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Review Article

Computational physiology and systems modeling in understanding human systems with artificial intelligence: Opportunities and challenges

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Abstract

Mechanistic inference and data-driven discovery are complementary strengths that come with converging forces of artificial intelligence and computational physiology in the quantitative study of human systems. Predictive modeling and simulation, through a combination of principled, biophysically informed models with machine-learning pipelines, allows high-fidelity reconstruction of physiological dynamics at molecular, cellular, organ and systemic scales; this convergence enables mechanistic hypothesis testing, virtual cohort experiments and accelerated parameter estimation challenging to each individually. Used in modern health care systems, such hybrid systems improve diagnostic sensitivity based on learned biomarkers, make it possible to plan therapy individually based on patient-specific virtual physiological models, and form the basis of large-scale monitoring and early warning by combining continuous sensor streams with electronic health records. The opportunities are high: better precision medicine, accelerated translational research by in-silico trials, more efficient allocation of resources, and more economical care delivery. However, significant issues remain, including data reliability (heterogeneity, missingness, and bias), important ethical issues (privacy, informed consent, fairness, and accountability) and low interpretability and provenance of AI-based predictions that impede clinical trust and regulatory acceptance. To achieve the full potential of this interdisciplinary paradigm, a tight standard of validation, clear reporting, data infrastructures that are interoperable and governance structures that reflect, closely align technological innovation with clinical, legal, and societal anticipations will be required.

Keywords: Artificial Intelligence (AI), Computational Physiology, Predictive Modeling, Digital Twins, Precision Medicine

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1. Introduction

The last 20 years have seen a frenzy of biomedical research propelled by the application of enhanced computational methods. Among them, artificial intelligence (AI) and computational physiology have become complementary frameworks to understand the structure, functional and dynamics of human biological systems. In its broad use, AI can be defined as computation techniques that can replicate the tasks traditionally done by human intelligence, i.e. pattern recognition, prediction, and decision-making. In biomedical science, AI includes the following separate yet interconnected paradigms machine learning (ML), which learns patterns and statistical correlations using complex data; deep learning (DL), which learns hierarchical feature extraction using multi-layered neural networks; and symbolic AI, which learns explicit rules of logic to be interpretable and reasoning-capable. Computational physiology by contrast deals with mechanistic, biophysically plausible models that model physiological processes at scales ranging down to ion channel kinetics and cellular signaling, and up to tissue level hemodynamics and the whole-organ behavior. A combination of these strategies forms the new paradigm of predictive modeling, which is herein described as a mix of empirical data and mechanistic theory that can be used to predict physiological states, disease progression, and therapeutic outcome.[1,2]

Computational and predictive models are important because they have the ability to solve the complexity of human physiology. Biological mechanisms are non-linear, adaptive and hierarchical and cannot be reduced merely

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through reductionist analysis. Models based solely on data, though able to provide high-dimensional predictive power, typically cannot be interpreted and do not generalize on other tasks or settings, outside the training environment. On the other hand, mechanistic models based on biophysical laws can be explanatory but they are constrained by the uncertainty of their parameters, the high costs of such computations, and biological pathway incompleteness. A balanced solution to this problem can be achieved with an integrated method, which integrates AI-based inference with computational physiology: the predictive power of the data-driven models can be used, and the explanatory validity of mechanistic models can be preserved. This hybrid paradigm offers a route to the understanding emergent behaviors in complicated human systems, not only to the generation of hypotheses but also clinical translation.

There are a number of clinical domains that demonstrate the transformational possibility of this integration.[3] Patient-guided cardiac models based on ML algorithms have been applied in cardiovascular medicine to forecast the risk of arrhythmia, optimize ablation therapy, or better management of heart failure. AI-improved network models are used in neuroscience to gain new understanding about the spreading of epileptic seizures and refine surgical plans. In metabolic diseases, hybrid modeling systems enable early warning of a dysregulated glucose dynamics, personalized insulin dosing, and the discovery of new treatment targets. In addition to these applications, integrative modeling is core to the creation of digital twins- virtual models of single patients, which continuously update themselves with live clinical data to model disease pathways and determine the best methods of treatment. Such developments can be seen to focus on both the scientific and translational usefulness of integrating AI with computational physiology, especially in precision medicine.[4]

This review is aimed at critically reviewing the intersection of AI and computational physiology to improve biomedical science. In particular, the review has four objectives. First, it provides a survey of conceptual and methodological underpinnings, providing the reader with a systematic overview of the way machine learning, deep learning, symbolic AI and mechanistic modeling are used in human physiology. Second, it summarizes representative case studies of cardiovascular, neurological, and metabolic to underscore the opportunities and the existing limitations. Third, it assesses the difficulty of the integration process such as data heterogeneity, model interpretability, population-wide validation, and ethics. Lastly, it presents suggestions on the future directions of research which should include standardized frameworks, explainable models, and clinically tested applications that can be transformed into real-life practice.[5]

These purposes are reflected in the organization of the article. Part I gives a conceptual summary of AI paradigms and mechanistic modeling methods in physiology. Section II reports about methodological mechanisms to combine data-driven and biophysical frameworks, such as hybrid models, multimodal data assimilation. In Section III, we provide clinical case studies in each of the major organ systems, demonstrating translational use and clinical effect. Section IV assesses challenges, including computational scalability, regulatory frameworks and equity of access. The final part is a conclusion that summarizes findings and provides directions with regards to research focus in the upcoming period of the innovation. Operationally, core concepts of several models and techniques are provided in **Table 1**table 1.[6]

Table 1: Operational definitions of core concepts in the review[3-7]

Term	**Definition**	**Relevance to human-system modeling**
Artificial Intelligence (AI)	Broad field of computer science focused on replicating intelligent behavior in machines. Includes ML, DL, and symbolic reasoning approaches.	Enables pattern recognition, predictive analytics, and decision support in biomedical systems.
Machine Learning (ML)	Data-driven algorithms that learn associations or predictive rules from large datasets.	Supports classification, risk stratification, and outcome prediction in clinical physiology.
Deep Learning (DL)	Subset of ML using multi-layered neural networks capable of capturing non-linear and hierarchical features.	Powers image analysis, signal interpretation, and multi-scale physiological modeling.
Computational Physiology	Use of mechanistic, mathematical, and biophysical models to simulate human systems across scales (molecular to systemic).	Provides interpretability and mechanistic understanding of biological processes.
Predictive Modeling	Use of statistical, AI-based, or mechanistic models to forecast disease progression or treatment outcomes.	Forms the bridge between theoretical models and clinical decision-making.

The intersection of AI and computational physiology is a strategic junction to learn more about human systems, bridge the divide between basic science and clinical practice, and shift in the direction of predictive, personalized, and preventative healthcare. This review aims to equip researchers, clinicians and biomedical engineers with the perspective needed to effectively and responsibly utilize these technologies by offering a systematic synthesis of methods, applications and challenges.[7]

2. Foundations of Computational Physiology

2.1. Historical background

Computational physiology is a subfield of systems biology and mathematical physiology that began to develop as a natural development of attempts to formalize biological processes in quantitative frameworks in the late 20thcentury. This was first rigorously biophysically modeled by Hodgkin and Huxley (1952) studying the ionic basis of neuronal action potentials and by Noble (1960s) studying cardiac electrophysiology, which became a paradigm of mechanistic simulation. These models showed that biological complexity was decomposable into mathematical equations that are able to reproduce emergent physiological behavior. A later development in the 1990s with the emergence of systems biology broadened this view to include the networks of interacting pathways, facilitated by the increase in computational capability and by the high-throughput data. Gradually, computational physiology became a field between reductionist experimentation and integrative modeling, and the scope of its applications was broadened, to include, e.g. the kinetics of single-ion channel systems, or virtual human models.[8]

2.2. Key models of physiological systems

Simulation of human systems has focused on three key areas, cardiovascular, neurological and metabolic physiology.

1. Models of cardiovascular: Multi-scale models of the heart, including the Luo-Rudy model and subsequently the Ten Tusscher-Panfilov model, have grown to become the standard models of cardiovascular simulation: action potentials, conduction, and arrhythmogenesis. Computational fluid dynamics (CFD) blood flow models, which are coupled with electromechanical simulations, can be used at the whole-organ level to reconstruct ventricular dynamics and hemodynamic responses.[9]

2. Neurological models: The Hodgkin-Huxley framework motivated a series of models of single-neuron excitability (FitzHugh-Nagumo, Morris-Lecar) to whole-brain neural networks. The present-day attempts include the Blue Brain Project, which uses the comprehensive biophysical modeling of cortical loops to recreate cognitive and pathological conditions. Network-level models further enable investigation of epilepsy, Parkinson's disease, and functional connectivity in resting-state brain networks.[10]

3. Metabolic models: Simulation of whole-body metabolism was induced by classical compartmental models (e.g. the minimal model of glucose-insulin dynamics by Bergman). Higher complexity systems biology frameworks, such as constraint-based modeling of metabolic fluxes and genome-scale metabolic reconstructions, have now modeled dynamic control of energy balance, glycemic regulation and endocrine interactions. These models, molecular, cellular, tissue and organ, make up a toolkit to study physiological processes in health and disease.[11]

2.3. Role of predictive modeling

Predictive modeling is the cohesive concept in any computational physiology since it allows models to not only recreate observed phenomena, but also predict responses of a system to untested conditions. Predictive models of arrhythmia in cardiovascular systems predict the onset of arrhythmias, steer ablation therapy, and refine pacing therapy. In neuroscience, they model the spread of a seizure, predict the results of cortical stimulation and offer virtual testbeds to neuroprosthetics. Predictive frameworks are used in metabolic systems to predict glycemic excursions, to optimise insulin dosing schedules, and to investigate the disease progression of diabetes and obesity. Notably, predictive modeling is more efficient in hypothesis generation, and the researchers have an opportunity to test virtual experiments, which are impossible or unethical in practice. Combined with real-world data and AI-based inferences, such models form the basis of the creation of digital twins, individualized virtual copies of the patient that recalibrate to clinical data streams.[12] Competencies in computational physiology started with decades of development of mechanistic models of many organ systems, and systems biology and high-performance computing enriched these models over time. The main contribution of predictive modeling is that it allows one to convert the mechanistic descriptions of the central phenomena to the dynamic, anticipatory ones, which can be viewed as a middle ground between experimental discovery and clinical translation.[13]

3. Artificial Intelligence in Biomedical Systems

3.1. Machine learning and deep learning applications in physiology

Machine learning (ML) and deep learning (DL) are forms of artificial intelligence (AI), which have become an essential part of recent biomedical studies, allowing the identification of the nonlinear patterns of physiological data. Unsupervised clustering algorithms as well as supervised algorithms (e.g. support vector machines, random forests) have been used on various types of physiological data, such as electrocardiograms (ECG) and electroencephalograms (EEG), and continuous glucose monitoring data. These techniques enable the early identification of arrhythmias, classification of the types of seizures, and forecasting of glycemic swings, respectively.[14] Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are found in DL architectures and are capable of automatically learning hierarchical features on raw data. CNNs are more successful in ECG classification and cardiac imaging analysis than conventional methods, and long short-term memory (LSTM) networks yield temporality in continuous physiological signals. Together, ML and DL enable a more accurate prediction and reveal some hidden physiological signatures that might not be available with traditional statistical techniques.[15]

3.2. AI-Based image analysis, diagnostics, and decision support

The field of medical image analysis is one field that has been particularly effective in the application of AI with DL models demonstrating expert level performance on the detection of subtle morphological features. CNN-based algorithms are used to identify coronary artery stenosis in cardiovascular imaging and to measure ventricular function in a high-fidel way. AI-based image segmentation in neurology assists in defining brain tumors, locating points of seizures, and drawing functional networks based on MRI and fMRI images. Likewise, with metabolic disorders, automated retinal image analysis helps to detect diabetic retinopathy early. Outside image interpretation, AI is also found in clinical decision-support systems (CDSS), and it combines multimodal patient data (e.g. genomics, imaging and physiological recordings) with AI to generate personalized risk estimates and treatment prescriptions. Such systems have proved useful in triage, diagnosis and optimized treatment, and may represent a way forward toward precision and evidence-based medicine.[16]

3.3. Role of AI in multi-scale modeling of human physiology

Though AI is highly efficient in data-driven inference, its combination with multi-scale mechanistic models is a crucial move in computational physiology. Multi-scale models represent molecular and cellular dynamics interactions up to tissue and organ scales, but are generally subject to parameter uncertainty and are computationally intensive. The solutions are given by AI based on parameter estimation, surrogate modeling, and dimensionality reduction. As an example, ML models capable of calibrating electrophysiological models of cardiac tissue have been trained on patient-specific ECG data, where DL-based emulators can make predictions in near-real time after large-scale simulations. Hybrid models, where AI supplements mechanistic simulations, have been used to model seizure behavior, to discover insulin-glucose control protocols and personalize heart failure treatment. Besides, the intersection of AI and multi-scale modeling forms the basis of the digital twin's concept--computerized patient-specific simulations that constantly change as new information is incorporated into them. The paradigm has potential in predictive diagnostics, adaptive therapy design and in silico clinical trials, developing new links between fundamental physiology and clinical practice.[17] The field of biomedical systems research has been transformed by AI with increased predictive power, more accurate diagnostic accuracy, and dynamic interactions with mechanistic models. Its contribution to multi-scale modeling indicates a paradigm shift to individual, data-driven, and physiology-guided healthcare.[18]

4. Integration of AI and Computational Physiology

4.1. Synergistic frameworks combining ai algorithms with physiological models

The AI-based inference and a mechanistic physiological model is a paradigm shift in biomedical research. Modern computational physiology uses biophysically plausible models, but they tend to be limited by missing parameters and high computational expenses. On the other hand, absolute data-driven AI methods are predictive but often not interpretable. Synergistic frameworks are designed to combine these methods: AI algorithms are used to perform parameter estimation, reduce the model and quantify uncertainty, and mechanistic models are used to give structure, biological plausibility, and causal interpretability. Such applications as the use of ML to calibrate cardiac electrophysiology models, reinforcement learning to optimize closed-loop insulin delivery systems, and DL-based surrogates to simulate computationally expensive simulations. These hybrid systems allow predict, validate and refine cycles, and the accuracy and explanatory depth improves. **Figure 1** provided conceptual Framework of AI-Computational Physiology Integration.[19]

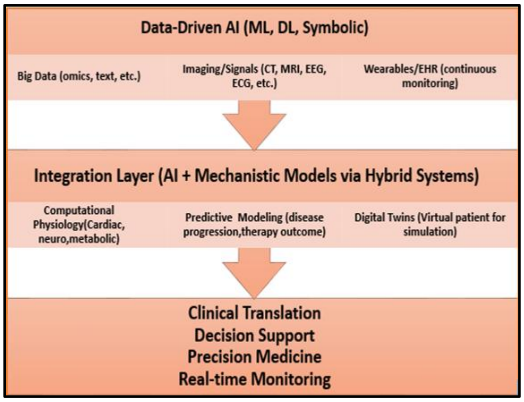

Figure 1: Conceptual framework for AI–Computational physiology integration[19-22]

4.2. Benefits for real-Time monitoring and precision medicine

The integration of AI and computational physiology offers distinct advantages for real-time monitoring and precision medicine. AI allows quick integration of on-going information streams of wearable sensors, electronic health records and imaging solutions whereas physiological models place this data in a mechanistic framework. This synergy enables the development of digital twins, a virtual patient avatar, which dynamically adjusts to current physiological conditions. Such systems real-time are able to anticipate the negative occurrences like arrhythmias, seizures, or hypoglycemic events to make early interventions. At the population level, these hybrid models improve simulations of clinical trials, decrease the use of animal trials, and fasten drug discovery. On an individual scale, they enable precision medicine to customize treatment plans to individual physiological and genetic profiles. In the end, this integration fills the gap between the data-rich clinical environments and the mechanistically informed personalized healthcare[20-22]

4.3. Case studies

4.3.1. Case study 1: Cardiac electrophysiology and arrhythmia prediction

Hybrid models have been effectively used to simulate cardiac electrophysiology to risk stratify arrhythmia. As an example, machine learning algorithms are initially used to predict ionic conductances and conduction properties on patient-specific ECGs. These measurements are then incorporated into mechanistically based ventricular models including the Ten Tusscher - Panfilov scheme, which models wave conduction and arrhythmogenic susceptibility. The resulting calibrated models are not only more accurate predictors of arrhythmia onset than entirely statistical approaches, but also provide mechanistic information of the electrophysiological substrate, hence informing ablation therapy and treatment planning on an individual patient basis.[23]

4.3.2. Case study 2: Neuro-computational models for seizure forecasting

The use of AI-based extraction of features on EEG data and integration with neural mass and neural field models has been used to simulate new seizure dynamics in epilepsy studies. Deep learning (e.g. LSTM networks) identify subtle pre-ictal information, whereas mechanistic simulations check how abnormal discharges propagate across cortical networks. This provides the opportunity to predict individualized seizures, which increases the accuracy and the lead time in such hybrid approaches. Notably, they also guide treatment therapies, such as closed-loop neurostimulation regimens that administer specific electrical impulses to their breakages prior to their clinical manifestation.[24]

4.3.3. Case study 3: Digital twin for glucose–insulin regulation

Another strong example of AI-mechanistic integration is the metabolic modeling. The systemic metabolism has traditionally been characterized by the Bergman minimal model of glucoseinsulin dynamics, which has its static parameters, thus restricting adaptability. Researchers have developed adaptive digital twins to manage diabetes by integrating learning algorithms of reinforcement learning into this system. These models feed the continuous glucose monitor (CGM) data and dynamically optimize insulin dosing, which is much better than the traditional open-loop and fixed-rule control systems. These digital twins are promising next-generation closed-loop artificial pancreas systems, in which real-time personalization minimizes the risk of hypo- and hyperglycemia.[25]

5. Opportunities

5.1. Advancements in personalized healthcare systems

Development of AI and computational physiology makes it possible to abandon the use of population-based care and create a more individually-oriented strategy of treatment. Digital twins may be built as a representation of patient-specific physiology by integrating genomic, imaging, wearable, and, electronic health record data into mechanistic infrastructures. These adaptive virtual models keep on updating with new data as they are received thus enabling clinicians to model various therapeutic situations prior to actual implementation. Examples include patient-specific heart simulation predicting arrhythmia risk and informing individualized ablation as well as metabolic twins predicting insulin therapy in diabetes. This is on the way to a genome medicine future wherein the treatment is preemptively tailored to the biological and environmental environment of individual patients.[26]

5.2. Acceleration of clinical research and drug discovery

AI-augmented physiological modeling offers substantial benefits in clinical research and pharmacological innovation. In silico clinical trials can be performed using virtual patient cohorts generated by mechanistic models that are calibrated to a population scale of data, eliminating the need to use expensive and time-consuming in vivo clinical trials. This speeds up testing of hypotheses, drug discovery and biomarker discovery. AI is also useful in the study of large multi-omics datasets with high dimensions, allowing the discovery of new therapeutic targets. These techniques coupled with mechanistic pharmacokinetic-pharmacodynamic (PK-PD) models make drug development pipelines more streamlined by forecasting drug efficacy, toxicity, and inter-patient variance. The end result of this synergy may be a reduction in the time between bench and bedside and an increase in the direct success rate of candidate therapies.[27]

5.3. Improved predictive modeling for disease progression and treatment response

Among the most promising ones is the possibility to predict disease progression and streamline treatment reactions. The hybrid AI-physiology models are placed in a vantage position to preempt non-linear disease progression in cardiovascular, neurological, and metabolic applications. In the case of an example, models that combine ML-derived biomarkers with mechanistic cardiac dynamics can be made to forecast heart failure exacerbations, and neuro-computational models predict seizure onset and guide adaptive neuromodulation therapies. AI-based radiomics combined with tumor growth models improve the prediction of treatment response and the risk of relapse in oncology. The same predictive abilities do not only inform clinical decision-making, but also make it possible to have dynamic, adaptive interventions- where therapy is updated on the fly in response to new patient trajectories.[28]

5.4. Cost-effective and scalable healthcare interventions

In addition to scientific and clinical progress, AI combines with computational physiology has a potential to bring cost-efficient and scalable healthcare services. AI-boosted diagnostic tools, decision-support systems, and simplified surrogate models of complex simulations also lower the cost of complicated processes and specialist intervention. An example of this can be lightweight predictive models based on mechanistic frameworks that can be implemented in low-resource environments through mobile health platforms, where early disease detection and monitoring can be regarded. In addition, such systems reduce the financial cost of healthcare infrastructures by minimizing trial-and-error in therapy design, and hospital readmission due to proactive risk prediction. The democratization of access to high-end medical technologies in a wide range of population groups is an avenue due to the scalability of AI-powered, physiology-learned tools. The **Table 2**table 2 provides succinctly about AI/computational physiology integration opportunities.[29]

Table 2: Opportunities from integrating AI and computational physiology[23-29]

Opportunity Domain	Example Applications	Translational Impact
Personalized Healthcare	Patient-specific digital twins, individualized treatment simulations	Enables precision medicine with adaptive, real-time interventions.
Drug Discovery & Development	In silico trials, virtual screening, toxicity prediction	Reduces R&D costs, accelerates pipeline efficiency, and minimizes animal testing.
Predictive Disease Modeling	Cardiovascular risk forecasting, neurodegenerative progression models	Supports early intervention, improves prognosis, and guides resource allocation.
Healthcare Delivery	AI-powered monitoring devices, telemedicine decision support	Provides scalable, cost-effective access to advanced diagnostics and care.

6. Challenges

6.1. Data reliability, standardization, and interoperability

Data quality, consistency, and interoperability are key requirements to the utility of AI-driven computational physiology. Physiological data the data are frequently discontinuous between institutions, in heterogeneous modalities (e.g., imaging, biosensors, EHRs), and have noise, gaps, or measurement artifact. Lack of standardized data formats and annotation practices hinders effective integration and model generalizability. Moreover, there is the issue of interoperability between multi-scale data, such as on one hand molecular omics and on the other hand clinical imaging, in coherent computational systems. In the absence of powerful data harmonization mechanisms, there are high risks of bias, overfitting, and lower applicability of the results translated to other populations.[30]

6.2. Model interpretability and transparency in clinical use

Even though AI algorithms, especially the deep learning models, have high predictive accuracy, they tend to be black boxes and not interpretable. In clinical settings, lack of such explanations of model outputs becomes a serious impediment to trust, adoption, and accountability. Mechanistic models are interpretable because they are explicitly represented in physiological terms, but when such models are combined with opaque AI approaches transparency can be lost. The increasing demand is explainable AI (XAI) methods, which combine prediction with understandable insights, which can allow clinicians to comprehend causal mechanisms, justify predictions, and justify therapeutic choices. The absence of such interpretability undermines both clinical confidence and patient safety.[31]

6.3. Ethical considerations, including patient privacy and bias in AI models

Ethical issues are one of the key focuses of implementing AI-physiology models. Large-scale aggregation of sensitive health data leads to the risk of unauthorized access to or misuse of patient data. Also, AI models that have been trained to use biased or unrepresentative datasets can reinforce or exacerbate health disparities, especially in underrepresented groups. As an illustration, models obtained mainly on Western populations might not perform as well in heterogeneous populations across the globe and this could be restrictive in terms of equity in clinical outcome. The ethical frameworks should also deal with the problem of data security, algorithmic justice, informed consent, and accountability. These concerns are enhanced by the introduction of AI to physiological models because the errors can spread to treatment choices that directly affect the patient.[32-33]

6.4. Regulatory and governance barriers

The regulatory frameworks have not been able to keep up with the blistering development of AI-based biomedical technologies. Hybrid AI-mechanistic models differ with traditional medical devices, and are dynamic, adaptive, and constantly changing as new information is incorporated, making them harder to validate and certify. Present regulatory frameworks are mainly based on the inert, static technologies, and it is unclear how to assess safety, efficacy, and reproducibility of adaptive models. Moreover, the governance frameworks should also have clear guidelines of intellectual property, liability and accountability in the case of AI-informed decisions in determining the outcomes of patients. The wide introduction of these technologies in clinical practices will not be achieved without appropriate regulatory clarity and international harmonization.[34]

7. Future Perspectives

7.1. Emerging trends in computational physiology and AI integration

A further convergence of computational physiology and artificial intelligence is forthcoming in the next decade, enabled by high-resolution data acquisition, cloud-computation, and fusion of multimodal data. New directions are the combination of multi-omics data (genomics, proteomics, metabolomics) with biophysical models to decompose genotype-phenotype interactions. On the same note self-learning hybrid models, which can adapt in real-time will be able to project predictive accuracy beyond the static simulations. The other significant direction is the shift toward federated learning and decentralized AI solutions that can enable multi-institutional cooperation and maintain the privacy of data. These innovations together with high-performance computing and quantum simulation will likely broaden the scale and translational scope of AI-physiology models.[35]

7.2. Digital twins and virtual patient modeling

One of the most revolutionary paths is the creation of digital twins, a virtual constantly updated model of a specific patient, which absorbs multi-scale information in real time. Digital twins may be viewed as a dynamic transition between retrospective diagnostics and prospective, adaptive medicine, as digital twins can be tested virtually in vivo, and clinicians can see the results before making an intervention a reality. Examples that have already been demonstrated are digital twins of the heart to stratify the risk of arrhythmia, of the brain to predict seizures, and of the pancreas to control insulin closed-loop. The full-scale modeling of these models to population-sized virtual cohorts will facilitate in silico clinical trials, drug discovery and assessment of public health interventions. Digital twins are expected to form the basis of personalized and preventive medicine despite technical and regulatory challenges.[36]

7.3. Policy recommendations for ethical and responsible adoption

Responsible governance structures need to offset the transformative potential of AI-integrated computational physiology. The policymakers ought to focus on coming up with data interoperability standards, adaptive models validation measures, and standard reporting measures to ensure reproducibility. Systemic bias should be prevented by ensuring that ethical protection covers patient privacy, informed consent, and algorithmic fairness. Moreover, regulatory innovation must be able to fit dynamically continuously learning systems, which fail to fit traditional device-approval routes. Democracy of access and equitable adoption of digital infrastructure across different healthcare environments will require the use of public and private partnerships, cross-national collaboration, and investment in online infrastructure. Finally, a humanistic approach must be highlighted in the form of policies, according to which the development of technology is connected to clinical responsibility and social confidence.[37-38]

8. Conclusion

Artificial intelligence (AI) and computational physiology is a breakthrough in biomedical science, and it provides unprecedented possibilities in studying and controlling the complex human systems. It is possible to combine the prophetic power of information-driven models with the mechanistic exactness of physiological models to obtain both precision and understanding that neither alone can attain. The opportunities resulting out of this synergy include the creation of personalized healthcare systems or digital twins, the acceleration of drug discovery or the creation of cost-effective and scalable interventions. Translational potential of these frameworks is exemplified using case studies in cardiovascular, neurological and metabolic domains, with specific examples of these applications facilitating real-time monitoring, adaptive therapies, and precision medicine. However, there are major difficulties. Standardization, interoperability and reliability of biomedical data remains a limiting factor in model generalizability. Deep learning methods are considered potent, but they tend to be non-transparent, which serves as a barrier to clinical acceptance and adoption. Ethical issues such as privacy of patients, discrimination in training data, and fair access require immediate actions. Furthermore, regulative and governance frameworks are currently not well-adapted to the realities of ongoing changes in the AI–physiology systems, which constrains their incorporation into a regular clinical setting. In spite of these obstacles, the dynamics of the field are evident. There are new trends like federated learning, and multi-omics integration and high-performance simulations that are opening the door to more robust and adaptive hybrid models. When properly protected, digital twins and virtual patient cohorts have the potential to revolutionize clinical decision-making, decrease the use of animal models, and enter the new reality of predictive and preventive healthcare. AI and computational physiology the combination of AI and computational physiology presents a radical framework on which to develop the knowledge of human-system. When done in a responsible manner, it will not only enhance mechanistic understanding of health and illness but will also transform how healthcare is provided by turning it into a more predictive and less reactive process as well as generalize that of being really personalized.

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None.

10. Conflict of Interest

None.

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