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AI and ML Assessment of Performance-Based Financing Models in Health Care: A Review

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Abstract: *Performance-Based financing (PBF) has become an important strategy towards enhancing accountability, efficiency and quality in health care systems, especially in the developing countries. Nevertheless, the classic indicators system of PBF is usually associated with ineffective utilization of data, excessive bureaucracy, and poor coverage of the health outcome complexity. The paper will reflect how AI and ML will improve PBF model evaluation in order to support predictive analytics, anomaly detection, natural language processing, and improve the optimization of incentive structure. This suggest that the use of AI/ML tools could greatly enhance monitoring and evaluation, by increasing accuracy, scalability, and transparency and enabling fairer and more sustainable financing strategies. However, there remain issues of data quality, transparency of algorithms, constraints on resources, and associated ethical issues, such as bias, privacy and explainability. Finally, the study has revealed that AI/ML could be effectively integrated into PBF evaluation to help develop health financing systems but demands keen implementation, high-quality governance, and further research to make it fair and maintainable.*

Keywords: *PBF; Artificial Intelligence (AI); Machine Learning (ML); Health Financing; Predictive Analytics; Efficiency; Accountability; Digital Health; Sustainable Healthcare*

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1. 0 Introduction

Machine Learning (ML) and Artificial Intelligence (AI) have begun transforming various interdisciplinary fields by providing dependable solutions for data analysis, real-time decision-making, and autonomous navigation (Ufomba & Ndibe, 2023; Ademilua & Areghan, 2025a; Ndibe, 2024; Adjei, 2025a; Abolade, 2023; Adjei, 2025b; Ademilua & Areghan, 2022; Dada *et al*., 2024; Adjei, 2025c; Ademilua & Areghan, 2025a; Akinsanya *et al*., 2022; Utomi *et al*., 2024; Ndibe, 2025a; 2025b; Okolo *et al*., 2025; Ademilua & Areghan, 2025b; Ndibe & Ufomba, 2024; Okolo, 2023; Akinsanya *et al*., 2023).

Performance-Based Financing (PBF) is becoming an approach to health financing that aims at enhancing the effectiveness, transparency accountability and quality of health care delivery by tying provider reimbursement to quantifiable outcomes. In this model, the providers are financially rewarded in case of accomplishing predetermined standards of performance, which may include elevated rates of service utilization, better maternal and child health indicators, or superior standards of quality care (Meessen *et al*., 2011; Renmans *et al*., 2017). Compared to the traditional type of input-based financing, where funds are administered irrespective of achievements, PBF is focused on the outcomes, thus, aiming at developing a culture of accountability and performance in health systems (World Health Organization [WHO], 2022). Some of the key targets of PBF are the motivation of health workers, equitable access to essential services, rational use of limited resources and lastly strengthening health system responsiveness to the needs of the community (Witter *et al*., 2013).

PBF has been in use in the world since early 2000s, especially in LMICs. Rwanda is commonly referred to as a success story where PBF was introduced nationwide leading to positive results in maternal and child health, in addition to decentralized health systems governance strengthening in Rwanda (Basinga *et al*., 2011). An identical principle can be found in reports of similar initiatives in other countries, e.g., in Burundi, Mozambique, and Burkina Faso, where PBF schemes have started on lower levels and have subsequently been upscaled to meet systemic health-related issues (Okiror *et al*., 2024; Turcotte-Tremblay *et al*., 2020). In Mozambique, performance incentives were associated with large improvements in HIV prevention and maternal health services with more than two-thirds of health outcomes moving in the positive direction within 18 months of implementing performance incentives (Kruk *et al*., 2018). Although these are encouraging developments, findings on the long-term renewable nature of PBF, as well as the effectiveness of such a system across the board are mixed, particularly when differences in context, politics, and institutions are factored (Paul *et al*., 2018).

Performance-Based-Financing (PBF) has become one of the health financing mechanisms aimed at improving the efficiency, accountability, and quality of health care delivery by linking provider payments with a measurable result. In such a model, performance indicators (defined as increased service utilization rates, better maternal and child health outcomes, or the quality of care provided) are used, and the providers are offered financial incentives when these indicators are met (Meessen *et al*., 2011; Renmans *et al*., 2017). In contrast with traditional input-based financing, where resources are distributed irrespective of the results, PBF has the focus and accountability on outcomes, therefore aiming to instill the culture of performance and accountability in health systems (WHO, 2022). The main goals of PBF are to enhance motivation of health workers, facilitate access to easier services, rational use of available resources, and eventually support system responsiveness to the community (Witter *et al*., 2013).

PBF has been implemented throughout the world, with uptake increasing in low- and middle-income countries (LMICs) especially since the beginning of the 2000s. Rwanda has been one of the most frequently discussed success stories, whereby PBF has been implemented nationwide, leading to improvements in the health of children and mothers, and the decentralized health systems governance strengthening (Basinga *et al*., 2011). Other efforts to introduce such systems, like the ones in Burundi, Mozambique, or Burkina Faso, have been described, tracing the process of piloting PBF schemes and its subsequent expansion to meet fundamental health issues (Turcotte-Tremblay *et al*., 2020). In Mozambique, results driven by performance incentives have resulted in increased HIV prevention and maternal health services with over two-thirds of health measures reporting improvements in the first 18 months of the program implementation (Kruk *et al*., 2018). Albeit, these are encouraging tendencies, the data concerning the long-term sustainability and system-wide performance of PBF is rather mixed, particularly, accounting the contextual, political, and institutional peculiarities (Paul *et al*., 2018). In addition, such tools have the capability to enhance equity analysis by revealing the existence of latent biases in the provision of services and assist in making interventions more efficient. Combining AI, ML with PBF assessment can additionally provide finer insights into trends in performance and help ensure more consistent and transparent reporting, as well as create mechanisms of financing that will be efficient, yet sustainable.

This research focuses on investigating how to use AI and ML to better assess PBF models in health care. Precisely, it aims to explore the idea whether AI-driven analytics may improve the measurement of efficiency, equity and sustainability, as three key dimensions frequently mentioned when discussing the effectiveness of PBF. This study will fill the gap between the advanced computational approach and the health financing assessment and will be added to a relatively narrow field of literature concerning digital health innovations and their potential contributions to building stronger global health systems.

2.0 The Role of Artificial Intelligence and Machine Learning in Health Financing

2.1 Overview of AI/ML Applications in Health Economics and Financing

Artificial Intelligence (AI) and Machine Learning (ML) have been on the rise with regards to the field of health economics and health financing because they can process complex information and leverage decision-making and policy evaluation, Fig 1 shows the different applications of ML in health financing. ML is a derivative of AI and is a more specific field involving the algorithms that become intelligent by learning patterns in information to make a prediction or classification (Russell & Norvig, 2021). Health financing The use of these technologies is on the increase in health financing relating to the allocation of resources, prevention of fraud, cost estimation, evaluation of financing mechanisms such as Performance-Based Financing (PBF) (Shrestha *et al*., 2021). There are some kinds of AI/ML models that are applicable in this regard. Prediction of health expenditure and provider performance is usually done using supervised learning models (e.g., regression, support vector machines, and decision trees). Unsupersvised learning models (e.g., clustering and principal component analysis) can help to partition populations to implement targeted financing policies. The use of reinforcement learning is also being researched to optimize provider incentive structures in PBF in terms of paying providers different amounts depending on their performance and recalculating over time. Also, complex health financing datasets, including claims records, and electronic health data, are leveraged using deep learning models to improve predictions (Esteva *et al*., 2019). These models altogether can help in health systems to better maintain the risks, resource allocation and assessing the financing mechanisms more allocate resources, and evaluate financing mechanisms more efficiently.

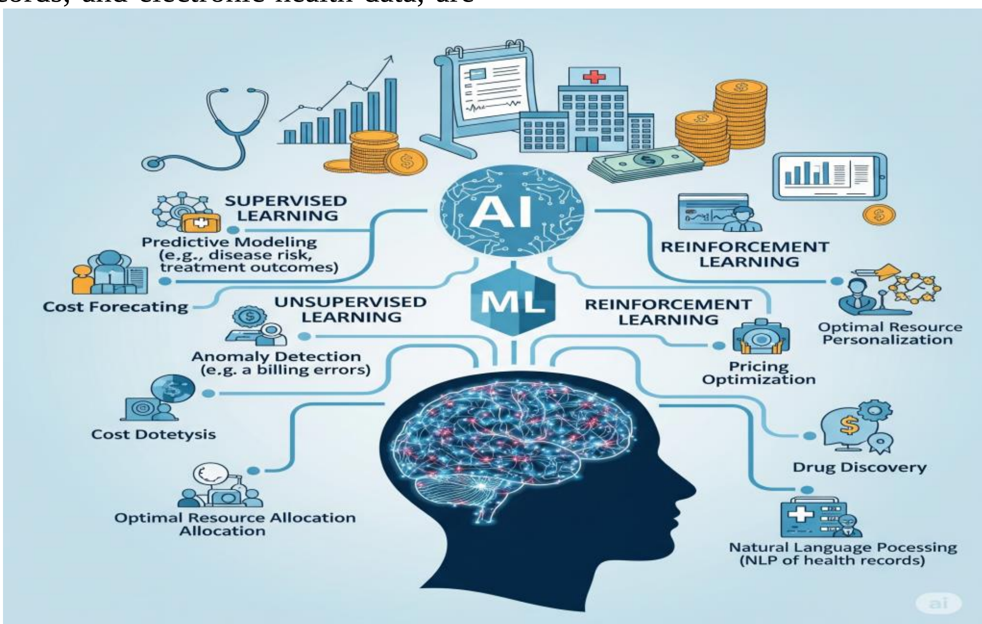

Fig. 1: Application of AI and ML in Health financing

2.2 Data-Driven Approaches to Performance Evaluation

Prior to the introduction of AI and ML, performance measurement within the health financing disciplines was based heavily on manual reporting methods, conventional econometric analysis and post-factum analysis. Nevertheless, these methods were not very efficient, precise, or without biasing factors because of incompleteness or delays in data (Ezeogu, 2023). Amid the proliferation of data-driven approaches, AI and ML can now access and evaluate vast and heterogeneous amounts of data in real-time, such as patient outcomes and patient provider performance indicators and financial records. Machine learning models have the potential of unearthing latent trends and relationships between finances and health outcomes and provide a more comprehensive analysis than the traditional approaches. As an example, ML can examine provider data of heterogeneous providers to identify poorly performing facilities or areas and influence policy approaches at that area (Obermeyer & Emanuel, 2016). Furthermore, it is possible to intersect natural language processing (NLP) to analyze the previously unstructured documents, e.g., clinical notes or policy reports, that were not easily included in financial analysis (Rajkomar *et al*., 2019). These evidence-based practices add more light, cover fewer circles that lack efficiency, and increase accountability in health financing systems.

2.3 Advantages of Predictive Modeling over Traditional Methods

AI / ML-based predictive modeling has several important benefits over existing evaluation methods (Table 1). It is usually more linear and needs to be modeled, which is not always appropriate when analyzing the non-linear interactions between financing and health outcome. Unlike them, predictive ML models are flexible and can get more accurate with. time as more data becomes available (Deliu & Chakraborty, 2022). In PBF, predictive modeling will allow both policy formulators and managers to predict provider performance, patient outcomes, and costs implication of financing policies in the future. This is a prediction capability that underpins a proactive as opposed to a reactive response, a vital aspect of resource-limited health systems (Amarasingham *et al*., 2014). In addition to that, predictive analytics powered by AI can be used to model various financing scenarios, which will give decision-makers an opportunity to test the trade-off between efficiency, equity, and sustainability. Predictive models are also more inclusive and less prone to biases that may be found in these problems using traditional methods because of multiple data sources used. In most aspects, the future of health financing turned out to be technologically advanced, as AI and ML integration into health financing represents a paradigm shift in the current approach, i.e., retrospective and manual evaluations, to proactive, data-driven, and adaptive systems with the potential to enhance health financing efficiency and equity.

Table 1: Advantages of Predictive Modeling over Traditional Methods in PBF (After Deliu & Chakraborty, 2022; Reddy & Kumar, 2016)

Aspect	Traditional Methods	Predictive Modeling with AI/ML
Analytical Assumptions	Assume linearity and rely on predefined models, limiting flexibility.	Capture complex, nonlinear relationships between financing mechanisms and health outcomes.
Adaptability	Static models that do not improve once developed.	Adaptive models that continuously improve accuracy as more data becomes available.
Decision-Making	Supports reactive adjustments after problems occur.	Enables proactive forecasting of provider performance, patient outcomes, and cost implications.
Scenario Testing	Limited capacity for simulating alternative financing scenarios.	Allows simulation of different financing strategies, supporting evaluation of trade-offs between efficiency, equity, and sustainability.
Data Integration	Relies heavily on a narrow set of variables and may overlook contextual factors.	Incorporates diverse data sources (clinical, financial, demographic), enhancing inclusivity and reducing bias.
Policy Relevance	Focused on retrospective evaluation.	Facilitates forward-looking, data-driven policymaking that improves financing efficiency and equity.

3.0 AI and ML Approaches for Assessing PBF Models

3.1 Supervised Learning for Outcome Prediction and Provider Performance Scoring

Among the most popular AI/ML-based methods of performance-based financing (PBF) assessment in the healthcare sector, supervised learning should be listed. These models are trained on labeled data so that an algorithm can predict the likelihood of patient satisfaction, coverage of services offered, or the success of treatment, among others (Shickel *et al*., 2018). As an example, regression models, as well as decision trees, can be used to predict health outcomes referring to the past performance data of providers, which can help policymakers identify which institutions have high and which have low performance. The scoring of the provider performance can also be enhanced with classification models like random forests or support vector machines that places ranks the facilities and allocate the resources accordingly (Rajkomar *et al*., 2019). Supervised learning can be used to reward performance in a more precise and data-driven fashion than can traditional, manual evaluations, due to the availability of large-scale health data (Fig 2). Such a predictive capacity can prove highly beneficial in resource-constrained settings where predictable resource utilization is vital to the sustainability and equity in health care funding.

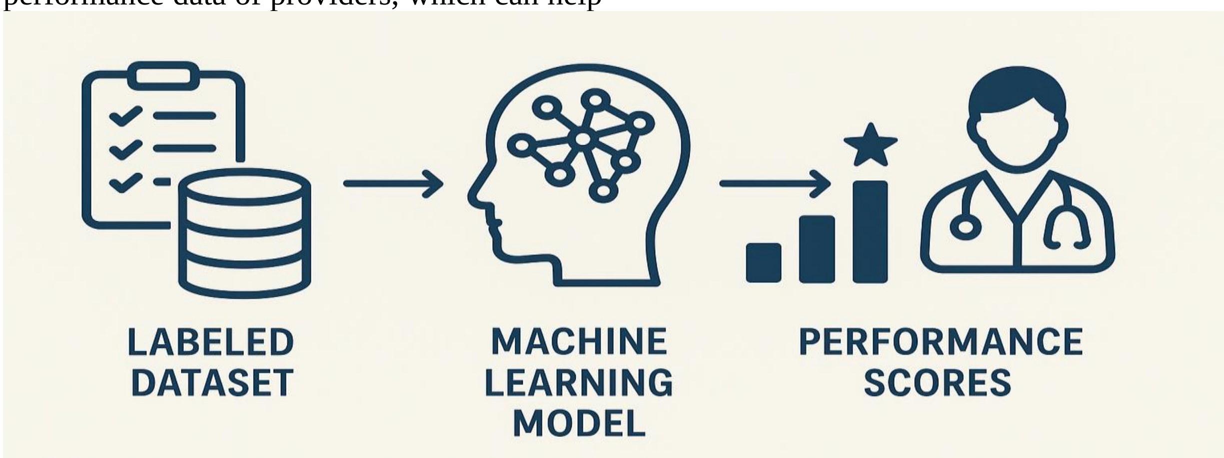

Fig 2: Supervised Learning for Outcome Prediction

3.2 Unsupervised Learning for Identifying Hidden Patterns in Financing Data

Unsupervised learning is also critical in discovering new structures and latent relations to a complex-healthcare financing data (Fig 3). In contrast to supervised models, unlabeled information is not needed in such algorithms, rather, creating a clustering or dimensional reduction that allows exposing the required patterns that could not be spotted right away (Huang *et al*., 2023). As an example, k-means and hierarchical clustering will identify the similar clustering of health facilities or providers by their performance profile such as inefficiencies and resources used. These lessons can be used to create individualized funding mechanisms that do not assume the same patterns of payment as other countries. Furthermore, unsupervised learning has the capability of providing insights on any kind of anomalies in financing flows or fraudulent claims, highlighting accountability and transparency in PBF systems (Miotto *et al*., 2017). Reduction dimension techniques such as principal component analysis (PCA) would also assist the policymakers to comprehend the multi-dimensional health financing data thus making interpretation easier. Therefore, unsupervised learning contributes and bolsters the identification of novel understanding, which can allow more responsive and situation-specific financing models.

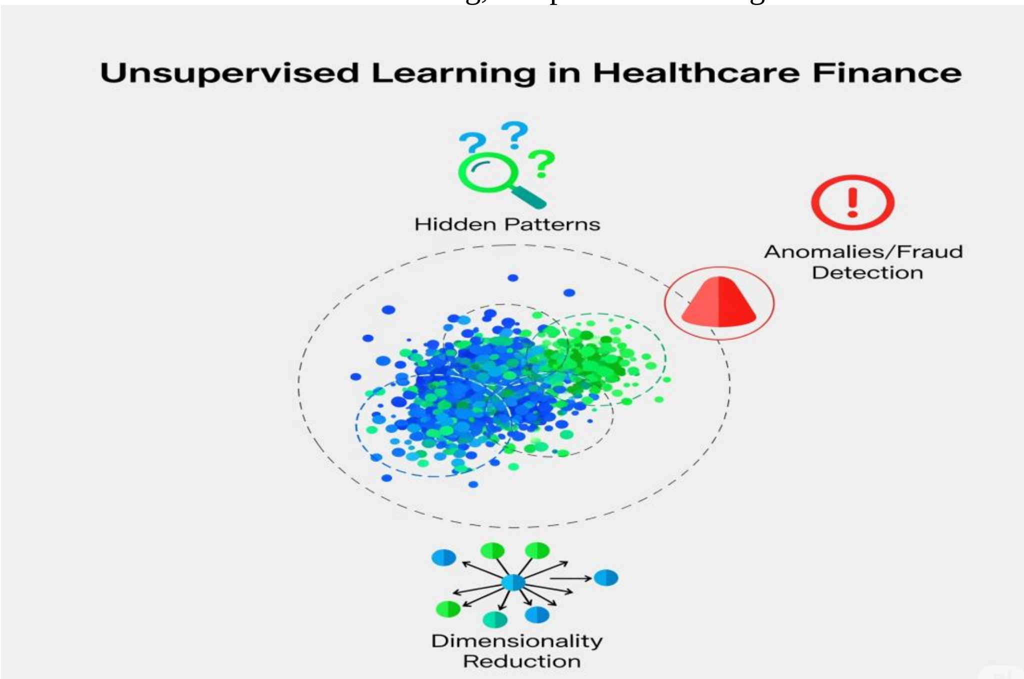

Fig 3: Unsupervised Learning in healthcare financing

3.3 Reinforcement Learning in Optimizing Payment Structures

Reinforcement learning (RL) offers a dynamic approach to optimizing payment structures within PBF frameworks by continuously learning from interactions between providers, patients, and financing systems. RL algorithms operate on a trial-and-error principle, where agents receive feedback from the environment in the form of rewards or penalties (Yu *et al*., 2021). In healthcare financing, RL can simulate various incentive structures to determine which ones maximize efficiency, service quality, and equity. For instance, dynamic payment adjustment models can be developed to reward providers based on both short-term achievements and long-term improvements in health outcomes. This adaptability makes RL particularly suitable for health systems where performance metrics and resource availability evolve over time. Moreover, RL can balance competing objectives, such as cost containment and service quality, providing a holistic optimization of PBF models (Gulshan *et al*., 2016). By continuously adapting to real-world conditions, reinforcement learning presents a promising frontier for sustainable and responsive health financing reforms.

3.4 Natural Language Processing (NLP) for Policy and Stakeholder Analysis

Natural language processing (NLP) widens the scope of AI in PBF evaluation, making use of unstructured textual information (in policy documents, the reports of stakeholders, and in patient feedback). As a multi-pronged issue, health financing is contextually dependent on political and social situations, and NLP offers the means of structured extraction of knowledge based on qualitative sources (Lohani, 2020). Sentiment lexicon could be used to analyse community feedback on their view of PBF schemes, and topic models to know whether there are some recurring themes in policy debates and media coverage. Moreover, NLP helps analyse a vast amount of reports and evaluations in an automated setting quickening the process and reducing resources. NLP can then be used in conjunction with structured data to help quantify financing measures which can then be combined with qualitative analysis to provide a more comprehensive assessment tool (Esteva *et al*., 2019). Such integration is helpful to make sure that financing models are not only efficient but also socially acceptable, equitable and responsive to the needs of various stakeholders.

4.0 Benefits, Limitations, and Ethical Considerations

Artificial Intelligence (AI) and Machine Learning (ML) give an opportunity and pose a challenge when used in the evaluation of Performance-Based Financing (PBF) models in health care. Their advantages entail the increase in accuracy and increase in the objectivity of scales, whereas their drawbacks concern the data and methodological limitations. Also, ethics like transparency and accountability, as well as bias, is another area that is important when developing systems based on AI/ML to be in health financing as it must be sustainable and unbiased.

4.1 Benefits of AI/ML in Assessing PBF Models

The capacity to analyze big, intricate information successfully and with enhanced accuracy compared to other traditional statistical techniques is one of the major advantages of AI and ML. In particular, with the help of predictive modeling, health systems can evaluate the performance of providers, identify their inefficiencies, and distribute resources more efficiently (Shamout *et al*., 2021; Rajkomar *et al*., 2019). This increases the strength of evaluations and decreases performance measurement subjectivity.

The other advantage is that of scalability The creation of the large-scale and cross-country-based datasets will allow using AI/ML systems to compare financing models in different countries and contribute to global health endeavors (Beam & Kohane, 2018). This scalability is what would make sure that evaluations are in line across various health systems and contexts.

In addition to this, AI boosts the transparency of PBF evaluation. Algorithms have the ability to monitor health service delivery in real-time providing decision-makers with timely assessments of the efficiency of funding and outcomes. As an example, Questioning-based dashboards can deliver performance reports to policymakers locally and nationally, thereby helping policymakers make swift decisions (Topol, 2019).

4.2 Limitations of AI/ML Applications

AI/ML approaches, such as those we discussed, have limitations despite the above advantages. One of the essential issues is data quality and availability as very many low and medium-income countries (LMICs) do not have quality health financing information (Rajkomar *et al*., 2019). Inconsistent or preselected information may provide inappropriate models thus impeding their applicability in PBF evaluation. The other shortcoming is the interpretability of AI/ML models. More complex algorithms like deep learning can be treated as black boxes, so the policymakers might not be able to find out how the results are calculated (Ghassemi *et al*., 2021). This interpretability loss can result in diminishing trust in recommendations by AI. Lastly, AI/ML may not be implemented in resource-limited health systems due to resource constraints, including a skilled workforce, poor infrastructures, and prohibitive computational costs (Shamout *et al*., 2021).

4.3 Ethical Considerations in AI/ML-Based PBF

Ethical issues are of concern in the implementation of AI/ML in health financing. Among the least urgent problems is algorithm bias. Since models take as input the expression of a pre-existing inequality, AI models that are learned on such data are most likely to reproduce unfair structure in resource access (Obermeyer *et al*., 2019). Information privacy and security are another moral issue. Health financing data are very personal and also sensitive institutional data. AI/ML models are not sufficient to guarantee the risk-free use of such models without appropriate safeguards, which can endanger vulnerable populations to the risks of data misuse or data breaches (Gasser & Almeida, 2017). Finally, decision-making accountability and transparency should be discussed. Policy makers and medical workers should have clear guidelines that determine who is to blame and who is to be held responsible due to a mistake, biasness, or unintentional outcomes as a result of an AI-driven assessment (Floridi & Cowls, 2019).

5.0 Conclusion and Future Direction

This study identifies the potential of Artificial intelligence and Machine learning (AI and ML) to enhance the assessment of Performance based financing (PBF) models in the health sector. AI/ML solutions allow predictive modeling, automated normalcy detection and real-time performance monitoring to be displayed, making them more robust, transparent, and scalable than preceding evaluation frameworks. Their utilization can increase the effectiveness of resource allocation, the fairness of health services provision, and accountability based on data-driven results. Yet, despite the quality of data, interpretability of the models, lack of resources, and ethical considerations, it is necessary to exercise caution in their implementation. Whereas AI/ML may streamline performance tracking and funding models, their success is limited by resolutions to red-tap problems in health data governance and infrastructure, and skepticism about algorithmic decision-making.

~~5.2 Future Directions~~

Future research should focus on developing hybrid evaluation frameworks that integrate AI/ML methods with traditional health economics approaches to balance predictive accuracy with interpretability. Efforts are needed to improve the availability and quality of health financing datasets, particularly in low- and middle-income countries, through investments in digital infrastructure and standardized reporting systems. Advancing explainable AI (XAI) techniques will be critical for enhancing transparency and stakeholder trust in algorithm-driven recommendations. Moreover, ethical safeguards—including bias detection, data privacy protections, and clear governance structures—must be institutionalized to ensure fairness and accountability. Finally, pilot studies and cross-country collaborations can provide evidence of scalability, contextual adaptability, and long-term sustainability of AI/ML-enhanced PBF systems, paving the way for broader adoption in global health financing reforms.

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Not applicable

Competing interests

There are no known financial competing interests to disclose

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Availability of data and materials

The data supporting the findings of this study can be obtained from the corresponding author upon request

Authors' Contributions

FDO conceptualized the study, supervised the review process and finalized the manuscript. CMD reviewed business and management perspectives on PBF and contributed to drafting. JUH provided clinical insights and contextualized health outcomes. TSM analyzed health policy dimensions and coordinated references. EO synthesized sociological perspectives and edited sections. IJN reviewed governance and accountability frameworks. OA examined management implications and improved structure. AA contributed to financing models, AI and ML applications and critical revisions.