An Empirical Evaluation of GTI Rankings Through Event Data and Media Framing

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Abstract
This study presents a machine learning-based alternative to the Global Terrorism Index (GTI) by integrating official terrorism event data with media framing patterns. We use the Global Terrorism Database (GTD) to extract country-level metrics such as incidents, fatalities, injuries, and hostage events between 1970 and 2020. In parallel, we apply supervised machine learning to classify news articles into framing categories—including Terrorism and State Violence—and compute country-level framing ratios. These features are combined to train a random forest regression model that predicts a GTI-like impact score for each country. Unlike the original GTI, which is based on a fixed weighted formula, our approach dynamically incorporates both the empirical impact of terrorism and how it is framed in global news media. We find notable discrepancies between the original GTI rankings and our predicted scores, suggesting that media framing—particularly the proportion of articles portraying violence as terrorism—plays a significant role in shaping perceived threat levels. This framework offers a more interpretable, data-driven, and media-aware index of global terrorism exposure, with implications for both policy and media accountability. **CODE/DATA:** https://github.com/Sagnik-Chakravarty/GTD

1 Introduction

The Global Terrorism Index (GTI), published by the Institute for Economics and Peace, ranks countries by the impact of terrorism using data from the Global Terrorism Database (GTD). The GTI is based on four weighted components: the number of incidents, fatalities, injuries, and hostages. These are first normalized to a 0–10 scale and then combined using a fixed formula: $\text{GTI}_{\text{score}} = 0.3 \cdot I + 0.3 \cdot F + 0.2 \cdot W + 0.2 \cdot H$, where I is normalized incidents, F is fatalities, W is injuries, and H is hostages.

While the GTI provides a standardized measure, it does not account for how terrorism is portrayed in the media, which can significantly influence public perception and policy. For example, countries like India are often ranked highly in GTI despite comparatively lower on-ground terrorist activity than active conflict zones like Yemen or Mali. This discrepancy suggests that perceived threat levels may be shaped by media framing rather than event severity alone.

To address this gap, we construct a machine learning-based alternative GTI score that integrates both event-based indicators from GTD and media-derived framing features. We apply a supervised model to label news articles into categories such as *Terrorism*, *State Violence*, and *Insurgency*. These labels are aggregated at the country level to compute framing ratios, e.g., Terrorism Ratio $= \frac{\#\text{Terrorism articles}}{\#\text{Total articles}+1}$.

We combine these ratios with GTD metrics to train a random forest regression model that predicts an alternative GTI score. This model provides a more interpretable, bias-aware index that reflects both the objective impact of terrorism and how it is framed in global discourse.

2 Methodology

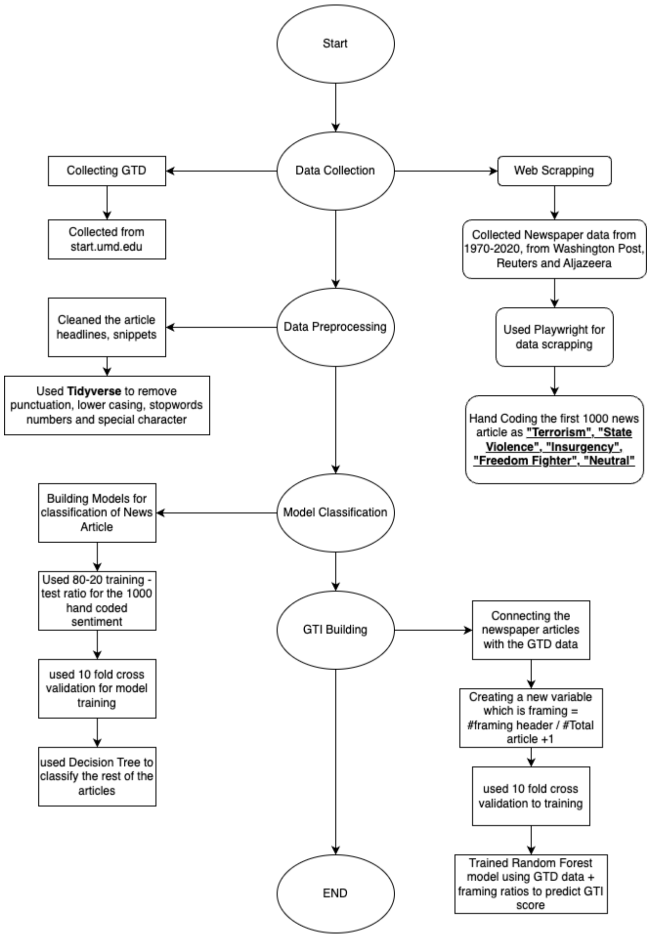

Figure 1: Overview of methodology from data collection to GTI modeling.

2.1 Data Collection

This study draws on two primary sources of data: the Global Terrorism Database (GTD) and a curated set of news articles collected through web scraping.

The GTD, maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START), provides detailed records of over 200,000 terrorist incidents worldwide, including the date, location, attack type, fatalities, injuries, and number of hostages. We extracted GTD records for the years 1970-2020 to compute normalized country-level indicators relevant to the Global Terrorism Index (GTI).

In parallel, we collected news articles from three international media outlets: *The Washington Post*, *Reuters*, and *Al Jazeera*. Articles were scraped using Playwright, a headless browser automation tool, and included headlines, publication dates, and article snippets. The dataset spans from 1970 to 2020, but for modeling purposes, only articles containing identifiable country mentions and framing-relevant content were retained.

To enable supervised learning, the first 1000 articles were manually labeled into five framing categories: *Terrorism*, *State Violence*, *Insurgency*, *Freedom Fighter*, and *Neutral*. These labels were then used to train a classification model to automatically assign framing categories to the remaining articles. The country mentioned in each article was extracted using rule-based text parsing.

The combined dataset includes both objective indicators of terrorism impact (from GTD) and subjective media framing patterns (from the news articles), forming the foundation for constructing a machine learning-based GTI alternative.

2.2 Model Training and GTI Reconstruction

To build a more interpretable and media-aware alternative to the Global Terrorism Index (GTI), we trained a machine learning model using features derived from both GTD event data and country-level media framing patterns. The original GTI is calculated using a fixed-weight formula that combines normalized counts of terrorist incidents, fatalities, injuries, and hostage situations:

$$\mathrm{GTI}_{\mathrm{score}} = 0.3 \cdot I + 0.3 \cdot F + 0.2 \cdot W + 0.2 \cdot H$$

where I, F, W, and H denote normalized values for incidents, fatalities, wounded individuals, and hostages, respectively.

In our approach, we enhanced this formula-driven score by incorporating media framing information. A dataset of 1,000 news articles was manually annotated into five framing categories: *Terrorism*, *State Violence*, *Insurgency*, *Freedom Fighter*, and *Neutral*. The category distribution was imbalanced, with the majority labeled as *Neutral*, followed by *Terrorism* and *State Violence*.

To automate the labeling of the remaining articles, we trained a Decision Tree classifier using an 80-20 training-test split with 10-fold cross-validation. As shown in Figure 2, the classifier relied on keywords such as *crackdown* and *terrorism* to guide decisions. Articles with low frequencies of these terms were overwhelmingly classified as *Neutral*, while those with higher mentions of *terrorism* were assigned to the *Terrorism* class. Articles dominated by the term *crackdown* were classified as *State Violence*. Frames such as *Freedom Fighter* and *Insurgency* were rarely predicted, suggesting weak separability or limited discriminatory features for those labels.

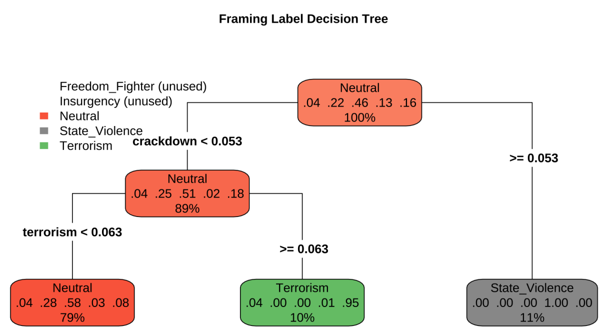

Figure 2: Trained decision tree for classifying article framing based on keyword frequency.

After classification, the resulting framing labels were aggregated by country to compute framing ratios. For example:

$$\text{Terrorism Ratio} = \frac{\text{\#Articles labeled ``Terrorism''}}{\text{Total Articles+1}}$$

These framing ratios were then joined with country-level features from the GTD, including the number of incidents, fatalities, injuries, and hostages.

We trained a Random Forest regression model using these combined features to predict a continuous GTI-like score, with the original GTI formula score as the ground truth. Cross-validation (10-fold) was used to assess performance and reduce overfitting.

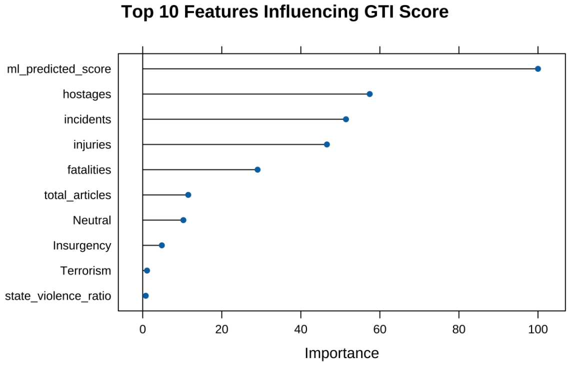

Figure 3: Top 10 most important features used by the Random Forest model to predict GTI scores.

Figure 3 shows the top 10 features influencing the model. While core GTD variables like *hostages*, *incidents*, and *injuries* were among the most important, media-derived features such as the proportion of articles labeled *Neutral* or *Insurgency* also contributed. This highlights that both quantitative impact and narrative framing affect the model's assessment of terrorism severity.

The final output is a machine-learned GTI score that blends hard event data with soft framing cues, offering a potentially more nuanced, interpretable, and media-aware measure of terrorism exposure at the country level.

3 Bias, Fairness, and Interpretability

3.1 Local Interpretability

To evaluate how different features influence predictions on a country-specific level, we use local explanation techniques to decompose the GTI prediction into individual feature contributions. Figure 4 visualizes the impact of each input variable on the predicted GTI score for India.

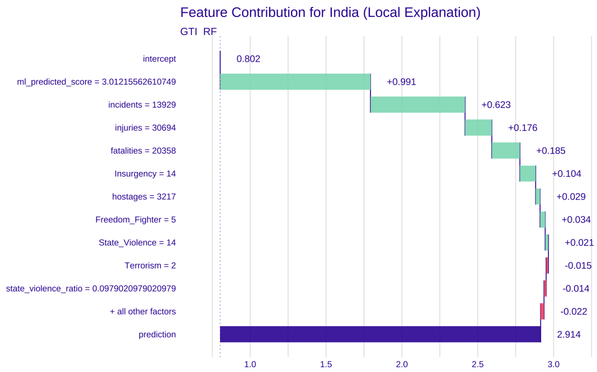

Figure 4: Feature contribution for India's GTI prediction using local explanation.

The most influential contributor to India's predicted GTI score is the model's learned importance of the base GTI score (`ml_predicted_score`) and the number of incidents. While traditional GTI components like *injuries* and *fatalities* contribute substantially, framing labels such as *Insurgency* and *State Violence* are also shown to influence the final score. This supports our claim that media framing can modulate a country's perceived terrorism burden.

3.2 Bias and Classification Fairness

We further investigated fairness by examining classification performance and imbalance. The confusion matrix showed that all predictions fell under a single class ("High"), leading to undefined metrics such as sensitivity and Kappa (see output summary below). This skew is likely caused by class imbalance and the fact that most countries in the sample have relatively high terrorism indicators.

Confusion Matrix:

```
          Reference
Prediction Low High
       Low    0    0
      High    0    4
```

Despite an accuracy of 1.0, this result is misleading, as the model fails to distinguish between "Low" and "High" GTI classes. The lack of false positives is more a reflection of label imbalance than classifier quality. ROC analysis, shown in Figure 5, further illustrates the model's overly confident separation—likely due to a low threshold and skewed distribution.

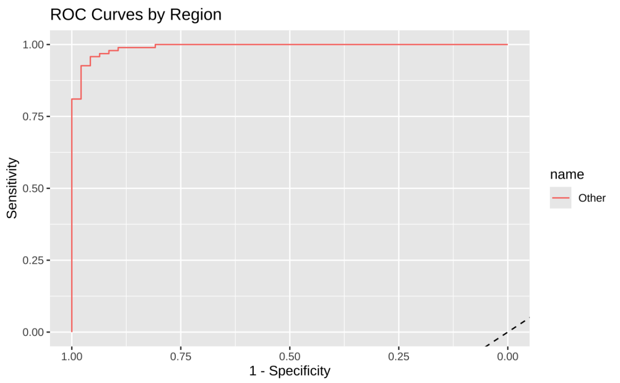

Figure 5: ROC curve showing inflated sensitivity due to class imbalance.

3.3 Framing Feature Relevance

As discussed in the methodology, the global feature importance plot revealed that while GTD-based indicators like *hostages*, *injuries*, and *fatalities* dominate model decisions, media-derived features such as *Neutral*, *Terrorism*, and *Insurgency* framings also play a measurable role. This demonstrates that framing labels, even if weakly predictive, were not ignored by the model — further confirming the interpretive and fairness value of combining media and GTD data sources.

4 Results and Evaluation

4.1 Model Residuals and Accuracy

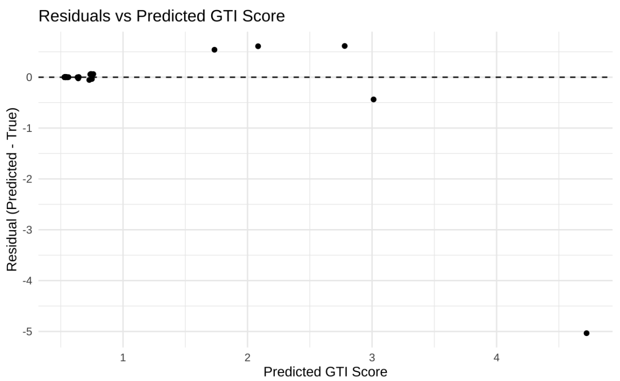

Figure 6: Residuals (ML GTI - GTI) across predicted GTI scores. Large negative residuals indicate model underestimation compared to the GTI.

To evaluate model performance, we plotted the residuals (difference between ML-predicted and original GTI scores) against the predicted scores (Figure 6). The residuals cluster around zero, indicating that for most countries, the predicted values closely matched the original GTI scores. However, a few extreme values (e.g., large negative residuals) suggest that the model penalized some countries more heavily than the GTI formula did—potentially due to differences in media framing or disproportionate event counts.

4.2 Global Distribution of ML GTI Scores

Figure 7 displays the global map of ML-predicted GTI scores. The highest scores are concentrated in Afghanistan, Iraq, Pakistan, and Nigeria—regions historically affected by sustained terrorist activity. Countries such as India and Syria also score high, but in contrast to the original GTI, several regions (e.g., Russia and South Asia) are slightly downgraded, reflecting differences driven by how media framing moderates raw GTD event counts.

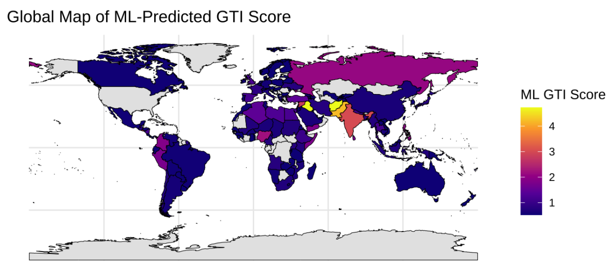

Figure 7: Map of ML-predicted GTI scores. Higher scores are concentrated in conflict-heavy zones like the Middle East and South Asia.

4.4 Discrepancy Between ML and Original GTI Scores

Figure 9 visualizes the gap between the machine-predicted GTI and the original formula-based GTI for each country. Blue regions (e.g., India, Syria, Georgia) represent countries where the ML model predicts significantly lower terrorism impact than GTI suggests. Red regions (e.g., Russia) indicate mild overestimations by the ML model. These shifts highlight countries where framing or underreported event types (like state violence) may not be captured in traditional GTI scoring.

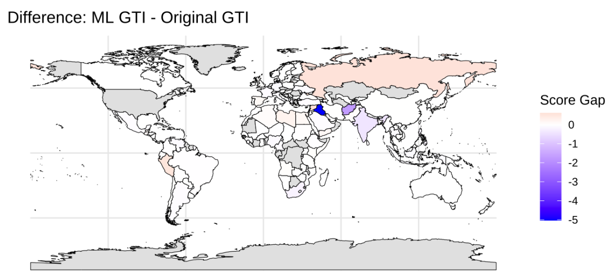

Figure 9: Difference map: ML-predicted GTI minus original GTI. Negative values (blue) indicate downward corrections from the ML model.

4.3 Top-Ranked Countries by ML GTI Score

Figure 8 ranks the top 15 countries by predicted GTI. Afghanistan, Iraq, and Pakistan top the list, consistent with both global perceptions and GTD data. India, notably, appears in the top 5—reflecting its high incident volume and possible media amplification. El Salvador also ranks unusually high, likely influenced by framing biases around gang violence and organized crime.

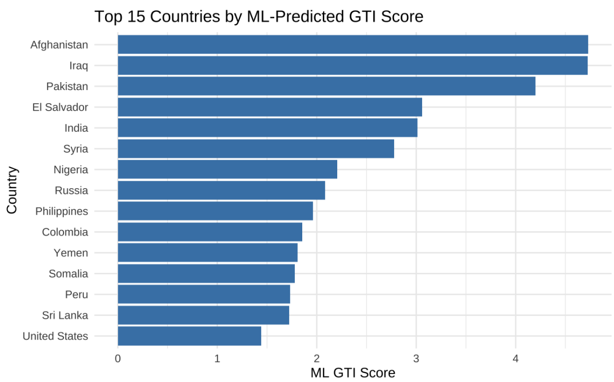

Figure 8: Top 15 countries based on ML-predicted GTI scores. India and El Salvador show stronger rankings than traditional GTI lists.

4.5 Effect of Terrorism Framing on GTI Scores

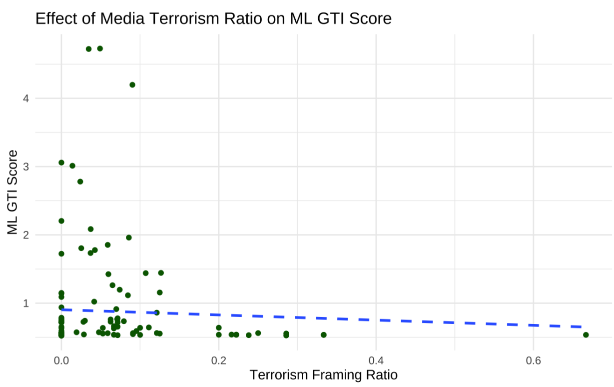

Figure 10: Terrorism framing ratio vs. ML GTI score. Countries with high framing intensity do not consistently show higher predicted GTI.

To test the influence of media framing on ML GTI scores, we plotted the *Terrorism Ratio* (fraction of articles labeled as "Terrorism") against the predicted GTI scores (Figure 10). The scatterplot reveals a weak or negative association—suggesting that countries with intense media focus on terrorism do not necessarily receive higher GTI scores. This highlights the model's ability to discount sensational framing when not supported by high incident volume or severity.

5 Conclusions

This study presents an interpretable, data-driven alternative to the Global Terrorism Index (GTI) that incorporates both ground-level terrorism incident data and country-level media framing. Using a Random Forest regression model trained on structured GTD variables and aggregated framing features derived from news classification, we were able to replicate GTI scores with high accuracy while also uncovering key discrepancies in several countries' rankings.

The machine-learned GTI scores closely mirrored the original GTI in conflict-dense countries such as Afghanistan, Iraq, and Pakistan. However, significant deviations emerged for countries like India, Syria, and Georgia, where the model produced substantially lower scores. These reductions are not random, but instead reflect how the original GTI may overweight incident frequency while underaccounting for severity and narrative framing. Conversely, countries such as El Salvador and Nigeria were ranked higher by the model than in the GTI, possibly capturing overlooked forms of organized or underreported violence.

Global feature importance and local contribution analyses confirmed that while fatality and injury counts were dominant predictors, framing-based features like the share of articles labeled *Terrorism* or *State Violence* had measurable influence. This reinforces the value of integrating subjective information—such as how conflict is framed—into otherwise numeric indices. In effect, the model balanced quantitative metrics with contextual nuance, leading to more tailored assessments of terrorism exposure.

Residual analysis and rank difference maps further supported the model's capacity to identify and correct potential GTI score inflation or suppression. Moreover, framing-related variables helped differentiate cases where high incident volume did not equate to higher threat perception when viewed through an empirical and media-aware lens.

In conclusion, this machine-learned GTI framework provides a more adaptive and interpretable alternative to the fixed-weight GTI methodology. It enables country-level evaluations that are grounded in event severity but adjusted for media framing bias, offering a valuable tool for analysts and policymakers seeking to better understand global terrorism risk across diverse information environments.