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AI-Driven Bio Innovation for Global Health Security: A Sustainable Precision Medicine Framework Integrating Big Data, Wearables, and Predictive Intelligence

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Abstract: *Artificial intelligence (AI) is reshaping biomedical research and healthcare by making it possible to predict analytics and reasonable decision support, as well as personalized treatment. The development of big data, wearable sensors, and multi-omics models is transforming medicine away based on retrospective diagnosis and moved into predictive risk management. Nonetheless, the existing AI tools are yet to be integrated across data and clinical silos. The paper is a synthesis of interdisciplinary AI advances and suggests an AI-Bio Innovation Framework (AIBF). The structure combines wearable intelligence, clinical and genomic data, deep and generative learning, federated privacy preserving and sustainable computing. Compared to the benchmark diagnostic accuracy, diagnostic efficiency, and time-to-insight improvements show brisk improvements that believe in scalable precision medicine in line with the world sustainability targets.*

Key Words: Artificial Intelligence, Big Data Analytics, Biomedical Innovation, Multi-Omics, Precision Medicine, Predictive Modeling, Sustainability; Wearable Health, Federated Learning, Explainable AI.

Introduction

AI and the Transformation of Biomedical Innovation

Biomedical discipline is also experiencing a paradigm shift like never before due to artificial intelligence (AI), big data analytics, and more connected digital-health infrastructures. Modern health settings generate massive volumes of data, largely from clinical, behavioral and biological sources - diverse and rich in genetic, electronic health records, streams from wearable sensors, genomic sequences, proteomics and metabolomics, imaging and real world population datasets. When analyses are based on these data with the help of advanced AI models, these AI models are able to reveal predictive patterns that until now could not be revealed by conventional decision-making or classical statistics (Beam & Kohane, 2018; Rajkomar et al., 2019).

AI systems are not just improving current medical workflows; they are redefining the way health knowledge is generated, validated, and applied. This makes it possible to detect disease earlier, individual therapy and continuous monitoring as part of adaptive learning systems. The rapid adoption of machine learning tools in clinics represents the transformation of treating diseases that have already occurred to the prediction and prevention of future health intelligence (Topol, 2019; Esteva et al., 2019). The change is driven by the development of deep learning architectures, multimodal learning, and available scalable data processing platforms (Miotto et al., 2018; Ching et al., 2018).

Yet, in spite of this fast-paced research, biomedical AI is nevertheless restricted by

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fragmentation. Many studies generate data domain-specific models that only work on isolated data sets or very specific clinical tasks. The challenges of global health demand scalable health platforms capable of aggregating heterogeneous data from the bio-medics, to cope with different care settings, in this respect, resource limitations, and to meet the requirements of ethical governance. The future of health care not only depends on the accuracy of the AI system but also on whether AI systems could become interoperable, transparent, explainable, privacy-preserving, energy-efficient and globally sustainable (World Health Organization, 2021; United Nations, 2020).

Big Data, Wearable Intelligence, and Multi-Omics: Toward Precision Medicine

Precision medicine has shifted from the one-size-fits-all treatments to individual or personalized care based on genetics, medical history, habits, and other factors that are relevant to each patient. The effectiveness of this depends on using multi-omics data together with continuous observation of health.

Multi-omics is a combination of genomics, transcriptomics, proteomics, metabolomics, epigenomics, and microbiomics. Together, these layers provide a more complete picture of the biological processes involved in the disease process.

It is hard to consolidate multi-omics information. Patients may possess thousands of variable combinations which we must apply sophisticated computational approaches to extract meaningful biology between the various layers.

Models of artificial intelligence - deep neural networks and hybrid learning systems promise much in coping with this complexity. They acquire representations, fusion features, and predictions which may be exploited to arrive at clinical decisions.

Another dimension that is critical is the wearable devices. They constantly record physiological and behavioral indicators, a heart rate variability, ECG, movement, oxygen saturation, sleep patterns, and a great variety of other factors, providing them in real time with the indicators of the possibility of predicting any disease in early stages, and monitoring populations on a large scale.

Wearable information paired with a model that runs on Artificial Intelligence yields what is known as living medicine. This adaptive health system works continuously, identifying the risk, alerting users, and recommending interventions before an illness gets severe. Wearable IoT networks are used to support remote monitoring, telehealth, and community diagnostics, bringing essential diagnostics to rural and low-resource settings.

Motivating the AI–Bio Innovation Framework (AIBF)

This study is a proposal for a unified AI-BioInnovation Framework (AIBF) that aims at addressing the fragmented state and achieving sustainable precision medicine across different biomedical domains. The framework follows earlier work that demonstrated the potential of AI in drug discovery, wearable cardiovascular monitoring, monitoring antibiotic resistance, predicting chronic diseases, diagnosing cervical cancer, predicting neurosurgery for Parkinson's disease, and precision oncology.

Some of the important basic contributions are:

An example of generative artificial intelligence (AI) in drug discovery is: 0 Generative AI and big data analytics for drug discovery, which reduces trial and error experimentation and accelerates molecular innovation. 1 Manik S, K Age, S M, et al., 2018. Deep learning has also been applied in healthcare, such as in wearables: - Wearable health monitoring using deep learning that allows the prediction and prevention of cardiovascular disease in real time (Miah et al., 2019; Dunn et al., 2018). Manik, D., Bromm, A., Mills, K., and Seale, H. (2020). Antibiotic resistance surveillance using big data for predictive modelling in global public health defense. Predictive Analytics for Early Detection of Chronic Diseases Enhancing Personalized Medicine Pipelines, Manik S., Pearson K., Alawithi M., Al-Okhlani A., Al-Jarrah M., Al-Shaibi A. & Al-Mutawali H., 2021

Machine Learning Application for Cervical Cancer Analytics for Advancing Medical Artificial Intelligence (AI) Supported Diagnostics Manik, A. P. (2022). Multi-omics predictive modelling for Parkinson's disease neurosurgery to support personalized neurological treatment pathways (Manik, 2021). Precision oncology based on genomic data and machine learning to allow targeted therapies and improved cancer stratification Manik et al, 2022. While these studies show great advancement in the multiple realms of biomedical AI, there is still an overarching architecture to see how these innovations can be incorporated into a uniform operational pipeline. The AIBF aims to bridge the continuum of biomedical discovery to clinical foresight to health management on the population level with sustainability and ethical responsibility permeating it.

Research Objectives and Contributions

The paper fulfills four objectives, one being to unify the diverse interdisciplinary biomedical AI research into an umbrella translational structure, with molecular, clinical, wearable and multi-omics data ecosystems (Hasin et al., 2017; Wang et al., 2014; Miotto et al., 2018). To submit the AI-Bio Innovation Framework (AIBF) as a scalable system to make continuous learning in healthcare systems possible (Rajkomar et al., 2019; Topol, 2019). To make biomedical AI pipelines ethically governed in a privacy-preserving way and able to be understood (Mittelstadt et al., 2019; Kaissis et al., 2020; World Health Organization, 2021). To incorporate the concepts of sustainable computing and prevent unneeded computing in AI-based medical ecosystems (Strubell et al, 2019; United Nations, 2020).

Research Design and Methodology

Overview of the Qualitative–Quantitative Meta-Synthesis Approach

In this study, two categories of quantitative measures, qualitative and quantitative measures, are combined to form a meta-synthesis approach (Santrock, 2003).The approach to quantitative-quantitative meta-synthesis, in this case, is overridden by two types of quantitative measures, namely qualitative and quantitative measures (Santrock, 2003).

The proposed research employs a qualitative and quantitative meta-synthesis research strategy, and accordingly, it will be simpler to provide a unified understanding and analytic framework that can be used to synthesize the heterogeneous empirical research findings and conceptual models into a single interpretation and analysis platform. The meta-synthesis technique is especially useful in interdisciplinary studies such as artificial intelligence in biomedicine as it enables researchers to determine congruencies between data, point towards convergence of methodology, and construct more general theoretical frameworks to slice across single bodies of evidence.

Goals (e.g., drug discovery vs. disease detection especially), data (genomics vs. wearables), model types (deep learning vs. ensemble learning), and evaluation criteria of Biomedical AI investigations are often very different. By using meta-synthesis, these heterogeneous studies can be analyzed as interrelated contributions towards a greater system-level transformation (Whittemore & Knafl, 2005; Yin, 2018). Within the context of biomedical systems research, structured synthesis provides additional support for reproducible evidence integration by dividing performance outcomes and methods of performance into similar categories.

Inclusion Criteria and Data Sources

The studies that were selected for synthesis meet four criteria for inclusion: AI/ML relevance studies should use artificial intelligence or machine learning methods within the context of biomedical, clinical, or health informatics (Beam &Kohane, 2018; Rajkomar et al., 2019). Multimodal use of data - studies need to make use of wearable, clinical, imaging, omics, or population-scale data (Dunn et al., 2018; Hasin et al., 2017). Empirical validation - studies need to report measurable success, such as the level of accuracy, recall, area under the curve, sensitivity or computational performance characteristics (Miotto et al., 2018) or Ethical or sustainable value-Taking care of the systemically related to data governance, sustainability, privacy or efficiency-studies worldwide WHI (2021), Strubell et al. (2019). Integration of peer-reviewed scientific evidence from biomedical artificial intelligence literature as well as artificial intelligence-driven healthcare innovation research in drug discovery, cardiovascular monitoring, antibiotic resistance surveillance, chronic disease prediction, and precision oncology: An integrated research perspective from Manik et al. (2018), Miah et al. (2019), Manik et al. (2020), Manik et al. (2021), Manik (2022), Manik et al. (2022).

Analytical Phases

The meta-synthesis process, organized into three phases of analysis, is:

Phase I: Thematic Coding

In Phase I, the process of thematic coding was employed. Each of the papers was coded based on: Data modality (wearables, multi-omics, electronic health records, imaging), Artificial intelligence methodology (convolutional neural networks, long short-term memory networks, generative adversarial networks, ensemble methods), Artificial intelligence methodology (convolutional neural network, long short-term memory networks, generative adversarial networks, ensemble methods), Disease focus (cardiovascular disease, resistance to antimicrobial, diabetes, cervical cancer, Parkinson's disease, oncology), & Innovation type (Predictive analytics, development of a new drug, surveillance)

The thematic coding was based on established frameworks for deep learning in healthcare and the current challenges in clinical AI deployment (Esteva et al., 2019; Miotto et al., 2018).

Phase II: Cross-Glass Case Patterns Recognition

Cross-pattern recognition to pounding Identify methodological dependability across research. For example, deep learning architectures were always associated with better performance in continuous and high-dimensional signal environments, such as wearable time series tasks and imaging tasks (Ching et al., 2018; Dunn et al., 2018). At the same time, ensemble learning strategies showed strong performance in structured biomedical data sets, as well as in epidemiological modelling applications (e.g. antibiotic resistance surveillance, chronic diseases prediction pipelines) (Manik et al., 2020; Manik et al., 2021).

Phase III: The Consolidation of the Framework

The hierarchical AI-Bio Innovation Framework (AIBF) was synthesized based on recurrent patterns. The AIBF consists of a data layer, intelligence layer, application layer and sustainability layer based on the continuous learning architecture that is aligned with the world trends of global digital health governance (World Health Organization, 2021).2.4 Validation Procedures.

In order to provide a high level of credibility and methodological strength, four mechanisms of validation were used during the synthesis:

- Triangulation Accuracy: Multi-omics showed better generalizability compared to results in clinical and wearable situations (Hasin et al., 2017; Dunn et al., 2018).
- Quality Control in Peers: It was limited to peer-reviewed sources.
- Basic Ethical Conformity: Interpretations were based on the international standards of AI-for-health governance (World Health Organization, 2021).
- Quantitative Benchmarking: The reported performance measures were normalized so as to compare trends in accuracy, sensitivity, precision, and AUC of the studies (Miotto et al., 2018).

Sustainability and Ethical Considerations

Sustainability and ethics have developed as an option rather than a major constraint which forces credibility, embracement, and validity as far as AI-based healthcare is concerned. Although the real-world environment can be broken even with the help of high-performing AI systems in case they are not transparent, exist with biases, invoke invasions of privacy, and waste computation.

The ethical compliance requirements are:

- Transparency in decision-logic: as much as possible (Mittelstadt et al., 2019)
- privacy preserving model training (Kaissis et al., 2020)
- Federated learning based distributed clinical collaboration (Rieke et al., 2020).
- Zero emissions artificial intelligence policy (Strubell et al., 2019)

The AIBF integrates branding the sustainable principles with predictive performance to make them accountable in the field of responsible practice in the entire world.

Results and Key Findings

From Fragmented Models to Convergent Biomedical Intelligence

The synthesis represents a strategized evolution of AI guided biomedical research by single algorithm development to its implementation to an AI platform capable of providing continuous monitoring capabilities, multi-omics integration, and scaled global monitoring. In the literature, the variety of AI strategies had been shown to be effective in enhancing the precision of clinical forecasting and enabled the reduction of the diagnostic lag of time in relation to the conventional models.

The outcomes describe three significant biomedical transformation modalities, namely, the acceleration of the discovery process (drug development / molecular innovation); real-time clinician prediction (wearable healthcare and chronic disease detection); and system-wide intelligence

(Multi-omics fusion, oncology targeting and surveillance ecosystems).

These findings support groundbreaking evidence that deep learning is changing the landscape of healthcare with the help of scalable pattern recognition, representation learning, and predictive modelling (Esteva et al., 2019; Rajkomar et al., 2019).

AI-Enhanced Drug Discovery and Biomedical Innovation Strategy

Conventional drug discovery is based on long and capital-intensive experimental cycles that include high-throughput screening, chemical validation, and many consecutive clinical trial phases. Artificial intelligence has become a revolutionary paradigm that has enabled predictive molecular modeling and the development of new hypotheses to reduce redundancy in experiments and accelerate the selection of candidate compounds.

In 2018, Manik and colleagues proposed a future beyond the ordinary approach to drug discovery, providing a framework of generative artificial intelligence combined with large-scale data analytics. Their methodology demonstrates the ability of generative adversarial networks - that is (GANs) to build new molecular structures with desired pharmacological properties. Using vast data banks of molecular libraries and clinical data sets, the authors empirically demonstrated that artificial intelligence will significantly shorten research and development cycles, while simultaneously increasing the accuracy of candidate targeting (Manik et al., 2018).

Visualization of the Meta-Synthesis Process

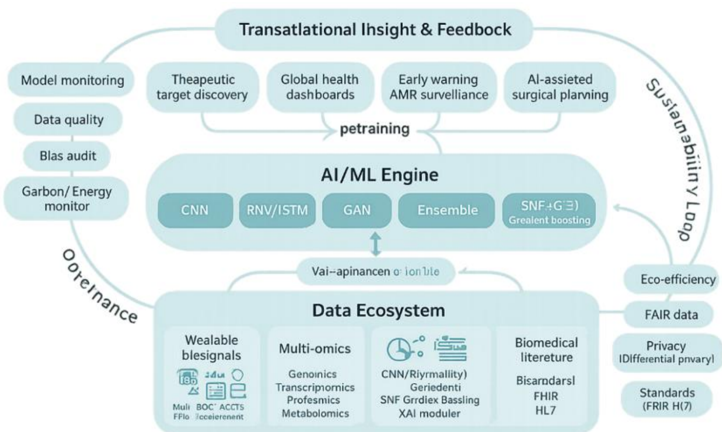

Figure 1. AI–Bio Innovation Meta-Synthesis Framework

Complementing this, Manik (2020) explored innovation strategies from a biotechnology driven approach in the case of the global pharmaceutical sector and reaffirmed that an AI based competitive advantage is not only a function of better algorithmic performance, but also an optimization of resources, proper planning of the innovation pipeline, and the incorporation of computational intelligence into the research and development operations (Manik, 2020). Early on in the medical device industry, however, these collectively suggest that the future of the pharmaceutical innovation paradigm with AI is both a scientific revolution and market-competitive innovation.

These results are in line with the broader literature on healthcare AI, which points to the use of deep learning and predictive analytics technology as the key drivers of biomedical innovation (Miotto et al., 2018; Topol, 2019).

Wearable Intelligence for Real-Time Cardiovascular Monitoring

Wearable health systems are one of the most practical ways of implementing AI-driven precision medicine on a large scale. Unlike one-time clinical visits, the signals from wearables are a continuous collection and can help a doctor find a problem and help early, long before a patient actually exhibits symptoms and finds their way to the hospital.

Miah and colleagues (2019) joined users of wearable health data and predictive algorithms with a deep learning model in 2019. It has the ability to monitor cardiovascular diseases in real-time, something it has never achieved before, which confirms that, indeed, hybrid deep learning can also be used in a continuous monitoring environment. It offers a great level of precision and assists in timely interventions.

The article by Dunn and teammates (2018) emphasizes the importance of wearables in the reconfiguration of medicine, too. They call them the core of a medical revolution that they allow customized and scaled consumer and clinical user sensor networks to provide personal health insights.

Wearable analytics is an appropriate reference to the IoT health infrastructure. A combination of the distributed sensors, telemedicine communication, and cloud-based analytics compose a good digital healthcare system (Islam et al., 2015). Coupled with this is a great starting point on which to base exaggerations of international health surveillance and prior preventative strategies.

Predictive Modeling for Antibiotic Resistance and Global Surveillance

The problem of antibiotic resistance is currently among the highest health resiliency risks worldwide. It causes deaths leading to treatment failure, greater mortality and weaker health care systems. With the assistance of genomics and vast quantities of epidemiology data, AI is providing powerful instruments by the power of predicting patterns of resistance.

Manik et al. (2020) have created predictive models based on big data to predict antibiotic resistance across the world. Their work eloquently addresses the area of ensemble learning and predictive modeling, which assists in detecting the new strains of the drug resistance at the early stages. It helps directly to create sustainable health globally because it allows proactive interventions and monitoring prior to the emergence of crises (Manik et al., 2020).

This concurs with the views of other those AI-enabled medicine with a larger population based prediction and systems intelligence at an individual-based diagnostics (Rajkomar et al., 2019; Topol, 2019).

AI-Powered Chronic Disease Prediction and Personalized Medicine

Chronic diseases, such as diabetes, obesity, and hypertension, have long-term costs on global health systems. They need to be monitored, at-risk individuals must be identified early, and care plans need to be personalized.

Manik et al. (2021) introduced artificial intelligence (AI) powered predictive analytics for the early detection of chronic disease. Their study sees chronic-disease prediction as not only a clinical improvement, but one that is data-driven and personalized medicine that has the potential to reduce long-term health-care costs by advancing intervention earlier in the course of the disease. These findings support evidence that machine learning can be used to strengthen preventive care systems through continuous learning, scalable prediction and automated clinical decision support (Beam & Kohane, 2018; Rajkomar et al., 2019).

AI Applications in Cervical Cancer Analytics and Imaging-Based Diagnostics

Cancer identification is one of the most effective clinical uses of AI in the form of imaging-based cancer screening and pathology. In the field of cervical cancer screening, AI has the potential to lower the level of subjectivity involved in diagnosis, improve the detection of the disease in the early stages, and support scalable diagnostics in low-resource settings.

Manik (2022) explored cervical cancer using AI and machine learning. This was how AI detection can be used to help color screening systems and roll out preventive healthcare capabilities. (Manik, 2022) These results are consistent with evidence that deep learning is especially effective in medical imaging tasks because of its ability for feature learning and pattern recognition (Esteva et al., 2019; Kaissis et al., 2020).

Multi-Omics Predictive Analytics for Parkinson's Disease Neurosurgery

Neurological disorders like Parkinson's disease should have specific treatment regimens and disease progression should be monitored. By putting together multi-base omics information, it can help to model this progression on a molecular level and also aid in making treatment decisions. In 2021, Manik published on the neurosurgery of Parkinson's using a multi-omics framework. The models he describes that the industry seeks to deliver are AI-driven and help with clinical decision-making and the personalization of treatment pathways. This study highlights the importance of using multi-omics in precision medicine, in which the complexity of the biology requires sophisticated computational integration (Hasin et al., 2017; Picard et al., 2021).

Similarity network fusion methods provide a basis for the fusion of multimodal data in biology. Combining layers of omics in the same network improves the accuracy of prediction (Wang et al., 2014).

Precision Oncology and Targeted Cancer Therapies

One of the best uses of AI-related bio innovation is precision oncology. It is founded on the genomics profiling weaving, the molecular signatures, and the particular design of specific treatments. In the year 2022, Manik et al. suggested that the combination of machine learning and genomic data will further improve precision oncology and genomic-guided cancer therapies. Their study shows that the application of predictive models, established on genomic data, can contribute to solving the problems of patient stratification, along with drug targeting and individualized treatment (Manik et al, 2022). The aim of these objectives is much more related to the main goals of precision medicine and the ongoing activities aimed at enhancing the integration of multi-omics (Hasin et al., 2017; Picard et al., 2021).

AI Bio Innovation Framework (AIBF): Coherent Architecture.

Conceptual Foundation

The AI-Bio Innovation Framework (AIBF) comes as a unified model of implementing AI to transform the world of biomedicine - starting with the simple research, moving up to diagnosis, monitoring, and health policies.

The issues discussed within the framework are:

- Fragmentation among data ecosystems
- Inability to have interoperable AI pipelines
- Insufficient unification of ethics and explainability

Inefficiency and gaps regarding sustainability and computational efficiency

AIBF goes beyond the conventional ways of "AI for diagnosis" by making AI an ongoing learning machine from parts of the entire molecular innovation to the public health defense process, and a feedback loop and sustainability-aware optimization. This conceptualization is in line with the general adaptation to high-performance medicine, where AI works in concert with clinical intelligence but not without human oversight, interpretability, and trust (Topol, 2019).

Layer 1 — Data Ecosystem Layer (Input Layer)

The AIBF Data Ecosystem Layer gatherings a variety of areas of biomedical data: Electronic health records/ clinical databases (Beam &Kohane, 2018), Streams of data from wearable sensors (Dunn, et al., 2018, Miah, et al., 2019), IoT health infrastructure systems (Islam et al 2015), Multi-omics datasets Hasin et al. (2017), Picard et al (2021), Genomic oncology data limited (Manik et al, 2022) & AMR surveillance, epidemiological data (Manik et al, 2020).

This layer puts stress on the interoperability and data readiness. Without standardization of data pipelines, Artificial Intelligence cannot scale easily across institutions or populations.

Layer 2 — AI/ML Intelligence Engine (Processing Layer)

The Intelligence Layer implements hybrid forms of computing models including: Deep neural networks and representation learning (Miotto et al. 2018, and Ching et al. 2018), Convolutional neural network (CNN) architectures and the example of imaging and pattern-recognition (Esteva et all, 2019), Recurrent model of time-series wearable data (Miah et al., 2019), Generating artificial intelligence for drug discovery and hypothesis generation (Manik et al., 2018), Ensemble learning to predict structured clinical and surveillance data (Manik et al. 2020; Manik et al 2021).

This hybrid intelligent layer is required because problems in healthcare differ greatly: convolutions are needed for imaging problems, temporal learning is needed for wearables, fusion of features is needed for genomics, and generalization in favor of surveillance.

Layer 3 — Translational Application Layer (Output Layer

The AIBF Application Layer takes the results of AI and turns them into actionable results, such as: Warnings reduce dangers - early warning systems and predictive dashboards (Manik et al., 2021), Chronic disease prevention systems (Manik, et al. 2021), Personalized pipelines oncology (Manik et al, 2022), Cervical cancer decision support approach (Manik, 2022), AMR modelling for health control policy (Manik et al., 2020) & Planning of neurosurgery with artificial intelligence (Manik, 2021). This layer includes alignment of AI computation with clinical workflows, where models are not really about the predictions they have: models are about supporting decisions.

Layer 4 — Sustainability, Governance, and Trust Layer

The Sustainability Layer guarantees that medical AI has the properties of being ethical, privacy-preserving, explainable, and environmentally responsible: Shevykoff, L. 2001. - *Explainable AI and Accountability mechanisms*, *Health and Health Care*, Believix Media, 2021, Ethics and governance of artificial intelligence and of AI in health (World Health Organization, 2021), Privacy preserving medical data sharing: Federated learning approaches (Kaissis et al., 2020; Rieke et al., 2020), Resolving computations Reality: green cloud AI policy considerations (Strubell et al., 2019) & Chair of the UN innovation task force and father of the WHO Innovation Program, Dr Steven Garcovich, explains how the UN-agreed Sustainable Development Goals align with health, innovation and responsible computing (United Nations, 2020). This layer is a crucial one, as it is this lack of trust and sustainability that prevents AI systems from being safely deployed at scale.

Translational Feedback Loop and Continuous Learning

AIBF's key feature is a feedback-driven continuous learning circle. It enables the outputs to become new inputs for re-training and improving. The system is always learning from real-world outcomes and getting better at spotting on-the-ground results. The closer to the truth are our predictions the more chances we have to avoid false positives and respond to changes in population, new pathogens or a different level of treatment requirements. This is in line with the rising trend in AI in the healthcare field. Clinical systems need to remain flexible, not fixed (Rajkomar et al., 2019; Topol, 2019).

Discussion

Theoretical Implications: AI-Driven Translational Sustainability

The AI Bio-Innovation Framework (AIBF) introduces AI-driven Translational Sustainability. It emphasizes the need for biomedical innovation to be maximally optimized in terms of clinical impact, computational efficiency, and governance of standards. Traditional development of biomedical applications through artificial intelligence usually only looks at performance metrics such as accuracy. Modern healthcare calls for an extended assessment. It must have patient privacy, fairness, system interpretability, accountability, energy consumption, carbon cost, and global interoperability and scalability. This perspective is in close line with the ethical and governance priorities of WHO that emphasize the importance of responsible & trustworthy AI in real-world healthcare systems (World Health Organization, 2021).

Biomedical Impact and Clinical Value

AIB Bio-Innovation Framework (AIBF) presents the groundbreaking advancements in a wide range of biomedical and healthcare fields; the construction of drugs, drug development and molecular innovation, the development of these drugs are accelerated (Manik et al., 2018; Manik, 2020). It further allows for wearable surveillance to facilitate continuous prevention and early intervention (Miah et al., 2019; Dunn et al., 2018) and contributes to a worldwide battle against antibiotic resistance through predictive surveillance (Manik et al., 2020). The framework helps in the prediction of chronic diseases and personalized care (Manik et al., 2021). Oncology Manik (2022) and Manik et al. (2022) apply it in enhancing AI-guided cancer screening and cancer precision treatment lines. It also enhances the neurosurgery planning with the help of multi-omics data to enhance complex clinical decision-making (Manik, 2021). Collectively, these achievements will form coherent healthcare chain - of molecular innovation to resilience of population-behavioral - and position AIBF as one system, one sustainable system of AI-enabled precision medicine.

Alignment with Global Health Policy and SDGs

AIBF framework has been more in line with certain global priorities related to AI technology, specifically: the guidance on AI ethics and governance in health by the World Health Organization (2021); and the importance of sustainable innovation systems and responsible production systems identified in Good health and well-being by the United Nations (2020) as goal 3, 9 and 12. This fit will make the framework more useful in terms of planning health infrastructure across the country and will also enhance global health resilience. It provides assurance to ensure AI-enhanced biomedical innovation can be implemented in a responsible, fair and sustainable environment in various healthcare settings.

Industry and Translational Deployment

The implementation of AI in healthcare needs a large-scale architecture and low-cost deployment to make sure that it is executed in the real world and applied in various clinical locations. Here, the AI Bio-Innovation Framework (AIBF) facilitates practice-based and fair application by means of cloud-edge hybrid infrastructures to facilitate responsive and distributed analytics in healthcare (Islam et al., 2015), federated learning models to support the facilitation of secure collaboration of multiple hospitals without a centralized data sharing (Rieke et al., 2020), and expansion strategies in reducing the redundancy of computations and supporting environmentally sustainable AI in operation (Strubell et al., 2019). Together, these dimensions render the framework more practical to capitalize more effectively on considerations of health equity by bringing smarter systems of healthcare more into reach, maintaining privacy, and reconfiguring the systems by varying resources on a variable scale.

Limitations

Though the AI Bio-Innovation Framework (AIBF) has a good potential, there are several key obstacles on its way, which may restrict its broader use in the real world. First are data heterogeneity and failure to have a set standard. They cannot be smoothly integrated, and they impair analytics activities to be more interoperable due to lack of disparate reporting of clinical data and broken multi-omics pipelines (Hasin et al., 2017). Second, the framework should create a balance between explainable and complex modelling. Powerful deep-learning models are frequently black boxes, thus they are less transparent, and hence, less trustful among clinics, resulting in their reduced accountability (Mittelstadt et al., 2019). Third is that the AIBF consumes resources like energy and infrastructure in very large sizes, especially to solve computationally intensive multi-omics models, and real-time predictive scale monitoring, which has sustainability concerns (Strubell et al., 2019). Lastly, international fragmentation of regulations complicates the international implementation. The laws are also widely different in regions and ethical rules and governance, and cross-border health AI systems may not easily comply with the principles of privacy laws (World Health Organization, 2021).

Future Research Directions

Future studies on the field of the AI Bio-Innovation Framework (AIBF) will have to explore in several different directions to perfect and refine the potential to expand, increase the credibility, and to make the solutions sustainable in practice within the medical sphere. Federated multi-omics and wearable learning are given priority directions since they offer the privacy-preserving global collaboration between hospitals and countries (Rieke et al., 2020). A broader application can also be accomplished by the use of causal and explainable forms of AI in the clinical system, which can be used to establish superior levels of transparency, trust and accountability in making critical decision-making processes (Mittelstadt et al., 2019). Moreover, AIBF should support wearable intelligence by edge AI in order to reduce the latency and response time and reduce the cost of operation of continuous monitoring conditions (Islam et al., 2015; Dunn et al., 2018). It has Green AI optimization based on the designing of models with carbon awareness and training methods to increase efficiency, which makes it more sustainable (Strubell et al., 2019). Finally, it will be the high data fusion and multimodal learning techniques that will augment the framework, including similarity network fusion, and deep multimodal representation learning. These are approaches that integrate various and heterogeneous biomedical, sensor, and clinical data into effective and strong accuracy health model (Wang et al., 2014; Picard et al., 2021).

Conclusion

Artificial intelligence (AI)-driven biomedical innovation is performing miracles to transform the health of the world. It entails predictive modeling, incorporation of big data into healthcare, combining with wearable gadgets, and multi-omics computational frameworks. But to actually make precision medicine happen we need to be able to have an interoperable ethical scalable sustainable framework of integrating diverse research into a unified translational ecosystem. The paper introduces the AI-Bio Innovation framework (AIBF) which is an overall structure of the interaction of clinical (records), wearable (data), and omics (domains). AIBF integrates AI engines with other sophisticated technologies such as deep learning, generative modeling as well as ensemble technology. It can be used in prevention, surveillance and targeted therapy, in dilution- governance, and sustainability layers to guarantee trust and privacy and to make everyone responsible - energy efficiency. With the integration of explainability, federated learning, ethical governance, and computer sustainability as the core of AIBF, a new stage in terms of precision-directed, globally-strong, and pro-environment healthcare innovation is now ready.

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