation, and decision-making capabilities, while AI contributes rapid prediction, optimization, and knowledge extraction from complex datasets. The interaction between these components enables improved prediction accuracy, reduced computational cost, enhanced interpretability, and more reliable engineering decision support.

Figure 1 illustrates the proposed Human–AI collaborative intelligence framework for thermal-fluid systems. The framework establishes a human-in-the-loop environment where numerical simulations, artificial intelligence, and engineering expertise operate synergistically to address complex thermal-fluid challenges. Such collaborative intelligence is expected to play a central role in future Digital Twin platforms, smart thermal management systems, and autonomous engineering environments.

IV. ARTIFICIAL INTELLIGENCE TECHNOLOGIES FOR THERMAL-FLUID ENGINEERING

Artificial Intelligence has emerged as a transformative technology in thermal-fluid engineering by enabling data-driven prediction, optimization, and real-time decision support. Unlike conventional numerical simulations that require repeated solution of governing equations, AI models can learn complex relationships directly from data, significantly reducing computational time while maintaining acceptable predictive accuracy [1]–[4]. Consequently, AI techniques are increasingly being integrated with traditional computational frameworks to improve the efficiency and intelligence of thermal-fluid systems.

➢ *Machine Learning*

Machine Learning (ML) algorithms identify patterns and relationships within large datasets to develop predictive models without explicitly programmed governing equations. Supervised learning techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting models have been successfully employed for heat transfer prediction, fluid flow estimation, fault diagnosis, and performance optimization [1], [2].

In thermal-fluid engineering, ML models serve as surrogate models capable of replacing computationally expensive numerical simulations. Such models enable rapid estimation of engineering parameters and facilitate optimization studies involving large design spaces.

➢ *Deep Learning*

Deep Learning extends conventional machine learning by utilizing multi-layer neural network architectures capable of learning highly nonlinear relationships. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures have demonstrated significant potential in turbulence modeling, flow reconstruction, thermal image analysis, and spatio-temporal prediction problems [3], [7], [8].

The ability of deep learning models to extract hierarchical features from complex datasets makes them particularly attractive for high-dimensional thermal-fluid applications.

➢ *Physics-Informed Neural Networks*

Physics-Informed Neural Networks (PINNs) represent one of the most significant developments in scientific machine learning. Unlike conventional neural networks, PINNs incorporate governing differential equations directly into the training process, thereby ensuring physical consistency and reducing dependency on large datasets [9]–[14].

Recent investigations have demonstrated the successful application of PINNs to heat transfer, boundary-layer flow, magnetohydrodynamic transport, reactive nanofluids, and coupled multiphysics systems [9]–[14], [34]. Furthermore, PINNs offer considerable potential for developing Digital Twin environments capable of real-time prediction and adaptive learning.

➢ *Explainable Artificial Intelligence*

Although AI models provide powerful predictive capabilities, their adoption in engineering applications requires transparency and trustworthiness. Explainable Artificial Intelligence (XAI) techniques aim to interpret model behavior and quantify the influence of input parameters on prediction outcomes [19], [20].

Methods such as SHAP, LIME, feature importance analysis, and sensitivity assessment enable engineers to understand model decisions and establish confidence in AI-assisted solutions. Consequently, XAI serves as a critical component of Human–AI collaborative intelligence frameworks.

➢ *Digital Twins and Engineering Copilots*

The convergence of AI, numerical simulations, and sensor technologies has accelerated the development of Digital Twins—virtual representations of physical systems capable of real-time synchronization and predictive analysis [21]–[25]. Digital Twins continuously integrate operational data, numerical simulations, and AI models to support monitoring, optimization, and decision-making.

More recently, Large Language Models (LLMs) and engineering copilots have emerged as intelligent assistants capable of supporting engineers during model development,

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data interpretation, and technical decision-making processes. Such technologies are expected to play an increasingly important role in future Human–AI collaborative environments.

V. APPLICATIONS OF HUMAN–AI COLLABORATIVE INTELLIGENCE IN THERMAL-FLUID ENGINEERING

The integration of artificial intelligence, numerical simulations, and engineering expertise is transforming thermal-fluid engineering across multiple application domains. Human–AI collaborative intelligence enables faster prediction, improved optimization, enhanced interpretability, and more reliable engineering decision-making compared with conventional computational approaches. As a result, collaborative intelligence frameworks are increasingly being adopted in energy systems, heat exchangers, manufacturing processes, HVAC technologies, microfluidics, and Digital Twin environments.

Figure 3 illustrates the progressive evolution of thermal-fluid engineering from traditional experimental investigations toward Human–AI collaborative systems. The convergence of numerical simulations, machine learning, physics-informed learning, and Digital Twin technologies is accelerating the development of intelligent engineering platforms capable of real-time prediction and decision support.

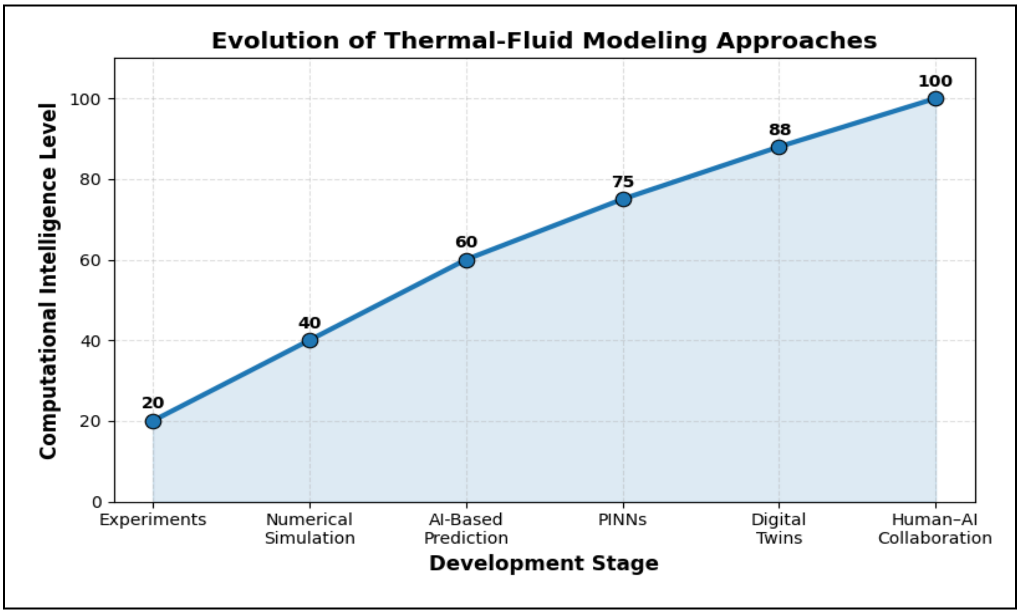

Fig 3 Evolution of Computational Intelligence in Thermal-Fluid Engineering from Conventional Experiments to Human–AI Collaborative Systems.

- *Energy Systems*

Energy systems represent one of the most important application areas of Human–AI collaborative intelligence. Machine learning models can rapidly predict thermal performance, optimize operating conditions, and improve energy efficiency, while engineers provide physical interpretation and operational guidance. Collaborative frameworks have demonstrated significant potential in power plants, renewable energy systems, thermal storage technologies, and energy management platforms. Similar surrogate-modeling strategies have recently been explored in MHD heat transfer and nanofluid transport problems, demonstrating significant reductions in computational cost while maintaining predictive accuracy [30]–[36].

- *Heat Exchangers and Thermal Management*

Heat exchangers are critical components in industrial and energy applications. Human–AI collaboration facilitates rapid estimation of heat transfer coefficients, pressure drops, and thermal effectiveness using surrogate models trained on numerical and experimental data. Engineers can subsequently validate AI-generated predictions and ensure compliance with operational constraints. Such approaches significantly reduce computational effort while maintaining engineering reliability. Recent thermal-fluid investigations involving slip flow, porous media transport, radiative heat transfer, and two-phase systems further highlight the suitability of AI-assisted modeling frameworks for engineering optimization [31]–[35].

- *HVAC and Smart Buildings*

The integration of AI with HVAC systems enables intelligent control, predictive maintenance, occupancy-based optimization, and energy-efficient operation. Human expertise remains essential for interpreting system behavior and establishing operational strategies. Consequently, Human–AI collaborative intelligence provides a practical pathway toward smart and sustainable building management.

- *Digital Twins and Smart Manufacturing*

Digital Twins represent one of the most promising applications of collaborative intelligence. By integrating sensor data, numerical simulations, and AI models, Digital Twins provide virtual representations of physical systems capable of real-time monitoring and predictive analysis. Human operators can interact with these systems to validate recommendations, assess risks, and support engineering

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decisions. Such capabilities are increasingly being adopted in manufacturing, aerospace, automotive, and process industries.

➢ *Emerging Application Opportunities*

The growing adoption of explainable AI, Physics-Informed Neural Networks, and engineering copilots is creating new opportunities for Human–AI collaborative intelligence. Future systems are expected to combine real-time sensing, adaptive learning, uncertainty quantification, and human expertise within unified computational environments.

Table 1 summarizes the major AI technologies employed in thermal-fluid engineering and their corresponding advantages and limitations.

Table 1 Comparison of AI Technologies for Thermal-Fluid Engineering Applications.

Technology	Major Strength	Limitation	Representative Applications
Machine Learning	Fast prediction	Data dependency	Heat transfer prediction, optimization
Deep Learning	Nonlinear learning capability	Large training datasets	Turbulence modeling, flow reconstruction
PINNs	Physical consistency	High training complexity	PDE-based thermal-fluid systems
Explainable AI	Model interpretability	Additional computational effort	Engineering decision support
Digital Twins	Real-time monitoring and optimization	Infrastructure requirements	Smart manufacturing and energy systems

As summarized in Table 1, each AI technology offers unique advantages for thermal-fluid engineering. However, none can independently replace engineering expertise. Therefore, Human–AI collaborative intelligence provides a balanced framework that combines physical understanding, computational efficiency, and intelligent decision support for complex engineering applications.

VI. CHALLENGES AND FUTURE DIRECTIONS

Despite significant advancements in artificial intelligence, Digital Twins, and scientific machine learning, several challenges continue to limit the widespread adoption of Human–AI collaborative intelligence in thermal-fluid engineering. Addressing these challenges is essential for developing reliable, trustworthy, and scalable engineering systems capable of supporting future industrial applications.

➢ *Data Availability and Quality*

The performance of AI models depends heavily on the availability of high-quality datasets. In thermal-fluid engineering, experimental data are often expensive, time-consuming, and difficult to obtain. Furthermore, inconsistencies in measurement techniques, operating conditions, and data preprocessing procedures may adversely affect model reliability and generalizability. Future research should focus on standardized datasets, benchmark repositories, and hybrid data-generation strategies combining experiments, numerical simulations, and synthetic data.

➢ *Physical Consistency and Generalization*

Although machine learning and deep learning models demonstrate strong predictive capabilities, they may generate physically unrealistic predictions when operating beyond their training domain. Physics-Informed Neural Networks have partially addressed this limitation by incorporating governing equations into the learning process; however, challenges related to convergence, scalability, and computational efficiency remain. Future developments should emphasize physically consistent AI models capable of robust generalization across diverse thermal-fluid applications. The importance of physical consistency becomes particularly evident in thermal-fluid systems involving coupled transport phenomena, slip effects, porous media, and reactive nanofluids, where purely data-driven models may fail to capture governing physics adequately [30]–[36].

➢ *Explainability and Trustworthiness*

Engineering applications require transparent and interpretable decision-making processes. Black-box AI models often create difficulties in understanding the rationale behind predictions and optimization recommendations. Explainable Artificial Intelligence techniques such as SHAP, feature importance analysis, and sensitivity assessment have improved model transparency; however, additional research is required to establish trustworthy Human–AI collaborative environments suitable for critical engineering applications.

➢ *Real-Time Digital Twin Integration*

Digital Twins require continuous synchronization between physical systems and virtual models. Achieving real-time prediction, adaptive learning, and dynamic model updating remains a challenging task, particularly for complex multiphysics systems involving large computational requirements. Advances in edge computing, cloud-based simulation platforms, and reduced-order modeling techniques are expected to facilitate more effective Digital Twin deployment.

➢ *Human–AI Interaction and Engineering Copilots*

The future success of collaborative intelligence depends on effective interaction between engineers and AI systems. Human operators must be able to understand, validate, and modify AI-generated recommendations. Emerging engineering copilots powered by large language models and scientific AI technologies may significantly improve communication between human expertise and computational intelligence. Consequently, future research should focus on developing interactive, transparent, and user-centric engineering support systems.

Table 2 summarizes the major challenges and future research opportunities associated with Human–AI collaborative intelligence in thermal-fluid engineering.

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Table 2 Future Research Opportunities for Human–AI Collaborative Intelligence in Thermal-Fluid Engineering.

Research Area	Current Challenge	Future Opportunity
Machine Learning	Data dependency	Hybrid physics-data models
PINNs	Training complexity	Real-time scientific AI
Explainable AI	Limited interpretability	Trustworthy engineering systems
Digital Twins	Synchronization challenges	Autonomous predictive platforms
Engineering Copilots	Early-stage development	Intelligent engineering assistants
Human–AI Collaboration	Limited integration frameworks	Standard engineering workflow

As summarized in Table 2, future developments are expected to focus on physically consistent AI models, explainable decision-support systems, adaptive Digital Twins, and intelligent engineering copilots. The convergence of these technologies will ultimately enable Human–AI collaborative intelligence to become a standard paradigm for next-generation thermal-fluid engineering systems.

VII. CONCLUSION

Human–AI collaborative intelligence represents a significant paradigm shift in thermal-fluid engineering by combining the complementary strengths of human expertise, numerical simulations, and artificial intelligence. Traditional computational approaches such as FDM, FEM, FVM, and CFD continue to provide physically consistent and reliable solutions for complex heat transfer and fluid flow problems. However, increasing computational demands and the need for real-time prediction have accelerated the integration of machine learning, deep learning, Physics-Informed Neural Networks, explainable artificial intelligence, and Digital Twin technologies into engineering workflows.

This review examined the evolution of thermal-fluid modeling from conventional experimental and numerical approaches toward intelligent Human–AI collaborative systems. The fundamental principles of thermal-fluid modeling, major computational frameworks, emerging artificial intelligence technologies, and representative engineering applications were discussed. Furthermore, a Human–AI collaborative intelligence framework was presented to demonstrate how engineering expertise and computational intelligence can operate synergistically to improve prediction accuracy, computational efficiency, interpretability, and engineering decision-making.

The analysis revealed that while artificial intelligence offers substantial advantages in surrogate modeling, optimization, and real-time prediction, human expertise remains essential for physical interpretation, model validation, uncertainty assessment, and strategic decision-making. Consequently, the future of thermal-fluid engineering is unlikely to be characterized by fully autonomous AI systems; rather, it will be driven by collaborative environments in which human intelligence and artificial intelligence complement one another.

Future research should focus on the development of physically consistent AI models, trustworthy explainable systems, adaptive Digital Twins, and intelligent engineering copilots capable of supporting complex thermal-fluid applications. The convergence of these technologies is expected to establish Human–AI collaborative intelligence as a foundational component of next-generation thermal-fluid engineering systems, enabling more efficient, transparent, and sustainable engineering solutions.

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