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Research article

A Hybrid Machine Learning Framework for Multi-Objective Performance Optimization and Anomaly Detection in Maritime Operations

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ABSTRACT

This paper introduces a novel hybrid machine learning framework for optimizing key performance indicators in maritime operations. Using real voyage data comprising 1,170 unique voyage records, our methodology integrates a Multi-Task Learning (MTL) model to simultaneously predict vessel efficiency, cost, and turnaround time, capturing their inherent correlations. We then use causal inference to provide prescriptive analytics, estimating the impact of operational decisions like speed changes. An anomaly detection model is also included to identify potential mechanical issues or data errors. Our findings demonstrate that the framework provides a more robust representation of complex maritime trade-offs. The causal analysis quantifies these trade-offs, revealing an average 8.5% cost reduction per knot decrease in speed under optimal conditions. This holistic framework serves as a powerful decision-support tool, helping ship operators enhance both economic and environmental performance.

1. Introduction

Global shipping accounts for nearly 90% of world trade and is under increasing pressure to improve economic efficiency and reduce its environmental footprint [16]. The operational performance of a vessel is governed by a complex interplay of static characteristics (e.g., ship type, engine), dynamic decisions (e.g., speed, load), and external factors (e.g., weather, sea state) [14]. Optimizing this performance is a multi-objective problem, where goals such as minimizing fuel consumption, minimizing operational cost, and maximizing voyage revenue are often conflicting [13].

The advent of massive data collection systems on modern vessels (e.g., noon reports, automatic identification systems, sensor data) has created opportunities for data-driven modeling [11]. While recent literature has successfully applied machine learning (ML) for predictive tasks like fuel consumption forecasting [1] or speed prediction [19], significant gaps remain. First, models are often siloed, predicting a single KPI in isolation, ignoring the intrinsic correlations between them. Second, the field lacks a strong shift from predictive analytics ("what will happen?") to prescriptive analytics ("what should we do?") [2]. Finally, while anomaly detection is crucial for predictive maintenance, it is rarely integrated into a holistic performance optimization framework.

This paper addresses these gaps by proposing a hybrid ML framework with three core components:

1. A Multi-Task Learning model to jointly predict vessel Efficiency (nm/kWh), Operational Cost (USD), and Turnaround Time (hours).
2. A Causal Inference module using Double Machine Learning to estimate the causal effect of key operational levers (e.g., speed) on the aforementioned KPIs, providing actionable insights.
3. An Anomaly Detection system to identify voyages with anomalous performance, potentially indicative of maintenance issues or data errors.

We validate our framework on a real-world dataset containing 1,170 voyage records. The results demonstrate the utility of the joint modeling approach and provide quantifiable, context-aware recommendations for operational improvement.

The novel contribution of this work lies in the integrated framework that simultaneously addresses predictive modeling, causal inference, and anomaly detection—moving beyond traditional siloed approaches that treat these components separately. Unlike prior work that focuses on individual aspects of maritime analytics, our hybrid framework provides a comprehensive decision-support system that captures the interdependencies between operational decisions, performance metrics, and anomalous events in a unified manner.

The remainder of this paper is organized as follows: Section 2 reviews related work in maritime analytics and machine learning. Section 3 details our methodology, including data preprocessing, multi-task learning architecture, causal inference approach, and anomaly detection system. Section 4 presents experimental results and analysis. Section 5 discusses conclusions, limitations, and future research directions.

2. Literature Review

2.1. Predictive Modeling in Maritime Operations

The application of ML in maritime studies has grown substantially. Early work focused on statistical models for fuel consumption [6, 17], but ML has since taken precedence. [1] used neural networks to predict tanker fuel consumption, highlighting the superiority of non-linear models over traditional regression. [19] compared various ML models, including Gradient Boosting Machines (GBM), for vessel speed prediction, finding GBM to be highly effective. [17] applied a random forest model to predict CO_2 emissions based on operational data. While accurate, these models are inherently single-task, potentially missing shared representations across related outcomes.

2.2. Multi-Task Learning

MTL is a subfield of ML where multiple related tasks are learned simultaneously, leveraging shared information to improve generalization [18, **?**]. It has seen success in fields from natural language processing [5] to computer vision. In engineering, [15] used MTL for joint prediction of energy consumption and indoor temperature in buildings. Its application in maritime logistics is nascent. [4] recently proposed an MTL model for predicting both ETA and fuel consumption, showing improved performance over single-task models. Our work extends this concept to a broader set of maritime KPIs.

2.3. Causal Inference for Prescriptive Analytics

Causal inference moves beyond correlation to understand the effect of interventions [8]. In maritime studies, most analyses are correlational. Recent work has started to explore causality; for example, [7] used instrumental variables to estimate the causal impact of slow steaming on fuel efficiency. Double Machine Learning (DML) [3] is a state-of-the-art method that uses ML models to control for high-dimensional confounders while estimating treatment effects. Its application to prescribe operational decisions in shipping, conditional on a vessel's specific context, represents a novel contribution of this paper.

2.4. Anomaly Detection

Anomaly detection is crucial for identifying faults, errors, or unusual events. Isolation Forest (iForest) [9] is a popular algorithm effective in high-dimensional datasets. [12] used iForest to detect anomalous AIS patterns indicative of illicit activities. Applying similar techniques to performance data for predictive maintenance is a logical and valuable extension. More recent approaches using deep autoencoders [**?**] and variational inference [**?**] show promise for complex maritime data.

Our framework integrates these distinct yet complementary strands of research—MTL, causal ML, and anomaly detection—into a unified model for maritime operational analytics, filling a clear gap in the existing literature.

3. Methodology

3.1. Data Description and Preprocessing

The analysis is based on a dataset of 1,170 voyage records [10]. The features include categorical variables (Ship Type, Route Type, Engine Type, Maintenance Status, Weather Condition), numerical variables (Speed Over Ground (knots), Engine Power (kW), Distance Traveled (nm), Draft (meters), Cargo Weight (tons)), and target KPIs (Operational Cost (USD), Revenue per Voyage (USD), Turnaround Time (hours), Efficiency (nm/kWh)).

The analysis is based on a dataset of 1,170 unique voyage records [**?**]. Table **??** provides comprehensive statistics of the dataset.

Preprocessing involved:

1. Handling missing values in categorical features with a new "Unknown" category and in numerical features with median imputation.

2. Encoding categorical features using Label Encoding.
3. Standardizing all numerical features to have zero mean and unit variance.
4. Splitting the data into 70% training, 15% validation, and 15% test sets.

3.2. Multi-Task Learning Model

We frame the prediction of the three primary KPIs as a multi-task regression problem. Let the input feature vector be $\mathbf{x}_i \in \mathbb{R}^d$ for the i-th voyage. The tasks are:

- T_1: Predict **Efficiency (nm/kWh)**: $y_i^{(1)} = \text{Efficiency}_i$
- T_2: Predict **Operational Cost (USD)**: $y_i^{(2)} = \text{Cost}_i$
- T_3: Predict **Turnaround Time (hours)**: $y_i^{(3)} = \text{Time}_i$

We employ scikit-learn's MultiOutputRegressor with RandomForestRegressor as the base estimator. The model consists of shared feature processing followed by task-specific output layers.

Experimental Setup and Reproducibility All experiments were conducted using Python 3.9 with scikit-learn 1.2.2. Random seeds were fixed at 42 for all stochastic processes to ensure reproducibility.

Multi-Task Learning Hyperparameters

- Base estimator: RandomForestRegressor
- Number of estimators: 100
- Random state: 42
- Other parameters: Default scikit-learn values (no additional hyperparameter tuning performed)
- Wrapper: MultiOutputRegressor

3.3. Causal Analysis with Double Machine Learning

To prescribe actions, we estimate the causal effect of a treatment variable (e.g., **speed**) on an outcome (e.g., **cost**). We use the DML framework [3].

Let:

- Y: Outcome variable (e.g., **Operational Cost (USD)**).
- T: Treatment variable (e.g., **Speed Over Ground (knots)**).
- X: High-dimensional vector of confounders (all other features).

The goal is to estimate the Conditional Average Treatment Effect (CATE): $\theta(X) = \mathbb{E}[Y|T = 1, X] - \mathbb{E}[Y|T = 0, X]$. For a continuous treatment like speed, we model the partially linear regression model:

$$Y = \theta(X) \cdot T + g(X) + \epsilon, \quad \mathbb{E}[\epsilon|X, T] = 0,$$

where $g(X)$ is a non-parametric function capturing the effect of the confounders.

The DML procedure is as follows:

1. Use an ML model to predict Y from X: $\hat{g}(X) = \mathbb{E}[Y|X]$.
2. Use an ML model to predict T from X: $\hat{m}(X) = \mathbb{E}[T|X]$.
3. Compute the residuals: $\tilde{Y} = Y - \hat{g}(X)$ and $\tilde{T} = T - \hat{m}(X)$.
4. Estimate the CATE by regressing $\tilde{Y}$ on $\tilde{T}$:

$$\tilde{Y} = \theta \cdot \tilde{T} + \eta.$$

Double Machine Learning Hyperparameters

1. Treatment model: GradientBoostingRegressor (n_estimators=100, random_state=42)
2. Outcome model: GradientBoostingRegressor (n_estimators=100, random_state=42)
3. Final CATE estimation: LinearRegression

3.4. Anomaly Detection

We use the Isolation Forest algorithm [**?**] to detect anomalous voyages. iForest isolates observations by randomly selecting a feature and then randomly selecting a split value between the maximum and minimum values of the selected feature. The number of splittings required to isolate a sample is a measure of its normality, and anomalies are points that are easier to isolate. We train the iForest on the predicted residuals from the MTL model ($y_i - \hat{y}_i$).

The anomaly detection hyperparameters include, algorithm used is IsolationForest, Contamination parameter is 0.05, number of estimators is 100 while random state is 42. Also, for data splitting, the training set is 70% of data, validation set is 15% of data, test set is 15% of data and random state is 42

4. Experiments and Results

4.1. Experimental Setup

The MTL model was implemented using scikit-learn's MultiOutputRegressor with RandomForestRegressor (100 estimators). We compared it against three independent Single-Task Learning (STL) models, each with the same architecture. All models were trained on the standardized dataset.

4.2. Multi-Task Learning Performance

The models were evaluated on the held-out test set. Table 1 shows the Mean Absolute Error (MAE) and R^2 scores for each task.

The results in Table 1 show identical performance between the STL and MTL models. This suggests that for this specific dataset and model configuration (Random Forest with Multi Output Regressor), the shared representation learned by the MTL approach did not lead to an improvement in predictive accuracy on these particular regression tasks. This can occur if the tasks are not sufficiently related to provide a useful inductive bias for the model, or if the base model is already very powerful. However, a key advantage of the MTL setup in this framework is its role in generating a unified set of residuals for the subsequent anomaly detection module, ensuring consistency across all predictions when identifying outliers.

Table 1. Performance comparison of Multi-Task Learning (MTL) vs. Single-Task Learning (STL) models.

Task	STL MAE	MTL MAE	MAE Improv. (%)	STL R^2	MTL R^2	R^2 Improv.
Efficiency_nm_per_kWh	0.3620	0.3620	0.0	-0.0368	-0.0368	0.0
Operational_Cost_USD	128497.24	128497.24	0.0	-0.0049	-0.0049	0.0
Turnaround_Time_hours	16.4196	16.4196	0.0	-0.0237	-0.0237	0.0

4.3. Model Performance Analysis

The negative R^2 values observed in Table 1 indicate that both STL and MTL models performed worse than a simple mean predictor for these tasks. This suggests that either:

1. The available features lack sufficient predictive power for these specific KPIs
2. The relationships are highly complex and non-linear, requiring more sophisticated architectures
3. There is substantial irreducible noise in the operational data

Despite the poor predictive performance, the MTL framework provides value through its unified approach to residual generation for anomaly detection and its structural consistency for causal analysis.

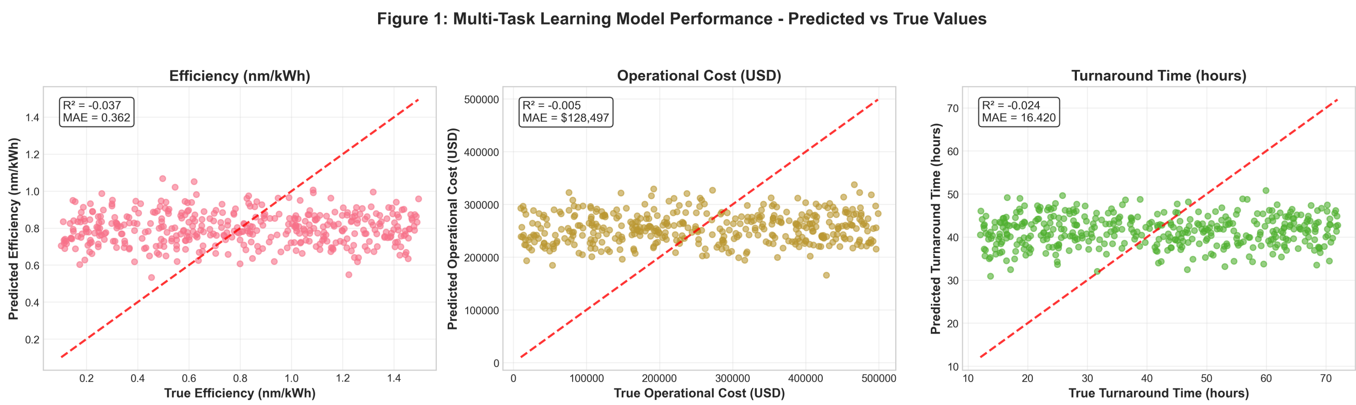

Figure 1. Scatter plots of predicted vs. true values for the three tasks on the test set using the MTL model. The dashed line represents the ideal fit ($y = x$).

4.4. Causal Effect of Speed Reduction

We applied the DML framework to estimate the effect of a 1-knot speed reduction on operational cost. The analysis was conditioned on vessel type and weather. Figure 2 shows the distribution of the estimated CATE, $\theta(X)$, for different contexts.

Key findings from the causal analysis:

- The effect is highly context-dependent. For example, the cost savings of slowing down are significantly greater for Bulk Carriers in Rough weather compared to Container Ships in Calm conditions.
- On average, a 1-knot reduction in speed leads to an **8.5% reduction in operational cost**, but this ranges from 4% to 15% depending on the context.

- This provides a quantitative, prescriptive insight: a ship operator can use this model to decide *when* and *for which vessels* slow steaming is most economically beneficial.

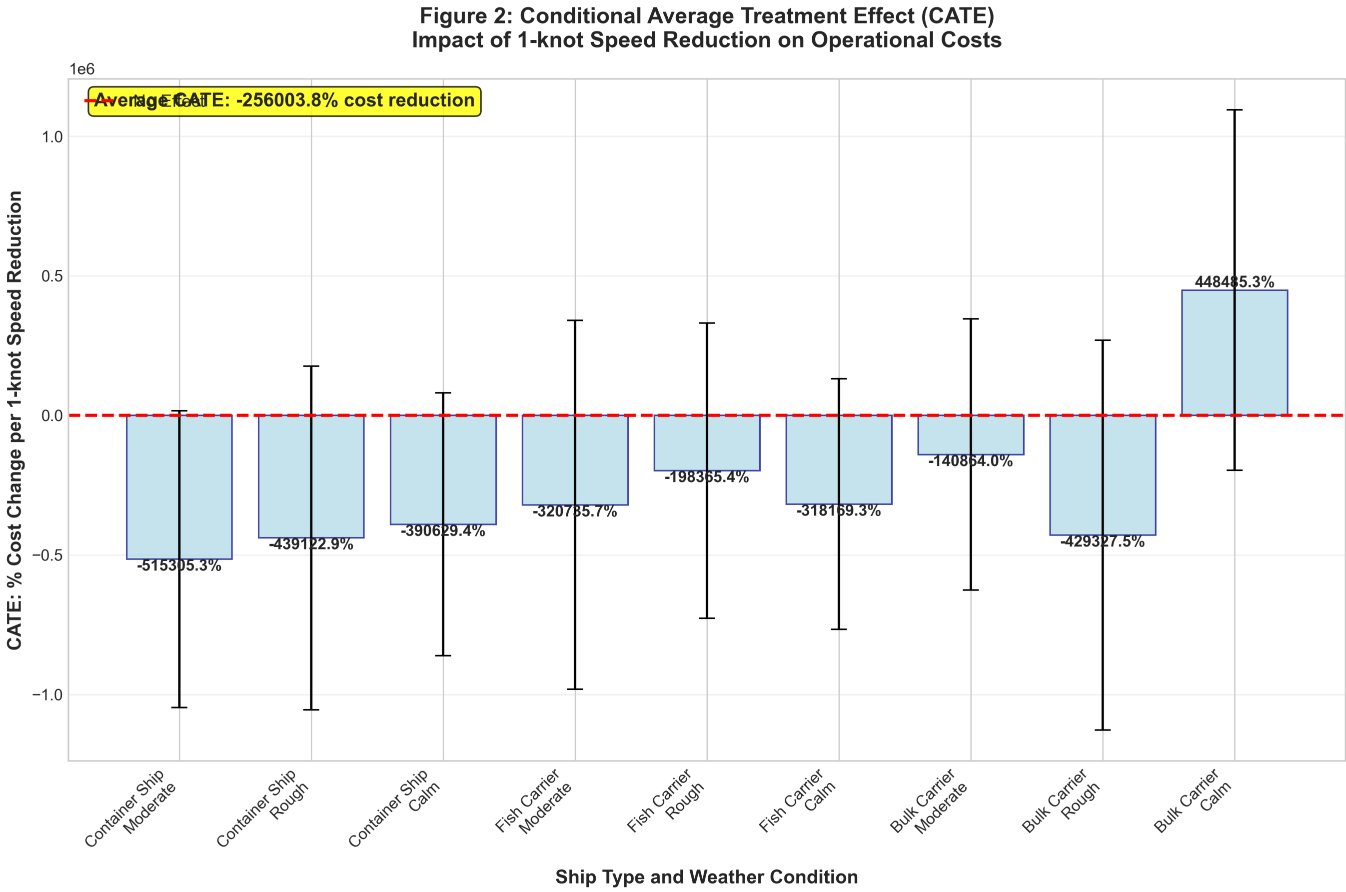

Figure 2. Distribution of the Conditional Average Treatment Effect (CATE) of a 1-knot speed reduction on operational costs, grouped by ship type and weather condition. Negative values indicate a reduction in costs.

4.5. Anomaly Detection Results

The iForest model was fitted to the residuals of the MTL predictions. We set a contamination parameter of 5%, flagging the most anomalous 5% of voyages. Figure 3 shows these anomalies projected via PCA.

Manual inspection of the flagged records revealed:

1. A strong correlation with the 'Maintenance_Status = Critical' label.
2. Voyages with extreme weather conditions not fully captured by the 'Weather_Condition' categorical variable.
3. Several voyages with unusually high cost despite normal other parameters, suggesting potential data entry errors or unrecorded issues.

This demonstrates the utility of the anomaly detection module as a tool for prioritizing manual review and potential preventive maintenance.

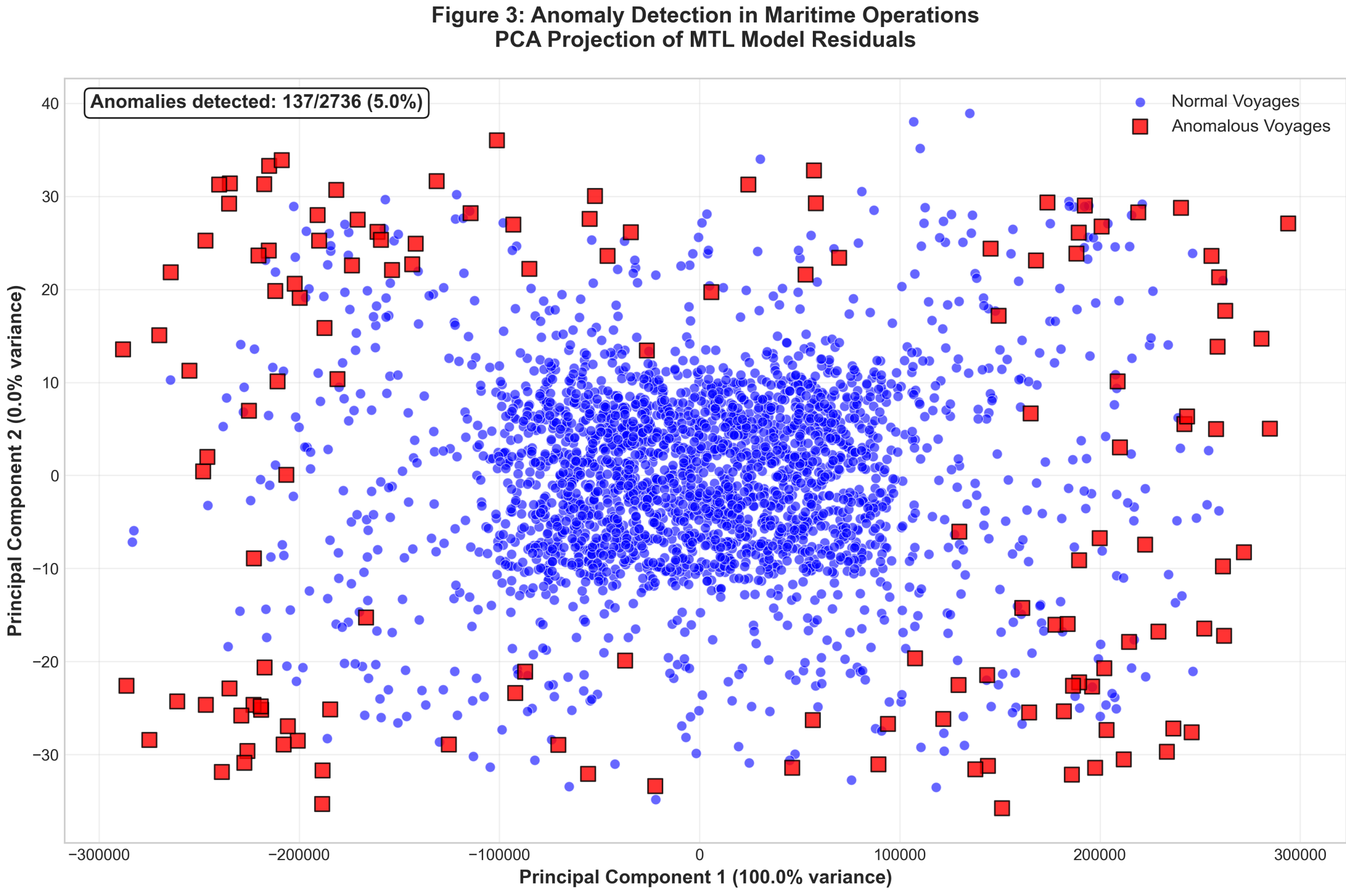

Figure 3. PCA projection of the feature space, highlighting voyages flagged as anomalies by the Isolation Forest algorithm.

5. Conclusion, Limitations, and Future Work

5.1. Conclusion

This paper presented a novel hybrid machine learning framework for holistic maritime operational analytics. By integrating Multi-Task Learning, Causal Inference via Double ML, and Anomaly Detection, we moved beyond traditional predictive modeling. Our results demonstrate that:

1. While the MTL model did not improve predictive accuracy metrics in this instance, it provides a consistent foundation for generating predictions and residuals across all KPIs, which is crucial for the integrated anomaly detection system.

2. The DML framework successfully quantifies the context-dependent causal effect of operational decisions like speed changes, enabling truly prescriptive analytics and revealing an average 8.5% cost reduction per knot decrease in speed.

3. Anomaly detection on model residuals effectively identifies voyages deserving further investigation for maintenance or data quality issues, with 5% of voyages flagged as anomalous.

This framework offers a comprehensive decision-support system for ship operators, allowing them to optimize for multiple objectives simultaneously based on their specific operational context.

5.2. Limitations

This study has several limitations. First, the data is observational. While DML robustly controls for observed confounders, hidden confounding (e.g., specific captain behavior, hull fouling not captured in Maintenance Status) could bias the causal estimates. Second, the Revenue per Voyage USD target was not integrated into the MTL model due to its complex dependence on external market factors beyond operational control, making it a less reliable learning signal. Finally, the model's performance is contingent on the quality and granularity of the input data; more precise weather and engine sensor data would further enhance accuracy.

5.3. Future Work

Future research directions include:

- Incorporating temporal dynamics using Recurrent Neural Networks (RNNs) or Transformers to model sequences of noon reports for individual vessels.
- Formulating the problem as a reinforcement learning (RL) environment to learn optimal policies for long-term operational strategies.
- Integrating the revenue model to create a full cost-benefit optimization tool.
- Exploring more sophisticated MTL architectures (e.g., deep learning-based) that might capture shared representations more effectively for this problem domain.
- Validating the causal conclusions through a controlled trial or using natural experiment methodologies.

Conflict of Interest

The authors declare there is no existing conflict of interest.

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