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AI-driven healthcare financial models: Ethical frameworks for balancing profit and access in precision medicine in the US

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Abstract

Precision medicine has the potential to change the U.S. healthcare system by customizing treatments for each person. However, its high costs make it hard for everyone to get the care they need. Artificial intelligence (AI) is being used more and more in financial modeling to make healthcare operations and profits better, from predicting insurance claims to allocating resources. But without ethical protections, these AI-driven financial models could make things worse by putting profit ahead of patient access. This paper offers an extensive analysis of reconciling profitability with equity in precision medicine via ethical AI frameworks. We analyze cutting-edge applications of AI in healthcare financing and scrutinize ethical issues related to bias, equity, and justice in precision medicine. Based on this body of work, we suggest a strong way to judge the ethics of AI financial models that includes the ideas of openness, responsibility, and inclusion. This work is new because it combines AI-driven financial decision-making with ethical principles to make sure that cost-effectiveness and profit goals don't get in the way of patients getting personalized care. Two case studies, supplemented by comparative tables and figures, demonstrate how the proposed framework can facilitate the development and evaluation of AI financial models in precision medicine. The results show that AI-driven financial models can be profitable in the long run while still making advanced healthcare accessible to everyone. This is useful information for health organizations, policymakers, and AI developers.

Keywords: Artificial Intelligence; Healthcare Finance; Precision Medicine; Ethics; Health Equity; Access To Care; Responsible AI; U.S. Healthcare System.

1. Introduction

Precision medicine, which involves customizing medical treatment to fit each person's needs, is changing the way doctors work, thanks to improvements in genomics and data analysis. This method has a lot of potential to improve outcomes in the US, but it usually costs a lot for specialized tests and treatments [7]. Healthcare stakeholders are increasingly using AI-driven financial models to keep these costs down and make more money. AI systems can look at huge amounts of data to predict costs, improve billing, and help make smart investments in precision medicine. For instance, machine learning models have been used to accurately predict health insurance claims and find cost drivers [4]. This could help insurers and providers cut down on waste and use their resources more effectively. These new ideas come at a time when people are looking closely at healthcare costs and organizations are trying to find a balance between making money and providing the best care.

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But using AI in healthcare finance raises important moral issues. An algorithm that is mostly used to predict costs or maximize profits may unintentionally favor situations that make it harder for patients to get the care they need. Previous occurrences have already shown the risks: A commonly used health risk algorithm was discovered to undervalue the requirements of Black patients by utilizing healthcare expenditure as a surrogate for illness [3]. Using cost as the main factor meant that patients who had trouble getting care and therefore had lower costs were not given as much priority for care management programs. This is a clear example of how profit-oriented modeling can conflict with fair access. If these biases are not dealt with, they can make health differences worse [2]. The U.S. healthcare system has a lot of unfairness, and AI tools shouldn't make the gap between people who can pay for personalized treatments and those who can't any bigger.

Ethical frameworks are necessary to direct the advancement and implementation of AI in this field to ensure that financial optimization does not compromise patient welfare. Recent commentary stresses a multi-pronged approach to advancing health equity and ethical AI use, such as involving the community, using data in a way that includes everyone, and making algorithms clear [2]. In precision medicine, this means including a wide range of people in data sets, making sure that the goals of AI models match those of public health, and being open about how financial algorithms affect different groups of patients. Experts are currently inquiring about the integration of justice and inclusion principles into cost-effectiveness calculations [8]. This paper's main question is: How can AI-driven financial models in precision medicine be made and tested in the U.S. to find a balance between making money and making sure everyone has access to care? We address this question by analyzing the existing landscape of AI in healthcare financing and the ethical dilemmas it poses, subsequently proposing a framework to guarantee that profit-oriented models adhere to fundamental ethical principles.

Our contributions are as follows: (1) We provide an extensive literature review of AI applications in healthcare financial modeling and ethical considerations in precision medicine, integrating these two fields. (2) We suggest a strong way to judge the ethics of AI financial models based on ideas from bioethics and AI governance. (3) We present an innovative framework that amalgamates financial sustainability metrics with ethical standards, offering direction for reconciling profit and accessibility. (4) We demonstrate our methodology through case studies and comparative analyses, incorporating figures and tables that encapsulate best practices and frameworks. This work seeks to educate healthcare policymakers, AI developers, and hospital financial officers on economically and ethically sound strategies for leveraging AI in precision medicine.

Figure 1 The "quadruple aim" framework in healthcare (enhancing patient experience, improving population health, reducing cost, and improving provider work life). Aligning AI-driven innovations with these aims emphasizes that cost reduction should advance affordability and access alongside quality improvement

In the following sections of this paper, we will first look at other research on AI in healthcare finance and ethical frameworks for precision medicine (Section II). Next, we explain in detail our suggested method for ethically evaluating financial models (Section III). Section IV shows the results and a discussion, including case studies that use our framework and tables that compare important ethical and financial indicators. In the end, we finish with suggestions and ideas for the future in Section V to make sure that AI-driven financial models in precision medicine serve both profit goals and the public good.

2. Background and Literature Review

2.1. AI Financial Models in Healthcare

AI technologies have quickly made their way into the financial operations of healthcare, with the goal of making economic decision-making more accurate and efficient. Health insurance and payments: One area where machine learning is being used is to help with insurance claims and cost predictions. Alam et al. (2024) show that advanced machine learning models, like gradient boosting, can accurately predict the costs of health insurance claims. They also find that smoking status and BMI are two of the most important factors that affect costs [4]. By automating claims processing and pointing out risk factors, these models promise big savings for insurers by making their operations more efficient. AI algorithms are also used to find false claims or strange billing patterns, which helps protect against losses. Predictive analytics have also been used in health financing policy. For example, models can help figure out the best payment rates and co-payment structures for providers by simulating how different plans affect budgets and out-of-pocket costs [1]. Studies in this area indicate that AI can offer detailed insights to policymakers regarding the establishment of reimbursement rates or the formulation of insurance plans that ensure fiscal equilibrium [1].

Cost optimization and resource allocation: Hospitals and health systems use AI to predict how many people will use their services, improve their supply chains, and use their resources in a way that saves money. Predictive models can predict how many patients will come in and how long they will stay, which helps with staffing and capacity planning [1]. AI-powered decision support systems have been created to help with scheduling operating rooms and allocating emergency medical resources. This cuts down on waste and costs. For instance, one study used AI to make a model for allocating medical emergency resources, which showed better response strategies in big emergencies [1]. Machine learning also helps find patients who are costing a lot of money so that intervention programs can help them. But, as we said before, using only cost as a standard can be a problem. Obermeyer et al. found that a commercially used algorithm put patients in order of priority for a care management program based on how much they were expected to spend on healthcare. This unintentionally made it harder for Black patients to sign up for the program, even though they had the same medical needs but had historically spent less on healthcare [3]. This shows that financial models need to be carefully planned so that they don't make existing unfairness worse.

AI is also being used to make it easier for patients to get financial help and care, which is a good thing. Recent research shows that machine learning can help find patients who are likely to have trouble with medical bills or following through on treatment because of the cost. These patients can then be referred to financial counseling or assistance programs [1]. An AI system could look at demographics, clinical data, and payment histories to figure out who will need charity care or flexible payment plans. This would let providers or insurers step in before the need arises. This app combines cost-cutting with caring: providers can avoid bad debt while patients get help staying connected to services. Initial research indicates that these models may be combined with participation in state or federal assistance programs, facilitating patients' understanding of insurance choices and subsidies [1]. In short, AI-powered financial tools in healthcare can do a lot of things, from maximizing operational efficiency and profit (like finding fraud and cutting down on unnecessary spending) to improving patient-centered financial strategies (like making payment plans more accessible). The challenge is to make sure that trying to save money doesn't get in the way of meeting patients' needs.

Table 1 provides an overview of representative AI applications in healthcare financial modeling, illustrating their goals and associated ethical considerations.

Table 1 Examples of AI Applications in Healthcare Finance and Ethical Considerations

Domain & AI Application	Primary Financial Goal	Potential Benefits	Ethical Considerations
Insurance – Claim cost prediction & fraud detection	Reduce claim payouts, set premiums accurately, prevent losses	Lowers insurance costs, potentially reduces premiums; flags fraudulent or wasteful claims for investigation	Bias/Fairness: Algorithms must not unfairly inflate premiums for certain groups. Transparency: Difficult for consumers to understand premium calculations.
Provider/Hospital – Resource allocation (staffing, beds) and revenue cycle management	Optimize operational costs and maximize billing capture	Improves efficiency (e.g., right-sizing staff to demand); ensures all	Patient Impact: Overemphasis on revenue could encourage unnecessary procedures.

		services are billed, boosting revenue	Equity: Allocation models might inadvertently favor profitable service lines over essential services for vulnerable communities.
Precision Medicine Programs – Patient selection for high-cost therapies (using AI risk scores)	Ensure cost-effective use of expensive treatments (e.g., genetic therapies)	Maximizes health benefit per dollar by targeting those most likely to benefit; controls drug spending	Access: May deny or delay cutting-edge therapy for patients not flagged by the model (false negatives). Bias: If training data lacks diversity, certain populations may be underrepresented in "high-benefit" predictions
Pharmaceutical/Industry – AI-guided drug pricing and development investment	Set drug prices to maximize ROI; choose R&D projects with highest payoff	Supports financial sustainability of precision medicine innovation; faster development of lucrative therapies	Justice: High prices set by AI optimization can limit access to life-saving drugs. Neglected Diseases: Profit-driven models might ignore treatments for rare or low-income population diseases, widening health gaps.
Patient Financial Services – Predict who needs financial aid or flexible plans	Reduce uncompensated care; improve bill collections without denying care	Anticipates patients' financial needs; improves access by adjusting payment plans; lowers bad debt for provider	Privacy: Uses personal financial and health data – must ensure data security. Stigma: Need to avoid profiling that could label patients as "high risk" for non-payment in a discriminatory way.

Key: ROI = return on investment, R&D = research and development.

AI financial models can make healthcare much more efficient and save a lot of money, as shown in Table 1. However, each use case has its own set of ethical standards. The U.S. healthcare system is mostly based on the market, so AI could help keep costs down. However, there are big social responsibility issues at stake. When it comes to insurance, for example, algorithms that set premiums or coverage must be thoroughly tested for bias so that they don't unfairly punish people because of false links between health costs and things like ZIP code or race. AI might help hospitals find service lines with better margins, but leaders shouldn't only focus on making money and ignoring the health needs of the community. AI-based selection of patients for therapy must be based on clinical need and fairness, not just cost-effectiveness. This is especially important for precision medicine programs, where treatments can cost tens or hundreds of thousands of dollars. To do this, we need to include ethical guidelines in the design and use of models, which is something we talk about more in our methodology.

2.2. Ethical Challenges in Precision Medicine

The arrival of precision medicine exacerbates enduring ethical dilemmas in healthcare by introducing sophisticated—and frequently costly—interventions. Fairness and access: One of the most important worries is that not everyone in society will benefit from precision medicine [7]. Patients with more money or good health insurance are more likely to be able to pay for genetic tests, personalized therapies, or concierge precision health programs. On the other hand, marginalized groups may not be able to afford these things. This "precision gap" could make health differences that are already there worse. For instance, rural or low-income patients might not get early treatment if genomic screening for cancer risk is only available in urban academic medical centers or is only covered by some insurance plans. So, making sure that everyone has equal access is a very important moral duty. Some people say that precision medicine projects need to actively include a wide range of people and make a concerted effort to make healthcare more accessible. If they don't, precision medicine could make healthcare inequality worse by accident [7]. For precision medicine to be fair, drug prices, insurance coverage, and outreach efforts must all be taken into account so that advanced treatments are not just available to a few people.

Cost and fairness: Many precision therapies, like gene therapies and targeted drugs, are very expensive, which makes people wonder if resources are being used fairly. How should healthcare systems choose who gets a treatment that works really well but costs a lot? Utilitarian and egalitarian views are often at odds in ethical discussions. A utilitarian view might say that resources should be given to those who are most likely to benefit from them (maximizing total benefit), while an egalitarian view might say that everyone has an equal right to care, even if it costs more. There is no central body in the U.S. that decides who gets what, but health systems and insurers do this math when they decide on coverage and formularies. More and more people are asking for clear criteria for these decisions that include moral principles. For example, some experts say that equity weights or thresholds should be added to cost-effectiveness analysis in precision medicine. This would make sure that treatments for underserved groups are not automatically ruled out as "not cost-effective" because they are at a disadvantage in society. The seminar series at UNC in 2024 directly asked, "When and how should cost-effectiveness be taken into account when making genomic screening programs, and how can we make sure that justice, equity, and inclusion are included?" [8]. This shows that people understand that traditional economic evaluations need ethical guidelines to stop discrimination against people who might be more expensive to treat, like people with rare diseases or complicated conditions.

AI and data representation bias: Big data, like genomic data, electronic health records, and clinical trials, and AI tools are what precision medicine uses to get insights. AI models can pick up and keep those biases if the data they are based on isn't diverse enough (for example, if it doesn't include enough people from certain ethnic or socio-economic groups). A model may forecast diminished success rates or elevated risks for treatments in underrepresented groups due to insufficient knowledge, potentially resulting in reduced investment in those sectors. This is a problem in both science and ethics. It is important to make sure that data is representative and to check AI models for bias. The Centers for Disease Control and Prevention (CDC) has stressed that AI needs to be managed carefully because it can make health differences worse if it isn't used properly [2]. When AI makes financial decisions, bias could show up in models that systematically favor patients from well-served populations (who have rich data histories) when allocating resources, or, on the other hand, flag patients from disadvantaged backgrounds as "high risk" in a way that could be misused (for example, by charging them higher premiums). Before using these kinds of models, an ethical framework must require techniques for finding and fixing bias, like fairness metrics, bias correction algorithms, or including social determinants of health.

Privacy and consent are also important ethical issues. Precision medicine often uses sensitive information, like genomic data and family history, as well as AI models that use this information to help make financial decisions, such as deciding whether or not to insure someone or whether or not they are eligible for certain programs. Balancing profit and access in an ethical way also means protecting patient privacy and getting informed consent for how data is used. Using genetic information to guess future costs or health needs in an AI financial model comes close to breaking privacy laws and ethical rules about genetic discrimination (like GINA – Genetic Information Nondiscrimination Act). So, a strong ethical approach would include protecting patients' privacy and being open with them about what data is being used in financial algorithms.

Ethical rules that are already in place: Several organizations have put forth principles for ethical AI in health that are very applicable in this context. In 2021, the World Health Organization (WHO) put out guidelines on AI ethics that stressed human dignity, safety, openness, and fairness [9]. It specifically says that AI for health should promote fairness and inclusion. This is in line with the idea that AI-driven programs, including financial ones, should help all parts of society, not just the ones that make the most money. The American Medical Association (AMA) has also come up with an AI ethics framework that looks at AI through the lens of the "quadruple aim" of healthcare. According to this view, an AI system is reliable if it makes the patient experience better, improves population health (including equity), lowers costs, and makes provider workflow better [6]. The AMA framework links lowering costs to making things more affordable and accessible. It says that payment and coverage for AI systems should depend on how well they help with those goals [6]. This means that an AI tool that saves money but makes it harder to get to is not in line with the framework. These guidelines are a starting point for making more specific ethical rules for AI financial models used in precision medicine.

In conclusion, the literature indicates a dual imperative: utilize AI and data to improve the economics of precision medicine while simultaneously integrating ethics to ensure equity and fairness. This paper seeks to bridge the gap between abstract ethical principles and practical methods for assessing and directing AI financial models. In the following section, we put forth a methodology to accomplish this, drawing on the insights from contemporary research and the ethical guidelines examined herein.

3. Methodology: Evaluating Financial Models through an Ethical Lens

We present a methodology that incorporates ethical assessment into the lifecycle of model development and deployment to guarantee that AI-driven financial models achieve a balance between profit and accessibility. This methodology is based on the best practices from different fields, such as AI ethics, health technology assessment, and bioethics. It is meant to be clear, organized, and useful. Figure 2 shows the framework, which is made up of steps that happen one after the other and feedback loops that help things get better all the time.

3.1. Defining stakeholders and goals

We start by listing all the important stakeholders and what they stand for. In the context of a precision medicine financial model, stakeholders are people who have a stake in the system, such as healthcare providers (hospital finance officers, clinicians), payers (insurance companies, government programs), patients (from different socio-economic backgrounds), and regulators. These stakeholders need to say what the AI model's goals are in addition to just financial metrics during workshops or planning sessions. For instance, a hospital that wants to use AI to make sure resources are used in the best way possible should set not only profit or cost-saving goals, but also equity goals (like keeping service levels high for patients who don't get enough care) and quality-of-care outcomes. It is very important to make these goals clear so that they can be built into the model. This step is in line with the idea of "design for values," which means that profit is just one of many values. It makes sure that fair access is a clear priority from the start, not an afterthought.

3.2. Ethical Requirements and Criteria Definition

We use input from stakeholders and existing ethical frameworks to come up with clear standards that the AI model must meet. This could mean:

Fairness standards: For example, the model's suggestions or predictions shouldn't unfairly hurt any protected group (like race, gender, socioeconomic status, etc.). We put this into action by choosing fairness metrics that are appropriate for the use case, like demographic parity, the equal opportunity difference, or the disparate impact ratio. For example, if the AI model is supposed to suggest which patients should get a certain expensive treatment, one condition might be that the approval rates for the treatment for minority and majority patients should not differ by more than a certain amount, unless there is a good clinical reason for it.

Transparency and explainability: stakeholders must be able to understand why the model made a certain decision or gave a certain output. We may need the model to give reasons for its financial advice that people can understand, like scores for how important each feature is. Patients and providers should know why decisions that affect access are made, like when insurance is denied or approved.

Accountability measures: make sure that someone is clearly responsible for keeping an eye on the AI. For instance, set up a review board or committee (with ethicists or patient representatives) that will check the model's results for ethical compliance on a regular basis. This is based on governance frameworks, such as the AMA's idea that developers, deployers, and doctors should have clear roles in overseeing AI [6].

Requirements for privacy and security: make sure you follow HIPAA and other rules; use de-identified data whenever possible; and protect patient financial and genomic data with strong cybersecurity.

Patient-centered metrics: Set metrics that show how many patients can get care or what happens to them, like the percentage of eligible patients who get therapy, the number of cases of financial hardship that go down, or the health outcomes that get better in lower-income quartiles. These will help balance out metrics that only look at costs.

By making these criteria official, we make what is basically an ethical checklist that the AI model must be judged against. This is like a requirements specification in traditional software, but it also includes ethical requirements. One of the most interesting things about our method is that it treats ethical constraints as equally important as technical performance metrics from the start.

3.3. Preparing Data with Fairness in Mind

Next, you'll need to gather and prepare the data for model training in a way that meets the ethical standards that have been set. If the goal is to make sure things are fair, the data scientists should look for representation biases in the training dataset on their own. Some techniques are:

Bias audit of data: look at whether important demographic groups are well-represented and whether target labels could show biases in society. For instance, if past spending is a label (as in the Obermeyer case), be aware that this could lead to bias because of historical under-service [10]. Someone might choose to use a different label (like real health outcomes instead of cost) or change the labels to make them fairer.

Augmentation or re-sampling: If some groups are not well represented, think about oversampling them or adding more data (if possible) to make sure the model doesn't learn false correlations.

To protect privacy as an ethical duty, use de-identification or federated learning when working with sensitive personal data.

This stage uses methods from the new field of responsible AI data engineering to make sure that the model's base is morally sound. It is much easier to stop a model from learning bias than to fix it later, which is why we stress this point.

3.4. Model Development with Ethical Constraints

When developing the machine learning model (whether it’s a regression, random forest, neural network, etc.), we incorporate the ethical criteria into the modeling process. In some cases, this means using constrained optimization or multi-objective optimization: for example, training the model not only to minimize error/cost but also to satisfy a fairness constraint (there are algorithmic techniques like fair logistic regression, or adding a penalty in the loss function for unfair outcomes). In other cases, it might involve a two-step modeling approach: first predict an outcome (like cost or risk), then apply a decision rule that is adjusted for equity (for instance, ensure a certain quota or give a lift to minority group scores to offset biases). We also prioritize interpretable models where possible (e.g., decision trees or rule-based systems) when transparency is critical, or use model explanation tools (LIME, SHAP values) for complex models to maintain insight into the decision logic.

Importantly, the development phase should include ethical impact simulations. Before any real deployment, we simulate how the model’s decisions would play out on a virtual population that mirrors the real patient demographics. Using historical data, we can ask: if the model had been in use last year, who would have gotten the therapy or financial aid and who wouldn’t? How would profits and patient outcomes differ from actuals? This simulation can reveal potential ethical red flags (e.g., the model would have excluded 20% more minority patients from a program than current practice – indicating a bias issue). Stanford Health Care’s “FURM” (Fair, Useful, Reliable Model) assessment approach exemplifies this by conducting value-based simulations and even financial projections as part of evaluating AI tools. They perform an *ethical review to identify value mismatches, simulations to estimate usefulness, and financial projections to assess sustainability* before an AI model is greenlit. We incorporate a similar concept: if our simulations indicate that profit objectives and access objectives conflict (a value mismatch), we iterate on the model. This might involve tweaking the model, adjusting thresholds, or reconsidering features that are driving unfair outcomes.

3.5. Deployment with Monitoring and Governance

Once the model meets the predefined performance and ethical criteria in testing, it can be deployed, but with strong monitoring in place. We establish key performance indicators (KPIs) not only for financial outcomes (e.g., cost savings, reduction in default rates) but also for ethical outcomes (e.g., no increase in disparity of who receives services, patient satisfaction, complaint rates). During deployment:

We may start with a pilot phase or “silent” mode where the model makes recommendations that are double-checked by humans before fully automating decisions. This is akin to the silent deployment used to answer critical questions about AI performance in practice.

Implement a feedback channel: Frontline staff or affected patients should have a way to report concerns if the model’s decisions seem inappropriate or harmful. For instance, if an oncologist finds that an AI denies coverage for a genomic test for a patient who clearly needs it, there should be an override and a mechanism to feed that scenario back into model improvement.

Regular audits: At set intervals (monthly, quarterly), the interdisciplinary oversight committee reviews the model’s outputs across different groups. Are there signs of bias creeping in over time? Are the cost savings aligning with improved (or at least not worsened) patient access statistics? This echoes the recommendation in frameworks like FURM to monitor AI models’ performance and impact continuously, including any ethical issues flagged. If certain thresholds are breached (say the gap in service provision between groups widens), pre-planned mitigation strategies should kick in. This might include retraining the model with new data, adjusting the algorithm, or in extreme cases, suspending the model.

Scenario planning: We maintain procedures to update the model as external conditions change – for example, if a new expensive therapy emerges or if policy changes (like new insurance regulations) alter the landscape, the model's assumptions should be revisited. Part of ethical stewardship is ensuring the AI adapts and does not become obsolete or harmful under new circumstances.

3.6. Evaluation and Iteration (Continuous Improvement)

Ethical evaluation is not a one-time checkbox but an ongoing process. We document the outcomes of the model's decisions and compare them to our ethical objectives regularly. This could involve qualitative and quantitative evaluation:

Quantitatively, measure how well the model's deployment has balanced profit and access. For instance, calculate the financial savings achieved and compare against metrics like reduction (or increase) in disparity of care. If a model was introduced to contain costs of a precision medicine program, did it also maintain the same level of access to that program for low-income patients as before? If not, why, and can adjustments fix that?

Qualitatively, gather feedback from patients and providers about the system's fairness and transparency. Perhaps patient surveys could reveal if patients felt any denial of service was unjust, or if the presence of the AI system improved their experience by making processes faster/ more consistent.

Benchmark against ethical guidelines and any new standards. The regulatory environment for AI is evolving; for example, the Biden administration's 2023 Executive Order on AI calls for standards to ensure AI systems are safe and unbiased in healthcare. Our model should be evaluated for compliance with emerging regulations and standards.

This stage closes the loop: insights from the evaluation feed back into model updates or even into rethinking the stakeholder objectives. In doing so, the methodology fosters a learning health system for AI ethics – always measuring and enhancing how well the financial model aligns with both profit motives and moral imperatives.

Figure 2 Multi-stage ethical AI evaluation framework (planning, development, and deployment) adapted for healthcare financial models. Responsibilities of key parties – developers, deployers (health institutions), and physicians – are delineated across phases to ensure the AI system addresses meaningful goals, works as intended, is monitored for bias and effectiveness, and can be overridden or adjusted by humans when necessary. This layered oversight helps integrate ethical safeguards into every step of AI financial model implementation

Figure 2 (derived in part from AMA guidelines [6]) illustrates that ensuring ethical compliance is a shared responsibility: AI developers must build and test models for fairness; healthcare organizations (deployers) must establish oversight and make final decisions on sensitive matters; and clinicians or staff must remain empowered to veto or appeal algorithmic decisions in the interest of patient care. The framework visualizes checkpoints such as legal review of algorithms (for compliance with laws and equitable use), bias correction protocols, ongoing monitoring, and clear accountability at each stage. By following this structured methodology, an organization can institutionalize ethical review alongside financial review for any AI system under consideration. Our approach resonates strongly with recent proposals like the Stanford FURM framework, which integrated ethical assessment, usefulness simulation, and financial sustainability checks into a test-and-evaluation pipeline for AI in healthcare. The novelty here is tailoring such a process specifically to financial models in precision medicine and explicitly focusing on the profit-access balance.

4. Results and Discussion

In this section, we discuss how the above methodology can be applied and present analyses of two scenarios that exemplify the tension between profit and access in AI-driven precision medicine. We also compare relevant ethical frameworks and outcomes using tables to synthesize key insights.

4.1. Case Study 1: AI for Therapy Allocation in Oncology

Scenario: Consider a large hospital network deploying an AI model to decide which cancer patients should receive a new precision medicine therapy – an expensive, genomic-based treatment – under a limited budget. The AI model (a predictive algorithm) estimates each patient's likely benefit from the therapy (in terms of improved survival) versus cost, and recommends prioritization accordingly. Financially, the goal is to maximize the overall health benefit within budget ("bang for buck"), effectively a cost-effectiveness approach automated by AI.

Ethical tension: Left unchecked, this model might consistently favor patients with certain characteristics that correlate with better outcomes – for instance, younger patients or those with fewer co-morbidities – since they might have higher expected benefit from the therapy. Consequently, older patients or those from disadvantaged backgrounds (who often present later with more advanced disease) might be de-prioritized. This raises ethical issues of justice (should a life-year for an older or sicker patient be valued less?) and potential indirect discrimination. There is also a profit motive subtext: younger, healthier patients might incur fewer complications and therefore less cost, which aligns with financial efficiency but not necessarily with societal values about giving everyone a fair chance at treatment.

Application of methodology: Using our framework, the hospital first involved oncologists, ethicists, patient advocates, and financial officers to set objectives. They agreed that while maximizing survival per dollar is important, the model must also uphold the principle of equity – for example, not systematically excluding patients above a certain age or of a certain demographic from accessing the therapy. An ethical criterion was set: the distribution of the therapy should reflect the patient population demographics and clinical need, not just the algorithm's ranking of cost-effectiveness. The data used to train the model was checked for bias: it turned out the clinical trial data for the drug under-represented minority patients, so the model was less certain about their outcomes. Recognizing this, the developers applied a bias correction – they incorporated external data and consulted clinical experts to avoid the model pessimistically underestimating benefit for those groups simply due to lack of data. They also added a rule that any patient with an aggressive tumor marker (regardless of other factors) should be strongly considered, to ensure nobody who could significantly benefit is automatically filtered out by cost projections alone.

On simulation, the initial AI model without constraints did show a concerning trend: patients from lower-income ZIP codes were 30% less likely to be recommended the therapy, largely because those areas correlated with later-stage diagnosis in the data, lowering predicted benefit. With the ethical adjustments (e.g., including a fairness constraint and a policy that some portion of the budget is reserved for high-need cases), the revised model brought this disparity down to under 5% difference, while only slightly reducing the total predicted health gain achieved. This indicates that a small trade-off in efficiency yielded a large gain in equity, an outcome the stakeholders deemed acceptable and indeed desirable. The model was deployed with these safeguards, and outcome tracking began.

Results: In early results after deployment (hypothetical for discussion), the hospital observed that the AI-assisted allocation did improve overall survival outcomes within the fixed budget, confirming the financial model's utility. Importantly, the composition of patients receiving the therapy was diverse and corresponded to disease severity rather than ability to pay or navigate the system. The hospital's ethics board reviewed the first 6 months of decisions and found no evidence of systematic bias: patients of different backgrounds with similar clinical profiles had roughly equal chances of getting the therapy, meeting the fairness criterion. Financially, the hospital avoided about $2 million in costs by optimizing allocation (as compared to a first-come, first-served or physician discretion method that might over-utilize the drug). Patient access, measured by the proportion of eligible patients who actually received the therapy, was maintained at prior levels for all groups, with a slight increase for historically underserved groups (thanks to the outreach and supportive measures implemented in parallel). These results suggest that ethical AI frameworks can enable win-win scenarios: the institution saved costs (profit sustainability) and patients did not experience a decline in access – in fact, access equity improved in some respects.

Discussion: This case underscores the practicality of our methodology. By weaving ethical considerations into the AI's design (e.g., constraints to reduce bias against sicker patients) and having oversight, the hospital could achieve its cost goals without unethical exclusion of patients. It also highlights a key insight: pure utilitarian AI recommendations in healthcare need to be moderated by principles of justice to be acceptable. The slight sacrifice in efficiency in the model's decision-making is analogous to society's choice to not always maximize utility at the expense of fairness. Our framework facilitated a data-driven approach to find that balance, quantifying the trade-offs. Additionally, this scenario demonstrates the importance of transparency – because the model was explainable, clinicians understood why certain patients were prioritized and could communicate to those who weren't in a clear, justified manner (e.g., "the therapy is predicted not to be effective for your cancer subtype, but you are getting an alternative"). This maintained trust and prevented feelings of arbitrary rationing.

This example also connects with broader ethical frameworks: The Belmont Report principles of beneficence and justice are mirrored here – beneficence in maximizing overall health outcomes, and justice in fair distribution. AI allowed a more precise beneficence calculation, and our ethical constraints ensured justice. Furthermore, such a model would align with WHO's call that AI should *"promote equity, fairness and inclusiveness"* [5], showing it's possible in practice with careful design. It also resonates with the AMA's quadruple aim: we reduced cost and burden on providers (who no longer had to agonize over allocation decisions alone) while aiming to maintain patient experience and population health equity [6].

4.2. Case Study 2: AI in Insurance Pricing and Coverage

Scenario: A health insurance company utilizes an AI-driven financial model to set premiums for emerging precision medicine services and to identify which services require prior authorization. The model analyzes patient data, including genetics and social factors, to predict future healthcare costs more accurately than traditional actuarial methods. The goal is to price plans and manage coverage in a way that keeps the insurance fund solvent (profitability) while offering competitive premiums.

Ethical tension: Insurance inherently involves tension between cost control and access. An AI model could theoretically segment risk very finely – for example, identifying a subset of patients with certain genetic markers as very high cost and either pricing their premiums much higher or requiring heavy utilization review on their care. While this protects the insurer's finances and perhaps lowers premiums for others, it could make insurance or needed treatments unaffordable for those individuals, undermining the risk-pooling principle that is meant to promote solidarity in health financing. There is also potential for discrimination: even if not along traditional lines like race or gender (which would be illegal to use in pricing), proxies could emerge (zip code correlating with race, genetic traits correlating with ethnicity). Moreover, the complexity of AI could make it hard for consumers to understand why their coverage was denied or priced a certain way, eroding trust.

Application of methodology: Recognizing these risks, the insurer's leadership applied our ethical framework in developing the AI pricing model. Stakeholders included compliance officers (aware of regulations like ACA rules on not discriminating by health status), patient advocates, and actuaries. They defined objectives that included not just predictive accuracy for costs but also ethical underwriting guidelines: for instance, the model should not create "insurance ghettos" where certain groups face unaffordable rates, and it should abide by community rating principles where applicable. An ethical criterion was set that any AI-driven stratification must be tested for disparate impact: if a protected group ends up paying systematically more or being denied coverage more often, that's unacceptable. They also included a duty-to-care clause in objectives: profit strategies should not deny medically necessary care.

During data preparation, the insurer was cautious about what variables to include. They deliberately excluded variables like credit score or income that some insurance models use to predict adherence or cost, because using those can penalize the poor – raising fairness issues. They included medical and genetic data but decided to group certain genetic findings into broader risk categories rather than individual markers, to avoid overly fine-grained discrimination. The model chosen was a relatively interpretable one (perhaps a generalized additive model) so that the contribution of each factor to risk could be examined. In model training, they used regularization techniques to prevent overfitting to small correlations that could just reflect noise or systemic bias. They also tested a constraint: ensuring the model's premium recommendations adhere to a cap on variance – effectively limiting how much more one person could be charged compared to another of the same cohort, capping disparity.

Results: On initial testing, the AI model improved cost prediction by 15% over traditional methods (meaning it could more accurately forecast which patients would incur high expenses). This allowed the insurer to set premiums at levels that would likely cover costs with less uncertainty (a financial win). However, analysis of the model's output revealed a concern: patients from certain rural areas were being flagged for higher risk (and thus higher premiums) primarily due to lack of local providers leading to more complications – a systemic issue rather than individual health status. Simply following the model's output would punish those patients for geographical healthcare disparities. Recognizing this, the insurer adjusted the model or its use: they implemented a policy that regional healthcare access issues would not be counted against individuals – instead, those predictions would be used to invest in telemedicine and care coordination in those areas (an example of a non-obvious ethical solution that emerged from model insights). In effect, they treated that risk not as a pricing factor but as a signal for where to improve services.

After deployment with these adjustments, the insurer monitored outcomes. They found that the AI model did allow them to moderate premium increases overall – premiums rose slower than medical inflation, because the cost predictions helped manage spending. Importantly, an audit showed that no demographic group saw disproportionate increases: for instance, premiums as a percentage of income remained stable across different races and incomes in their customer base, satisfying equity checks. The number of prior authorization denials did not spike for any particular group either. In fact, the model's better targeting of high-cost cases for care management led to improved health outcomes for those patients (for example, those identified at-risk got enrolled in care programs earlier, reducing hospitalizations). This aligns profit with patient good – high-risk patients got more attention, costs were controlled, but through better care, not denial of care.

However, the ongoing monitoring did catch one issue: the model's algorithm for prior authorization began flagging a new genomic test as "low value" because short-term data showed little immediate benefit. Clinicians argued that the test was too new and its long-term impact wasn't captured yet. Upon review, the insurer agreed and adjusted the model to approve the test for certain patient categories despite the initial cost flag. This shows the need for human judgment and updates – an ethical learning process.

Discussion: This case illustrates the delicate interplay of AI, insurance economics, and ethics. With our framework, the insurer managed to use AI to enhance financial performance (predictive precision lowers uncertainty and can reduce unnecessary spending) while upholding fairness. The critical interventions were choosing model features wisely (not including socio-economic proxies for risk), setting policies on how model outputs are used (not rigidly following an output that would marginalize a group, but rather addressing the root cause), and maintaining transparency and override options.

It also highlights the regulatory aspect: U.S. insurers are constrained by laws and public policy – for example, they cannot use genetic information in underwriting for health insurance (thanks to GINA). Our methodology's stakeholder step would catch that and ensure compliance is baked in. But beyond legal compliance, the insurer voluntarily took steps guided by ethics, such as capping premium differentials to avoid highly divergent treatment of customers. This could be seen as implementing the principle of solidarity in health insurance via algorithm (spreading risk broadly). Interestingly, by doing so, they likely built trust and reputation which has long-term financial benefits as well – ethical practice and profit are not mutually exclusive here.

From a broader perspective, this aligns with the idea that responsible AI is also good business. If the AI had simply optimized profit by charging the sickest exorbitantly or denying many claims, it could lead to public backlash, regulatory crackdowns, or losing customers – undermining profit in the long run. Instead, balancing profit with fairness as we advocate can create sustainable models. This case also underscores the importance of accountability: the insurer had a mechanism to continually audit the AI (somewhat akin to internal "algorithmic accountability reports"), which is increasingly recommended by experts [5]. By catching and correcting issues (like the genomic test denial), they demonstrate learning and adaptation – hallmarks of an ethically aligned AI system.

Comparative Analysis of Frameworks: We can distill lessons from these scenarios and related literature by comparing a few conceptual ethical approaches to balancing profit and access.

Table 2 summarizes different ethical frameworks or decision philosophies and how each would handle the profit-access trade-off in precision medicine scenarios, providing a clearer view of the options.

Table 2 Ethical Frameworks for Resource Allocation in Precision Medicine and Their Implications

Framework/Approach	Guiding Principle	Policy/AI Decision Stance	Implications for Profit vs Access
Utilitarian (Cost-Effectiveness)	Maximize total health benefit relative to cost (greatest good for greatest number)	Allocate precision therapies to those with highest expected health gain per dollar; invest in interventions with best cost–benefit ratio	Profit: Strongly supported by reducing waste and focusing resources where most efficient. Access: May limit access for high-need, high-cost patients (seen as inefficient), risking exclusion of vulnerable groups.
Egalitarian (Equal Access)	Every person has equal right to healthcare resources, regardless of cost or benefit	Provide precision medicine broadly; minimize or forbid decisions based on ability-to-pay or predicted cost-effectiveness	Profit: Can be undermined; very expensive as resources are used without regard to cost, challenging sustainability. Access: Maximizes equity in access – all who could benefit are offered treatment, but possibly at the cost of overall efficiency (fewer total treated if resources exhaust).
Prioritarian (Needs-Based)	Prioritize those worst off (medically or socio-economically), giving weight to the most vulnerable	Allocate resources first to patients with the most severe illness or disadvantage, even if cost per outcome is higher; AI might include a "vulnerability index" to boost such patients in ranking	Profit: Moderately impacted – directs funds to more complicated cases that may yield less profit; requires subsidization. Access: Improves access for marginalized or sicker patients, promoting equity at some efficiency cost; aligns with ethical calls to reduce disparities.
Market-Driven (Profit-Maximization)	Let financial incentives drive allocation; treatments go to those who can pay or yield financial return	Set high prices for precision medicine; AI might prioritize patients with better insurance or likelihood of adherence (to ensure success)	Profit: Maximized in short term – high revenues and low financial risk. Access: Severely constrained – only affluent or well-insured get access; exacerbates health disparities; risks public and regulatory backlash.
Hybrid (Value-Based Care)	Balance patient outcomes with cost; seek "optimal value" – improve health outcomes while controlling costs, often via incentives for quality	Use AI to identify interventions that yield both good outcomes and cost savings (e.g., preventive genomics for high-risk patients); share savings for re-investment in access programs	Profit: Maintained or improved by eliminating low-value care and avoiding expenses on ineffective treatments. Access: Potentially improved by reinvesting savings into broader coverage (e.g., funding genomic screening for underserved groups) – a win-win if executed properly. This approach aligns with frameworks like AMA's, which tie cost reduction to enhanced access.

In Table 2, the utilitarian approach corresponds to a pure cost-effectiveness strategy – something an unconstrained AI might emulate by default. It tends to favor profit (or at least efficiency) but can harm equitable access, as seen in our Case 1 initial model that would have excluded many older or complicated patients to save resources. The egalitarian approach is the opposite extreme, ensuring maximum access but potentially at unsustainable cost – not typically how any real-world system operates, but it's the ethic behind certain public systems' promises (and an ideal we strive toward within practical limits). The prioritarian approach is notable for precision medicine because it intentionally directs resources to those in greatest need (which often correlates with those who would otherwise be left out in a profit-only scheme). AI could operationalize this by incorporating need-based weighting. The market-driven approach, while common in a laissez-faire sense, clearly poses ethical problems in healthcare – our analysis discourages this as a sole strategy, given the moral mandate of medicine. Finally, the hybrid value-based care approach is increasingly promoted in the U.S. – it's essentially what our paper advocates: using AI to find strategies that both improve outcomes and manage costs, and crucially, using the gains from efficiency to *bolster* access, not just line profits [6].

These frameworks illustrate that the way we design AI financial models implicitly chooses one of these ethical stances. Our work makes that choice explicit and argues for the hybrid model that aligns economic and ethical value. Notably, the U.S. Centers for Medicare & Medicaid Services (CMS) have been pushing value-based reimbursement models, which encourage providers to save costs *while* improving quality. An AI financial model under a value-based paradigm can be a powerful tool to identify where waste can be cut without harming patients, and where savings can fund broader inclusion of services (for example, covering a genetic test for more people because downstream it prevents expensive illnesses).

4.3. Further Discussion: Policy and Future Outlook

Our investigation also has policy implications. Regulators are increasingly aware of AI's role in healthcare and the need to ensure it doesn't compromise patient rights. For example, the FDA and CMS have been considering guidelines for clinical AI tools, and it is plausible that financial algorithms affecting coverage could come under similar scrutiny. One recommendation from our work is that healthcare organizations adopt internal ethical AI review boards (if they haven't already) to oversee algorithms that impact patients, akin to institutional review boards (IRBs) for research. These boards should include ethicists, patient representatives, and data scientists, and they should review AI systems pre-deployment and at intervals, using frameworks like ours or others to evaluate impact. This proactive governance could preempt stricter external regulation by demonstrating self-regulation.

Another point is the importance of transparency to the public. If, say, an insurance company uses AI to help determine coverage, being open about that process can build trust. Publishing an annual report on how AI is affecting claims or access, including metrics on fairness, would be a practice in line with corporate social responsibility. It also allows external stakeholders (researchers, advocacy groups) to offer feedback or hold organizations accountable. There are calls in the AI ethics community for Algorithmic Impact Assessments – essentially audits of algorithms for bias and fairness – especially in sensitive areas like healthcare [5]. Embracing such assessments can be part of future best practices.

From a research perspective, one area needing attention is quantifying the long-term outcomes of using AI financial models. While we have discussed immediate effects (who gets treatment, immediate cost savings), what about long-term societal impact? If AI restricts access to precision medicine for some, does that widen health outcome gaps over decades? Conversely, if AI helps better allocate resources now, does that lead to overall improved health and productivity in the population that offsets costs? Interdisciplinary studies that connect health economics, ethics, and AI will be valuable to answer these questions.

Lastly, our discussion has focused on the U.S., but the profit vs. access tension exists globally in different forms (public systems ration care more explicitly, private systems via price). The principles we outlined can inform global health as well – for example, low- and middle-income countries might use AI to decide how to spend limited budgets on precision medicine; our ethical approach would advocate for including equity so that rural or poorer populations aren't left out. International bodies like WHO are indeed advocating for such frameworks [5], and our work provides a concrete instantiation.

5. Conclusion

AI-driven financial models in precision medicine present both an opportunity and a responsibility for the U.S. healthcare system. On one hand, these models can greatly enhance efficiency, reduce waste, and help sustain the financial viability of offering advanced personalized therapies. On the other hand, without deliberate ethical guidance, they can reinforce or even worsen inequities in who benefits from medical innovation. In this paper, we have argued that balancing profit and access is not only a moral imperative but is achievable through thoughtful design and governance of AI systems. We presented a comprehensive overview of current AI applications in healthcare finance, highlighting scenarios where profit motives and ethical healthcare converge or clash. Building on real-world cases and existing ethical guidelines, we proposed a methodology and framework that embed equity, transparency, and accountability into the lifecycle of AI financial tools.

The novelty of our approach lies in operationalizing ethical principles—such as fairness and justice—alongside financial metrics in a systematic way. By applying this framework to case studies, we demonstrated that incorporating ethical constraints can still yield efficient outcomes, and often leads to more sustainable long-term results (as trust and fairness tend to improve acceptance and compliance). The comparative analysis of ethical frameworks reinforced that a hybrid value-driven approach best serves the dual goals of healthcare: to heal and to be financially sustainable. Encouragingly, our findings align with emerging trends in policy and professional guidelines: there is a convergence towards the idea that AI in healthcare must be "responsible AI," delivering value *and* upholding humanistic values.

For stakeholders across the healthcare spectrum, a few key recommendations emerge from this work. Healthcare providers and insurers deploying AI models should institute formal ethical review processes and multidisciplinary oversight, ensuring that algorithmic decisions are subject to human judgment especially in borderline cases. AI developers should engage with ethicists and domain experts early to define what success means for a model beyond accuracy – incorporating metrics for fairness and access. Policymakers and regulators should consider frameworks for audit and transparency requirements for AI systems that influence who gets care (similar to financial auditing of insurers, there could be "equity auditing"). Additionally, involving patients in the loop – through communication and feedback mechanisms – will be vital for maintaining trust in an AI-mediated system.

In closing, precision medicine represents the forefront of medical progress, and AI-driven financial models will undoubtedly play a central role in determining how that progress is delivered to patients. By adhering to ethical frameworks that balance profit and access, we can ensure that this new era of medicine is not only precise in a scientific sense but is also just and inclusive. The U.S. healthcare system, with its vast resources and innovation capacity, has the chance to lead by example in this domain. The journey toward ethical AI in healthcare finance is ongoing, and we hope this paper provides both a conceptual foundation and practical guidance for moving forward. With continued research, open dialogue, and conscientious governance, AI can be harnessed to create a future of precision medicine that is profitable, pioneering, and equitable for all.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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