# Advancing Trust in Real-World Healthcare AI: A Framework for Enhanced Transparency and Fairness

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## Abstract

Healthcare Machine Learning (HML) models are revolutionizing the healthcare industry, promising improved patient outcomes and enhanced public health. However, the black-box nature of HML models raises concerns about bias and trust. To ensure these models are reliable and trustworthy, examining the data they use and evaluating their transparency, fairness, and accountability alongside their predictive abilities is critical. This study presents a six-year systematic review of risk prediction HML models using the MIMIC clinical research database (CRD). The results were striking: for the popular MIMIC IV – Intensive Care Unit (ICU) mortality task, a naive baseline outperformed the state-of-the-art (SOTA) model, showing not only better predictive performance but also improved fairness among different patient groups, though some unfairness remains. These results highlight the urgent need for a robust framework to enhance the trustworthiness of HML models. We propose a three-step framework: (i) a 'Datasheet for CRD' to promote data transparency and identify inherent data bias, inspired by recent recommendations for datasheets in datasets; (ii) a 'Model Card' detailing model characteristics, providing interpretable results and evaluating performance across demographic groups, inspired by model cards for model reporting; and (iii) a 'Fairness Report' to thoroughly assess and address any biases related to sensitive attributes, promoting fairness across all groups. This framework will assist practitioners in identifying data anomalies using the datasheet, model structure and its usage using the model card and fairness results and its impact from the fairness report, thereby fostering the development of trustworthy HML models.

## 1 Introduction

Machine learning (ML) has become a powerful tool in the healthcare industry, enabling the development of accurate prediction models that can significantly improve public health outcomes [85, 103]. However, in the high-stakes context of healthcare, ensuring trustworthy and fair predictive outcomes is crucial [84]. Despite significant progress in HML, unfairness still exists due to biases in data and algorithms [6, 16, 71]. These biases can perpetuate through the model's complex, black-box nature, resulting in unfair results and decreased stakeholder trust. It is essential to address these concerns

Preprint. Under review.

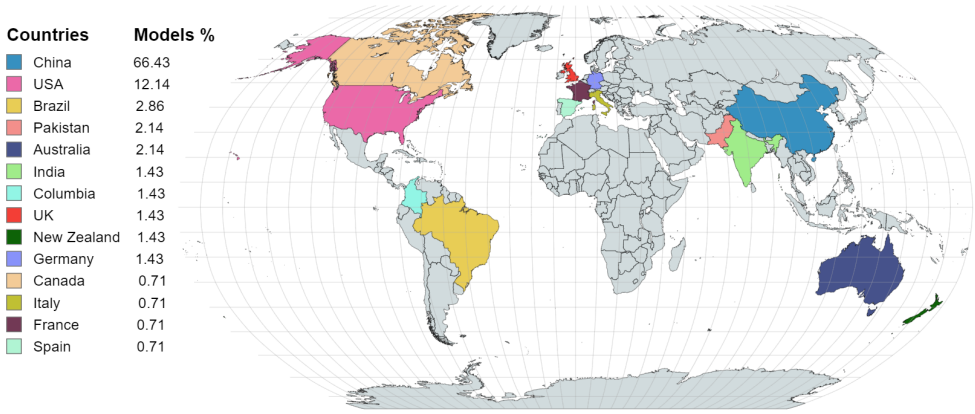



Figure 1: Distribution of HML models using MIMIC data worldwide from 2018 to 2024. The country list represents the widespread usage of MIMIC data for healthcare predictions globally, and the % value indicates the HML model researched by the respective country.

to ensure that the benefits of HML models are accessible to everyone, regardless of race, gender, or socio-economic status.

Fair ML is an active area of research focusing on how models can perpetuate inequalities and the ways to address them [11, 12, 35, 52, 72, 86, 87, 132]. Popular ML fairness strategies aim to assess and reduce algorithmic discrimination by imposing fairness constraints during model training [20, 49, 60, 73]. However, one of its inherent limitations is the data itself, which encodes real-world biases and inconsistencies, making it difficult to achieve fairness in healthcare settings [7]. This insight can be traced back to 2018, when Chen et al. [11] proposed that the predictive fairness evaluation must consider model training in the context of the input data.

To investigate the progress towards fairness in HML, we analyze the state of fair HML research through the lens of Medical Information Mart for Intensive Care (MIMIC) [45, 46] database, one of the most popular CRD [87]; see Figure 1 for its popularity across the world. Our survey identified ICU mortality prediction as the most widely researched task in MIMIC III/IV. To analyze the ICU mortality task, we compared the performance and fairness properties (across ethnicity) of the SOTA: DuETT [1] [48] with simple baseline models (such as XGBoost) on MIMIC IV. Surprisingly, we find that the SOTA model is outperformed by XGBoost not only in performance but also in terms of its fairness properties, with disparate impact (DI) fairness metric revealing substantial inequalities across ethnic subgroups [2]. This demonstrates that despite more than half a decade since [11], it has been challenging to incorporate fairness in HML modeling, highlighting a need to reconsider it in the context of (i) the task and (ii) the data driving the model, and ways to make it a central part of any HML analysis.

The aforementioned example is not to undermine the work conducted by SOTA; it is to highlight the complexities involved in accomplishing HML fairness. For instance, MIMIC IV is a large database, which makes it especially challenging for practitioners to focus on modeling and fairness concurrently since they may only be interested in a small section of it. With recent calls in the community to develop 'Datasheets for Dataset', spearheaded by Gebru et al. [27], we develop a blueprint to enable the next generation of HML that is trustworthy and fair. Specifically, we introduce the 'Datasheet for CRD (MIMIC IV v2.0)', a comprehensive data-centric resource for practitioners tailored for complex CRDs. Here, we call for the data and tasks to take center stage in any HML modeling to accomplish fairness. To this end, our datasheet is designed to support practitioners in detecting data anomalies across the database and analyzing task-specific associations between features and the target, enabling equitable decisions in HML modeling.

[1] DuETT is considered SOTA in this study for its reported superior performance metrics with MIMIC IV for ICU Mortality task, comprehensive evaluation in comparison with a varied baseline for different tasks and its innovative technique. However, no fairness metrics were reported by the paper.

[2] Moreover, note that MIMIC IV originates from Boston, and its use world-wide further underscores a need to understand its characteristics for downstream applications.

For trustworthy HML modeling, model techniques and considerations play a crucial role in addition to the data. It is essential to know how a model was trained, the data it was exposed to, and its expected behavior in various scenarios [74]. This information is vital for identifying potential biases and understanding the model's limitations. Our 'Model card' provides detailed documentation of ML models, including their intended use, performance metrics, and evaluation results across different demographic groups. It facilitates informed decision-making by providing a comprehensive overview of a model's strengths and weaknesses, promoting transparency. It enables practitioners to assess whether a model is suitable for deployment in sensitive applications like healthcare, where the implications of biased or inaccurate predictions can be life-altering. We followed the 'Model Cards for Model Reporting' [74] framework to report on the analyzed HML models.

So, we advocate for the following three-step framework to build a trustworthy HML model. (i) a 'Datasheet for CRD' to identify inherent data bias and build a fairness-centric HML; (ii) a 'Model Card' detailing model characteristics and evaluating performance across demographic groups; and (iii) a 'Fairness Report' to thoroughly assess and address any biases related to sensitive attributes. This approach is especially significant in the light of recent works in fairness theory, which establish that it is not feasible to satisfy all fairness criteria at once [91]. There have also been calls to include end-users in determining key fairness goals [83]. Yet, the lack of fairness in the analysis (by SOTA) is alarming. Therefore, using our framework together promotes data transparency, model reliability, and fair outcomes irrespective of their sensitive attributes. It also enhances the trustworthiness of HML models by ensuring that all relevant factors have been considered and communicated effectively. Our contributions to this study are as follows,

1. **Comprehensive Review of HML Progress:** Systematic survey spanning over half a decade of HML models trained on MIMIC III/IV.
2. **Investigation of the challenges faced by fair HML** via an analysis of ICU Mortality prediction in MIMIC. Here, we rigorously compare the performance of the SOTA on this task with naive baselines to demonstrate that the current HML is struggling to incorporate fairness evaluation [3].
3. **Comprehensive 'Datasheet for CRD (MIMIC IV v2.0)':** To spark advances in fair HML and to aid practitioners, we present a comprehensive datasheet for MIMIC IV v2.0 CRD, highlighting data inconsistencies across the database and includes task-specific feature-target analysis to streamline fairness evaluations for equitable decision-making in HML models. The datasheet is made available at `https://anonymous.4open.science/r/DatasheetCRD-1F00/README.md`
4. **Model card for the HML models:** We provide comprehensive model cards for HML risk prediction models, which report on model details, performance metrics, train/val/test information, and its intended use.
5. **HML model fairness report:** We provide a detailed report on the fairness of the analyzed HML models concerning the highly correlated sensitive attribute to evaluate the model's performance across demographics.

## 2 Systematic Survey on MIMIC trained HML models

We conducted a six-year systematic survey from 2018 to 2024 to examine MIMIC-trained HML models to identify common prediction tasks, monitor progress, and assess the field's current state.

### 2.1 Survey Method

PubMed and Google Scholar databases were extensively searched because of their medical focus, broad coverage, and potential to uncover emerging trends beyond specialized databases. We adopted a broad search term (see Appendix A.1) approach following [28] to capture extensive research on MIMIC-trained HML models. Only 220 studies were included after the initial abstract and title screening, as shown in Table 3 in Appendix A.1.

Following PRISMA guideline [77], studies were screened to exclusively consider those utilizing MIMIC III/IV—the recent publicly available database versions—as the primary data source. A total

[3]We surprisingly find that naive baselines outperform the SOTA on this task.

of 140 papers from both databases, including recent research up until February 2024, were selected after analyzing the citation count, methodologies used, and clarity of the work. The selected scientific works span conferences like NeurIPS, IJCAI, ICML, ICLR, AAAI, ACM FAccT, and journals like Nature, JAMA, JAMIA, BMC, PLoS One, etc.

We meticulously adhered to the TRIPOD guidelines, as outlined by Moons et al. in [75]. This adherence was pivotal in guiding our data abstraction, evaluation, and synthesis methodology (see Appendix A.1), specifically identifying and addressing data bias. The TRIPOD guidelines provided a comprehensive framework that ensured our approach was systematic, methodical, and transparent, facilitating the development of robust, fair, and reliable HML risk prediction models.

### 2.2 Healthcare Risk Prediction Task

We grouped the selected research works based on the predicted task and observed that ICU mortality is the most extensively studied HML prediction task worldwide ( 70%). It is closely followed by ICU readmission and ICU length of stay (LOS). The comprehensive list of the HML prediction tasks is included in Appendix A.2. Our survey found that about 67% of HML models trained on the MIMIC CRD came from China [4], with significant contributions from the USA, Brazil, Pakistan, Australia, and India, as shown in Figure 1. These findings highlight that ICU mortality prediction is a key area within HML models, making it the main focus of the study.

## 3 Problem Formulation

Without losing generality, we only consider the ICU mortality prediction task, formulated as a binary classification task in this study. Let the binary label $y_i \in \{0, 1\}$ for the $i$-th patient; where $y_i = 1$ denotes mortality and $y_i = 0$ survival. We define the sparse irregular time series dataset $\mathcal{D} = \{(\mathbf{s}_i, \mathbf{X}_i, y_i)\}_{i=1}^{N}$ of $N$ observations.

For each patient $i$, $\mathbf{s}_i \in \mathbb{R}^S$ is a sensitive attribute vector like age, gender, insurance, etc. But, based on our analysis results in this study, ethnicity is used. $\mathbf{X}_i$ is the multivariate time-series data represented by $\mathbf{X}_i = \{(t_j, x_j, v_j)\}_{j=1}^{M}$ for $M$ observations. It is a tuple containing time $t_j$, event feature $x_j \in \mathcal{X}$ representing the physiological/clinical indicator, and its corresponding value $v_j \in \mathbb{R}$. So, in this study, the model $f(\cdot)$ is trained with the data $\mathcal{D}$ to predict $\widehat{y}$, given by

$$\widehat{y} = f(\mathcal{D}) \tag{1}$$

DuETT and STraTS are modeled to predict ICU Mortality using the data $\mathcal{D}$; however, for the time-series (TS) LSTM model, we use the same data, but the dataset is formatted as $\mathcal{D}^t = \{(\mathbf{X}_i^t, y_i)\}_{i=1}^{N}$ with the sensitive attribute being a part of the features $x_j$. In the case of non-time-series/static models, the mean values of the TS feature over the time $t_j$ are calculated to construct $\mathbf{X}_i^s = \{(x_j^s, v_j^s)\}_{j=1}^{M}$ of the dataset $\mathcal{D}^s = \{(\mathbf{X}_i^s, y_i)\}_{i=1}^{N}$.

Given these predictions, we then use the fairness metrics defined in section 3.2 to evaluate the models.

### 3.1 Healthcare ML Fairness Measurements

Fairness in HML ensures equitable model performance and decision-making across diverse patient groups, avoiding bias based on sensitive attributes like ethnicity, gender, or age [5].

As mentioned above, for each patient $i$, $\mathbf{s}_i \in \mathbb{R}^S$ is a sensitive attribute vector. We performed a comprehensive statistical analysis to identify the most closely associated sensitive attribute with the target variable. Chi-square analysis revealed a significant association between ethnicity and ICU mortality, identifying it $s_i^{eth}$ as the sensitive attribute. This informed our selection of fairness group metrics [25] to evaluate disparities across ethnic groups. In the subsequent sections, we omit patient index $i$ for notational simplicity.

[4] Over 90% of the research is focused on predicting mortality

[5] Fairness metrics are evaluated on any available sensitive attributes. However, unfairness might exist because of unrecorded sensitive attributes as well

The ethnic attribute $s^{eth}$ is categorized into five groups: Asian, Black, Hispanic/Latino, White, and Other. For fairness assessments, we compare pairs of these groups, and the function priv$(\cdot)$ assigns status for the sub-groups, $a$ for `'privileged'` and $b$ for `'protected'` based on the ethnic groups being compared. The ground truth is denoted by $y$, and the model $f(\cdot)$ prediction is $\widehat{y}$.

### 3.2 Fairness Metrics

Fairness metrics in machine learning serve as quantitative benchmarks to evaluate and ensure that algorithms perform equitably across all user groups, particularly when decisions impact individual's lives. Various fairness metrics exist, each with different implications for model assessment, and based on our analysis results, group fairness metrics are used in this study. It provides unbiased risk assessments across all demographic groups, preventing systematic over- or under-prediction for any group.

**Demographic Parity**, which advocates for equal opportunity allocation, stipulates that the probability of a favorable outcome should be independent of the sensitive attribute [21], i.e. the probability of a positive prediction should be equal across different ethnic groups.

$$\mathbb{P}(\widehat{y} = 1|\text{priv}(s^{eth}) = a)) = \mathbb{P}(\widehat{y} = 1|\text{priv}(s^{eth}) = b)) \tag{2}$$

**Equalized Odds**, a metric that promotes equal performance, requires equal decision rates for privileged and unprivileged groups and is defined as [10], i.e. the model's decision rates for predicting an outcome should be the same across different demographic groups, given the actual outcome.

$$\mathbb{P}(\widehat{y} = y|\text{priv}(s^{eth}) = a, y) = \mathbb{P}(\widehat{y} = y|\text{priv}(s^{eth}) = b, y), \quad \forall y \in \{0, 1\} \tag{3}$$

**Equal Opportunity** advocates equal true positive rates across different ethnic groups [122], aiming for fairness in model sensitivity.

$$\mathbb{P}(\widehat{y} = 1|\text{priv}(s^{eth}) = a, y = 1) = \mathbb{P}(\widehat{y} = 1|\text{priv}(s^{eth}) = b, y = 1) \tag{4}$$

**Disparate Impact**, a group metric that assesses the ratio of favorable outcomes for unprivileged to privileged groups. It evaluates the ratio of positive predictions from one ethnic group to another, with a value of 1 indicating perfect fairness.

$$\frac{\sum(\text{priv}(s^{eth}) = a, \widehat{y} = 1)/\sum(\text{priv}(s^{eth}) = a)}{\sum(\text{priv}(s^{eth}) = b, \widehat{y} = 1)/\sum(\text{priv}(s^{eth}) = b)} \tag{5}$$

In addition to evaluating their predictive accuracy, we assess the fairness of HML models to measure their trustworthiness. This assessment is crucial because these models are trained on the data sourced from CRD that may contain societal biases. Without fair data assessment, there's a risk that these models could unintentionally perpetuate existing biases.

## 4 Datasheet for Clinical Research Database

Understanding the inherent data and its inconsistencies during modeling is essential to achieve data-centric fairness. Practitioners may find it challenging to navigate the documentation while concentrating on modeling and fairness due to the breadth of the database [46], as they might only be interested in datasets relevant to their task. So, we present the 'Datasheet for CRD'[6] for MIMIC IV v2.0 as shown in Appendix A.4 Figure 5.

The datasheet for MIMIC IV v2.0 includes:

1. An expanded overview of the MIMIC IV database, adapted from the [27] template to cover all CRD intricacies.

[6]Our comprehensive 'Datasheet for MIMIC IV v2.0' can be accessed at `https://anonymous.4open.science/r/DatasheetCRD-1F00/`

2. A detailed composition section highlighting the CRDs unique structure and potential biases, incorporating MIMIC IV modules like 'Hosp', 'ICU', MIMIC IV-ED, MIMIC IV Notes, and MIMIC-CXR.
3. Custom queries tailored to the CRD, providing a deep understanding of data collection, composition, and task-specific usage, prefixed with '+' in the datasheet. For instance, *'Can/How the dataset be/are constructed from the MIMIC database?'* replaces general questions like *'What is the composition of the dataset?'*.
4. An analysis section offering insights into selecting sensitive attributes for HML prediction tasks (ICU Mortality, Length of Stay, Readmission) and appropriate fairness metrics.

More than just an inventory, this datasheet provides essential transparency, detailing the database structure, data collection methodologies, management practices, data inconsistencies, and key fairness considerations.

# 5 Utilizing Datasheet for Database in modeling - ICU Mortality prediction task

To explore the link between clinical data and fairness in healthcare predictions, we benchmarked static models like Logistic Regression (LR) and XGBoost, as well as time-series models like LSTM and STraTS, against the SOTA DuETT model for ICU mortality prediction.

## 5.1 MIMIC Database

The datasheet provides detailed information on the motivation, collection, composition, and usage of MIMIC CRD. Table 1 summarizes the general demographic characteristics for ICU Mortality of MIMIC IV. The sensitive attribute statistics and the complete feature lists (see Table 4) are provided in Appendix A.3.

Table 1: Breakdown of Sensitive Attributes in MIMIC IV v2.0 ICU Mortality dataset: Distribution of patient demographics across gender, age, ethnicity, language, and insurance type, highlighting the diversity and potential biases inherent in the database.

| Gender | | | Age | | | Ethnicity | | | Language | | | Insurance | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Patient** | **Count** | **%** | **Range** | **Count** | **%** | **Group** | **Count** | **%** | **Type** | **Count** | **%** | **Type** | **Count** | **%** |
| Female | 25671 | 44.3 | 0-17 | 0 | 0 | Asian | 1701 | 2.9 | **English** | **52077** | **89.8** | **Other** | **27262** | **47** |
| **Male** | **32328** | **55.7** | 18-29 | 6315 | 10.9 | Black | 6565 | 11.3 | ? | 5922 | 10.2 | Medicare | 26385 | 45.5 |
| | | | **30-49** | **13868** | **23.9** | Hispanic/Latino | 2228 | 3.8 | | | | Medicaid | 4352 | 7.5 |
| | | | 50-69 | 13702 | 23.6 | **White** | **39522** | **68.1** | | | | | | |
| | | | 70-89 | 11264 | 19.4 | Other | 7983 | 13.8 | | | | | | |
| | | | 90+ | 12859 | 22.2 | | | | | | | | | |

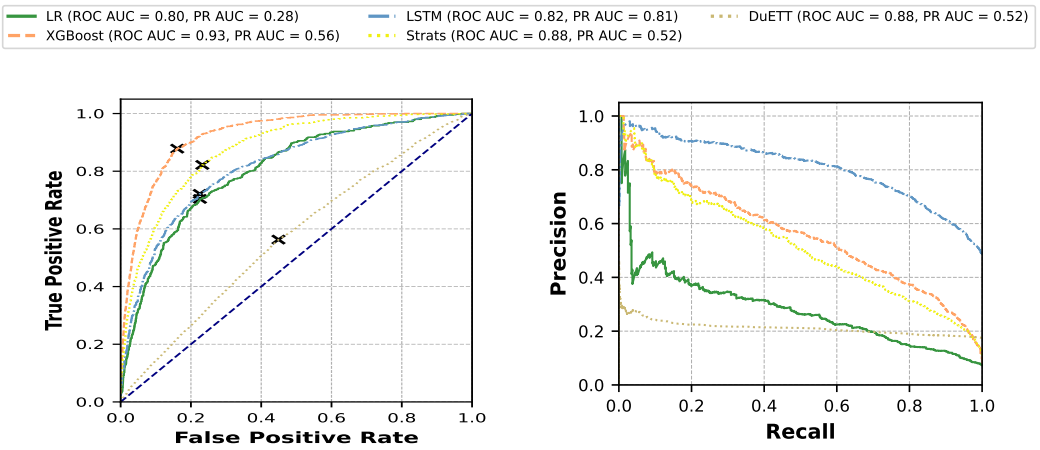
## 5.2 Experimental setup

To examine how fair the predictions of the SOTA model are, we conducted a series of experiments against several baselines on the MIMIC IV dataset. We adopted an 80:20 split for the training and test sets. The models were trained for up to 1000 epochs until the validation loss stopped improving for 10 continuous epochs, applying a 10-fold cross-validation for 3 Monte Carlo runs. The target of the model is to predict the probability of mortality ($\widehat{Y}$) following ICU admission of the patient. The experiments were conducted on NVIDIA GeForce RTX 2080 Ti GPU and the entire implementation code are available on this GitHub page.

## 5.3 Experimental Results

We highlight our results in Table 2, which reports the mean and standard deviation of the performance metric over 3 Monte Carlo runs. Our evaluation comprised static baselines like LR, XG Boost, and TS baselines like LSTM, STrats [102] with the SOTA DuETT [48] [7].

[7] Physionet 2012 Challenge code of the DuETT is only made online. We used the DuETT architecture provided in [48] and replicated it for the ICU Mortality task for evaluation




(a) ROC Curve

(b) PR Curve

Figure 2: Prediction performance analysis across models. Panels (a) and (b) show the ROC-AUC and PR-AUC of the models, respectively, and the operating points in (a).

### 5.3.1 Model Performance Evaluation

We used the Receiver Operating Characteristic Area Under the Curve (ROC-AUC) and Precision-Recall Area Under the Curve (PR-AUC) metrics to compare model performance comprehensively. These comparisons, derived from 3 Monte Carlo simulations to ensure statistical robustness, are visually represented in Figure 2. Surprisingly, the XG Boost model demonstrated a significant performance uplift, outperforming STrats by 6.44% and SOTA by 59.6% in ROC-AUC, as detailed in Table 2.

Table 2: Comparative Analysis of ICU Mortality Prediction: Predictive performance of models trained on MIMIC IV v2.0, contrasting static and time-series models as reflected by the ROC-AUC and PR-AUC curves for 3 Monte Carlo runs.

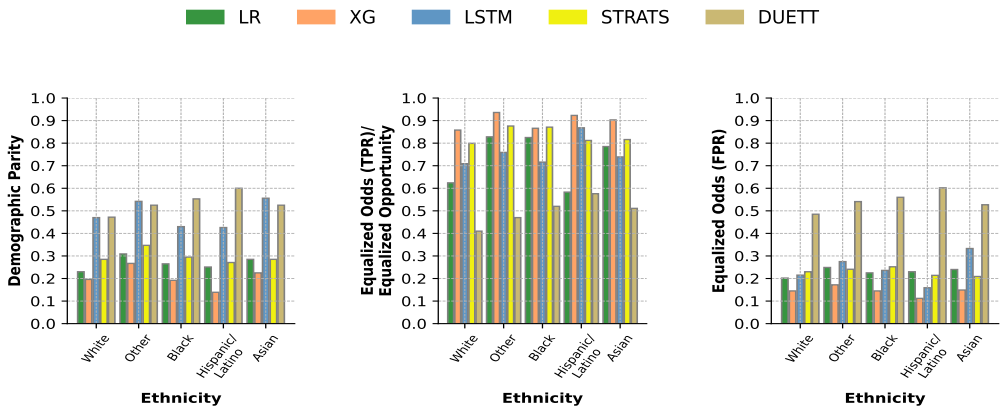
| **Type** | **Model** | **ROC-AUC** | **PR-AUC** |
|---|---|---|---|
| Static | LR | 0.805±0.012 | 0.276±0.005 |
| | **XG Boost** | **0.926±0.006** | 0.551±0.007 |
| Time series | **LSTM** | 0.886±0.003 | **0.807±0.011** |
| | STraTS | 0.870±0.002 | 0.520±0.006 |
| | **DuETT (SOTA)** | **0.580±0.028** | **0.220±0.005** |

**Model Card:** A model card detailing the model specifications, training/testing process, data usage, its expected behavior in various scenarios, and its intended use in addition to the above performance results will add another layer of transparency most needed in building trustworthy HML models. This information can help ML practitioners identify potential algorithmic bias quickly and understand model limitations. Detailed model cards for all the analyzed HML models are available here.

### 5.3.2 Model Fairness Assessment

To evaluate the ethical aspects, we assessed each model using established fairness metrics to identify the biases and disparities across ethnic groups. The results, summarized in the Appendix A.5 Table 5, revealed notable variations in the HML model's fairness. Figures 3(b) and 3(c) show how XG Boost consistently surpassed the SOTA model in both Equalized Opportunity (EOp) and Equalized Odds (EO) metrics, highlighting its superior fairness profile. Additionally, Figure 4 illustrates Demographic Parity (DP) disparities across ethnic categories, notably where the SOTA model still manifests considerable bias despite achieving higher DP scores than XG Boost.

**Fairness Report:** In addition to the 'Datasheet for database' and the 'Model card', the 'Fairness report' is also imperative for building a trustworthy HML model. It will list all information related to




(a) Demographic Parity (b) Equalized Opportunity (c) Equalized Odds

Figure 3: Analysis of fairness metrics for each model across ethnic subgroups. Panels (a), (b), and (c) show the comparative analysis for demographic parity (DP), equalized odds for TPR (also known as EOp), and FPR, respectively. Inconsistency drawn from these metrics reveals the extent of fairness exhibited by each model, highlighting the interplay between algorithmic performance and demographic impact.

(a) LR (b) XG Boost (c) LSTM

(d) STraTS (e) DuETT (SOTA)

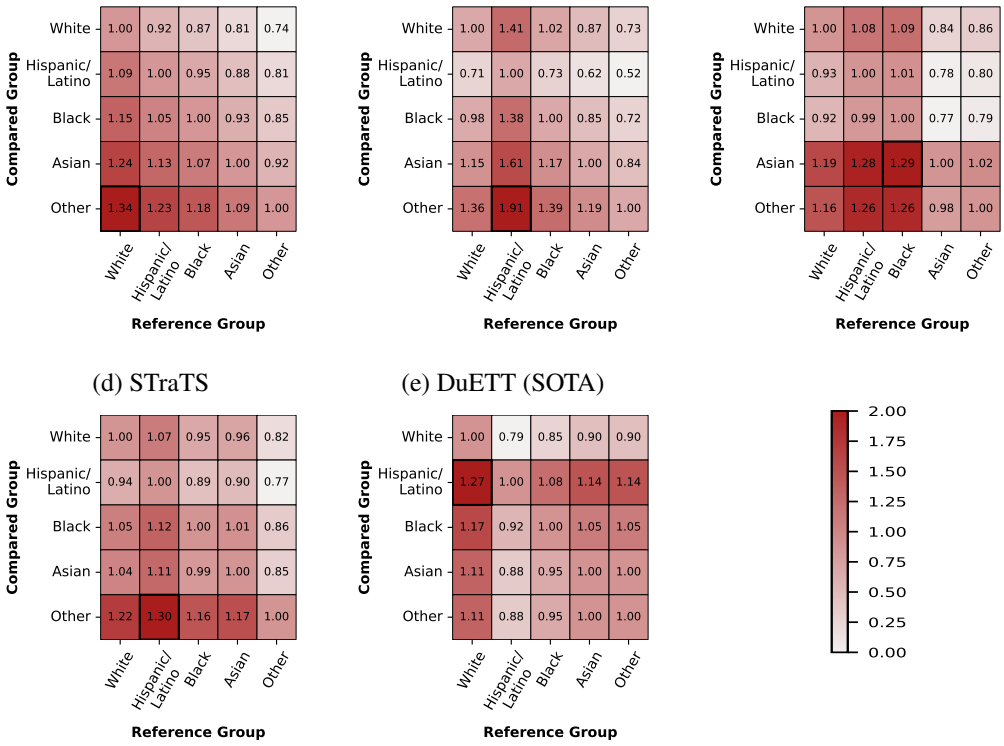



Figure 4: Heatmaps illustrating disparate model impact across ethnic subgroup groups. Red < 1.0 indicates the disparity of the model against the compared group, Red > 1.0 reflects the model's disparity against the reference group and the value of 1.0 shows parity against the comparison. Highlighted cells represent the most disparate subgroup comparison.

HML fairness, evaluation metrics, fairness performance, bias mitigation steps, and recommendations. A detailed fairness report is provided in Supplementary Section C.

## 6 Discussions, Limitations, and Future Work

Trustworthy healthcare machine learning models are essential for ensuring accurate, transparent, and unbiased predictions, improving patient outcomes, and fostering confidence among healthcare providers and patients. Our findings highlight the complex challenges of embedding fairness into HML models, emphasizing the need to address data quality, usage practices, and inherent biases in CRD data. The observed discrepancies in fairness metrics [8] across models, underscoring our framework's necessity, including a 'Datasheet for Database', 'Model Card', and 'Fairness Report'. This approach enhances model accuracy and ensures equitable treatment from HML systems.

**Synthetic Data Generation Enhanced by Datasheets:**

As we advance toward synthetic data generation, the Datasheet for CRD is crucial. It is imperative to recognize that synthetic data, derived solely from CRDs like MIMIC, do not fully capture the global patient population as addressed in Section 1. Combining synthetic datasets with real patient data from diverse locations ensures global representation. By using the datasheet to identify and address data gaps in addition to it, we facilitate the creation of enriched synthetic datasets that better mirror the global patient population.

**Limitations and Future Work:** This study focuses mainly on HML model fairness concerning sensitive attributes, especially ethnicity. Yes, it is necessary to evaluate the fairness of the model based on the sensitive attributes to analyze the bias, but it does not fully explore other correlated variables, such as socio-economic status, access to healthcare, pre-existing health conditions, and treatment quality, which also impact the model's prediction outcome. Our future work will include obtaining and analyzing these details from other CRDs such as eICU [80] and HiRID [40] [9] and develop a datasheet for those to offer a more comprehensive understanding of the factors influencing model fairness. All information provided in this study and the 'Datasheet for database' adhere to the strict policies of handling medical data, safeguarding patient privacy, and maintaining research integrity. We strongly discourage any misuse of the provided datasheet or survey/analysis results, including but not limited to developing algorithms/models with negative societal impacts.

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## Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] See Section 5.
   (b) Did you describe the limitations of your work? [Yes] See Section 6.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Section 6.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you ran experiments (e.g. for benchmarks)...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] See Section 5.2
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 5.2.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] See Section 5.3.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Section 5.2.
3. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] See Section 5.3.
   (b) Did you mention the license of the assets? [Yes] Listed in detail in our "Datasheet for database'.
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] 'Model card' and 'Fairness report' for HML risk prediction models.
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes] Obtained access from Physionet owners to work on this study.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] We worked with already publicly available data.

# A Appendix

## A.1 Systematic survey

PubMed is searched using *('Medical information mart for intensive care AND MIMIC AND MIMIC-IV') AND ('machine learning' OR 'artificial intelligence' OR 'deep learning' OR 'neural network' OR 'prediction model')* search terms yielding 819 works whereas, Google Scholar yielded 1000 records with the search term *'machine learning'|'prediction model'|'artificial intelligence'|'deep learning' AND 'MIMIC IV'|'the medical information mart for intensive care'|'MIMIC III'*.

We abstracted information on:

Table 3: Inclusion and Exclusion Criteria of MIMIC trained Healthcare ML Studies.

| Criterion | Included | Excluded |
|---|---|---|
| Study Design | Study that develops a prediction model | Review articles, database innovation studies, medical data mining studies, etc |
| MIMIC | III/IV | Other older versions |
| Outcome | Mortality, Readmission, LOS, Phenotype labeling/ICD code grouping | Other outcomes |
| Performance | AUC, sensitivity, specificity, accuracy, etc | No reported performance |

1. The CRD recorded demographic variables like Age, Gender, Ethnicity, Insurance, Marital status and Language,
2. Consideration of demographic variables in the dataset and its selection/rejection criterion based on feature engineering and
3. Algorithm used for the model and its final prediction outcome.

### A.2 HML Risk prediction tasks

1. **Mortality Prediction** [1–4, 8, 9, 14, 17, 18, 23, 24, 26, 31–34, 36, 38, 39, 41–44, 47, 50, 53–56, 58, 59, 61, 63–67, 70, 76, 78, 79, 81, 82, 88–90, 94–96, 98–100, 104, 106, 109–114, 117–120, 123, 124, 126–131, 133] - Predict the likelihood of a patient dying.
   (a) In-hospital and ICU [22, 117] - Estimating the risk of a patient dying during their hospital stay and in ICU.
   (b) Short-term [68, 124] - Assessing the risk of death shortly after ICU admission, typically within 2-3 days.
   (c) *Long-term* [1, 57] - Evaluating the likelihood of death over a longer period, typically from 30 days up to a year after hospital discharge.
2. **Length of Stay (LOS)** [15, 19, 29, 30, 61, 93, 95, 95, 105, 107, 108, 115]
   (a) Predicting the duration of hospital stays for admissions, focusing on stays longer than 3 and 7 days. A custom number of days is also a topic of research interest.
3. **Readmission** [13, 101]
   (a) Identifying patients at risk of returning to the hospital within 30, 60, 90, 120 days, or custom time frames after discharge.
4. **Phenotype Labeling and ICD-9/10 Code Grouping**
   (a) *Phenotype Labeling* [116, 125] - Classifying patients into specific groups based on clinical data for disease prediction and treatment customization.
   (b) *ICD Code Grouping* [37, 51] - Categorizing diseases based on diagnosis codes to streamline classification.
5. **Specific Health Conditions**
   (a) *Heart failure* [2, 53] - Predicting the occurrence, progression, and prognosis of heart failure in patients, using historical and real-time health data.
   (b) *Chronic Kidney Disease (CKD)* [97, 121] - Assessing the risk and progression of CKD to inform treatment plans and manage patient health outcomes.
   (c) *Chronic obstructive pulmonary disease (COPD)* [62] - Forecasting COPD exacerbations and identifying patients at higher risk for hospitalization or severe outcomes.
   (d) *Coronary artery disease (CAD)* [117, 119] - Utilizing clinical data to predict the development or worsening of CAD for early intervention.
   (e) *Sepsis* [5, 121] - Early detection and prediction of sepsis in hospitalized patients to improve treatment response and survival rates.
   (f) *Cancer* [69] - Leveraging patient data to predict cancer risks, progression, and treatment responses.
   (g) *Ventilation failure* [92] - Predicting the risk of ventilation failure in critically ill patients to guide intervention strategies.

### A.3 Sensitive attribute statistics of MIMIC IV ICU Mortality data

**Sensitive attribute statistics of MIMIC IV ICU Mortality data**: We followed the work of Meng et al. [72] and grouped Ethnic demography into 5 categories based on the geographic origin. Data contains 68% of the White population followed by the Other (13.8%) subgroup. Age is categorized into 6 buckets 1 following the work of Röösli et al. [87]. 24% are of 30 to 49 and 50 to 69 age bins followed by 70 to 80 (23.6%). Children below 17 are not part of this CRD. Gender-wise, only Males and Females are recorded, while 56% of the patients are Males. Medicaid, Medicare, and Other were the 3 types of Insurance listed, with English being the only language recorded, whereas others are left as '?'.

All the TS features and the above-mentioned static variables are listed below. There are inconsistencies like in-hospital expiry information and hospital admit and discharge timestamps, detailed in the datasheet. The admission table contains multiple reports of the same patient's death, leading to inconsistencies. However, the owners of MIMIC have mentioned the potential for bias within the CRD.

Table 4: Time series and Static features of MIMIC IV used to train all the analyzed models for ICU mortality task

| **Variable** | **Type** |
|---|---|
| minute | Time series |
| ALP | Time series |
| ALT | Time series |
| AST | Time series |
| Albumin | Time series |
| Albumin 25% | Time series |
| Albumin 5% | Time series |
| Amiodarone | Time series |
| Anion Gap | Time series |
| BUN | Time series |
| Base Excess | Time series |
| Basophils | Time series |
| Bicarbonate | Time series |
| Bilirubin (Direct) | Time series |
| Bilirubin (Indirect) | Time series |
| Bilirubin (Total) | Time series |
| CRR | Time series |
| Calcium Free | Time series |
| Calcium Gluconate | Time series |
| Calcium Total | Time series |
| Cefazolin | Time series |
| Chest Tube | Time series |
| Chloride | Time series |
| Colloid | Time series |
| Creatinine Blood | Time series |
| Creatinine Urine | Time series |
| D5W | Time series |
| DBP | Time series |
| Dextrose Other | Time series |
| Dopamine | Time series |
| EBL | Time series |
| Emesis | Time series |
| Eoisinophils | Time series |
| Epinephrine | Time series |
| Famotidine | Time series |
| Fentanyl | Time series |
| FiO2 | Time series |
| Fiber | Time series |

| Variable | Type |
|---|---|
| Free Water | Time series |
| Fresh Frozen Plasma | Time series |
| Furosemide | Time series |
| GCS_eye | Time series |
| GCS_motor | Time series |
| GCS_verbal | Time series |
| GT Flush | Time series |
| Gastric | Time series |
| Gastric Meds | Time series |
| Glucose (Blood) | Time series |
| Glucose (Serum) | Time series |
| Glucose (Whole Blood) | Time series |
| HR | Time series |
| Half Normal Saline | Time series |
| Hct | Time series |
| Height | Time series |
| Heparin | Time series |
| Hgb | Time series |
| Hydralazine | Time series |
| Hydromorphone | Time series |
| INR | Time series |
| Insulin Humalog | Time series |
| Insulin NPH | Time series |
| Insulin Regular | Time series |
| Insulin largine | Time series |
| Jackson-Pratt | Time series |
| KCl | Time series |
| KCl (Bolus) | Time series |
| LDH | Time series |
| Lactate | Time series |
| Lactated Ringers | Time series |
| Lorazepam | Time series |
| Lymphocytes | Time series |
| Lymphocytes (Absolute) | Time series |
| MBP | Time series |
| MCH | Time series |
| MCHC | Time series |
| MCV | Time series |
| Magnesium | Time series |
| Magnesium Sulfate (Bolus) | Time series |
| Magnesium Sulphate | Time series |
| Metoprolol | Time series |
| Midazolam | Time series |
| Milrinone | Time series |
| Monocytes | Time series |
| Morphine Sulfate | Time series |
| Neosynephrine | Time series |
| Neutrophils | Time series |
| Nitroglycerine | Time series |
| Nitroprusside | Time series |
| Norepinephrine | Time series |
| Normal Saline | Time series |
| O2 Saturation | Time series |

| Variable | Type |
|---|---|
| OR/PACU | Time series |
| Crystalloid | |
| PCO2 | Time series |
| PO intake | Time series |
| PO2 | Time series |
| PT | Time series |
| PTT | Time series |
| Packed RBC | Time series |
| Pantoprazole | Time series |
| Phosphate | Time series |
| Piggyback | Time series |
| Piperacillin | Time series |
| Platelet Count | Time series |
| Potassium | Time series |
| Pre-admission Intake | Time series |
| Pre-admission | Time series |
| Output | |
| Propofol | Time series |
| RBC | Time series |
| RDW | Time series |
| RR | Time series |
| Residual | Time series |
| SBP | Time series |
| SG Urine | Time series |
| Sodium | Time series |
| Solution | Time series |
| Sterile Water | Time series |
| Stool | Time series |
| TPN | Time series |
| Temperature | Time series |
| Total CO2 | Time series |
| Urine | Time series |
| Vacomycin | Time series |
| Vasopressin | Time series |
| WBC | Time series |
| Weight | Time series |
| pH Blood | Time series |
| pH Urine | Time series |
| first_careunit | Static |
| gender | Static |
| anchor_age | Static |
| insurance | Static |
| language | Static |
| marital_status | Static |
| ethnicity | Static |

### A.4 Datasheet for Database

### A.5 Fairness metrics Results for HML models

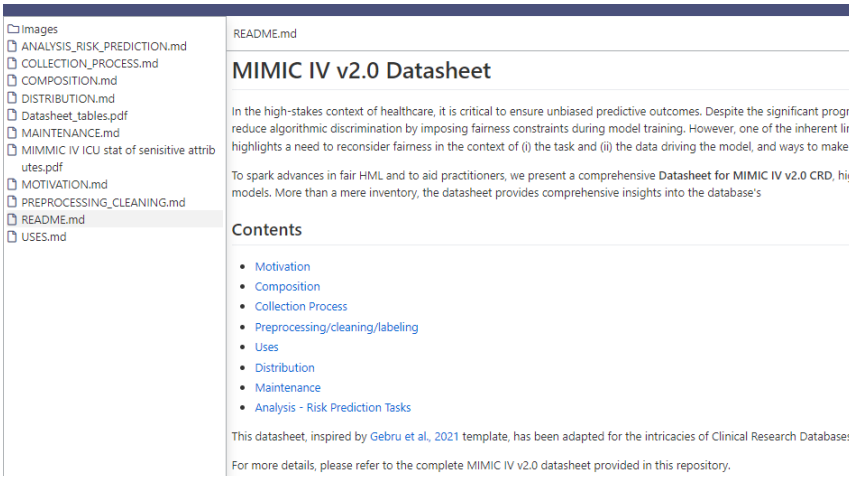


Figure 5: Snapshot of our comprehensive datasheet webpage, tailored for the MIMIC IV v2.0 database.

Table 5: Evaluation of Fairness Metrics (Demographic Parity (DP), Equalized Odds for True Positive Rate (TPR)/Equalized Opportunity (EOp), and Equalized Odds for False Positive Rate (FPR)) Across Model Types: This table presents a comparative analysis of fairness metrics for different models, stratified by ethnic groups.

| **Type** | **Models** | **Ethnicity** | **DP** $\leftrightarrow$ | **EO(TPR)/ EOp** $\uparrow \leftrightarrow$ | **EO(FPR)** $\downarrow \leftrightarrow$ |
|---|---|---|---|---|---|
| Static | Logistic Regression | White | 0.230 | 0.624 | 0.202 |
| | | Other | 0.309 | 0.828 | 0.249 |
| | | Black | 0.265 | 0.825 | 0.225 |
| | | Hispanic/Latino | 0.251 | 0.583 | 0.230 |
| | | Asian | 0.285 | 0.785 | 0.240 |
| | **XG Boost** | White | 0.196 | 0.858 | 0.145 |
| | | **Other** | **0.267** | **0.936** | **0.171** |
| | | Black | 0.192 | 0.866 | 0.145 |
| | | Hispanic/Latino | 0.139 | 0.923 | 0.112 |
| | | Asian | 0.225 | 0.903 | 0.149 |
| Time Series | LSTM | White | 0.460 | 0.709 | 0.215 |
| | | Other | 0.534 | 0.759 | 0.275 |
| | | Black | 0.421 | 0.716 | 0.236 |
| | | Hispanic/Latino | 0.426 | 0.868 | 0.159 |
| | | Asian | 0.545 | 0.739 | 0.333 |
| | STraTS | White | 0.289 | 0.799 | 0.230 |
| | | Other | 0.352 | 0.876 | 0.241 |
| | | Black | 0.304 | 0.871 | 0.252 |
| | | Hispanic/Latino | 0.271 | 0.812 | 0.214 |
| | | Asian | 0.299 | 0.816 | 0.209 |
| | **DuETT (SOTA)** | White | 0.473 | 0.410 | 0.485 |
| | | Other | 0.525 | 0.470 | 0.541 |
| | | Black | 0.553 | 0.520 | 0.560 |
| | | **Hispanic/Latino** | **0.600** | **0.580** | **0.603** |
| | | Asian | 0.525 | 0.511 | 0.527 |