Exploring the Economic Impacts of Algorithmic Bias in AI-Based Healthcare Systems

تحليل الآثار الاقتصادية للتحيز الخوارزمي في أنظمة الرعاية الصحية المعتمدة على الذكاء الاصطناعي

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Abstract

The COVID-19 pandemic demonstrated the dismal insufficiency of the whole healthcare system in all countries, including the resource distribution and the diagnostic cycle. Another important but underemphasized concern was the presence of algorithmic biases, coded in the crisis of emergency interventions, with a negative implication on already existing disparities in health, and an exponential contribution to the impact of the crisis itself. All of these forms of biases were overrepresented in the vulnerable populations, resulting in poor health outcomes and incurring high economic costs, primarily in triage algorithms to allocate scarce resources. This paper offers the general model of the economic effect of algorithmic bias in the COVID-19 pandemic, both directly (the health care spending, hospitalization, intensive care unit), and indirectly (e.g., the loss of productivity due to the excess number of fatalities). The study measures the extent to which biases contributed to the global economy in two different conditions: mild (5%) and severe (15%) by simulating the two conditions, and the results are used to determine the impact of the bias on economic stability at the country and global levels. According to the results, the presence of algorithmic bias, especially in high-income countries, is one of the contributors to a large portion of the loss of money, as supported by the fact that in the vast majority, the indirect expense of excess death and loss of productivity. The conclusion of the paper provides practical policy suggestions as to how to reduce these economic predispositions in the event of future health crises, but more equitable, transparent, and accountable emergency response mechanisms are required.

Key words: *Algorithmic Bias, Economic Impact, Healthcare Systems, COVID-19, Emergency Response*

ملخص

أظهرت جائحة كوفيد-19 قصورًا واضحًا في كفاءة أنظمة الرعاية الصحية في مختلف دول العالم، بما في ذلك آليات توزيع الموارد وسلسلة إجراءات التشخيص. ومن القضايا المهمة التي لم تحظ بالاهتمام الكافي خلال الأزمة وجود تحيزات خوارزمية تم تضمينها في آليات التدخل الطارئ، الأمر الذي انعكس سلبًا على الفجوات الصحية القائمة أصلًا، وأسهم بصورة متزايدة في تعميق آثار الأزمة. وقد ظهرت هذه التحيزات بشكل أكبر بين الفئات السكانية الأكثر هشاشة، مما أدى إلى نتائج صحية سلبية وتكاليف اقتصادية مرتفعة، لا سيما في خوارزميات الفرز الطبي (Triage) المستخدمة لتخصيص الموارد الصحية النادرة. تقدم هذه الدراسة نموذجًا عامًا لتقدير الأثر

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الاقتصادي للتحيز الخوارزمي خلال جائحة كوفيد-19، سواء بشكل مباشر مثل زيادة الإنفاق الصحي، وحالات التنويم في المستشفيات، والعناية المركزة، أو بشكل غير مباشر مثل فقدان الإنتاجية الناتج عن ارتفاع عدد الوفيات. كما تقيس الدراسة مدى إسهام هذه التحيزات في الاقتصاد العالمي في حالتين مختلفتين: حالة تأثير معتدل (5%) وحالة تأثير شديد (15%)، وذلك من خلال محاكاة هاتين الحالتين واستخدام النتائج لتحديد أثر التحيز الخوارزمي في الاستقرار الاقتصادي على المستويين الوطني والعالمي. وتشير النتائج إلى أن وجود التحيز الخوارزمي، خصوصًا في الدول مرتفعة الدخل، يُعد أحد العوامل التي تسهم في جزء كبير من الخسائر الاقتصادية، وهو ما يتضح من ارتفاع التكاليف غير المباشرة المرتبطة بزيادة الوفيات وفقدان الإنتاجية. كما تقدم هذه الدراسة مجموعة من التوصيات والسياسات العملية التي تهدف إلى الحد من هذه الآثار الاقتصادية في حال حدوث أزمات صحية مستقبلية، مع التأكيد على ضرورة تطوير آليات استجابة طارئة أكثر عدالة وشفافية.

الكلمات المفتاحية: *التحيز الخوارزمي، الأثر الاقتصادي، أنظمة الرعاية الصحية، كوفيد-19، الاستجابة للطوارئ.*

1. INTRODUCTION

The COVID-19 pandemic has demonstrated how vulnerable healthcare systems are around the world [1]. The spread of the virus was extremely rapid, forcing countries to deal with unprecedented problems of responding to an increased number of cases and the resulting resource overload [2]. It was not only the direct costs associated with healthcare, but the economic consequences of lockdowns, workforce participation, and long-term consequences of COVID-19-related morbidity that contributed to the economic impact of the pandemic [3]. Although the focus of the global health community has been on flattening the curve, an aspect of the response that is frequently ignored is that systems used to control the health crises have algorithmic biases [4]. These systems were frequently created based on triage algorithms meant to allocate the limited medical resources available when the use of diagnostic devices was applied in the testing stage and in case identification, which depended on some assumptions that inadvertently privileged some groups of individuals over others. As a result, vulnerable populations, with the least access to healthcare, were disproportionately affected, worsening the existing health disparities faced by disadvantaged populations and resulting in an increased overall economic cost of the pandemic [5].

There is an increasing concern that algorithmic bias caused by emergency management systems could have enduring consequences on health outcomes and economic stability that are more profound than anyone could have imagined [6]. Inequities in accessing care have always been a problem within health systems, yet the COVID-19 crisis led to their level becoming particularly acute [7]. The algorithms determining the allocation of resources during emergencies, like when allocating ICU beds, ventilators, or testing, were typically set to maximize efficiency as opposed to equity [8]. This may have helped prevent the direct impact of the pandemic, but had a secondary impact of increasing the rate of death and worsening the economic impact, particularly on the marginalized and impoverished groups. During the crisis, the lack of transparency in the algorithm development and implementation process, combined with the excess of algorithmic decision-making at the time of the crisis, has caused these biases to be tested and eliminated [9]. Besides being an ethical issue, it has been demonstrated to jeopardize the future economic viability of a post-pandemic recovery, particularly in low-income locales that will already be experiencing deteriorated healthcare infrastructure [10].

This research seeks to propose a solution to all these problems by quantifying in a systematic way the economic cost of algorithmic bias in COVID-19 emergency response systems. In particular, the indirect (e.g., productivity loss due to excess mortality) and the direct healthcare costs (e.g., the price of hospitalization and ICU operations) generated by the biased resource allocation and diagnostic procedure are simulated. Additionally, the economic cost of these biases is defined by defining two cases of bias: Mild (5%) and Severe (15%), which are then applied to a global data set of key pandemic mortality drivers, including ICU load, hospital admissions, testing rates, and positivity rates. Assessing these costs at both the global and the country level, we seek to offer an in-depth examination of the monetary weight that algorithmic biases carried during the COVID-19 crisis. The study also provides policy implications and suggestions to reduce the economic impact of a future outbreak within the health context through the establishment of a more just and transparent response infrastructure.

The contributions that this research makes, in particular, are:

- **Modeling the economic impacts of algorithmic bias:** A framework to measure the impact of algorithmic bias on health outcomes (excess deaths, hospital admissions) and the resulting economic cost at the global scale has been developed.
- **Defining and simulating bias scenarios:** The potential distortions of both the diagnostic and treatment systems in the times of the COVID-19 pandemic were simulated to create two bias scenarios (Mild 5% and Severe 15%). These situations are implemented in various important drivers such as the capacity of the ICU, hospital admissions, testing rate, and positivity rate.
- **Estimating global and country-level costs:** Based on the data available on COVID-19 mortality rates at the country level, hospital capacity, testing, and socio-economic aspects, we approximate the economic cost of such biases on the global scale, as well as cross-regional, cross-income, and cross-efficiency in healthcare.
- **Exploring temporal and compositional dynamics of costs:** The changes in monthly cost profiles in various countries and the changing economic burdens during the pandemic are examined, with a particular focus on the timing and the nature of direct, indirect, and system costs.

The remainder of this paper is organized as follows: Section 2 entails a detailed review of the current literature on healthcare-related algorithmic bias and its economic consequences, especially in the times of the COVID-19 pandemic. Section 3 provides the methodology that determines the economic costs of algorithmic bias, including the sources of the data, model specification, and bias conditions. Chapter 4 gives the outcome of the analysis, the economic costs of both the Mild (5%) and the Severe (15%) bias scenario at the global and country level, with emphasis put on the temporal and compositional dynamics of costs. Lastly, Section 5 wraps up the research by offering recommendations useful in mitigating the economic consequences of algorithmic bias in future health crises.

2. LITERATURE REVIEW

Application of Artificial Intelligence (AI) has already resulted in paradigm shifts in the health, financial, and infrastructural sectors, including handling crisis scenarios, including the COVID-19 pandemic. AI-powered solutions have been designed to help solve many issues, such as managing pandemics, predicting financial distress, and assigning healthcare resources. However, there are data heterogeneity, cybersecurity, privacy, and more explainable aspects among others in such a system. It has been observed in other studies that AI could contribute significantly to the improvement of decision-making processes, resource allocation, and detection of health risks in time, and even reduce healthcare disparities. Whatever means these things are improved, the moral concerns, the prejudice of algorithms, and data disclosure still remain a negative effect on the future use and usability of AI in these spheres.

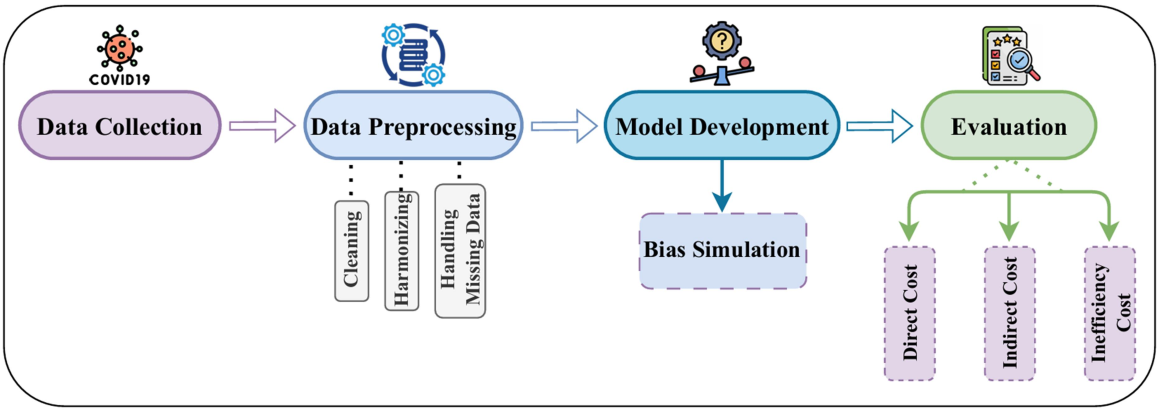
Aderamo et al. [11] developed an AI-based pandemic management system to apply to an offshore oil platform environment to safeguard workers and provide continuity of work during a global health crisis. Already, they foresaw health-monitored, machine-learned breakout-identification and automatically allot the resources to foretell the dissemination of the infections, to apportion the volume of PPE and quantity amounts of supplies, and to control the responses according to the real-time communication criteria. Nevertheless, there were also some drawbacks in the framework connected with the need to combine the sources of heterogeneous data. When working with remote offshore systems, it is necessary to have a constant connection; the impossibility of protecting privacy and cybersecurity might hinder their popularization. Conte [12] investigated the use of hi-tech AI-based solutions in financial distress prediction of Italian SMEs and demonstrated that the models could not only identify the initial signs of insolvency but also 5 years in advance and, thus, avoid the implementation of proactive solutions. Drawing on the significance of explainability and transparency in AI models to serve managerial decision-making, the paper has pointed out issues impacting the adoption of AI models, including data ethics, managerial literacy, over-reliance on algorithms, and regulatory conformity that could limit their broad use in organizational settings. Analyzing real-time information that may show health risks (e.g., respiratory illnesses and heat-related ailments), Baklola and Terra [13] explored the potential of AI adoption to control health risks during the large-scale event. They found that AI contributed positively to resource allocation and medical outcomes at large events, but concerns over accountability, algorithmic bias, and privacy of data were still observed and had to be carefully managed to achieve ethical and responsible use. NWEKE and Oshoke [14] considered how AI, climate-resilient infrastructure, and cybersecurity can integrate into the publicly available healthcare sector of Nigeria and identified opportunities and threats. They identified two major policy and implementation gaps that could expose AI-based health technologies to cyberattacks and climate-related disruptions, and called on an integrated cybersecurity framework in alignment with resilient infrastructure, ethical application of AI, and strong regulatory measures to play a role in establishing sustainable and secure health care delivery. Ogundeko-Olugbami and Ogundeko [15] explored how AI-enhanced predictive analytics can be used to address health disparities in the entire healthcare system of the U.S. and, specifically, marginalized groups. They applied NLP and machine learning demonstrated themselves to assist in the early detection of a disease, personal care, and resource allocation, and also to create barriers to entry, the phenomenon of algorithm bias, data transparency, and patient privacy, and to reform the policy and bring radical change to the systems and make them more equal. Nwakobe, Okafor, and Ilouno [16] showed that AI-enabled predictive models can be used to improve early detection, real-time tracking, and targeted intervention, should an outbreak be detected. They discussed their needs, though their study was carried out on the establishment of the quality and details of prediction and specially created responses, but also addressed the issues of constraints on access to data and models utilization, ethics, and the general value of the interdisciplinary team to enhance health systems worldwide. Nasir, Khan, and Bai [17] took the ethical aspects of deep learning in medicine very seriously, and they proposed a responsible AI system intended to focus on transparency, fairness, accountability, and human-centered regulation. They found out that the apolitical dilemmas which they chose were data biases, lack of explainability, and contextualization, and that concerted efforts to design shared standards of AI ethics, as well as to organize activities, are highly desirable and needed to assist the problem of protecting AI technologies and fairly distributing them. Chakilam and Rani [18] presented the use of AI despair neural networks in the healthcare insurance claim analysis, where predictive modeling moves beyond finance to the healthcare decision-making process. They proved that AI-based technology could streamline real-time insurance benefits, financial, and policy development processing to retain patients and promote service loyalty. They had also discovered, however, two issues of cumulative information, dynamism in cost estimation, and feasibility in mass use of things, and they simultaneously had found out that much of that would be improved before they could do that.

Although the potential is, indeed, gigantic, the resource management, as well as the economic systems, will be resolved to addressed, so that the application(s) of AI solutions become accountable and acceptable, due to the ethical issues, the data confidentiality, and the explainability of the AI models, among the other concerns presented in the literature. The continued development of AI systems will necessitate continued efforts to strike a balance between innovation and transparency, fairness, and accountability, especially when dealing with the high-stakes domain of healthcare and response to pandemic outbreaks.

3. METHODOLOGY

This section describes the approach to the estimation of the economic cost of algorithmic bias in the health emergency systems during the COVID-19 pandemic. The method uses econometric models, counterfactual simulations, and cost valuation to determine the off-pathway effects of bias scenarios on health and economic variables. Figure 1 provides the conceptual framework and elaborates on the key components of the model, such as the bias operator, dependent and independent variables, and the sources of data that are used to calibrate the model. The simulation accounts for the economic costs of resource misallocation and diagnostic shortfalls using two different bias scenarios (Mild 5% and Severe 15%), as well as country-level and global economics (hospital admissions, ICU capacity, and testing rates).

Fig.1. Workflow of this research



3.1 Dataset Description

The study utilized a national daily panel, which has roughly 166,326 country-day observations and 67 variables; its focus is on COVID-19. This data was created by Our World In Data in cooperation with the University of Oxford. The study activities are based on calendar day t of a country as a unit of analysis. The data includes four subcategories: (i) epidemiology (e.g., new_deaths_smoothed, new cases smoothed), (ii) health-system capacity (icu patients, weekly hospital admissions, bed restrictions per-thousand-pop, etc.), (iii) diagnostics (new tests, positive rate), (iv) socioeconomic control (population, GDP per-individual). Its brief overview is given in Table 1.

Table 1. Summary of dataset and sample construction (national daily panel; aggregates removed; 7-day lags)

Aspect	Detail
Unit of analysis	Country-day (national level)
Size & scope	≈166,326 rows; 67 variables; multi-country
Time index	Daily; date parsed to ISO and sorted within location
Outcome (dependent variable)	new_deaths_smoothed
Key drivers (lagged 7 days)	icu_patients_lag7, weekly_hosp_admissions_lag7, new_tests_lag7, positive_rate_lag7

System capacity	hospital_beds_per_thousand
Socioeconomic context	population, gdp_per_capita (ffill/bfill within country)
Inclusion/exclusion	Drop aggregates with iso_code = "OWID_*"; keep rows with outcome observed and ≥2 lagged drivers
Transformations	ISO date parsing; country-day ordering; within-country ffill/bfill; 7-day lag construction
Optional scaling	Per-capita (per 100k); main models use levels with fixed effects

3.2 Data Preprocessing

Prior to the development of the models, a rigorous preprocessing pipeline was performed to prevent an attack on the integrity, completeness, and internal consistency of the OWID-style country-day panel. This involved balancing identifiers and dates, eliminating aggregate rows, stabilizing structural variables, and preparing clinically motivated lags to match predictors and outcomes.

1. **Harmonization and basic QC:** Bad corrections in daily flows (common in backfills) are considered missing instead of force to zero, and flows are non-negative, treated as an outcome (new_deaths_smoothed) to eliminate the day-of-week/reporting effect, with none generated where not necessary, which is a moving average of new-deaths in 7 days.
2. **Feature engineering:** Four lagged drivers are generated in each country i at $t-7$ with the following names: ICU, Hospital admissions, Tests, and positivity. To obtain a reporting index and an aggregation index, a monthly period index (year-month) is calculated.

$$x_{i,t-7} = L^7 \begin{bmatrix} ICU_{it} \\ HospAdm_{it} \\ Tests_{it} \end{bmatrix}$$

3. **Missing-data policy:** The outcome is never imputed. Having applied the "≥2 drivers" rule, the remaining missing drive in the design matrix is then forced to zero to prevent listwise deletion (a common practical practice when level differences are absorbed by fixed effects). Both robustness tests remove such zero-fills, and both tests are robust to the stability of coefficients.
4. **Outliers and sensitivity:** In sensitivity analyses, positivity and per-capita testing are winsorized at the 1st/99th percentile; other transforms (e.g., log1p) are explored.

$$z_{it}^{win} = \min\{q_{0.99,i}(z), \max\{q_{0.01,i}(z), z_{it}\}$$

5. **Leakage control:** The computed lags are based solely on earlier days; they do not use future

information. Temporal validation preserves the time order (below).

3.3 Operationalizing Algorithmic Bias

From an emergent response and diagnostics standpoint, algorithmic bias manifests as a systemic bias that is applied disproportionately to vulnerable subpopulations but may be reflected in national curves in terms of effective overloads (ICU/admissions) and shortfall/selection (testing/positivity). Let

$$x_{it} = \{ICU_{i,t-7}, HospAdm_{i,t-7}, Tests_{i,t-7}, PosRate_{i,t-7}\}.$$

Define a multiplicative bias operator B(δ) with $\delta = (\delta_{ICU}, \delta_H, \delta_T, \delta_P)$:

$$ICU^{(\delta)}_{i,t-7} = ICU_{i,t-7}(1+\delta_{ICU}),\ \ HospAdm^{(\delta)}_{i,t-7} = HospAdm_{i,t-7}(1+\delta_H),$$

$$Tests^{(\delta)}_{i,t-7} = Tests_{i,t-7}(1+\delta_T),\ \ PosRate^{(\delta)}_{i,t-7} = PosRate_{i,t-7}(1+\delta_P).$$

Triage/resource bias implies $\delta_{ICU,}\delta_H > 0$; diagnostic bias implies $\delta_T < 0, \delta_T > 0$. Scenario magnitudes have been assigned, a priori, 5% (mild, small) and 15% (severe, large), and have been widely varied in sensitivity analysis. Epidemiologically coherent ranges (PosRate ∈ [0,1]; flows ≥ 0) are clamped to all perturbed series.

Practically, bias is acting on subgroups; when measured on an aggregate panel, a subtractive net impact of bias would be equivalent to δ , a reduced-form shock, which would be consistent with known mechanisms of under-testing and delayed care.

3.4 Economic Valuation

This study values the bias-attributable health consequences in a cost-of-illness (COI) framework considering the societal viewpoint. All costs are calculated on a country-month basis and summed up to country totals and global totals. Total economic cost is obtained by valuing three components, which include direct medical costs, indirect productivity losses, and system inefficiency. Monetary values are presented in constant USD (base year mentioned in the Results); given possible differences in price levels between countries, monetary inputs may constantly be harmonized by either CPI or PPP adjustments. The value of each component was set to not exceed the value of the other to avoid counting the same outlay, e.g., the amounts spent on clinical treatment (direct) and the amount of the foregone output due to premature mortality (indirect), and the amount that was spent as unnecessary operational waste (system inefficiency).

3.4.1 Direct Healthcare Costs

Direct costs reflect other clinical costs caused by excessive use of the clinic due to bias (e.g., mis-triage, delay, which increases severity). Where $ExcessHosp^{(\delta)}_{i,m}$ refers to excess admissions (or admission-days) attributable to bias in country i in month m . The base formulation weighs them as general hospital bed-days; an ICU-specific form is also reported in the event that available information makes this possible.

$$C_{i,m}^{direct} = ExcessHosp_{i,m}^{(\delta)} \times Cost_{hosp\_day,i} \times LOS_i,$$

where $Cost_{hos\ \_day,i}$ is the average inpatient day cost and LOS_i is the mean length-of-stay. Parameters used in the baseline are $Cost_{hosp\_day} =$ 1200 USD and LOS = 7 days; the parameters of sensitivity analysis differ to a large extent in both directions. When there is an opportunity to isolate ICU days, the direct healthcare cost is calculated as

$$C_{i,m}^{direct,ICU} = ExcessICUdays_{i,m}^{(\delta)} \times Cost_{ICU\_day},$$

and this is added to (or substituted for) general bed-day costs. In the absence of country-specific unit costs, $Cost_{hos\ \_day,i}$ can be scaled against a reference with income or health expenditure proxies (e.g., GDP_{pc_i} or current health expenditure per capita) or in terms of an elasticity, $\eta \in [0.6,1.0]$. This maintains the cross-country realism and preserves the assumptions.

3.4.2 Indirect Productivity Losses

Indirect costs estimate economic waste due to unrealized production due to excess mortality, which is attributable to bias. Age-specific data are not always available across our panel of countries, in which case a parsimonious human-capital valuation is chosen, benchmarked on GDP per capita and participation.

$$C_{i,m}^{indirect} = ExcessDeaths_{i,m}^{(\delta)} \times GDP_{pc_i} \times LFPR_i \times Y,$$

where GDP_{pc_i} is GDP per capita, $LFPR_i$ is the labor-force participation rate (or an employment-rate proxy), and is the years of productive years lost with expected productivity. The baseline sets Y = 3 years (conservative) and varies {1, 2, 3, 5} in sensitivity analysis. The human-capital approach suppresses larger social value (e.g., non-market labor, caregiving) and tends to give lower estimates than Value-of-Statistical-Life methodologies; we thus show ranges of sensitivity as well as highlight perspective.

3.4.3 System Inefficiency Costs

Bias may create preventable operational wastes despite the cost of clinical treatment being settled, e.g., ambulance misroutes resulting in unnecessary repeat ED visits, wasted capacity when the correct facility is not reachable, and redundant diagnostic results because of incomplete access. Captured as a proportional add-on to direct costs, system inefficiency costs are calculated as:

$$C_{i,m}^{system} = \phi \cdot C_{i,m}^{indirect}, \quad \phi \in [0,1]$$

The baseline uses $\phi = 0.25$ as a base case and tests $\phi \in \{0.10, 0.25, 0.40\}$ with sensitivity analysis. This economic model does not include counting twice of spending by avoiding loading the indirect losses, but loading only the clinic's spending. In case more detailed operations data are available (e.g., dispatch logs), we can use ϕ as a transparent shadow price of misallocation, and we can even use it to simulate a queueing/flow model.

3.4.4 Total Cost and Reporting

Under a specific bias on each resulting bias-attributable excess usage (strategy) with country i and month m we operate by the total economic burden, calculated as: (i) direct medical expenditures on bias-attributable excess usage of the resources of a hospital; (ii) indirect productivity burden on a bias-attributable excess mortality; (iii) system inefficiency, which is an avoidable waste in operations, represented as a fraction of direct costs. All the values are calculated on a country-month basis in constant USD (base year mentioned in Results) to eliminate any double-counting.

$$C_{i,m}^{total} = C_{i,m}^{direct} + C_{i,m}^{indirect} + C_{i,m}^{system}.$$

The country-month values are aggregated into country totals and then into global totals. To ensure comparability, the per-capita costs are also reported in USD per 100,000 population:

$$C_{i,per100k}^{total} = \frac{100000}{population_i} \sum_{m} C_{i,m}^{total}.$$

For distributional impacts, it is possible to stratify a result by income group, region or health-capacity quintile (e.g., hospital_beds_per_thousand). We also show component shares (direct vs. indirect vs. system), to see the agents working to produce total costs, and scenario decomposition (diagnostic-only vs. triage/resource-only shocks) to assign effects to particular instances of bias.

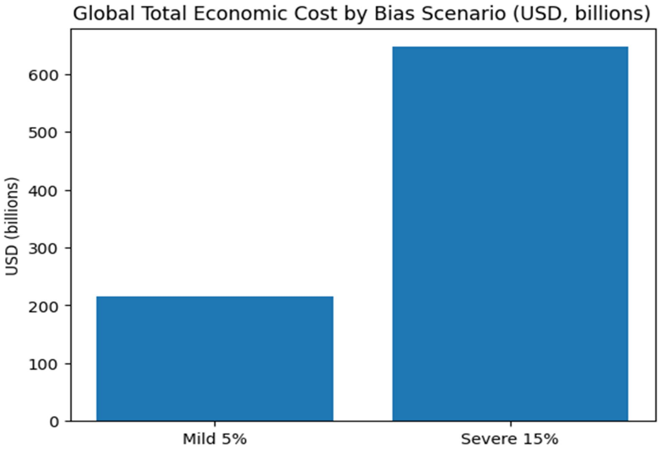
4. RESULTS AND DISCUSSION

This section presents the results of our study of the economic cost of algorithm bias in health emergency systems in the COVID-19 pandemic. Beginning by mentioning the total costs in the Mild (5%) and Severe (15%) bias cases, the analysis of the costs distribution in all three direct, indirect, and system inefficiency aspects is presented. The time dynamics of these expenses, their changes during significant pandemic waves, and the differences in economic burden on the country level are also examined.

4.1 Global Economic Burden Under Bias Scenarios

Figure 2 shows the post-aggregation of the global total economic cost in all the country-month estimates of the model and valuation framework. The global burden of biases under the Mild (5%)-bias and Severe (15%)-bias would be around $\$2.2\times10^{11}$ (USD, billions) and $\$6.5\times10^{11}$, respectively. The nearly threefold amplification between the Mild and Severe bias shocks reflects the multiplicative bias shocks on the same epidemiological process and the linear forecast from perturbed drivers to excess outcomes to costs. In line with country-level decompositions, the largest portion of the overall global total is the indirect component (productivity losses due to excess deaths), while reduced shares are made up of direct medical and system-inefficiency costs. Since the valuation is linear with respect to key parameters (hospital-day cost, LOS, productive years Y, inefficiency factor ϕ), while a global totals scale predicts sensitively in sensitivity analysis, the qualitative ordering and the gap between the top and bottom cases (scenarios) do not change.

Fig.2. Global total economic cost by bias scenario (USD, billions). Bars show aggregated totals for Mild (5%) and Severe (15%) bias



4.2 Country-level economic burden under bias scenarios

The top ten countries associated with the highest bias-attributable economic costs are given in Table 2 and Table 3. The concentration of losses in big, high-income countries is very high in both cases. In the case of Mild (5% bias), the burden is seen to be highest in the United States (≈ $80.0 billion), Germany (≈ $11.5 billion), France (≈ $9.8 billion), Spain (≈ $8.3 billion), and finally, Italy (≈ $6.6 billion). The United Kingdom, the Netherlands, the countries of Chile, and Belgium are also in the top ten. At a Severe (15%) bias, all of the rankings are the same, with the magnitudes scaling approximately in proportion to the ranks: the United States to 1st place of ≈ $240.0 billion, Germany to 3rd place of ≈ $34.4 billion, France to 4th place of ≈ $29.4 billion, Spain to 5th place of ≈ $25.0 billion, and Italy to 6th place of ≈ $19.9 billion.

Table 2. Top 10 Countries by Total Cost - Mild 5%

location	**excess_deaths_Mild_5%**	**excess_hosp_Mild_5%**	**direct_cost_usd**	**indirect_cost_usd**	**system_cost_usd**	**total_cost_usd**
United States	23230.12	1638473	1.38E+10	6.28E+10	3.44E+09	8E+10
Germany	4445.744	152622.7	1.28E+09	9.87E+09	3.21E+08	1.15E+10
France	4096.47	235060.8	1.97E+09	7.32E+09	4.94E+08	9.79E+09
Spain	3745.06	194351.4	1.63E+09	6.31E+09	4.08E+08	8.35E+09
Italy	2657.446	190013.9	1.6E+09	4.65E+09	3.99E+08	6.65E+09

Argentina	6410.309	0	0	6.05E+09	0	6.05E+09
United Kingdom	1434.598	246155.4	2.07E+09	2.71E+09	5.17E+08	5.29E+09
Netherlands	1789.064	26792.4	2.25E+08	4.22E+09	56264040	4.5E+09
Chile	3139.564	65222.35	5.48E+08	3.53E+09	1.37E+08	4.21E+09
Belgium	1735.363	38491.75	3.23E+08	3.61E+09	80832680	4.02E+09

In both tables, the totals of Severe (15%) are about 3× that of Mild (5%) in all countries. Such near-proportional scaling simply arises as a direct result of the multiplicative bias operator on the drivers and the linear outcome and cost mappings (§§3.5-3.8). There is also component-wise (direct, indirect, system) proportionality, as in the United States (≈ $80.0 b → ≈ 240.0 b) and Germany (≈ 11.5 b → 34.4 b). In other words, Argentina gives zero excess-admission costs (In both cases, the direct is 0, the system is 0) but reports huge indirect losses (≈ $6.05 b Mild; ≈ $18.15 b Severe). This implies that, in our proxy, the bias shock is manifested more by diagnostic/triage paths that induced changes in mortality than by measured hospital-admission overload. In countries like Spain and Italy, there appear to be large direct costs, but high indirect costs, which indicates that both triage/resource stress (through admissions/ICU load) and diagnostic shortage add to the overall burden. Hospital-based use, as opposed to mortality-based productivity losses, suggests that the relatively larger direct component (Mild: ≈ 39%) in the United Kingdom makes a considerable contribution to the decrease.

These shares are interpreted by two characteristics of accounting. First, system inefficiency is assumed to be a fixed portion of direct cost ($\phi = 0.25$); therefore, its value irrevocably aids in keeping up with the scale of direct medical expenditures. Second, indirect costs concur with excess death and with the product of GDP per capita discussions labor-force participation times productive years; therefore, people with high income bear a bigger burden of indirect costs, and people with big absolute shocks of fatalities receive a larger burden of indirect costs.

Table 3. Top 10 Countries by Total Cost - Severe 15%

location	excess_deaths_Severe_15%	excess_hosp_Severe_15%	direct_cost_usd	indirect_cost_usd	system_cost_usd	total_cost_usd
United States	69690.35	4915420	4.13E+10	1.88E+11	1.03E+10	2.4E+11
Germany	13337.23	457868.1	3.85E+09	2.96E+10	9.62E+08	3.44E+10
France	12289.41	705182.4	5.92E+09	2.2E+10	1.48E+09	2.94E+10
Spain	11235.18	583054.2	4.9E+09	1.89E+10	1.22E+09	2.5E+10
Italy	7972.337	570041.7	4.79E+09	1.4E+10	1.2E+09	1.99E+10
Argentina	19230.93	0	0	1.81E+10	0	1.81E+10
United Kingdom	4303.794	738466.2	6.2E+09	8.12E+09	1.55E+09	1.59E+10
Netherlands	5367.193	80377.2	6.75E+08	1.26E+10	1.69E+08	1.35E+10
Chile	9418.692	195667.1	1.64E+09	1.06E+10	4.11E+08	1.26E+10
Belgium	5206.088	115475.3	9.7E+08	1.08E+10	2.42E+08	1.21E+10

4.3 Temporal Dynamics of Bias-Attributable Economic Costs Across Pandemic Waves

The monthly series visualizes the change in bias-attributable total economic costs that are pandemic wave-dependent and country-specific in magnitude across the two scenario intensities. Values are monthly sums in constant USD (billions) of the model excess deaths/admissions plus the model valuation framework.

Fig.3. Monthly total economic cost under Severe (15%) bias for the top 3 countries

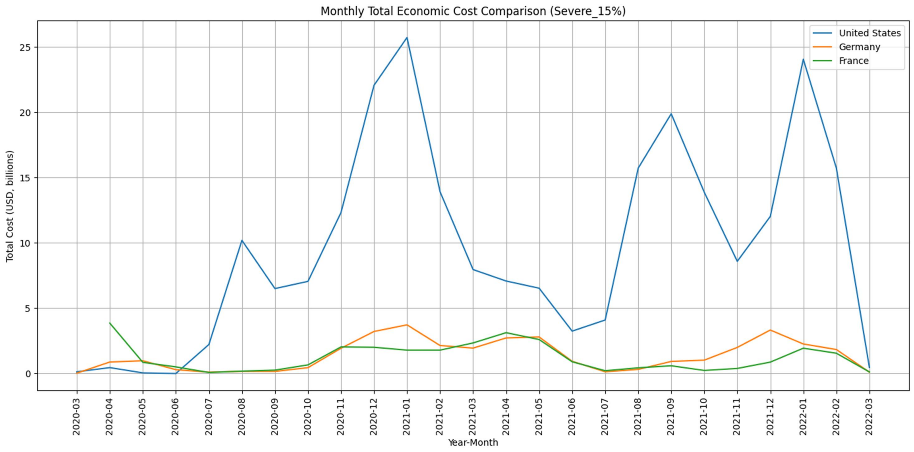


Figure 3 indicates that the wave pattern in all three countries is quite clear: the first crest is modest in spring 2020 and mostly strong in winter 2020/21, there is a remarkable trough in the middle of 2021 and a rebirth of the Delta-wave at the end of 2021, and finally the Omicron-period crest at the end of January 2022. The swings are greatest in the United States, which ranges between near zero in early 2020 and >20–25 billion USD in winter 2020/21, calming mid-2021, and spiking near the end of 2021 to early 2022, around a span of 2021 to 24 billion USD. Co-movement to Germany and France is of much lower relative quantities (single-digit billions at peaks) because of lower populations and smaller losses in GDP-per-capita-weighted productivity than in the U.S. The high correlation between the three series suggests that global waves (uplifted by the time effects in robustness) are responsible for a significant proportion of jumps between months, whereas the beginning size and incomes of nations largely regulate magnitude.

Fig.4. Monthly total economic cost under Mild (5%) bias for the top 3 countries

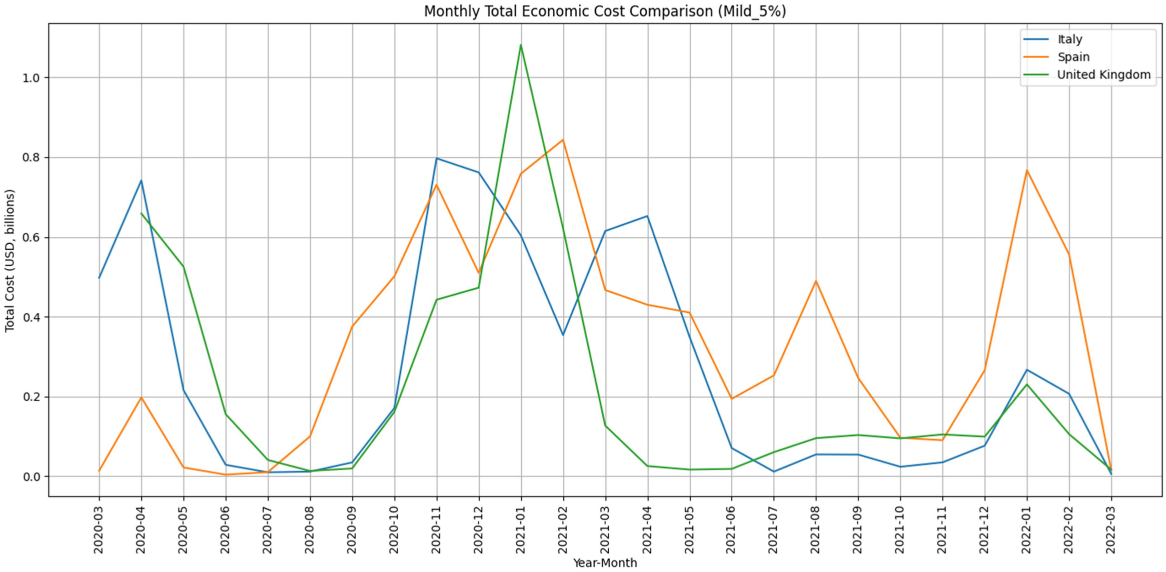
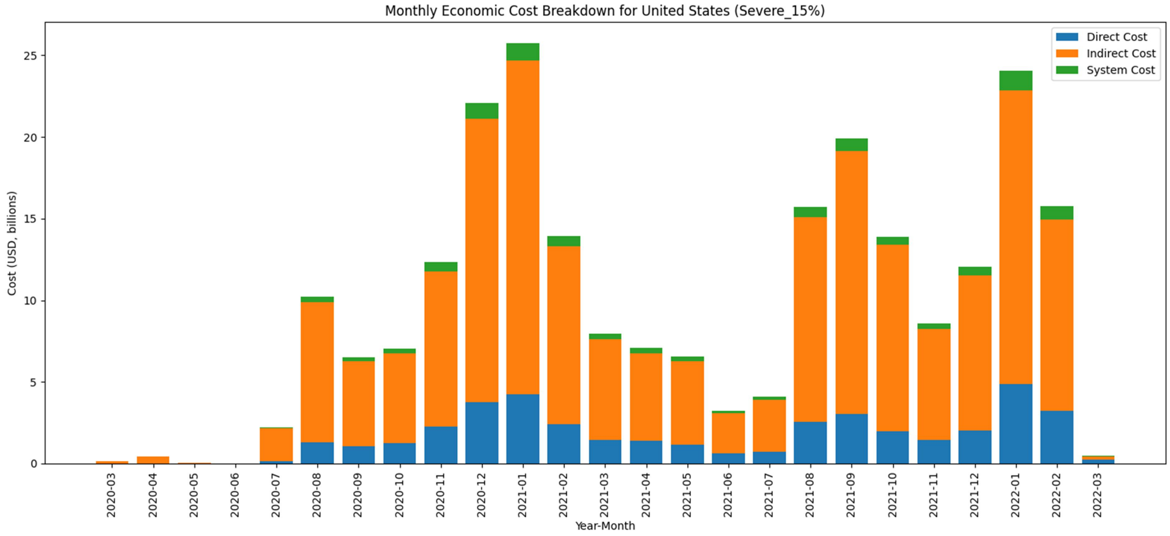


Figure 4 indicates that the cost per month ranges between sub-billion and approximately 1 billion USD, yet the seasonality can be noticed. Italy plateaus in late 2020 (≈0.8 b), then in the spring of 2021 (~0.6 b), and in 2021 further rises more modestly near the year-end. Spain appears to present a tri-modal profile, i.e., late-2020, early 2021, and early 2022, which is fitting second, third, and Omicron waves. The United Kingdom has a high January 2021 crest (≈1.1 b) and relatively minor late-2021 activity, which is also consistent with our previous component interpretation of UK totals having a relatively larger direct medical component (hospital-based outlays) and mortality-related indirect costs. All in all, the Mild Severe analogy goes in line with the linear mapping of the paper: all the same timings, steadily increased amplitudes, Severe ≈3× Mild in aggregate.

4.4 U.S. monthly cost decomposition under Severe (15%) bias

Figure 5 shows that indirect costs (productivity losses from excess deaths) dominate the U.S. burden throughout the period, with direct medical outlays a smaller but wave-sensitive component and system inefficiency a thin add-on that tracks direct costs by construction (ϕ fraction). Monthly amounts begin near zero at the start of 2020, followed by rises with regular series of waves: a first massive peak in December 2020-January 2021 (to about $25-26B) followed by a lull in mid-2021 then another Delta peak about August-October 2021 (to about ≈$15-20B) and another Omicron peak around the start of the year 2022 (to about 24B). At both ends, direct costs constitute a small fraction of the aggregate (about 75-85%), whereas indirect costs increase proportionally to the hospital load (about 1220 percent of the total at peaks); because the system costs are proportional to the direct outlays, costs in the system are also small (about 3-5%). The trend reinforces the two observations (i) timing is epidemiological, maximum costs coincide with national waves; and (ii) maximum is mortality-driven, mortality-induced indirect losses fuel the vast majority of the dollar expense even in response to an epidemic tide of hospital utilization.

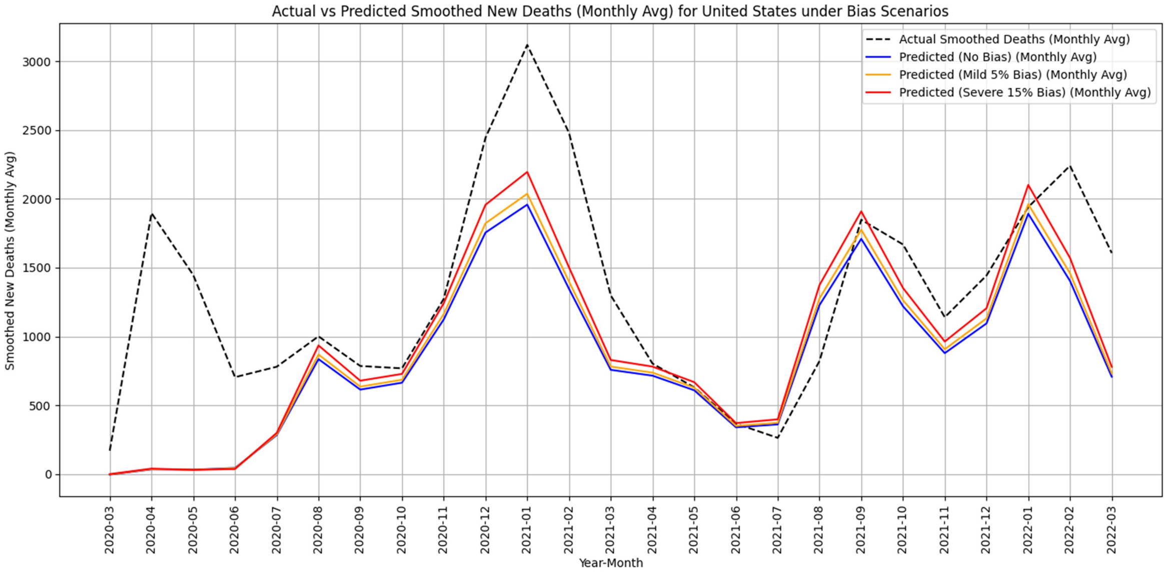
Fig.5. Monthly economic cost breakdown for the United States under the Severe (15%) bias scenario (USD billions)



4.5 Bias-scenario mortality counterfactuals (United States)

Figure 6 presents the comparison of the actual and model-predicted monthly averages of the cases of smoothed new deaths with three configurations: No-bias baseline (blue), Mild 5% bias (orange), and Severe 15% bias (red). The next predicted series are close in timing to the U.S. pandemic waves of summer 2020, winter 2020/21 (dominant crest), a mid-2021 trough, a Delta rebound in late 2021, and the Omicron crest in early 2022, suggesting that the lagged driver set (ICU, admissions, tests, positivity) models the month-to-month dynamics. According to design, the bias cases present upward shifts that are monotonic versus the no-bias line, so Mild (5%)-Severe (15%) is above the others; the interval between the colored lines is approximately proportional, which is characteristic of a multiplicative bias operator that works on a linear outcome model.

Fig.6. Actual vs. predicted smoothed new deaths (monthly average) in the United States

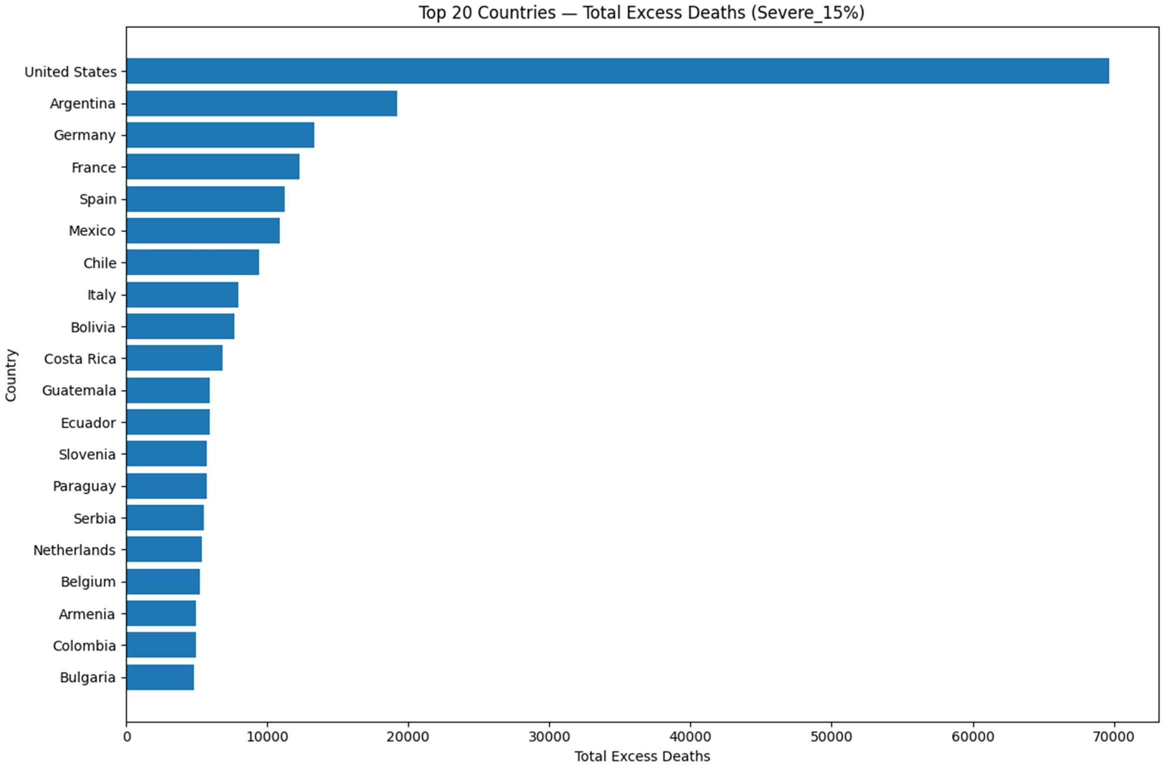


The most discontinuous deviations between actual and predicted are at the winter 2020/21 and Omicron peaks, where the reduced-form specification understates extreme surge - a well-known limitation when deaths rise more rapidly than lagged system variables, or when the reporting backlog is cleared in bursts. There is more correspondence between predictions and actuals between waves. The blue < orange < red scenario illustrates that triage/diagnostic bias, while leaving wave timing constant, is associated with increased mortality, and forms the basis of the cos increases reported in §4.1-4.3.

4.6 Top 20 excess deaths under severe bias (15%)

Figure 7 ranks countries according to the excess deaths attributable to the Severe (15%) bias scenario. The distribution is maximized, with the United States on the front line (almost 70k), the next group of Argentina (≈19k), Germany (≈13k), France (≈12k), and Spain (≈11k) and then the tail which has a considerable number of Latin American and European countries (e.g., Mexico, Chile, Italy, Belgium, Netherlands). This pattern reflects the time and magnitude of pandemic waves as well as the extent to which the bias operator magnifies ICU/admission loads and diagnostic shortfalls in both contexts.

Fig.7. Top 20 countries by total excess deaths under the Severe (15%) bias scenario



The excess-death rankings do not overlay economic rankings since cost also relies on GDP per capita, labor-force participation, and unit treatment costs. In endowment, Argentina will be on/near the top of excess deaths as compared to the other European countries that rank higher on the total cost; or the higher-income countries (e.g., Germany, France) will be able to translate the same burden of deaths into higher financial losses. This distinction highlights that primarily mortality burden and economic burden are different policy prisms: the greatest welfare benefits achieved by reduction of diagnostic/triage bias occur in areas with the greatest increases in deaths, and financial impacts are found in areas with the highest income and unit costs.

4.7 Discussion

The results of this study demonstrate that algorithmic bias is very costly economically to a healthcare system when talking about the Severe (15%) bias environment [19]. It is found that the total costs are dominated by the indirect costs (mainly the losses in productivity when excess mortality occurs) [20], particularly when the GDP per capita is high and the affected populations are large (high-income nations like the United States, Germany, and France). The indirect costs are increasing significantly in these countries, with the Severe bias case returning almost three times as much as the cost of the Mild bias condition case [21]. It is also interesting to note that Argentina offers one instance with high indirect costs, despite low direct healthcare costs, due to excess deaths and how diagnostic and triage biases have an uneven spread among vulnerable populations, irrespective of healthcare expenditures [22].

These economic costs coincided with the waves of the pandemic, as their peaks were observed at the end of 2020/the beginning of 2021 and the end of 2021, and the Delta and Omicron variants, respectively [23]. In the scenario of Severe bias, however, it is clear that the biases of healthcare response during such waves have an even more significant economic effect. As our findings indicate, algorithmic bias is not just detrimental to health indicators but also proves to be highly costly in monetary terms, which is why it stands as a critical policy area. Combating these biases and accessibility to diagnostics can individually reduce the mortality/economic price of given action, the resource allocation or resource prioritization within a given triage, and the prioritization of more reasonable healthcare algorithms in future healthcare crises.

5. CONCLUSION

The algorithmic bias in the healthcare systems, as mentioned in the proposed work, is an economic cost burden since, besides the health disparity, it was established that the bias also increased direct and indirect economic costs. The result shows that as the machine is partial, especially at the triage level and the diagnostics process, mortality rate and hospitalization rate were greater than the indirect form of cost by considering the rate of loss in productivity, as it is nearly half of the number of deaths due to other death rates. The poorest countries could not keep up with the biggest economic load that was transferred to the most successful countries, and the impact of these prejudices on the most vulnerable groups was magnified.

There are, however, some limitations to this study. Despite its inclusiveness, the economic model is modelled under certain assumptions of hospital capacity, health care cost, and productivity loss estimates, which may not be equivalent across countries and health care systems. Moreover, the research centers on direct and indirect costs, which in turn may not capture other economic effects of algorithms over time, including social and psychological effects. The specified model cannot be considered ideal since the bias is linear, and the complexity of the medical crisis in the real world is unlikely to be identical to that in an exemplified model.

This study provides a number of opportunities to conduct additional research in the future. Bias scenarios could be further refined with more detailed information on healthcare disparities in the future, and it is possible to include race, gender, and socio-economic status in the bias scenarios. The worldview of how to avoid biases through applying the science of algorithmic transparency and accountability can become a revelation of how we can create more sensible healthcare systems, too. Finally, another way to see the bigger picture of the economic impact of algorithmic bias on healthcare infrastructure and post-pandemic recovery is to extrapolate the analysis to its long-term implications.

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