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Frugal AI: Impact on Research Methodology

Dr. Sharique Ahmad[1]*, Ms. Subuhi Anwar[2], Dr Saeeda Wasim[3], Ms. Fatima Abbas Rizvi[4]

[1]Professor, Department of Pathology, Eras Lucknow Medical College and Hospital, Lucknow, Sarfarazganj, Hardoi Road, Era University, Lucknow, Uttar Pradesh, India 226003
[2]Research Scholar, Department of Biochemistry, Era University, Eras Lucknow Medical College and Hospital, Lucknow, Sarfarazganj, Hardoi Road, Era University, Lucknow, Uttar Pradesh, India, 226003
[3]Clinical Director and Senior Consultant, Nova IVF Fertility, Hazratganj, Lucknow, Uttar Pradesh, India-226001
[4]MBBS Student, Eras Lucknow Medical College and Hospital, Lucknow, Sarfarazganj, Hardoi Road, Era University, Lucknow, Uttar Pradesh, India, 226003

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***Corresponding author:** Dr. Sharique Ahmad
Professor, Department of Pathology, Eras Lucknow Medical College and Hospital, Lucknow, Sarfarazganj, Hardoi Road, Era University, Lucknow, Uttar Pradesh, India 226003

Abstract

Artificial intelligence [AI] has become an indispensable part of scientific and medical research, however, the exponential growth in model complexity and computational requirements has made AI adoption challenging for resource-limited settings. The concept of Frugal AI has emerged to address this gap by designing efficient, accessible, and sustainable AI systems that achieve comparable accuracy with reduced computational, financial, and environmental costs. In the context of medical research, Frugal AI enables data-driven discovery, diagnostics, and decision-making through low-cost, scalable, and adaptable methodologies. This review explores the evolution and influence of Frugal AI on research methodology in biomedical sciences over the past decade. It discusses its principles, technological innovations, and integration into experimental design, data management, and analytical frameworks. Furthermore, the paper critically evaluates the benefits and limitations of Frugal AI in medical research, highlighting its transformative role in improving accessibility, reducing bias, and fostering innovation in low-resource environments. Finally, it underscores the future perspectives of Frugal AI in achieving equitable, reproducible, and sustainable medical research worldwide.

Keywords: Artificial Intelligence, Biomedical, Health Science, Point-of-Care Monitoring, Drug discovery.

INTRODUCTION

AI has moved past an esoteric technology and has become a workhorse of health research and medical practice. From drug discovery to genomics to personalised medicine, it has completely transformed the way we view the data in the field of health science [1, 2]. However, AI advancement particularly the deep learning comes with enormous issues, significant cost of computation, excessive power consumption, and inaccessible resources [3]. Such gigantic models require colossal data, highest quality hardware as well as weight loads, and this implies that numerous research groups, particularly those located in low and middle-income nations, are not able to match [4]. That has compelled individuals to consider a Frugal AI style that is efficiency driven, sustainable, and reasonable to the environment [5].

Frugal AI is simply doing more by doing less. It advocates simplicity and efficiency and simple access without compromise of analysis rigor and predictive power. The concept contains such techniques as model compression, transfer learning, edge computers and low-cost data collection that are determined to use fewer resources but to remain reliable. Precisely, Frugal AI resembles responsible research and technology reducing waste and democratizing AI [6-9].

This is one game-changing practice in medicine. It allows researchers to plan cheap and inclusive experiments and workflows. For instance, frugal deep-learning models can run on low-power hardware, thus enabling on-device diagnostics or real-time data analysis in remote settings [10, 11]. These models are also adequate in assisting with the reproducibility in that they are easy to deploy and check under many varying research environments without involving huge compute infrastructures [12]. Moreover, they provide a level playing field, it allows limited-budget organizations to conduct high-quality data analysis, which helps to bridge the gap between well-financed and underdeveloped circles of researchers [13, 14].

In recent years, the relevance of Frugal AI has become increasingly evident in the biomedical community as researchers consider sustainability and ethics in technology use. The environmental impact in terms of energy consumption and carbon footprint has made largescale AI methods reportedly questionable in their scalability [15]. Frugal AI represents an alternative trajectory because of their attention to model efficiency and the reduction of redundancy without damaging scientific validity or transparency, it prefigures such trends across the world as sustainable innovation, open science, and fair healthcare. The recent hype of Green AI a collection of systems meant to be energy efficient and environmentally friendly has vivified cases of penury in computational research [18]. Combining these thoughts, Frugal AI has turned into one of the foundations of responsible and sustainable technological advancement [16, 17].

Thus, Frugal AI is a technology creation as well as an approach to research. It reinvents the way scientific research may be conducted, managed, and disseminated to ensure its accessibility around the world, promoting cooperation and accountability. This review will deconstruct the manner in which Frugal AI has transformed the operations of medical and biomedical research by affecting the data processing, model construction, practices of validation, and experimental design. It will also exploring the practical cases of how frugal AI principles have enhanced efficiency and accessibility in research.

LITERATURE REVIEW

Frugal AI belongs to the broader trend of sustainable innovation and fairness of technology to all the last few years have seen a growing number of studies investigating various ways in which AI systems can be so configured to achieve high performance on tasks with fewer resources. Articles published in 2017 and later provide a development of Frugal AI in the three principal directions: making models it efficient, developing new methods of research, and implementing these concepts in the clinic and diagnostics.

Frugal AI and its Conceptualized Framework:

The name Frugal AI was associated with the mainstream machine-learning community continuing to consume batches of big data, expensive GPUs, and huge amounts of energy [2017]. The paradox in costs of research began to draw the attention of researchers, AI was beneficial to decision-making and at the same time, increased the distance between well-funded and under-funded labs [4]. In 2020, the concept evolved into a philosophy of AI-to-all, which includes affordable, accessible, adaptable and sustainable [7]. The authors placed Frugal AI in terms of doing responsible computing and sustainable research design, such that frugality should be part of the design, rather than an addition to design afterwards [9].

Biomedical Frugal AI models have emerged as an actual game changer as more data collection redundancy is reduced, computational pipelines simplified and the carbon footprint diminished without reducing the analytical accuracy of the analysis point. According to another researcher, such systems rely extensively on lightweight architectures, ingenious quantization tricks and edge level computing- all of which collectively enable AI to be viable even in resource limited medical contexts. Their Frugal AI even acquired the name of the green AI equivalent due to its energy efficiency, interpretability and sustainability.

Algorithmic and Computational Efficiency in Medical AI:

Although we refer to the backbone of Frugal AI, it is all about the algorithmic efficiency. Ranging all the way down to model compression and pruning to quantization and low-rank factorization, much of the literature of 2018 through 2025 has concentrated on reducing compute time and energy spending.

Pruning and Compression of Models:

In an early systematic review, compression techniques to make AI sustainable showed up to 90 percent reduction in redundant network parameters without making accuracy compromise [7]. A pruned CNN with the chest X-ray data reduced the model size by 150 to 14 MB with a loss in the accuracy of only 1.3 percent only [17].

Knowledge Distillation and Quantization:

Quantization reduces memory and computation loads by converting high precision weights to a lower bit representation. In another study, quantized deep learning was used to ECG-interpreting portable devices, and this allowed real-time cardiac monitoring even without a GPU. There was also the use of knowledge distillation, where small models [students] are trained by larger models [teachers] but maintain diagnostic accuracy and remain inference sparse [18].

Edge and Tiny ML Deployment:

Frugal AI coincides with Tiny ML and Edge AI. In a recent paper, it was proposed that Biomed Bench is a collection of low-power MCU-suited biomedical AI benchmarks [13]. Smart wearables able to continuously monitor cardiorespiratory health can execute inference on board as opposed to sending data to a remote server, reducing power consumption and communication cost. Silva *et al.,* used the frugal design principles to develop a real-time defibrillation algorithm that achieved 99.6% specificity on an ultra-low power embedded processor [10]. These applications illustrate the way algorithms can cut down expenses and get AI calculation nearer to the point of care delivery.

Innovation Methodology in Medical Research:

Frugal AI has reversed the biomedical research methodology script. Previous research made use of large, central data, massive compute cluster, Frugal AI advocates small, reproducible, low-cost designs.

Transfer Learning and Data efficiency:

In biomedical research, the highest expense of the cost list is data collection. Among the frugal strategies used are transfer learning, few-shot learning and synthetic data generation. A study has illustrated that transfer learning has removed the necessity of large, annotated dermatology datasets thus attaining a high level of diagnostic accuracy [2]. An additional produced synthetic medical image using GANs to train lightweight CNNs in low -data environments [18].

Proactive Learning and Economical Approaches:

CoAI is a cost-conscious AI system that aids the measurement costs in the learning loop. It reduced the variables it needed using trauma triage and ICU mortality data and did not negatively affect performance [12]. This represents a paradigm shift to Frugal AI and balancing predictive and economic efficiency with each other instead of pursuing accuracy at an extreme cost.

Decentralized Collection of Data:

Frugal AI models are physically placed in wearable health research on devices to be directly analyzed on site. As an illustration, an author created a smartwatch-powered AI license of heart-rate correction in the instance of construction workers. The frugal algorithm consumed only 880 bytes of memory and maintained average error at less than 9bpm. Such systems reduce expenses and latency of data centralization, allowing large-scale and real-world experiments to be made possible [11].

Reproducibility and Accessibility:

A major pain point of biomedical AI papers is reproducibility. Frugal AI is involved by making sure experiments can be executed on a small-scale hardware. In one of the research projects, it was demonstrated that diagnostic AI can be implemented on the resource-poor hospital environment with lightweight, open-source tools [19]. This increases inclusivity, decreases dependence on several well-financed centers and promotes global cooperation.

Uses in Clinical and Diagnostic Usage

Frugal AI is demonstrating its value in diagnostics, monitoring, as well as epidemiology.

Diagnostics and Imaging:

In radiology, computationally thin models are run on-device, or in the cloud, based on diagnostics. A TB detection AI model based on edges was implemented on portable X-ray machines, achieving 93 % accuracy with a small power consumption on a cheaply available ARM processor. Ultrasound imaging and skin lesion classification with lightweight CNNs such as Mobile Net and Shuffle Net have been shown to have similar accuracy as much larger models, using only a tenth the amount of power [20, 21].

Remote and Point-of-Care Monitoring:

In the COVID-19 times, Frugal AI was used to make remote patient-monitoring, particularly in places with patchy internet or power. Wearables with Tiny ML costing low monitored vital signs and another group integrated frugal AI to indicate oxygen desaturation events based on low frequency pulse oximetry information [22, 23]. These systems reinforce the importance of the frugality of these systems in global health surveillance and telemedicine.

Drug Discovery and Systems Biology:

Frugal AI is used in the process of drug discovery to streamline some modelling using resource optimization. Sparse sampling, adaptive simulations and surrogate modelling reduce the computational cost of molecular docking and pharmacokinetic modelling [24]. It was even constructed in a lightweight form using transformers to make predictions of drug-target interactions using fewer parameters so that it could be run on common lab computers without specialized high-performance GPUs [25].

Such efficiency democratizes the process of computational drug discovery because small-scale laboratories can now be involved in the process of exploring AI-based research on pharmacology.

Public Health and Epidemiology:

Frugal AI models have also been used in epidemiological models. While in 2022 a low-complexity predictor was created that can model the spread of COVID-19 with only small amounts of data. It also used 80 % less energy compared with the conventional neural network models indicating that predictive performance does not have to suffer due to computational parsimony [26].

Sustainability and Ethical Dimensions:

More and more literature highlights the ethical and environmental sustainability of Frugal AI. In one paper, the carbon footprint of a large-scale AI model training was measured and it was found out that a single transformer has the power to produce more carbon dioxide than five automobiles over a lifetime. Scholars are currently adding environmental indicators like energy-per-inference and power consumption of the lifecycle to the attention of same of artificial intelligence models [15, 3]. The other author highlighted the need to incorporate sustainability into the research design of AI based on regulatory principles that promote energy-saving models and low impact computing [16]. Frugal AI therefore represents moral interaction with the environmental management and technological development. These ethical requirements are echoed in the aims of sustainable AI to a medical research community that has a mantra of the medical profession to do no harm. Last but not least, the ethical and governance aspects of introducing AI in low-resource healthcare environments should be studied further in terms of data privacy, equity, and accountability. This prepares the road to benchmarking, clinical validation, and cross-disciplinary collaboration, which future methodological research needs to solve.

Frugal AI: The Advantages and Disadvantages of Research Methods.

The concept of frugal AI in medical and biomedical studies suggests another paradigm of equilibrium between the innovation and restriction, ability and accessibility, economy and sophistication. Frugal AI philosophy is based on the premise of providing high-impact results using minimal resources and offering opportunities and challenges that should be carefully considered to offer rigor and sustainability.

In the methodological perspective, democratizing access to the tools of artificial intelligence can be listed among the most important benefits of Frugal AI. Traditional AI models can require substantial computational resources, thus ruling out small laboratories, low resource hospitals and academic centres in developing nations more frequently than otherwise. By comparison, Frugal AI uses lightweight code, data pipelines optimised, and edge-computing, which are well-performing on small hardware. Such accessibility makes more researchers belonging to a wider range of cadres pursue AI-driven approaches to encourage inclusiveness and involvement in global biomedical innovation. As a case in point, CNNs with low power have demonstrated to be effective in point of care diagnostics imaging or in handheld or smartphone-based devices that can perform a rapid overview of pathology and therefore brought AI out of tertiary healthcare facilities.

Other strengths of Frugal AI are that it is cost effective to conduct study and implementation. This will allow researchers to cut the costs on training by eliminating large data and computational overheads and attain model accuracy that is good enough to serve most medical applications. Such efficiency is achieved by using the transfer learning, knowledge distillation, and model pruning. As an example, transfer learning trains a pretrained model trained on a large dataset on a smaller and domain-specific medical dataset with little loss in time and agent resources with no loss in accuracy. This is of particular use in medical research studies, in which it can be quite costly, time-intensive and at times ethically challenging to obtain labelled data [6, 28, 1, 9]. Besides, Frugal AI contributes to the methodological sustainability with the rising criticism of large-scale AI models by considering their environmental effects, energy-efficient algorithms are a subset of a larger scientific agenda of sustainable and responsible research [17]. Various researchers have shown that when optimisation techniques, including quantisation and parameter sharing, are used it is possible to cut carbon emissions to as much as 90% of the levels in conventional deep-learning systems with little performance degradation [16]. Such focus on sustainable computation comes in line with the ethical and environmental deeds that are gradually placed on the biomedical research institutions that are often expected to bear the responsibility of their carbon footprint [12].

Nevertheless, the benefits should not be exaggerated, and their weaknesses and possible shortcomings should be distinctly stated. Basic problems of efficiency and performance occur. Even though frugal models are based on the idea of reduced resources [computational], their reduction could also involve the decrease in accuracy, especially in the biomedical field that needs high sensitivity and specificity. This issue is particularly intense in image classification in histopathology where smaller models may not be able to detect even small morphological features in contrast to large-scale convolutional models. As a result, there may be a reduction in diagnostic accuracy, particularly in the cases of the diseases in which the slight morphological changes have serious clinical implications [29, 30].

The other methodological issue is the quality of data and generalisability. Although frugally AI methods can use less costly or low-resolution data to justify lower computational expenses, they might introduce some kind of bias, as well as restrict extrapolation to other populations [6]. This is of particular concern to the low-resource contexts where an unreliable data gathering automatically creates an over-fitting or under-representation issue [31]. Frugal AI aims to democratise access, but its application can be applied carelessly. Therefore, may encourage inequity, even though models trained on smaller datasets are generalised [32].

Interpretability and transparency have been controversial. Even the cheaper and less elaborate models can continue to run through opaque learning mechanisms and this is a challenge to the very essence of reproducibility on which scientific research is based [33]. Moreover, compression and optimisation methods, which promote frugality can have a direct impact on interpretability by interrupting internal features hierarchies [28]. This presents an ethical dilemma especially in the biomedical context where explainability is essential to a clinical adoption and environmental approval. The other drawback is with regard to scalability and maintenance. Frugal AI systems can work well in resource-limited settings, but might not perform well in extensive clinical settings or multi-institutional research non-profit collaborations [34]. Local optimisation that helps in promoting performance in a particular setting may be considered a liability in situations where there is a need to generalise across different settings [6].

Besides, since frugal systems often make heuristic adaptation and context-dependent settings, over time maintaining and standardizing such systems with a growing dynamic research landscape where modalities of data are ever-changing becomes even harder as data modalities continually evolve [10]. This idea can be projected even further. Frugal AI must be cognized not only as the method of economising but as the philosophy of maximisation of the methodology. The effectiveness of its use in biomedical research will depend on how useful scientists can incorporate frugality in their experimental design without jeopardizing the scientific integrity. In that sense hybrid strategies in which thrifty model is used as a first-line diagnostic or screening tool and that is further confirmed by more elaborate models have been suggested as a viable compromise. These systems are a well-organized compromise between efficiency and reliability a sign of a developing responsible AI research ethos.

Frugal AI has a transformative potential of changing the way of conducting research and how it is conducted towards being more accessible, time-efficient and environmentally conscious. Nevertheless, the shift of imaginative innovation into perceived reliability requires continuous methodological development, sound data management and situational validation of the consequential validation. The way these restrictions can be identified and managed will define the difference between having Frugal AI as a long-term regularity of biomedical research across the globe or another resource-limited niche-based solution.

DISCUSSION

Frugal AI is a new dimension that reproduces the concept of the biomedical research approach altogether. It is not merely a technological innovation nor just a conceptual innovation in the way research is designed implemented and shared but it is a revolution that promises to herald efficiency, inclusivity and sustainability. This methodological dispute is a vivid example of the strong interdependence of scientific rigor and practical flexibility into the world as it testifies that a lot of resources are not essential to develop a good research but can be replaced by resourcefulness and optimisation.

The frugal AI has transformed the world of biomedical experimentation methodologically. Conventional research using data assumes vast amounts of data of high quality and strong computing resources [6]. On the contrary, Frugal AI is made using wafer-thin limits. Model compression, pruning, quantisation, and transfer learning techniques have also made possible similar predictive performance with smaller architectures

[8, 9]. This is a change of methodology to an efficiency-as-innovation culture, of which creativity substitutes brute-force computing. As a result, the channels of diagnostics image and genomics screening are now quicker, less expensive and supply repeated outcomes [14, 4].

More to the point, the introduction of Frugal AI to biomedical processes has produced a larger cultural change towards responsible research. Frugal systems can be used in the current climate of sustainability and equity by allowing laboratories and hospitals in resource-limited environments to do high-impact research without expensive infrastructure [12]. This democratization of AI research makes it easier to establish health networks both globally and regarding cross-border cooperation, particularly infectious diseases surveillance, telepathology, medical image inspection etc. [31, 7]. The idea of frugal AI has thus become a form of methodological equaliser which fills the gap between elite and resource-constrained worlds of research.

The other important aspect on the impact of Frugal AI has to do with the capability of reproducibility and transparency which has been a thorn in the flesh of the field of biomedical science. The architectures of lean AI models and their data requirements are simpler by default, which makes them easier to reproduce and verify [12]. This simplifies the process of independent verification among institutions, which enhances the credibility of AI-based research. Also, modular models are more explanatory, as they can be human controlled and interpreted, which is critical to clinical translation, especially when it comes to clinical translation [32, 33]. With an optimisation of frugality, algorithms tend to work out more in unstable conditions thus enhancing methodological robustness [16].

These advantages, however, also have subtle constraints that create responsible usage of Frugal AI. The most important debate still revolves around the balance between simplicity and sophistication. In complicated biomedical cases, as exemplified by multi-omics integration, molecular modelling or precision diagnostics, the dimensionality of features and heterogeneity of data can be more than the frugal architectures [29,30]. Therefore, some regions hold danger of becoming over simplistic or less accurate in the event that frugality is made a goal in itself, and reaches beyond the depth of the analysis. This stresses the need of using AI in a contextual way Frugal AI must add value to but not replace traditional high-capacity models on task wherein interpretability, energy efficiency or accessibility hold greater importance.

The other major methodological implication in the future is the issue of the trade-off between data economy and data diversity. Frugal AI typically trains on smaller or synthetic data to reduce the training overhead, though the lack of variety in the data restricts generalisability and causes bias [14]. This is particularly problematic in medical research wherein population genetics, imaging apparatuses and clinical procedure creates disparities in the distributions of data-structures. Without an adequate representation, frugal models provide inconsistent findings across demographics, which reduces their external validity. Combining frugal training with federated or collaborative learning models have become one of the promising approaches to increasing the diversity of models without disrupting the efficiency [hybrid research methodology] [34, 35].

Frugal AI has also triggered a reconsideration of the evaluation measures in the approach to research. Contrary to the fact that the traditional models are traditionally evaluated based on performance metrics like accuracy or AUC, frugal systems also provide new metrics, such as energy use, computation time, carbon footprint and costs affordability fifteen times [17, 36]. This broadened evaluation approach allows a comprehensive evaluation of quality of methodology with technical performance as part of sustainability and ethical responsibility. By doing that Frugal AI calls on researchers to rethink what good science will bring them and efficiency, equity, accessibility, and accuracy and novelty will be promoted as a set of values [34].

In a larger scope, Frugal AI creates ethical and environmental responsibility in biomedical science. The environmental footprint of the large-scale training of a model is disastrous one deep-learned model, in current estimates, may contribute to as many as several lives of necessary human activity, as discovered recently, according to recent estimates [37]. In this way by encouraging a scientific approach that can achieve sustainability in the world, Frugal AI is compatible with the objectives of global sustainability like the SDGs of the United Nations by a mere reduction in energy costs through leaner architectures [38]. This ethical bias makes AI-based science more trustworthy to people and frugal approaches become role models of socially responsible innovation [7].

Notably, frugal AI can be used in two aspects to save money and increase the agility and scalability of research. The use of low-resource AI systems is able to be quickly implemented into field research studies, outbreak research or clinical trials thus allowing rapid hypothesis testing and adaptive research study design [34]. Frugal machine-learning models were useful in fast screening and triage of diagnostic protocols in low-resource environments without traditional infrastructure needed during a pandemic like COVID-19 [39]. Such deployments demonstrate the way in which cost-effective methodological practices may achieve the objective of scientific responsiveness, especially in contexts of time or geographically sensitive research.

Nonetheless, standardisation and proper governance models are also needed to bring frugal AI into the biomedical methodology in a long-term manner. So far, there has not been much agreement on benchmarking protocols, reporting standards and particular procedures by which frugal models are validated [40]. Without such a framework, the absence of a consistent comparisons of frugal and conventional AI is likely to oppose the approval of regulatory and clinical adoption [41]. Reproducibility, comparability and ethical supervision of frugal AI research require that multifunctional metrics and clear-cut record keeping guidelines should be created.

Perspectives on Frugal AI in Research in the Future.

Frugal AI continues to face a future direction of approaches based on trust and cooperation a change required by equity in global research. One of the objectives is to overcome the black box problem with the advanced architectures like Neuro-Symbolic AI [NSAI] that combines both efficiency and computational efficiency with explicit and rationalistic reasoning and is capable of satisfying the high ethical standards necessary to use it in a clinical setting [41]. This added confidence will help in new collaborative models, one of which is Federated Frugal Learning [FFL]. FFL allows already existing institutions, particularly in genomics and rare diseases to share information and yet store data locally, and generate small transportable models, which operate in clinics constrained by resources [40, 38]. Moreover, the data collection process will be changed by Frugal AI. The scholars will develop Generative AI [GenAI] to generate highly diverse datasets which will improve upon the problem of data scarcity allowing Frugal AI to operate in drug discovery and any other data-intensive field [42]. Lastly, the design will be done in a sustainable manner. Green AI will replace Hardware-Aware Neural Architecture Search [NAS] and similar techniques which will automatically create energy efficient models in the first place making it a fundamental methodological requirement [43, 44].

Challenges and Limitation of FAI

Although it has positive aspects, the implementation of Frugal AI is seriously challenged by the vulnerability and loopholes in the governance.

The largest one is generalization failure: Frugal models, in particular compressed-architecture-based or Few-Shot Learning [FSL] based are brittle and very sensitive to changes of distribution. In cases where they are used on different and external groups the predictive validity may reduce drastically as it affects the validity of the scientific results [45, 41].

Ethical issues aggravate this issue: Since FSL is based on extremely small data groups it has the potential to increase the level of existing societal and demographic prejudices resulting in discriminatory research findings [46, 42]. In terms of operation the construction and optimization of these models, including the amount to be pruned, are complicated and they can only be developed with specialized skills as well as enormous computational resources [44]. Finally, there has been a deficit in governance due to the rapid technological advancements. The regulatory frameworks have failed to keep up with the capability of Frugal AI to execute on decentralized, edge devices and this has raised legal and ethical ambiguity regarding the liability and responsibility when a remote diagnostic tool makes a mistake [47].

As discussed, frugal AI has an influence on research methodology due to reasons other than technological efficiency. The philosophical revision of scientific priorities to which it has attained gives a value added to inclusivity, resource stewardship and ethical sustainability as key elements of methodological perfection. The change is more concerned with redefining the meaning of meaningful and responsible biomedical research in the twenty-first century rather than cost-effective innovation. However, the very prospect will require a delicate balance of efficiency and accuracy, simplicity and depth, and openness as well as responsibility. Such a balance would benefit frugal AI indeed making it an intervention of game changer to scientific progress that is equitable and sustainable provided that it is placed within a well-managing methodological framework.

CONCLUSION

The frugal AI has radically transformed contemporary biomedical and clinical research practice and has redefined scientific inquiry and its vision, creating a novel paradigm of scientific inquiry. The essence of its philosophy and that is to achieve the best production at the least cost of resources has aided democratization of access to advanced analytical tools, particularly in the low-resource context. Frugal AI helps to overcome the technological gap existing between high- and low-income research settings by focusing on efficiency, sustainability and inclusivity so that the innovation is no longer a problem of infrastructure.

Frugal AI goes beyond computational savings with regard to its methodological influence. It reinvents the definition of good science in the age of automation and with a plenitude of data. It promotes the creation of lean but strong models, flexible experimental designs, and environmental research designs. However, there are obstacles on the road to mainstreaming frugal AI. Problems of generalisation, interpretability and validation require careful consideration of the maintenance of scientific integrity. In essence, frugal AI is the change that the biomedical research is currently moving towards a more sustainable and fairer paradigm. It points out to the increasing realization that innovation does not necessarily lie only in technological breakthrough but also in the wise management of resources. Frugal AI with sound standards and moral governance can get us to a scientific discovery of the future with greater accessibility, efficiency, and global environmental sensitivity.

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