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Analyzing and Predicting Truck Travel Time Reliability

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16. Abstract:

Truck travel time reliability (TTTR) is one of the most important performance measures for assessing freight movement on the interstates. The Virginia Department of Transportation (VDOT) and the Virginia Office of Intermodal Planning and Investment have been reporting TTTR and setting performance targets as required by the Federal Highway Administration, as well as using TTTR in various project planning and performance measurement processes. This study aims to identify the locations and potential influencing factors of unreliable truck travel time, evaluate the effect of influencing factors, and develop models to predict the TTTR index for interstate highways in Virginia.

Using 7 years of probe speed and travel time data from the National Performance Management Research Data Set together with traffic volume, roadway, incident, and weather data maintained by VDOT, this study conducted descriptive and regression analyses to characterize the trends of TTTR and developed a hierarchical Bayesian model and random forest models to analyze and predict TTTR.

Hierarchical Bayesian models and random forest models achieved similar prediction performance, but the Bayesian model provides credible intervals for segment-level and network-level predictions to help VDOT planners better account for uncertainty in performance target setting and project planning. Traffic volume, crash frequency, the number of through lanes, and posted speed limit are the most significant factors in the Bayesian models and random forest models.

The study recommends that VDOT use the hierarchical Bayesian model to supplement the current method for setting freight reliability targets. Researchers developed an implementation plan that includes stakeholder engagement and technical assistance for the 2026–2029 performance cycle.

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FINAL REPORT

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Virginia Transportation Research Council
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ABSTRACT

Truck travel time reliability (TTTR) is one of the most important performance measures for assessing freight movement on the interstates. The Virginia Department of Transportation (VDOT) and the Virginia Office of Intermodal Planning and Investment have been reporting TTTR and setting performance targets as required by the Federal Highway Administration, as well as using TTTR in various project planning and performance measurement processes. This study aims to identify the locations and potential influencing factors of unreliable truck travel time, evaluate the effect of influencing factors, and develop models to predict the TTTR index for interstate highways in Virginia.

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INTRODUCTION

Efficient and reliable freight movement is essential to the economy. As freight demand continues to grow, the performance of the highway system for truck travel plays an increasingly critical role in ensuring the timely delivery of goods. Although average travel times provide a general indication of mobility, they do not fully capture the variability that freight carriers experience on a day-to-day basis. For freight carriers, unpredictable delays often translate directly into higher operational costs, schedule disruptions, and reduced system productivity (Culotta et al., 2019). Travel time reliability is a measure of consistency, predictability, and dependability in travel times, and it quantifies the extent of unexpected delay (Federal Highway Administration [FHWA], 2025a). Compared with the simple average of travel times, travel time reliability metrics can better quantify the benefits of transportation projects in improving the worst scenarios of unexpected delays. Incorporating travel time reliability metrics, such as buffer index, planning time index, and travel time index, can prioritize corridors with higher variability, guiding infrastructure investment and traffic management strategies to address reliability issues effectively (Lyman and Bertini, 2008). Truck travel time reliability (TTTR) is a key performance measure for understanding and managing truck traffic mobility. The Virginia Department of Transportation (VDOT) and many other transportation agencies have been using reliability metrics to help monitor and evaluate corridor performance, identify recurring and nonrecurring sources of delay, and prioritize investments that improve the consistency of truck travel.

The strategies for transportation agencies to improve TTTR often include Transportation System Management and Operations, capacity improvements, congestion management, and performance-based planning (Ahanotu et al., 2023). The performance-based planning and programming approach links investment decisions to desired outcomes such as better TTTR and reduced congestion. The Moving Ahead for Progress in the 21st Century Act (MAP-21) of 2012 requires state departments of transportation (DOTs), Metropolitan Planning Organizations (MPOs), and public transportation providers to establish highway systems performance targets to guide investments in projects that collectively make progress toward achieving the national goals for safety, infrastructure condition, congestion reduction, system reliability, freight movement and economic vitality, environmental sustainability, and reduced project delivery delays. Later, the Fixing America's Surface Transportation Act of 2015 reaffirmed the performance-based planning and programming requirements established in MAP-21. To fulfill those requirements, in 2017, FHWA published *National Performance Management Measures: Assessing Performance of the National Highway System, Freight Movement on the Interstate System, and*

Congestion Mitigation and Air Quality Improvement Program final rule (23 CFR Part 490) in the Federal Register. This final rule, also known as the PM3 rule, established six measures to assess the performance of the interstate and non-interstate National Highway System (NHS), truck traffic movement on the interstate system, and traffic congestion and on-road mobile source emissions for the Congestion Mitigation and Air Quality Improvement Program. The PM3 rule requires state DOTs and MPOs to report on NHS performance for both passenger and truck travel and set performance targets, forcing a performance-based approach to transportation planning. The truck traffic performance measure represents the reliability of travel times for trucks on interstates. FHWA defined the TTTR Index as the ratio of longer truck travel times (95th percentile) to a normal truck travel time (50th percentile) to calculate the TTTR measure.

In accordance with the PM3 rule, state DOTs and MPOs should set quantifiable 2- and 4-year interstate TTTR targets for each 4-year performance period. The 4-year targets represent anticipated performance at the end of the performance period, and the 2-year targets represent anticipated performance at the midpoint of the performance period. In the Mid Performance Period Progress Report, state DOTs may submit an adjusted 4-year target to replace an established 4-year target submitted before the first year of the performance period.

FHWA biennially assesses whether a state DOT has achieved or made significant progress toward established TTTR targets. It determines whether a state DOT has made significant progress toward the achievement of each 2- or 4-year TTTR target if either of the following conditions is met:

1. Actual performance is better than the baseline performance.
2. Actual performance is equal to or better than the target.

If significant progress has not been made, then the state DOT documents the actions it will undertake to achieve the travel time reliability targets in the next biennial performance report. Previous VDOT experience found that this documentation process could require significant time and effort, underscoring the importance of establishing appropriate TTTR targets.

According to §2.2-229 of the Code of Virginia, the Commonwealth Office of Intermodal Planning and Investment (OIPI) is responsible for developing the PM3 performance measures and targets related to NHS performance in Virginia for the Commonwealth Transportation Board’s approval. The 2- and 4-year targets for the 2026−2029 performance period shall be included in the baseline performance period report and submitted to FHWA by October 1, 2026. VDOT’s Transportation and Mobility Planning Division (TMPD) provided estimated TTTR targets for previous performance periods. Currently, TMPD uses a historical trend line method and time series models to predict the TTTR index. This approach does not explicitly account for the effect of reliability influencing factors, and therefore, they are not capable of estimating the changes of TTTR because of traffic pattern shifts and traffic improvement projects. A clear understanding of the factors that influence TTTR and a data-driven methodology to predict TTTR metrics are of continued importance to VDOT and OIPI.

Although some past VDOT projects have developed analytical models for travel time reliability prediction (Zhang et al., 2021; Zhao and Appiah, 2023), those methods aim to predict the 50th and 80th percentile travel times for calculating the level of travel time reliability for all traffic. It is unclear whether they are directly applicable to predicting truck travel time index (ratio of 95th to 50th percentile truck travel times). TMPD and OIPI are interested in data-driven approaches to identify the locations and causes of unreliable truck travel times and to predict TTTR metrics.

This study analyzed TTTR on interstates across Virginia using probe vehicle data, along with roadway and traffic characteristics. It evaluated TTTR performance across multiple temporal and spatial scales, identified trends and geographic patterns, highlighted locations that exhibit persistent reliability challenges, and developed statistical and machine learning models to predict TTTR.

PURPOSE AND SCOPE

The purpose of this project was to understand the factors that influence TTTR so that improved analytical methods can be created to support VDOT and OIPI's target-setting processes. The specific objectives were to:

1. Assess National Performance Management Research Data Set (NPMRDS) truck travel time data quality.
2. Identify the locations and causes of unreliable truck travel times.
3. Investigate the factors that affect TTTR.
4. Develop a methodology to predict TTTR metrics.

The scope of this study was limited to the interstate highway system in Virginia. The reliability metrics examined included TTTR, the 50th and 95th percentile truck travel times, and the level of travel time reliability (LOTTR). Statistical and machine learning models were developed for predicting a TTTR index. The results provide data-driven insights to support VDOT's planning, operations, and investment decision-making for improving TTTR and to support PM3-related performance reporting and target-setting activities.

METHODS

Researchers conducted the following major tasks to achieve the study objectives:

1. Literature review.
2. Data collection and preparation.
3. Data quality assessment.
4. Descriptive and statistical analysis of unreliable truck travel times.
5. Development of models to analyze and predict TTTR.

Literature Review

A literature review was conducted to understand the latest developments in TTTR analysis. The review focused on truck travel time data sources, TTTR metrics, influencing factors, and methods to predict future TTTR indexes for setting the target for the PM3 reliability performance measure.

Data Collection and Preparation

This study considered various factors that could affect TTTR, including traffic characteristics, roadway geometry, crash and non-crash lane impacting incidents, and adverse weather conditions. The study period was from 2019 to 2025. The COVID-19 pandemic years were retained in the analysis following the recommendation of this study's technical review panel. Including these years enables the evaluation of model robustness to account for unusual traffic fluctuations and major disruptions. The following sections describe the data sources and preparation procedures.

Data Sources

National Performance Management Research Data Set

The primary source of travel times in this study is NPMRDS. NPMRDS contains travel time and speed data collected from probe vehicles, with a spatial resolution defined by Traffic Message Channel (TMC) location codes (Schuman et al., 2024). TMC represents a unique, directional roadway segment, and nearly 2,000 TMCs exist for the 1,118 centerline miles of interstate highways in Virginia. NPMRDS data are available at 5-minute intervals, and it does not use imputed data. When no probes are observed during a given 5-minute interval, a null value is recorded. NPMRDS includes three datasets:

- Passenger vehicles.
- Trucks.
- All vehicle types: trucks and passenger vehicles combined.

Fifteen-minute interval data for all three datasets from 2019 to 2025 were downloaded through the Regional Integrated Transportation Information System (RITIS) Probe Data Analytics Suite and aggregated into five time-of-day periods (RITIS, 2025), which are defined by the PM3 rule:

1. 6:00 am–10:00 am, weekdays.
2. 10:00 am–4:00 pm, weekdays.
3. 4:00 pm–8:00 pm, weekdays.
4. 8:00 pm–6:00 am, all days.
5. 6:00 am–8:00 pm, weekends.

The datasets collected for this study include the following fields:

- TMC code, which is a nine-character identifier that includes a country code, location reference, segment type, direction indicator, and location identifier. Possible values for the segment type and direction indicator include "+," "-," "P," and "N." For interstate highways, a "+" or "–" indicates a segment between interchanges, and a "P" or "N" indicates a segment on an interchange.
- Length of TMC.
- Start and end coordinates: the latitudes and longitudes of the start and end points of a TMC.
- County or city: the jurisdiction in which a TMC segment is located.
- Timestamps: the beginning of a time interval.
- 15-minute average travel time.
- 15-minute average speeds.
- 15-minute traffic volume: NPMRDS volumes are estimated using annual average daily traffic (AADT) and average volume distribution profiles (RITIS, 2025).
- AADT.
- Annual average daily truck traffic, which was used with AADT to estimate the percentage of truck traffic.
- Data quality, which is an indicator of the minimum possible number of reporting vehicles in the chosen time interval. It is derived from the minimum possible number of reporting vehicles in each 5-minute epoch within the interval. Possible values for a 5-minute epoch include "A": 1–4 reporting vehicles; "B": 5–9 reporting vehicles; and "C": 10 or more vehicles. When aggregating at a 15-minute interval, A represents the minimum possible of 3 reporting vehicles (A for each 5-minute epoch), B indicates the minimum possible of 7 vehicles (2 epochs with A), and C represents the minimum possible of 11 vehicles (0 or 1 epoch with A).

VDOT-Maintained Data

The following data were collected from several VDOT databases:

- Linear Reference System: Linear Reference System shapefiles were used to obtain roadway attributes, including route name (RTE_NM), official state milepost, and traffic direction.
- Roadway attributes: Posted speed limit, number of lanes, the rural-urban designation, and VDOT operational region (Southwest, Northwest, Central, Eastern, and Northern) were obtained from the VDOT Traffic Operations Division Oracle database, the Commonwealth of Virginia Traffic Engineering Data Operations Portal.
- Crashes: Crash data, including Global Positioning System (GPS) coordinates, crash date, severity, and large truck involvement, were obtained from Virginia Roads, VDOT's open access data portal.
- Non-crash incidents: Non-crash incidents during the study period were obtained from VDOT's Transportation Data Hub. The attributes used included the time of the incident, time the lane was cleared, incident type, number of lanes closed, and location (route

name and milepost). This analysis uses only the incidents that blocked one or more travel lanes.

- Weather: Weather events (e.g., snow, ice, flood, storm) and the effects on roadways were obtained from the VDOT Transportation Data Hub. The weather impact is indicated by a road status field. The categories of road status include open, advisory, minor, moderate, severe, and closed or impassable.
- Terrian: Types of terrain (level or rolling) were provided by VDOT's Traffic Operations Division.

Data Preparation

Data quality screening, data cleaning, and conflation were performed. For each dataset collected, the data completeness, accuracy, and consistency were reviewed. The availability and quality of truck travel times in different time periods and across the study years were analyzed. The data quality screening could help clarify the limitations of NPMRDS, appropriately interpret the TTTR metrics calculated from this dataset, and inform further modeling decisions.

All datasets collected were assembled to create a combined dataset aggregated at the NPMRDS TMC level and 15-minute intervals. As Figure 1 shows, the datasets included timestamps, route names, and mileposts or GPS coordinates, and these keys were used to spatially join the datasets. Python™ scripts were developed to create the composite dataset. Very short TMC segments (less than 0.01 miles) were removed from the dataset. The final dataset contained 1,743 TMC segments with stable or consistent location information during the 7 study years.

Crash, non-crash incident, and weather data were aggregated at 15-minute intervals to match the temporal resolution of NPMRDS travel time and volume data. Crashes occurring in each 15-minute interval were summed for each TMC segment, analysis period, and year. Crash data for October through December 2025 were not available at the time of this study. Therefore, counts for 2025 were scaled up by a factor of $12/9$ to obtain equivalent yearly counts. Crashes were aggregated by analysis period. Applying the constant scale factor, it was assumed that the relative distribution of crashes by time of day for the first 9 months of the year remained the same for the last 3 months The total crash counts were converted to an equivalent number of crashes per mile-hour for every segment, period, and year combination. For non-crash, lane impacting incidents, the number of ongoing non-crash incidents during each 15-minute interval was counted for each segment. Because weather incidents often spanned multiple 15-minute interval periods, each 15-minute interval was categorized as either weather-impacted or not, based on the road status. Intervals were deemed impacted if the road status was moderate, severe, or closed during any portion of the 15-minute interval. Subsequently, for each segment, period, and year, a weather-impact risk score was computed based on the proportion of 15-minute intervals affected by weather.

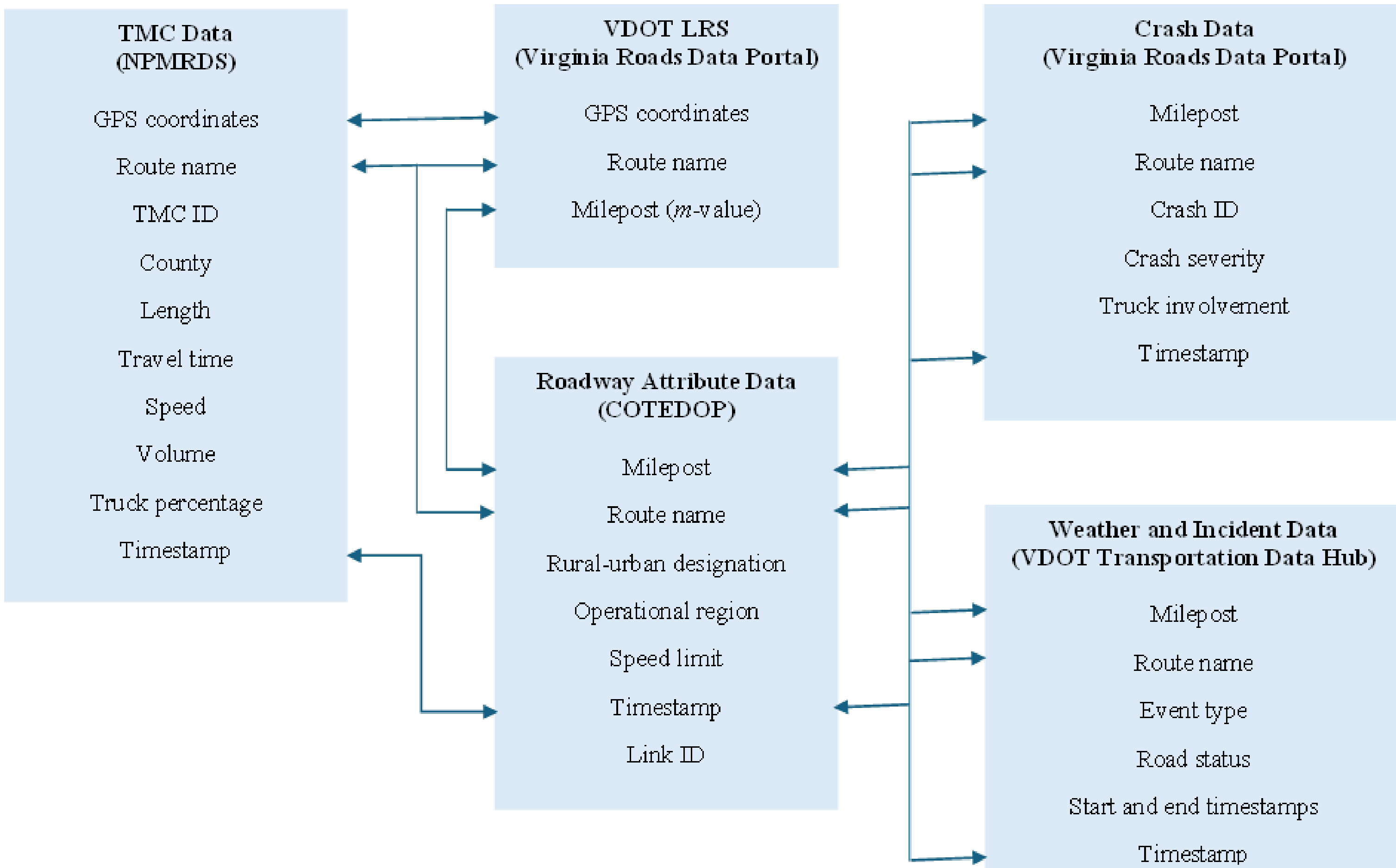


Figure 1. Datasets Assembled for the Study. The datasets were merged on the attributes where the arrows are pointing. COTEDOP = Commonwealth of Virginia Traffic Engineering Data Operations Portal; LRS = Linear Reference System; NPMRDS = National Performance Management Research Data Set; TMC = Traffic Message Channel.

Based on the route name, county and city, and rural-urban designation of the TMC segments in the final dataset, a new "corridors" variable (route-county-urban/rural) was created. This variable classifies TMC segments into clusters or "corridors" for later analysis. For example, all six TMCs in the dataset along eastbound Interstate 64 (I-64) in rural Alleghany County were placed into one cluster or considered to belong to the same corridor. A total of 225 corridors were thus defined for the 1,743 TMC segments, with membership ranging from 1 to 28 TMC segments per corridor. The length of these corridors ranges from 0.32 to 29.17 miles.

Calculate Reliability Metrics

Code scripts were developed to calculate travel times and speed percentiles and travel time reliability metrics for truck, passenger vehicle, and all traffic. The data pre-processing, percentile calculation, and travel time reliability metrics calculations followed FHWA's PM3 general guidance and step-by-step metric calculation procedures (Margiotta et al., 2018).

In accordance with the data requirements (23 CFR § 490.609) under the PM3 rule, when NPMRDS truck travel time on a TMC segment was not available for a given 15-minute interval (that is, data not reported or reported as "0" or null), the missing truck travel time should be replaced with the observed travel time for all traffic on that segment during the same 15-minute interval.

For each year from 2019 to 2025, the following metrics were calculated for each interstate TMC segment and each of the five analysis periods:

- 1–100th percentile travel times.
- 1–100th percentile speeds.
- LOTTR = 80th percentile travel time/50th percentile travel time.
- TTTR index = 95th percentile travel time/50th percentile travel time.

The PM3 TTTR measure, a length-weighted TTTR index for all interstate TMC segments, was computed using Equation 1.

$$Truck\ Travel\ Time\ Reliability\ Measure = \frac{\sum_{i=1}^{T} SL_i \times \max TTTR_i}{\sum_{i=1}^{T} SL_i} \quad \text{(Equation 1)}$$

Where:

i = TMC segment.
$maxTTTR_i$ = The maximum TTTR index of the five time periods, to the nearest hundredth, for segment "i".
SL_i = Length, to the nearest thousandth of a mile, for segment "i".
T = Total number of TMC segments.

Descriptive and Statistical Analysis of Unreliable Truck Travel Times

The distributions of travel time and travel time reliability metrics for trucks were compared across study years, time periods, and locations to understand the temporal and spatial variations in TTTR metrics. In addition, the travel time reliability metrics computed using truck, passenger vehicle, and all traffic datasets were compared using a one-tailed paired-*t* test to investigate the consistency across the travel time reliability metrics for different types of traffic flows to help understand whether different levels of trip planning are needed for truck and passenger vehicles. Descriptive statistics and linear regression models were created to help answer the following questions of interest to this study's technical review panel:

- Where are the unreliable truck travel times, spatially and temporally?
- Is the reduction or improvement of TTTR over time statistically significant?
- Is TTTR unreliable during all five analysis periods? When was the maximum TTTR index observed?
- Are the extremely high values of TTTR index outliers that need to be removed when calculating TTTR measures?

The potential correlations between the TTTR index and traffic crashes were examined. TMC segments with the highest TTTR indexes were reviewed to identify potential causative factors. A comprehensive analysis of the relationship between TTTR and its influencing factors was conducted using a Bayesian model in a subsequent section.

Development of Models to Analyze and Predict Truck Travel Time Reliability

Historically, VDOT has relied on a linear trendline method to analyze and predict TTTR. This approach does not adequately account for the factors influencing reliability, thereby limiting its capacity to quantify and predict changes in TTTR because of highway improvement projects and external factors. Furthermore, sudden disruptions such as the COVID-19 pandemic or major infrastructure projects can significantly alter travel patterns, making simple extrapolation of historical trends unreliable.

To address some of these challenges, this study explored two advanced techniques for TTTR analysis and prediction: hierarchical Bayesian and random forest (RF) models. A simple linear trendline model was used as the baseline because it represents the conventional and most commonly used approach for travel time reliability estimation.

Hierarchical Bayesian Model

The dataset assembled for this study consisted of seven TTTR observations from 2019 to 2025 for each TMC and time-of-day period. Hierarchical Bayesian models are an attractive alternative for modeling this dataset because they offer flexibility in estimating complex, interdependent relationships in short panels that might otherwise be under-identified, unstable, or overfit using standard statistical methods (Hsiao et al., 1998). Bayesian models use Markov chain Monte Carlo simulations and prior information to enhance estimation stability and forecasting precision (Abril-Pla et al., 2023; Zyphur et al., 2021). They allow partial pooling of information across segments and corridors, which improves estimation for segments with sparse or noisy data. The resulting posterior forecasts are probabilistic, providing credible intervals for uncertainty quantification.

Modeling Overview

A hierarchical Bayesian framework was developed to model the TTTR index, that is, the ratio of the 95th percentile to the 50th percentile truck travel time (*Q*95/*Q*50), on each TMC segment. The model sought to address four key challenges:

- Segment and corridor heterogeneity: Differences in truck travel time variability by segment and corridor due to factors such as geometry, roadway environment, and demand patterns.
- Time-of-day correlations: Interdependence between morning, midday, evening, and weekend travel patterns.
- Structural breaks: Changes in historical trends due to exogenous events (for example, the COVID-19 pandemic) or major infrastructure changes.
- Covariate influence: Segment- and corridor-level characteristics such as traffic volumes, number of lanes, speed limit, and rural-urban classification that systematically affect reliability.

By using Markov chain Monte Carlo simulations and explicitly modeling these sources of variation, the Bayesian framework provides probabilistic forecasts of reliability with credible intervals, allowing VDOT planners and engineers to quantify uncertainty and make informed decisions.

Response Variable and Model Formulation

The response variable was the ratio of the 95th percentile to the 50th percentile truck travel times.

$$y_{s,c,p,t} = \frac{Q95_{s,c,p,t}}{Q50_{s,c,p,t}} \qquad \text{(Equation 2)}$$

Where *s* indexes TMC segments, *c* corridors (or TMC clusters), *p* periods, and *t* years.

The response, for observation $i \equiv (s, c, p, t)$, was modeled using a Gamma distribution parameterized by its mean μ_i and scale parameter k.

$$y_{s,c,p,t} \sim Gamma(\mu_i, k) \qquad \text{(Equation 3)}$$

$$log(\mu_i) = \alpha + \alpha_c + \alpha_s + \sum_{b=0}^{B} \beta_{c,p}^{(b)} (Year_t - \tau_b)_+ + \theta^T X_s + \epsilon_i \qquad \text{(Equation 4)}$$

Where:

α = global intercept.
$\alpha_c \sim N(0, \sigma_c^2)$ = corridor-level intercepts.
$\alpha_s \sim N(0, \sigma_s^2)$ = segment-level intercepts.
$\beta_{c,p}^{(b)}$ = slope for corridor *c*, period *p*, and hinge *b* (piecewise linear slopes for structural breaks).

$(Year_t - \tau_b)_+ =$ hinge function: 0 before breakpoint τ_b, linear afterward.
$X_s =$ vector of segment-level covariates.
θ = regression coefficients for covariates.
$\epsilon_i \sim N(0, \sigma^2) =$ observation-level random effect to account for unobserved heterogeneity.

The model specification is hierarchical, capturing both corridor-level and segment-level effects. To account for major disruptions, the model includes hinge functions at specified break years: 2020 to capture the effects of the COVID-19 pandemic on truck travel behavior and 2022 to capture post-pandemic adjustment or infrastructure changes. Piecewise slopes allow the model to adjust trends and preserve continuity across pre- and post-break periods.

To capture time-of-day correlations (for example, congested mornings may affect midday and evening flows), the corridor-level slope vectors $\beta_{c,p}^{(b)}$ are modeled as multivariate normal with an LKJ prior (a weakly informative prior that favors modest correlations placed on the correlation matrix) (Lewandowski et al., 2009). This method allows the model to borrow strength across periods and quantify correlations in uncertainty.

The model specification also included segment-level covariates to capture systematic effects that influence travel time variability. Segment-level covariates explored in this study were:

- Traffic volume (period volume converted to hourly volume; log-transformed).
- Truck percentage.
- Number of lanes.
- Speed limit.
- Terrain type (level versus rolling).
- TMC segment type (mainline versus interchange area).
- Crash frequency.
- Weather impact risk (proportion of 15-minute intervals for a period that weather affected).
- TMC segment length.

Model Estimation and Analysis

The model was estimated with *PyMC*, an open-source probabilistic programming language for Bayesian modeling and inference using Python and advanced computational algorithms (Abril-Pla et al., 2023). Four Markov chains were run to obtain posterior distributions of model parameters with 1,000 tuning steps and 1,000 draws per chain. Weakly informative priorities, including normal and exponential priors for intercepts and covariate coefficients and LKJ prior for correlation matrices, were used to help provide stability and guard against overfitting. The segment-level covariates were standardized to ensure all variables are on the same scale. Data for 2019 through 2024 were used to train the model, and 2025 data were used for testing.

Posterior samples of model coefficients were used to address key research questions.

1. **Factors that affect TTTR.** The segment-level covariates provide direct insights into factors influencing TTTR.

2. **Corridor-level trends.** The study employed a multivariate correlation structure to explore the temporal evolution of TTTR across corridors, capturing both the correlations across the five time periods and the effects of structural breaks. Because the mean model is $log(Unreliability)$, a slope $\beta > 0$ means the "buffer" required for trucks is expanding. Setting a threshold such as $P(\beta > 0) \geq 0.9$ provides an objective criterion to create an "early warning system" for corridor deterioration. In essence, if 90% or more of the posterior samples for a specific β are positive, then that corridor may be flagged as "deteriorating." This approach was deemed attractive because it is not focused solely on identifying corridors with high TTTRs but rather those where the certainty of an upward unreliability trend is high, even if the average shift is small. As Table 1 shows, different threshold probabilities may be used to signal different warning levels and courses of action.

Table 1. Example Deterioration Threshold Probabilities and Possible Interpretation

Probability	Warning Level	Action
$P \geq 0.95$	Critical	Immediate investigation: unreliability is almost certainly worsening.
$P \geq 0.90$	Early Warning	Monitor closely: trend has shifted upward with high confidence.
$0.40 \leq P \leq 0.60$	Stable	No clear trend: the unreliability might be just noise or a random walk.
$P < 0.10$	Improving	Significant recovery: the corridor is becoming more reliable.

This approach directly addresses the technical review panel's desire for a methodology to help:

- Determine whether TTTRs of certain road segments or corridors are getting worse (or better) statistically during the analysis years.
- Identify potential improvement locations.
- Determine whether segments are reliable or unreliable during all five analysis periods or in only a subset of these periods.

With the posterior samples available, the deterioration probabilities can be calculated for every corridor and every period at each breakpoint and appropriately filtered to address the topics listed previously.

3. **Segment-level TTTR forecasts.** For a future year, the linear predictor (Equation 4) and the posterior samples of the model coefficients are applied to generate probabilistic forecasts. Exponentiating these forecasts provides a distribution of forecasted TTTR index for each TMC segment. Relevant statistics, such as the median forecast and 90% credible intervals (5th and 95th percentile forecasts), may be reported from the resulting posterior distributions.

4. **Network-level TTTR Index forecast.** The probabilistic forecasts generated at the segment level are aggregated to produce a TTTR index for the network. For each of the

4,000 posterior samples (indexed by iteration), a network-level TTTR index is calculated as the length-weighted average of the forecasted TTTR index across all segments, where for each segment, the maximum ratio across all five time periods is used. This method produces a distribution of network-level TTTR index forecasts from which the median forecast and corresponding credible intervals may be reported.

Bayesian Model Evaluation

The model was trained using 2019–2024 data and evaluated using 2025 data. Performance metrics included mean absolute error (MAE), root mean squared error (RMSE), *R*-squared (R^2), mean absolute percentage error (MAPE), bias, and the mean coverage and width of the 90% credible intervals.

Random Forest

RF models were developed to predict the TTTR index for each TMC. RF is one of the most widely used tree-based models. It is known for robustness to noise and the ability to model nonlinear relationships. RF constructs decision trees and combines their predictions to enhance accuracy and minimize variance. It is capable of capturing intricate interactions among features, such as the cross effect of traffic volume, capacity, and traffic incidents. RF is widely used for classifying congestion level and predicting travel time and speed, and studies consistently show that RF provides high prediction accuracy and stable performance across datasets (Liu and Wu, 2017). In this study, the Python *RandomForestRegressor* from the scikit-learn library was employed to develop the RF models. The hyperparameters adjusted included the number of trees, the maximum depth of trees, the minimum number of samples required to split, the minimum number of samples per leaf, and the number of features used for splitting. The hyperparameter tuning was conducted using Bayesian optimization with the Python *Optuna* library.

Target Encoding

Target encoding is a technique used in categorical variable encoding in which each category is replaced with a summary statistic (typically the mean, known as mean encoding) of the target variable for that category. This approach captures the relationship between the categorical feature and the target, often improving model performance, especially in high-cardinality categorical variables. It helps incorporate target information directly into the feature representation and reduce dimensionality compared with one-hot encoding, which creates binary vectors (1s and 0s) for all levels of the categorical feature.

As the corridor (route-county-urban/rural) feature has 225 unique values, using one-hot encoding to transfer this feature into 224 dummy variables for the RF model would lead to a high-dimensional feature space, causing a high risk of overfitting because decision trees can easily memorize patterns tied to specific categories. Also, one-hot encoding is uninformative with respect to the target value; that is, each corridor is assumed to have the same degree of association with TTTR, which does not reflect the reality. Using target encoding techniques can transfer the high-dimensional, categorical corridor feature into one numeric variable to improve RF model prediction performance.

Generalized Linear Mixed Model (GLMM) encoding is one type of target encoding, which uses GLMMs to encode categorical variables by modeling the relationship between predictors (e.g., the corridor variable in this study) and the target (TTTR index) and accounts for random effects or hierarchical data structures. The categories of corridor features were treated as random effects, and a linear mixed model was fitted with both fixed and random effects. Compared with the mean encoding, GLMM encoding handles categories better and reduces the risk of overfitting. In GLMM encoding, the estimated random effects or predicted values from the model can be used as encoded features, capturing complex dependencies and variability within grouped or nested data.

A lagged version of the GLMM encoding was used to prevent look-ahead bias. Only past data were used to generate the encoding for future values. For example, the encoded corridor variable in 2020 was fitted into a GLMM model using data in 2019, and the encoded corridor variables for 2022 to 2025 were fitted using data from their previous years. Because data in 2018 and earlier were not collected, for developing the RF model, only data after 2019 were used.

Variables Selection and Model Evaluation

A 2023 Virginia Transportation Research Council (VTRC) study by Zhao and Appiah (2023) found that to predict the 50th, 80th, and 90th percentile travel times (all vehicle types) for TMC segments on interstates using RF models, it was more accurate to create one model for each study time period than to build one model for all time periods with one-hot encoded variables for time periods. This study created RF models for each of the five study periods to predict TTTR.

The variables used in the Bayesian model as segment-level covariates were all tested to build RF models. However, not all the same variables were retained in the final RF models. RF models were created using different variable combinations, and the variables were selected through ablation experiments. Traffic volume and the number of lanes are constantly identified as important variables for predicting travel time reliability. Weather, crashes (total crashes, total fatal and injury crashes, or total truck crashes), and non-crash incident variables were tested individually. One RF model was created for each study period for each combination of input variables. Variable importance scores from the RF model and the accuracy of predictions are used for variable selection. The importance score is calculated using Equation 5.

$$Importance\ score\ (f) = \sum_{t \in trees} \sum_{s \in splits\ on\ f} \frac{n_s}{N_t} \cdot \Delta MSE_s \quad \text{(Equation 5)}$$

Where:

n_s = the number of samples at the split.
N_t = the number of samples in the tree.
ΔMSE = the decrease in mean squared error from the split.

Both the training and testing errors were measured using MAE, MAPE, RMSE, and R-squared, with the training error assessed through five-fold cross-validation.

Linear Trend Model

A linear trend model served as the baseline for this study. Data were grouped by TMC and analysis period. For each group, a simple linear regression ($y = mx + c$) was fit to the data for which year is the independent variable, and the TTTR index is the dependent variable. The models were fit using 2022–2024 data to capture post-pandemic trends, and the fitted models were then used to predict 2025 TTTR values along with their corresponding prediction intervals. Prediction intervals were calculated as shown in Equation 6 (Spiegelman et al., 2010).

$$\hat{y}_0 \pm t_{(\alpha/2,n-2)} \times \sqrt{MSE \times \left(1 + \frac{1}{n} + \frac{(x_0-\bar{x})^2}{\sum(x_i-\bar{x})^2}\right)} \qquad \text{(Equation 6)}$$

Where:

$\hat{y}_0 =$ predicted TTTR value for year x_0.
$n =$ sample size.
$\alpha =$ significance level.
$t_{\alpha/2,n-2} =$ critical value from the Student's t-distribution.
$MSE =$ mean squared error.
$\bar{x} =$ sample mean.

Model performance was evaluated using MAE, RMSE, R-squared, mean squared error, MAPE, bias, and mean 90% prediction interval coverage and interval width.

RESULTS AND DISCUSSION

Literature Review

The literature review provides an overview of data sources, performance metrics, reliability influencing factors for conducting TTTR analysis, and methods for predicting PM3 TTTR targets.

Data Sources for Truck Travel

Analyses of TTTR rely on a variety of data sources that capture the spatial-temporal patterns and operational characteristics of truck movements and general traffic conditions. Traditional data sources for truck volume and speed are loop detectors and weight-in-motion systems. These detector data are often equipped at limited locations. For example, VDOT currently maintains 301 continuous count stations on interstates that collect volume and speed on 610 directional road links; however, only 20% (122/610) have the capacity to collect truck volume (count by vehicle class). Speeds collected on these links are for all vehicle types, and none of the sites currently report truck-specific speeds.

The predominant data source of truck travel time is GPS data collected from commercial truck fleets and mobile devices, known as probe vehicle data. Large streams of probe data gathered from trucks have been processed and analyzed to monitor truck travel times, assess system reliability, and support investment decisions. Probe vehicle datasets can cover millions of data points over extensive regions and long periods, enabling the extraction of truck trips, routing patterns, and origin-destination flows (Ma et al., 2011; Thakur et al., 2015). The American Transportation Research Institute's (ATRI) truck GPS database is one of the largest truck travel databases in the world. It includes raw GPS data from nearly 1 million heavy-duty trucks across North America. ATRI truck GPS data enables the estimation of truck travel times along specific routes and the variability in these travel times. These GPS trajectories are used to compile ATRI's Annual List of Top 100 Truck Bottlenecks (ATRI, 2026). The Bureau of Transportation Statistics' (2026) Freight Mobility Initiative Database is also produced from this data source. Combining GPS-derived trips with observed truck volumes at different locations allows for the creation of origin-destination matrices that represent truck flows within and between states. Such matrices are critical inputs for truck travel demand models and infrastructure planning (Demissie and Kattan, 2022; Zanjani et al., 2015). Truck GPS data have been used in developing performance measurement programs that monitor TTTR on freight corridors. For example, Ma et al. (2011) used GPS data from thousands of trucks to compute truck travel times between traffic analysis zones and system reliability measures to guide infrastructure investment and operational decisions by public transportation agencies.

Although raw truck GPS data include frequent location points, they are not aligned to roadway segments, and additional processing, such as map-matching to roadway networks, stop identification, and trip segmentation, is required to transform the data into analytically useful formats (Greaves and Figliozzi, 2008; Thakur et al., 2015). Data processing can be computationally intensive. In a study on truck trips in Florida, the researchers produced 1.2 million truck trips traveling within, into, and out of the state from approximately 145 million GPS records during 4 months, using specialized algorithms to identify truck trip start and end points and characterize movements (Thakur et al., 2015).

Unlike the point-based and proprietary ATRI truck data, NPMRDS provides NHS network-based segment-level truck travel times and is free to use for state DOTs and MPOs with licensing under 49CFR 111. NPMRDS truck travel time is the most widely used truck travel dataset in the United States. It is fundamental for calculating the TTTR measure under the PM3 rule, and it has been integrated into FHWA's Freight Mobility Trends Analysis Tool (FHWA, 2025b). FHWA has also developed a 10-step process for work zone performance measurement using NPMRDS truck and all-vehicle data (FHWA, 2020). NPMRDS is the primary data source used by the state DOTs and MPOs for freight mobility analysis (Ahanotu et al., 2023). In addition to meeting the PM3 requirements, many state DOTs use NPMRDS truck data for evaluating and monitoring freight mobility. For example, VDOT's TMPD developed a TTTR Dashboard for analyzing, querying, and visualizing TTTR using an interactive map and table, summary statistics, and a customized graph (VDOT, 2026). The tool currently includes TTTR data from 2016 to 2025. New York State DOT (2025) used NPMRDS-derived TTTR and Annual Hours of Excessive Delay to flag primary truck traffic bottlenecks.

NPMRDS truck data are also used in many academic and applied research studies. Using NPMRDS and crash data on interstates in Louisiana from 2016 to 2022, Abedi et al. (2023) analyzed relationships across freight movement reliability, the economy, and truck operation safety. The researchers found that commercial vehicle user delay costs often account for about

50 to 70% of all user delay costs on those road segments during the analysis years, underscoring the economic stakes of freight unreliability. The study also found that the proportion of crashes involving commercial vehicles was increasing during the analysis years.

Probe vehicle data are the foundation for constructing databases of truck trips and estimating statewide freight flows (Zanjani et al., 2015). However, truck probe vehicle datasets often contain missing values because trucks make up a much smaller share of traffic than passenger vehicles, leading to sampling bias. Researchers have developed models to impute missing data in NPMRDS using loop detector data (Karimpour et al., 2019). Leveraging multiple data sources improves the robustness of truck travel time data and facilitates more detailed temporal and spatial analysis of freight movements, particularly for datasets with continuous missing values (Karimpour et al., 2019).

Reliability Performance Measures

With the rapid development of probe vehicle data, numerous travel time reliability measures have been developed using statistical techniques and probe datasets in the past 15 years. The commonly used travel time reliability measures applied to both all-vehicle and truck traffic include standard deviation; percentile-based measures such as the 50th, 80th, and 95th percentile travel times; and index-based measures such as planning time index, buffer time index, and travel time index. Other measures include the coefficient of variation, skewness, misery index, and so on. LOTTR is defined under the PM3 rule to determine whether an interstate or non-interstate NHS segment is reliable (LOTTR < 1.5), which is then used to calculate the performance measures to assess NHS performance—that is, the percent of the person-miles traveled on the interstate that are reliable and percent of the person-miles traveled on the non-interstate that are reliable. A comprehensive review of travel time reliability measures can be found in Lomax et al. (2003), Cambridge Systematics, Inc. et al. (2008), Margiotta et al. (2013), and Wu et al. (2016).

Past studies have investigated the relationships among commonly used travel time reliability measures for evaluating TTTR, but the findings have not been consistent. Duvvuri and Pulugurtha (2021) recommend using the planning time index, buffer time index, and travel time index for measuring TTTR because they are moderately or highly correlated with most descriptive truck travel time measures. Wu et al. (2016) found large deviations among TTTR measures and that the measures were not highly correlated. In addition, different TTTR measures produced different conclusions about unreliability even when using the same underlying data. Therefore, that study suggested selecting appropriate TTTR measures based on data availability, potential users, and the purpose of analysis.

Among the travel time reliability measures defined specifically for truck travel time, the two most commonly used measures are the TTTR index defined by FHWA and the truck reliability index (RI) defined by the American Association of State Highway and Transportation Officials. Both measures are established to meet the requirements in MAP-21. TTTR is defined as the ratio of longer truck travel times (95th percentile) to a normal truck travel time (50th percentile), whereas RI is defined as the ratio of the total truck travel time needed to ensure on-time arrival (often the 80th percentile travel time for RI_{80}) to the agency-determined threshold travel time (e.g., observed travel time or preferred travel time) (Liao, 2014). A lower TTTR index (closer to 1.0) on a segment means that 95% of travel times are near median values, indicating consistency in truck travel times. Higher ratios signal increased variability and unpredictability for freight operations. In the PM3 rule, FHWA did not define a threshold value of the TTTR index to differentiate between reliable and unreliable truck travel times. For RI_{80}, a value less than 1.5 is commonly considered reliable truck travel time, a value between 1.5 and 2 indicates moderate reliability, and a value greater than or equal to 2 indicates unreliable truck travel time.

Factors Influencing Truck Travel Time Reliability

Understanding the factors influencing TTTR is essential for developing models to predict the TTTR index. A range of factors related to traffic dynamics, roadway infrastructure, environmental conditions, and operational characteristics influence travel time reliability. The basic cause of unreliable travel time is the imbalance of travel demand and capacity, and the consequence of congestion (National Academies of Sciences, Engineering, and Medicine, 2013). The causes of unreliable truck travel time include factors in both the demand and supply sides, as well as freight-specific operational factors such as shipment characteristics and scheduling constraints. This study focused only on the factors in the demand and supply sides because they are of interest to VDOT stakeholders. Nonrecurring congestion, such as that caused by crashes, inclement weather, work zones, or special events, is a dominant contributor to unreliable travel time (Culotta et al., 2019; Kwon et al., 2011; Taylor, 2013). Other main factors on the supply side for interstate highways include capacity, bottlenecks, area type, terrain, and traffic operational factors (Mazloumi et al., 2009). Most existing studies on factors influencing travel time reliability use travel time data from all vehicle types. For a truck-specific study, Duvvuri and Pulugurtha (2021) found road functional class, number of through lanes, area type, AADT, and posted speed limit all show statistically significant but weak relationships with travel time reliability measures for trucks. Agricultural, light commercial, and residential land uses in the nearby area exhibit moderate to strong associations with TTTR measures.

Predicting Truck Travel Time Reliability for PM3 Target Setting

Accurate prediction of future TTTR index is critical to setting appropriate PM3 performance targets. Most state DOTs and MPOs, such as Washington State DOT, the Capital District Transportation Committee, and the New York State DOT, used a historical trend line and compound annual growth rate to forecast future TTTR index (Capital District Transportation Committee, 2023; Washington State DOT, 2018). Georgia DOT (2022) and Atlanta Regional Commission developed PM3 targets using time series forecasting, which considers factors including vehicle miles traveled, population, goods movement, projects that may positively affect system performance measures such as interchange, intersection improvement, intelligent transportation systems, managed lanes, passing lanes, and roadway widening. Connecticut DOT (2023) analyzed historical trends alongside variables including COVID-19 pandemic-related traffic shifts, gas prices, and vehicle miles traveled when developing TTTR targets for the 2022–2026 performance cycle. North Carolina DOT considered vehicle miles traveled growth, truck travel demand projected in the statewide multimodal freight plan, severe truck crashes, and planned capacity expansion projects that could positively affect historical trend extrapolations in setting targets (Lindsey et al., 2022). VDOT's TMPD also applies time series prediction to estimate TTTR and set the target using a method based on project benefit score. The report published by FHWA, *Approaches to Target Setting for PM3 Measures*, provides approaches available to state DOTs and MPOs for setting travel time-based performance targets (Lindsey et al., 2022), which outlines the use of data sources, forecasting tools, MPO coordination, stakeholder engagement, and peer exchange.

Truck Travel Time Data Availability

Calculating the PM3 TTTR measure requires replacing any missing 15-minute truck travel time with travel time for all vehicles in the corresponding time interval. Analyzing the completeness of truck travel times before and after imputation could help interpret TTTR metrics for monitoring and evaluating truck movement performance.

Data Availability

Figure 2 illustrates truck travel time availability both prior to and after data imputation. The bar plots in Figure 2 indicate that data availability was at its lowest in 2019, with observed improvements since 2021. The morning peak, evening peak, and midday periods have the highest availability of truck travel times. For these three periods, the percentage of 15-minute intervals with available data exceeded 90% before imputation and approached nearly 100% after imputation. During nighttime and weekends, the availability of truck travel times is generally around 70% before imputation, and it increases to approximately 80% after imputation for nighttime and exceeds 95% for weekends. This result demonstrates the robustness of data imputation.

The boxplots in Figure 3 show the percentage of imputed truck travel times. Across all periods, a general decline is observed in these percentages during the analysis years, and the changes are small from 2023 to 2025. The reduction in the percentage of imputed data may suggest an increase in truck volumes; however, it could also be attributed to changes in the NPMRDS source data (e.g., more truck data providers). Nighttime and weekend periods have a relatively higher proportion of imputed data, as indicated by the higher median value and wider interquartile ranges in the boxplots. Commercial truck traffic typically peaks during the early morning and around midday. Therefore, these periods usually have more complete truck travel time data. Although the percentage of trucks relative to overall traffic is generally higher at night, the total volume is less than in morning and midday periods. The outliers above the upper whiskers represent TMC segments with remarkably high percentages of imputed data, even for the periods that generally have better data coverage.

Table 2 shows the percentage of TMC segments with data available for more than 50% of the time for each analysis period. These statistics are derived from travel time data after imputation. Except for the lowest percentages, about 88%, observed during nighttime in 2019 and 2021, more than 90% of TMCs have data available for more than 50% of the time during the respective time periods. The highest data availability, 99.89%, occurs during the morning peak and midday periods in 2025.

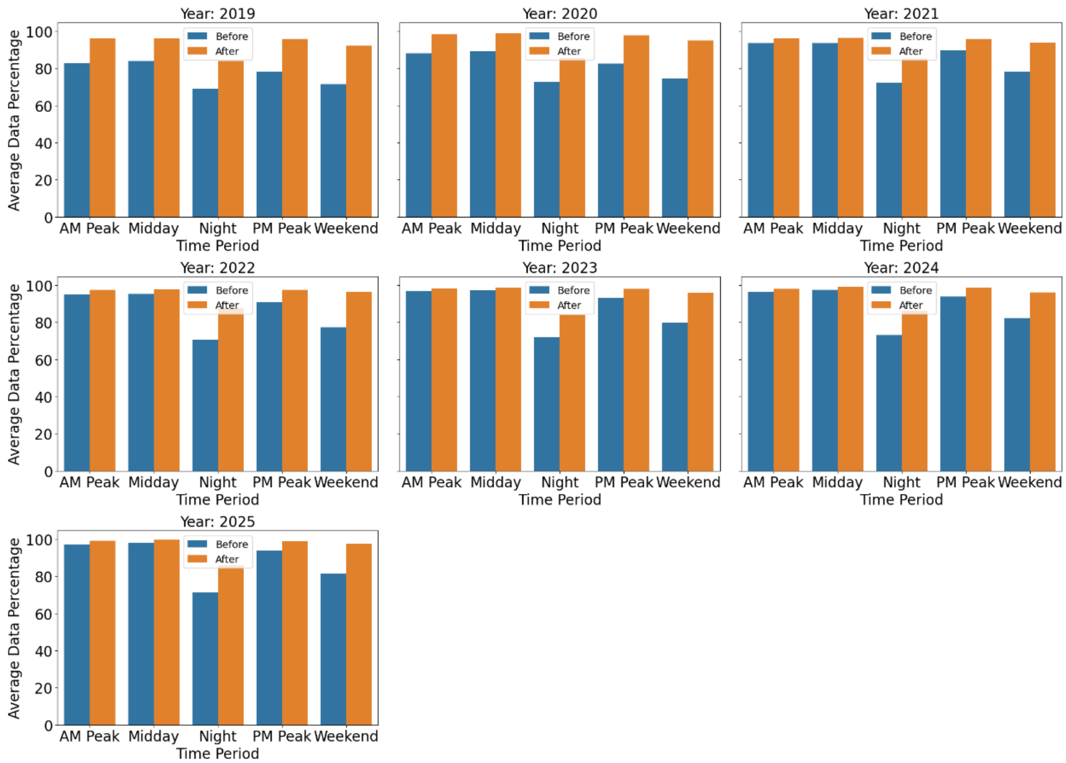


Figure 2. Availability of Truck Travel Times Before and After Data Imputation

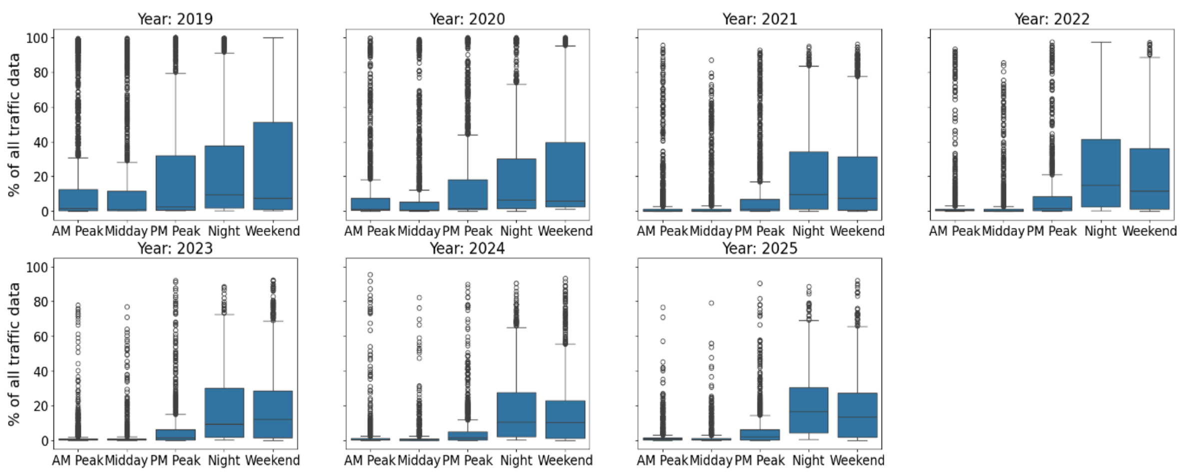


Figure 3. Distribution of the Percentage of Imputed Truck Travel Times by Period and Year

Table 2. Percentage of Traffic Message Channels with Data Available in More Than 50% of Time

	2019	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**
AM Peak	96.48%	99.19%	96.45%	97.67%	99.21%	99.00%	**99.89%**
PM Peak	96.48%	99.03%	96.45%	97.73%	99.06%	99.68%	99.84%
Midday	96.73%	99.30%	96.65%	98.09%	99.16%	99.63%	**99.89%**
Night	88.89%	94.10%	**88.26%**	92.09%	93.18%	95.88%	94.93%
Weekend	94.07%	98.16%	95.80%	97.88%	98.95%	98.68%	99.58%

Table 3 shows the percentage of TMC segments with more than 50% density A data. The statistics are based on truck travel times after the imputation. For the NPMRDS data aggregated in 15-minute intervals, density A indicates 3 or 4 reporting vehicles within 15 minutes, B indicates 7 to 9 reporting vehicles, and C indicates more than 11 reporting vehicles. Large proportions of low-density data may imply sampling bias. Because of low traffic volumes, nighttime had the highest portion of density A data. Between 2023 and 2025, more than 98% of the study TMC segments had more than 50% density A data during the night period. During midday hours, fewer segments had a high percentage of density A data. FHWA guidance on calculating PM3 performance measures does not establish any requirements regarding data density. Current literature lacks well-established guidelines on the minimum data density necessary to analyze highway performance using probe vehicle data. The National Cooperative Highway Research Program (NCHRP) Research Report 925 by Guerrero et al. (2019) suggested using data from at least seven reporting vehicles (density B) to analyze TTTR and the value of TTTR when enough data are available.

Table 3. Percentage of Traffic Message Channels with More Than 50% of Density A Data

	2019	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**
AM Peak	18.40%	16.68%	15.73%	**11.70%**	38.46%	27.86%	35.02%
PM Peak	35.65%	38.54%	23.93%	18.29%	54.51%	43.75%	43.90%
Midday	18.55%	14.36%	15.25%	12.23%	36.62%	21.85%	27.68%
Night	79.03%	79.59%	74.53%	82.84%	**99.58%**	98.47%	98.20%
Weekend	58.57%	57.86%	35.50%	31.37%	79.01%	71.77%	49.02%

Potential Effect of Data Imputation

Replacing null values in the NPMRDS truck travel times with all-vehicle travel times is the standard procedure for computing the PM3 TTTR index (Margiotta et al., 2018). To assess the effects of this imputation, reliability metrics were calculated with and without data imputation. Among the TTTR values computed for each TMC segment and time period in 2025, the difference between the imputed and non-imputed results was within 0.1 for 79% of them. As Table 4 shows, the largest differences in TTTR were observed on eastbound I-564 across four TMC segments during periods with low data availability, a high proportion of imputed values, and a predominance of Density A data. The TTTR values calculated using imputed data indicate comparatively reliable truck travel times, whereas those derived from truck-only data reflect highly unreliable conditions. The largest discrepancies were observed during the overnight period, when data availability ranged from as low as 7.57% to 32.25% even after imputation. Approximately 70% of values were imputed, and 99 to 100% of samples were Density A. The limited sample size is likely a primary contributor to these anomalies.

During the evening peak period, data availability was relatively higher. Figure 4 shows the speed cumulative distribution functions derived from truck-only, imputed, passenger-vehicle, and all-vehicle data, respectively. The cumulative distribution function curve based on non-imputed truck data lies below the others, indicating lower speeds, and it also shows a substantially wider distance between the 5th and 50th percentile speeds. The 5th percentile speed (corresponding to the 95th percentile travel time) derived from imputed data is more than 20 mph higher than that from non-imputed data. The cumulative distribution function from imputed data closely aligns with that of all-vehicle data because of the large share of substituted values, and passenger vehicles exhibit the highest speeds. Beyond the sample size limitations, operational characteristics on I-564 southbound, particularly the large volume of slow-moving trucks accessing the interstate from Norfolk International Airport terminals, may also contribute to the notably low 5th percentile truck speed and significant difference between truck and all-vehicle speeds. If the TTTR indexes computed from imputed data were used for TTTR performance evaluation other than PM3 reporting, a thorough review of underlying data conditions is essential to ensure that truck-specific issues are not overlooked and to avoid misrepresenting reliability on segments where imputation has a substantial influence. For the segments in Table 4, with the exception of one instance, the LOTTR values computed from the imputed and non-imputed datasets are consistent. Further research is needed to better understand the full effect of data imputation on TTTR metrics and to identify conditions under which imputation may introduce bias.

Table 4. Top 10 TTTR Indexes in 2025 Most Affected by Data Imputation

TMC Code	Route	Period	No Imputation		Imputation				
			TTTR	LOTTR	TTTR[a]	LOTTR	% Imputed Data	% Data Available	% Density A
110-04823	I-564S	Night	13.49	1.47	1.57 (– 11.92)	1.16	78.07	13.94	100.00
110N04824	I-564S	Night	7.86	1.22	1.45 (– 6.41)	1.14	79.24	13.76	100.00
110-04824	I-564S	Night	7.43	2.08	2.28 (– 5.15)	1.17	76.87	31.64	99.89
110P04909	I-564S	Weekend	3.67	1.14	1.33 (– 2.35)	1.10	90.01	33.67	100.00
110-04823	I-564S	PM Peak	3.66	1.13	1.50 (– 2.16)	1.11	72.24	80.56	80.62
110P04909	I-564S	PM Peak	2.89	1.13	1.29 (– 1.6)	1.12	75.48	40.04	100.00
110N04823	I-564S	Night	3.00	1.13	1.41 (– 1.59)	1.12	58.91	32.25	100.00
110-04824	I-564S	PM Peak	2.76	1.14	1.50 (– 1.26)	1.14	66.67	91.59	76.50
110P04909	I-564S	Night	2.72	1.17	1.54 (– 1.18)	1.16	68.69	7.57	100.00
110-04824	I-564S	Weekend	2.50	1.13	1.51 (– 0.99)	1.19	84.96	75.60	99.55

LOTTR = level of travel time reliability; TMC = Traffic Message Channel; TTTR = truck travel time reliability.
[a] Values in the parentheses indicate the changes after data imputation.

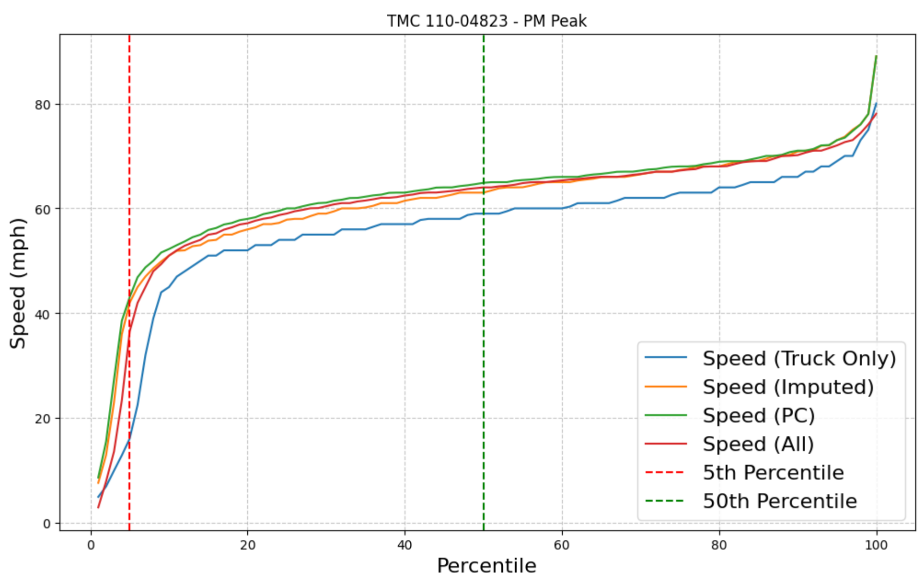


Figure 4. Speed Distributions on TMC Segment 110-04823 in Evening Peak Hours. PC = passenger car; TMC = Traffic Message Channel.

In the following analyses, the TTTR index was calculated using imputed data to ensure consistency with FHWA's guidance on calculating PM3 performance measures.

Descriptive and Statistical Analysis of Unreliable Truck Travel Times

The process of identifying unreliable truck travel times involves analyzing trends in TTTR, examining the maximum TTTR indexes by time and location, comparing TTTR metrics, and investigating potential causes of unreliability. To develop Bayesian and RF prediction models, very short segments (< 0.01 mi) and those without stable or consistent location information during the study years were excluded to ensure model stability; however, in this section of the descriptive analysis, all the TMC segments were included because calculating the PM3 TTTR measure requires including all segments unless the road is closed. A total of 2,047 unique segments were analyzed.

Truck Travel Time Reliability Trend Analysis

The analysis of temporal and spatial trends was conducted by comparing TTTR measures at both the statewide and route levels and examining the distribution of the maximum TTTR index of individual TMC segments.

Statewide Trends

Figure 5 provides the TTTR measures for the study years. The highest value of 1.54 was observed in 2019. This index significantly decreased to 1.29 in 2020 because of the COVID-19 pandemic and then subsequently rebounded to 1.47 in 2021. Slight declines occurred in 2022 and 2023, followed by an increase to 1.47 in 2024, matching the value observed in 2021. An increase of 0.01 from 2024 was observed in 2025. The drop in 2022 may be attributed to the after-effects of the pandemic, indicating decreased reliability in this transitional year. Unreliability increased from 2024 but was more stable compared with the years before. The historical trend of TTTR is generally consistent with the crash trends in Figure 6, with a few exceptions in 2022 and 2023. The observed trends in TTTR from 2022 to 2025 align well with the trends in fatal and injury truck crashes, although the rates of change differ. Truck crashes have increased since 2023. Crash data for December 2025 were not available at the time of this analysis and are therefore not included in this study. However, the number of fatal and injury truck crashes before December already exceeds those of previous years.

The number of non-crash incidents that blocked one or more lanes was also considered. The number of lane blocking incidents per year for the years from 2022 to 2025 was 36,465, 37,139, 36,204, and 35,470, respectively. The trend during these years does not align with the crash or TTTR trend and exhibits greater variability. Among the non-crash incidents that blocked a single lane, more than 55% were disabled vehicles, which typically block a shoulder rather than a travel lane. Because of the way lane closure information was entered and archived in VDOT's incident database, it is challenging to determine whether the closed lane was a shoulder or a travel lane. Shoulder closures would not affect the 95th percentile travel time that reflects extreme scenarios and thus would not affect the TTTR index. The Second Strategic Highway Research Program (SHRP 2) Project L03 found that the 80th percentile travel time, instead of the

95th percentile, can better reflect the “common” incidents that agencies can improve through operational strategies or infrastructure improvement (Margiotta et al., 2013). Therefore, the non-crash incidents are less likely to effectively reflect the trends of the 95th percentile travel time. On the other hand, severe crashes, like multi-vehicle crashes, are more likely to affect the 95th percentile travel time and TTTR.

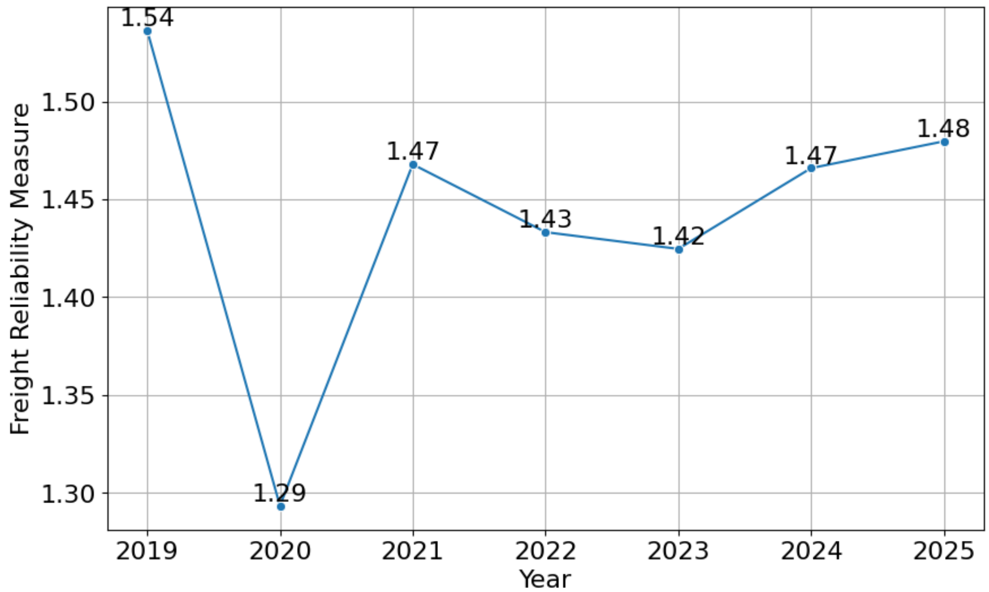


Figure 5. Truck Travel Time Reliability Measures During the Study Years

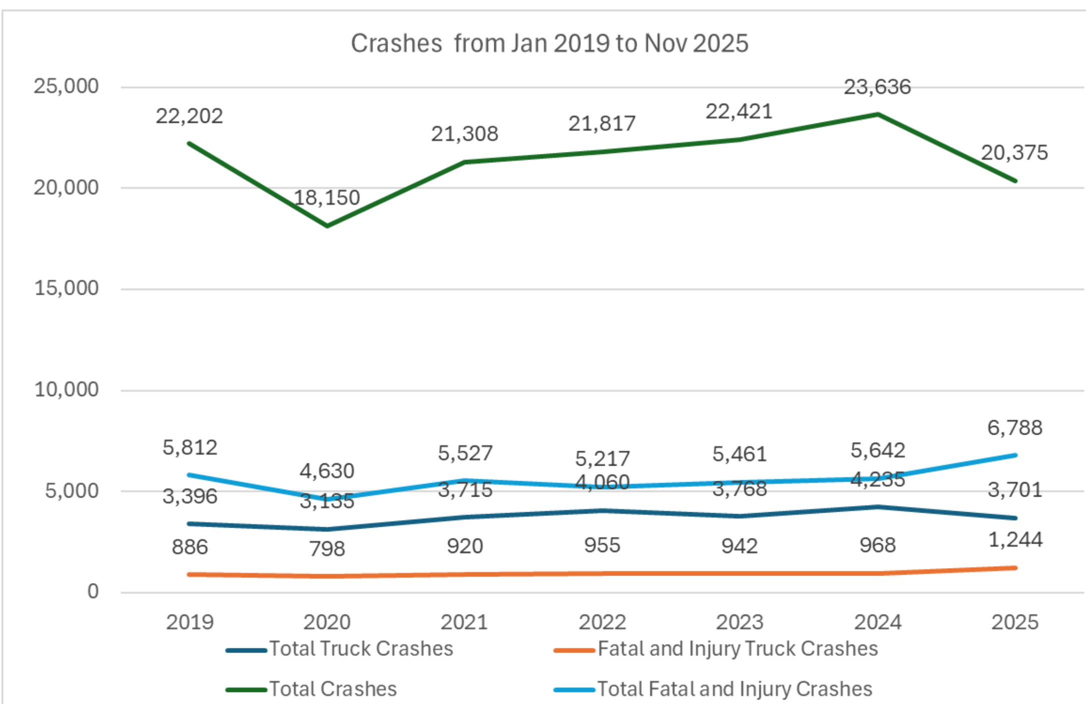


Figure 6. Total Number of Truck Crashes and All Crashes on Interstates from January 2019 to November 2025

Figure 7 shows the distribution of maximum TTTR indexes across individual TMC segments. The median value remains consistent during the study years; however, the interquartile range exhibits variability. This variability has generally decreased since 2022, indicating the stabilization of the interstate system. The maximum TTTR index observed was 17.20 in 2025.

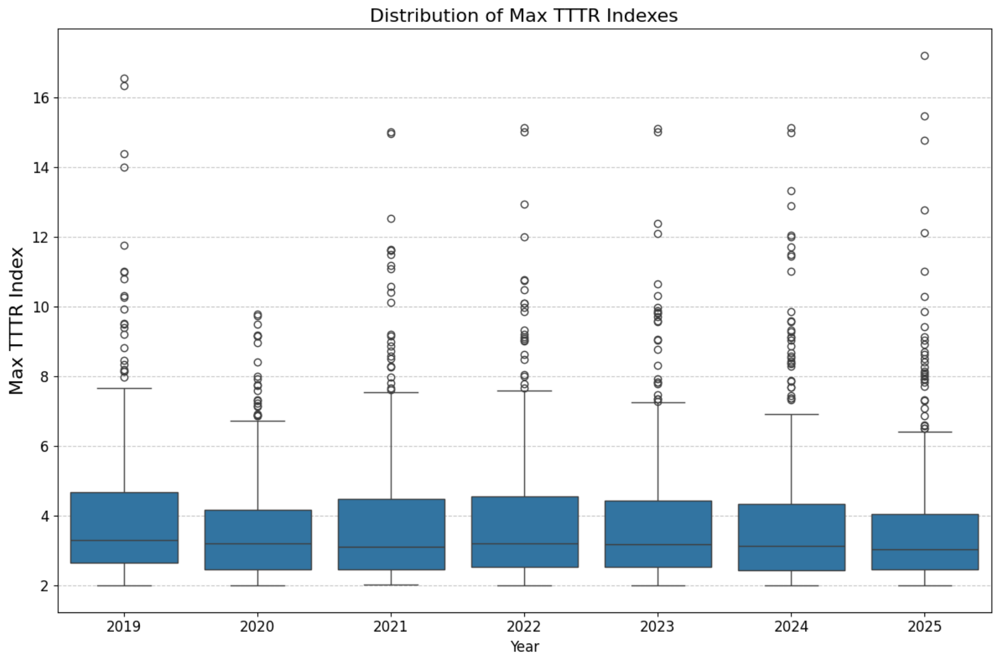


Figure 7. Distribution of Maximum TTTR Indexes. TTTR = truck travel time reliability.

Trends by Region and Route

The TTTR measure was calculated for each interstate route in five geographical regions of the state. The regions in Figure 8 are the same as VDOT's old operational regions. The Northern region includes primarily urban and suburban counties near Washington, D.C. The Southwestern and Northwestern regions consist primarily of rural interstates that are often in rolling or mountainous terrain, and the Central and Eastern regions consist of counties in the central and eastern parts of the state that are primarily flat.

Figures 9 to 13 show the TTTR measures for the five regions. Overall, unreliability has increased since 2022. Eastern and Northern regions show the highest variability, with respective standard deviations of 2.08 and 1.67. This result suggests that the freight reliability measure fluctuates more widely across different interstate routes and during the years within these regions. This observation could be attributable to the much higher traffic volumes and more dynamic traffic characteristics prevalent in the predominantly urban settings, and it also indicates a mix of highly reliable (e.g., I-464 southbound) and less reliable routes (e.g., I-664 eastbound) and significant changes in reliability for certain routes (e.g., I-395 northbound and I-495 northbound) over time. Northwestern and Southwestern regions show the lowest variability, with respective standard deviations of 0.21 and 0.33. The TTTR performance is more consistent within these regions, and the changes in reliability measures during the years are within a narrow range.

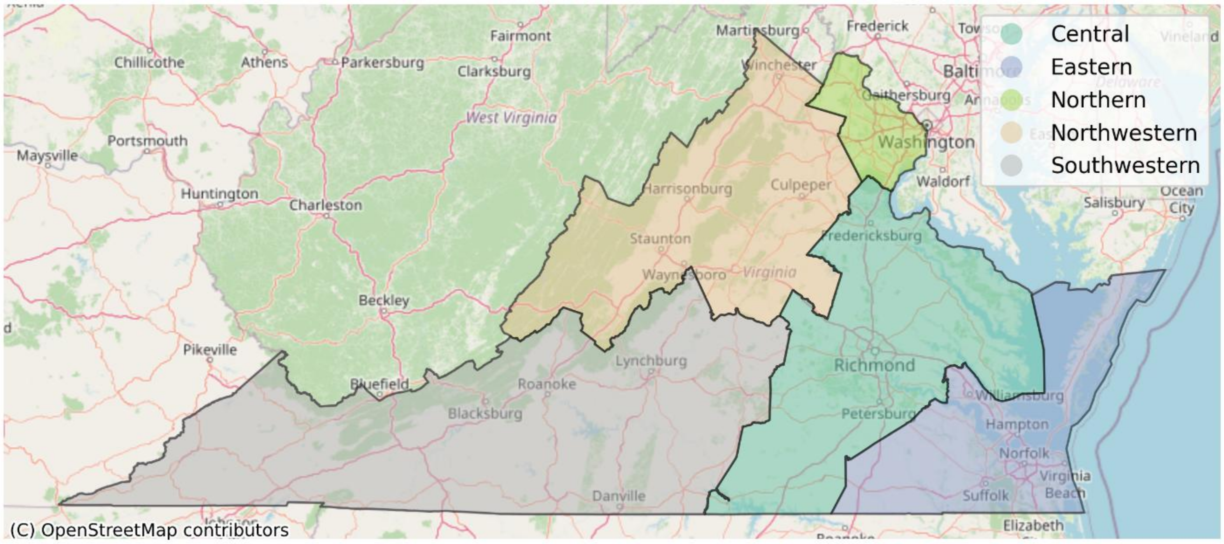


Figure 8. Virginia Department of Transportation Operational Regions

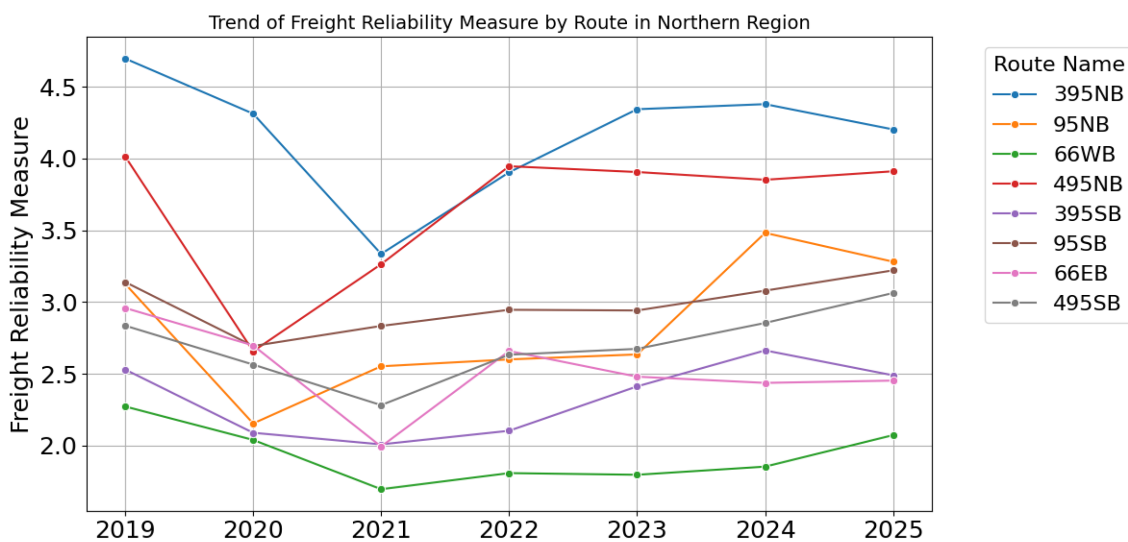


Figure 9. Truck Travel Time Reliability Measure in the Northern Region

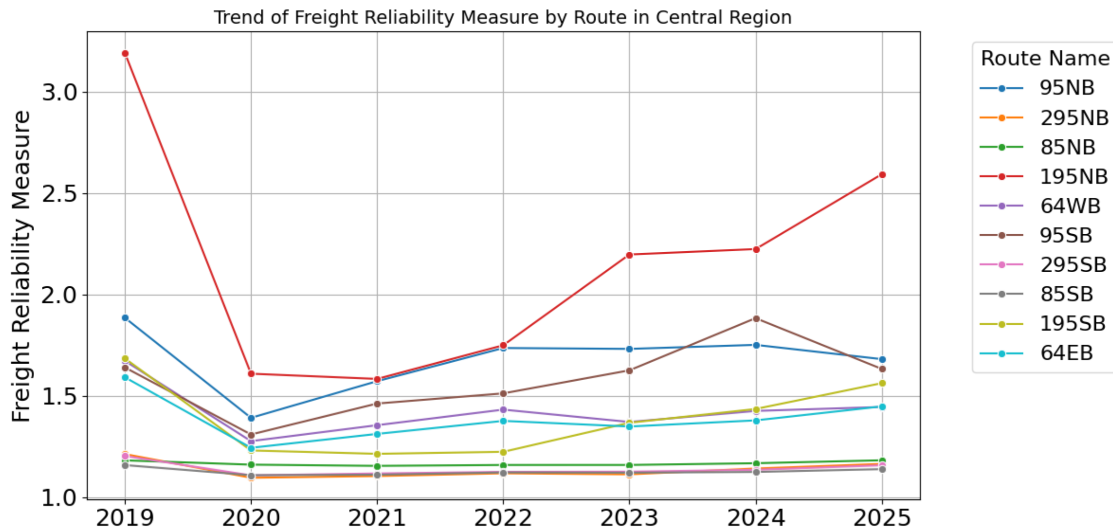


Figure 10. Truck Travel Time Reliability Measure in the Central Region

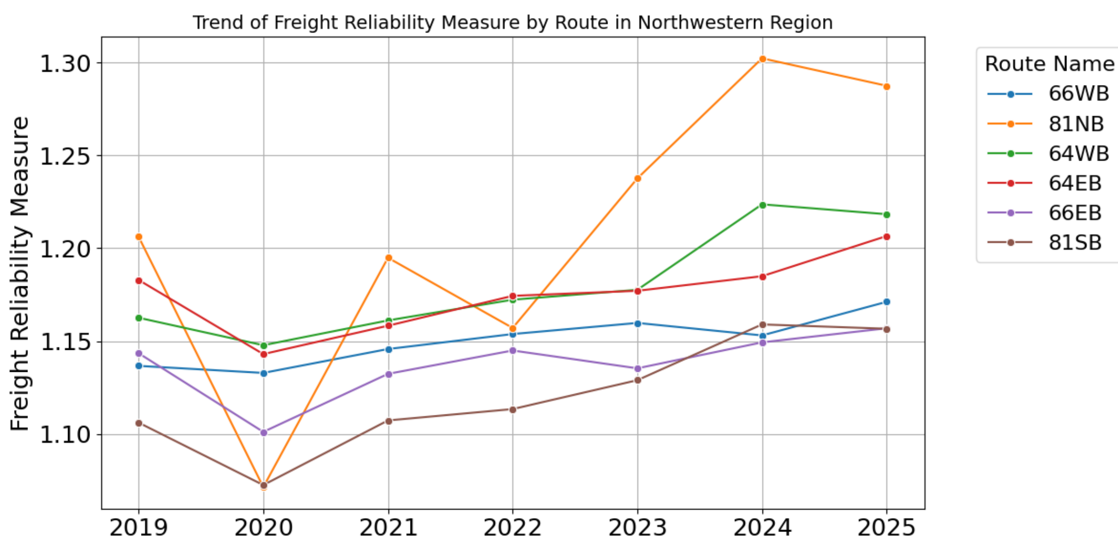


Figure 11. Truck Travel Time Reliability Measure in the Northwestern Region

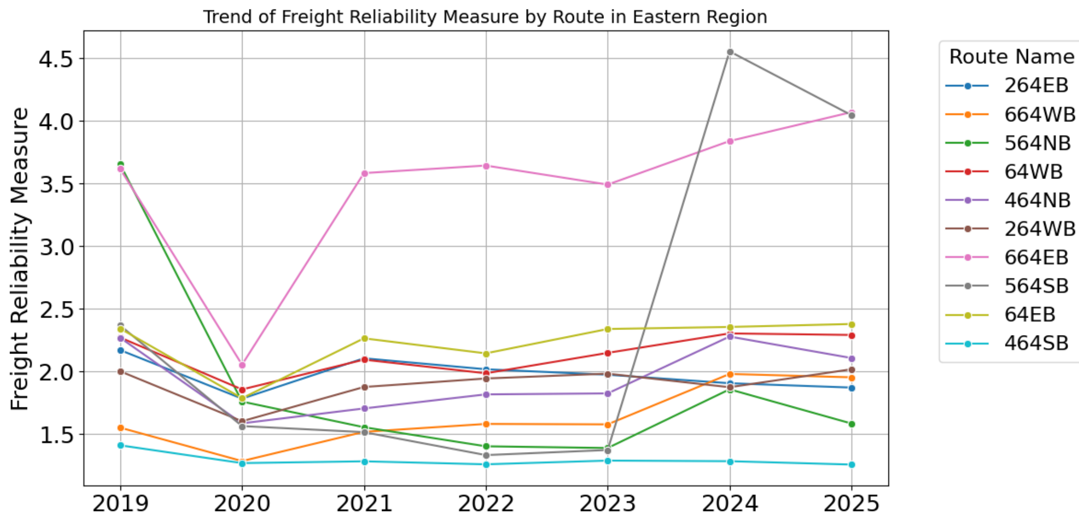


Figure 12. Truck Travel Time Reliability Measure in the Eastern Region

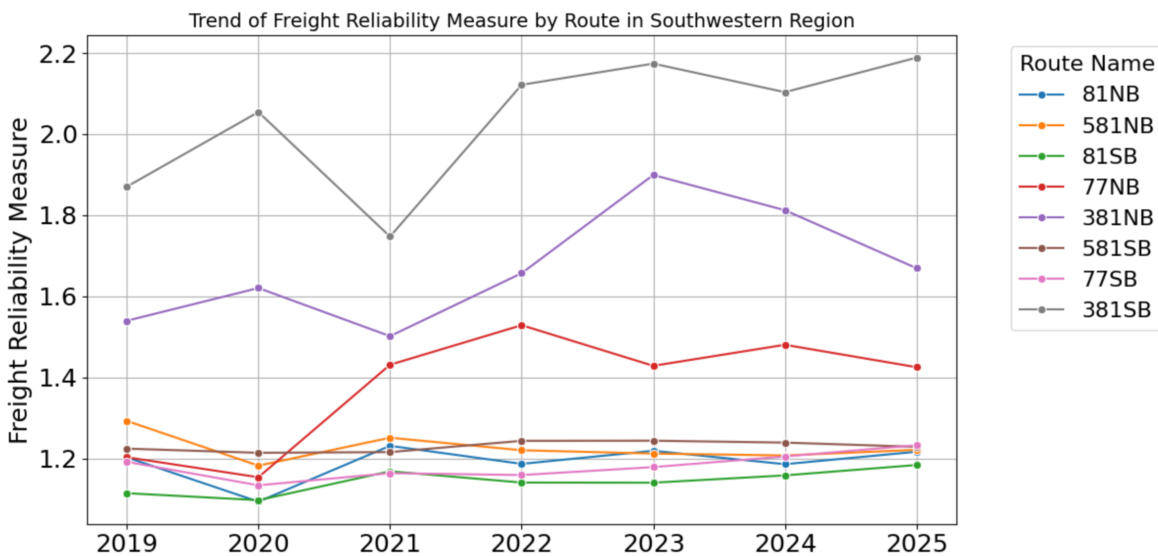


Figure 13. Truck Travel Time Reliability Measure in Southwestern Region

Linear regression models were developed to quantify annual changes, and Table 5 presents the results. The slope represents the rate of change per year, and the sign of the slope indicates the direction of change. The *p*-value determined whether the observed increasing or decreasing trend was statistically significant. The highlighted rows denote statistically significant changes in TTTR measures. From Table 5, the evidence is insufficient to determine whether the decreases in TTTR indexes are statistically significant for any of the routes with negative slopes. The TTTR index for I-564 southbound in the Eastern region is statistically increasing at a rate of about 1.13 per year, suggesting a decline in reliability. In addition, several routes, including I-295 and I-195 northbound in the Central region, I-95 northbound in the Northern region, I-77 southbound and I-81 southbound in the Southwestern region, and I-81 and I-64 eastbound in the Northwestern region, are observed to have statistically significant increasing TTTR indexes (decreasing reliability) during the study period but with a smaller rate of change.

Table 5. Trends of Truck Travel Time Reliability Measure Values by Route[a]

Region	Route	Slope	*p*-value	Route	Slope	*p*-value
Central	195NB	0.2557	0.0545	**195SB**	**0.1084**	**0.0009***
Central	**295NB**	**0.0168**	**0.0003***	**295SB**	**0.0107**	**0.0096***
Central	64EB	0.0245	0.4009	64WB	0.0094	0.8335
Central	85NB	0.0077	0.6205	85SB	0.0052	0.3192
Central	95NB	– 0.0146	0.7424	95SB	0.0607	0.1702
Eastern	264EB	– 0.0506	0.5715	264WB	0.0113	0.8936
Eastern	464NB	0.1323	0.2728	464SB	– 0.0011	0.915
Eastern	564NB	0.1013	0.2837	**564SB**	**1.1313**	**0.0012***
Eastern	64EB	0.0719	0.468	64WB	0.1072	0.216
Eastern	664EB	0.1625	0.6269	664WB	0.1518	0.1319
Northern	395NB	0.0931	0.6954	395SB	0.141	0.1628
Northern	495NB	– 0.0159	0.9532	495SB	0.147	0.1613
Northern	66EB	– 0.0645	0.419	66WB	0.0865	0.1425
Northern	**95NB**	**0.2887**	**0.0083***	95SB	0.0962	0.2835
Northwestern	**64EB**	**0.0105**	**0.0060***	64WB	0.0184	0.066
Northwestern	66EB	0.005	0.232	66WB	0.0045	0.2955
Northwestern	**81NB**	**0.0454**	**0.0057***	**81SB**	**0.0159**	**0.0066***
Southwestern	381NB	– 0.005	0.9699	381SB	0.013	0.9457
Southwestern	581NB	– 0.0001	0.9895	581SB	– 0.0049	0.7936
Southwestern	77NB	– 0.0259	0.6481	**77SB**	**0.0247**	**0.0060***
Southwestern	81NB	0.0057	0.6657	**81SB**	**0.0148**	**0.0133****

*Statistically significant at 0.01 level; **Statistically significant at 0.05 level. [a] Bold text indicates statistically significant changes in truck travel time reliability measures.

The trend analysis at the district level was also conducted. The results are in the Appendix.

Time of Day when Maximum Truck Travel Time Reliability Occurred

Between 2019 and 2025, the maximum TTTR index was observed in the night period for about 51% of TMC segments. Those segments are mostly in rural areas (Figure 14), and their maximum TTTR indexes are mostly below 1.5 (Figure 15), indicating reliable truck travel times. Each point in Figure 15 represents the maximum TTTR index for TMC in a given year. The maximum TTTR index was observed during the morning or evening peak periods in 32% of instances. For segments in urban areas with higher traffic volumes, the maximum TTTR index is more likely to occur in peak or midday periods. From Figure 15, the maximum TTTR indexes observed during evening peak hours show larger variance than those in all other time periods.

To understand whether the unreliable truck travel times were confined to a specific period or spanned across all time periods, TMC segments with a TTTR index greater than or equal to 2 in any given year were investigated. A TTTR index of 2 means that the 95th percentile travel time is more than double the normal travel time, indicating highly unreliable conditions. Between 2019 and 2025, out of 2,460 instances with a TTTR index greater than or equal to 2, only 58 instances (2%) exceeded 2 on the TTTR index on a TMC segment across all five periods. The distribution of the number of periods with TTTR index greater than or equal to 2, shown in Figure 16, indicates TTTR indexes were high in one or two specific time periods, rather than being consistently high across all periods. This fluctuation is much more common in 2019, 2024, and 2025 than in the other years.

Figure 14. Time Period when Maximum TTTR Index Occurred. TTTR = truck travel time reliability.

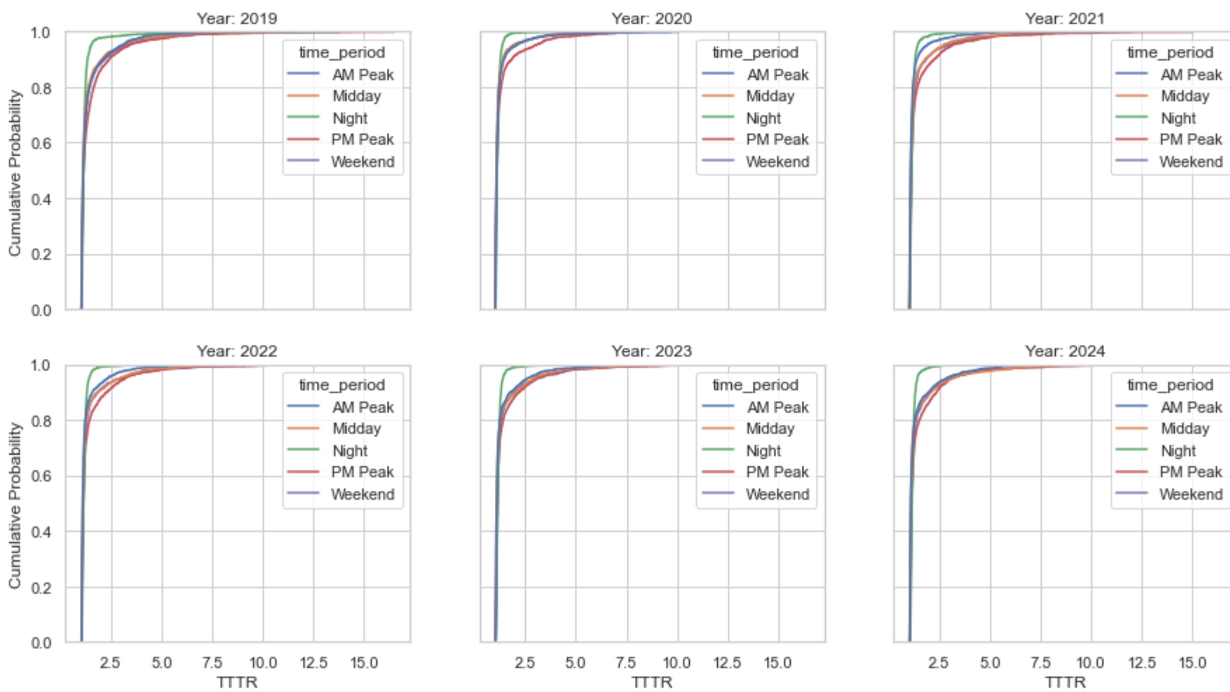


Figure 15. Distribution of Maximum TTTR Indexes. TTTR = truck travel time reliability.

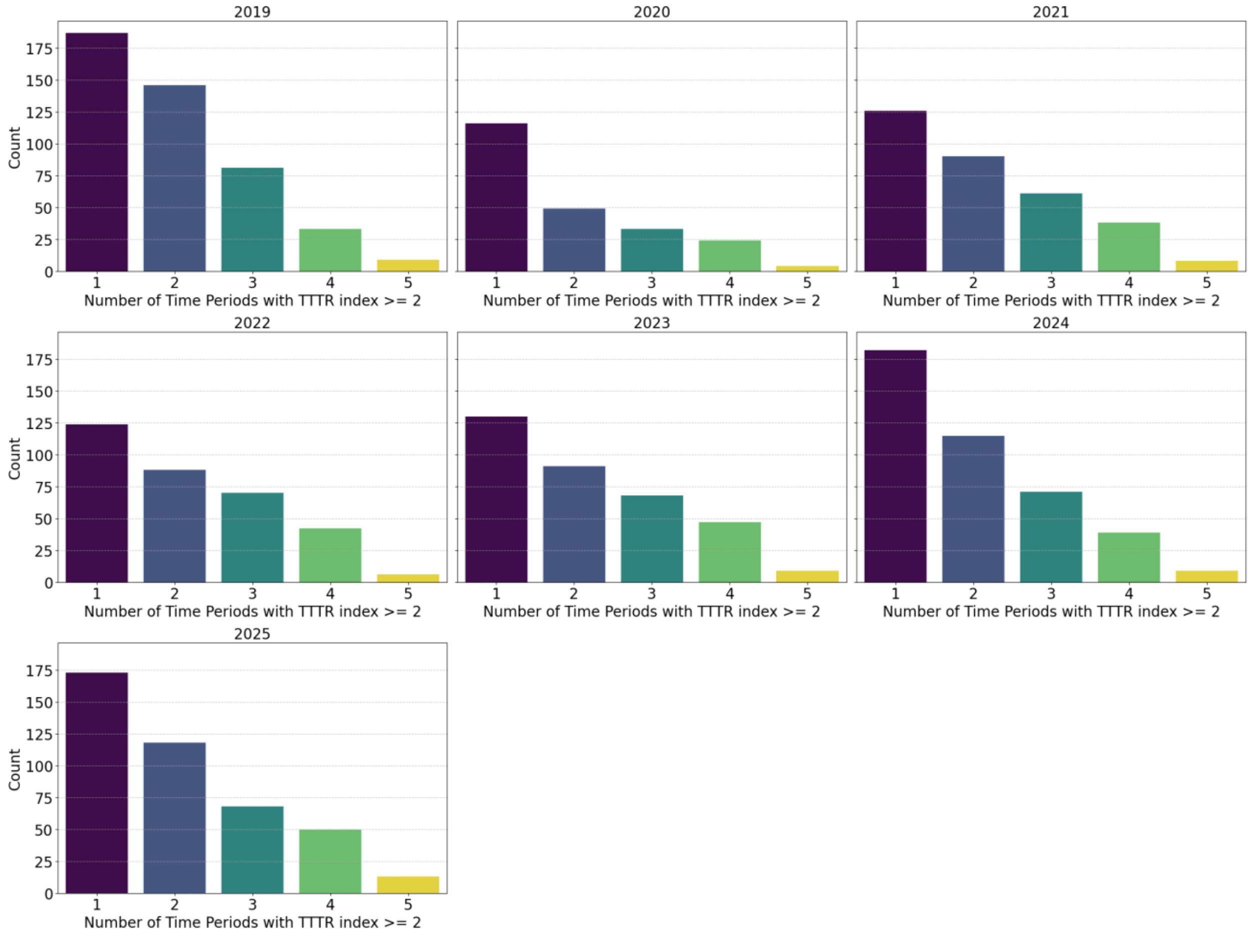


Figure 16. Distribution of Number of Periods with TTTR Index ≥ 2. TTTR = truck travel time reliability.

Truck Metrics Versus Passenger Vehicle Metrics

LOTTR is defined under the PM3 rule to measure the travel time reliability for general traffic. Agencies often look at LOTTR alongside TTTR to understand how general congestion affects the overall flow of all vehicles, including trucks. A LOTTR value of 1.5 or greater represents that a TMC segment is unreliable for all traffic types. Figure 17 shows the distribution of TTTR indexes by the reliability level of general traffic. The LOTTR value shown in Figure 17 was calculated using travel times of all vehicles. For TMC segments with a LOTTR value less than 1.5, the median TTTR value was approximately 1.1 across all periods. The upper whisker was highest for the evening peak, with a value of 1.55, indicating that TTTR indexes greater than this value are outliers in this plot. The upper whisker values for all other time periods were all below 1.5. The LOTTR value quantifies the typical delay on a segment, whereas TTTR measures the extreme delay. A high TTTR together with a low LOTTR means that although daily traffic conditions are generally acceptable, infrequent but severe disruptions occur, such as severe accidents or weather conditions, which disproportionately affect trucks, or the segment is an infrastructure bottleneck for trucks. For example, trucks have different operating characteristics than cars; on a segment with a steep grade, the “worst-case” travel time (95th percentile) could be significantly higher for trucks than for passenger cars. TTTR but not LOTTR can capture this unreliability. When prioritizing project investment using LOTTR, locations with reliable commuter travel but unreliable truck travel may be overlooked. When both the LOTTR and TTTR values are high, it indicates that the TMC segment is highly unreliable for all traffic types. This scenario often occurs at major bottlenecks with inadequate capacity or segments with a high crash frequency.

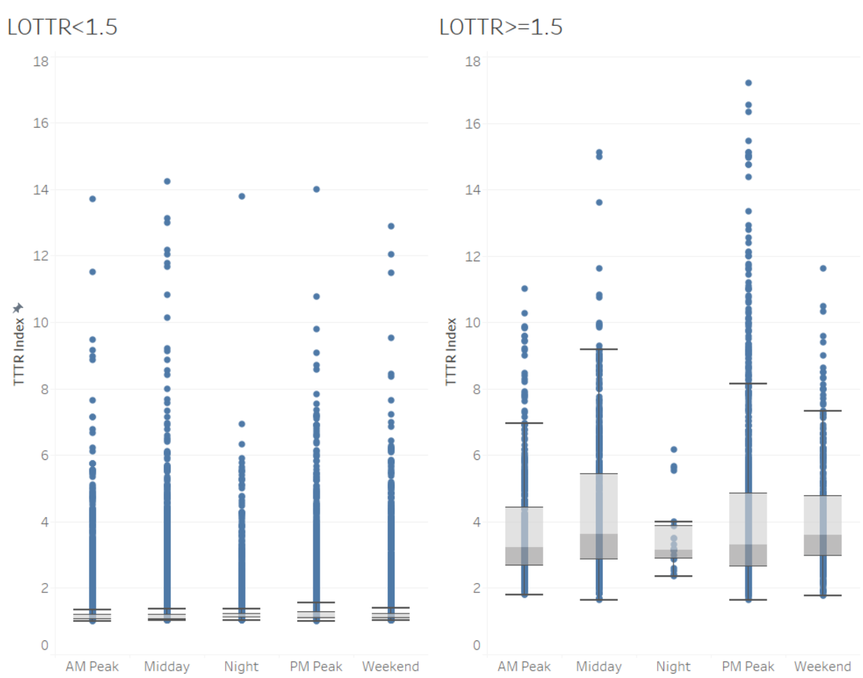


Figure 17. Distribution of TTTR Indexes by LOTTR. LOTTR = level of travel time reliability; TTTR = truck travel time reliability.

Past studies found that travel time and reliability measures computed using passenger car or all-vehicle data may not be applied to trucks, and the difference between performance measures could vary by area type, facility type, time of day, and day of week (Duvvuri et al., 2021; Jain and Pulugurtha, 2022). One-tailed paired *t*-tests were conducted to analyze if truck performance metrics are significantly less than those of passenger vehicles. The null and alternative hypotheses are:

- H_0: truck metric – passenger vehicle metric ≤ 0.
- H_a: truck metric – passenger vehicle metric > 0.

The *t*-tests were performed using data for all the interstates from 2019 to 2025, and Table 6 presents the results. Statewide, the median and 95th percentile travel times for trucks were significantly higher than those for passenger vehicles, indicating that trucks travel at slower average speeds than passenger vehicles. Figure 18 illustrates the TMC segments where the median truck speed is more than 10 mph lower than that of the passenger vehicles. They are predominantly in mountainous regions with rolling terrain. Except for the travel time reliability index for the evening peak period, the evidence is not enough to determine that the travel time reliability index (95th percentile/50th percentile) and LOTTR (80th percentile/50th percentile) for trucks are greater than those for passenger vehicles. Furthermore, the *p*-values close to 1 indicate the opposite direction is likely. This finding is probably due to the smaller difference between the 50th and 95th or 80th percentile travel times for trucks than for passenger vehicles. Because travel times vary by segment length at the same travel speed, speed percentiles were used to compare differences between truck and passenger vehicle traffic. Figure 19 shows the differences between the 5th percentile speed (corresponding to the 95th percentile travel time) and the 50th percentile speed (corresponding to the 50th percentile travel time) for trucks and passenger vehicles. The differences were frequently within 3 to 5 mph for trucks and 5 to 8 mph for passenger vehicles, likely resulting in a relatively smaller travel time reliability index for trucks. NCHRP Research Report 925 by Guerrero et al. (2019) suggested using statistical relationships between average and 95th percentile travel times to predict reliability changes resulting from improvement projects. Projects that reduce the differences between the 50th and 95th percentile truck travel times would positively affect TTTR.

Table 6. Results of One-Tailed Paired *t*-Test

Metrics	Average Difference	*t*-Statistic	*p*-Value	Average Difference	*t*-Statistic	*p*-Value
	Morning Peak			**Evening Peak**		
TTR Index	– 0.0134	– 5.9351	0.9999	0.0053	1.9015	0.0286**
LOTTR	– 0.0038	– 5.3937	0.9999	– 0.0028	– 1.8007	0.9641
Median travel time	4.2167	60.1892	0.0000*	4.0368	52.3093	0.0000*
95th percentile	4.0007	26.9253	0.0000*	4.6082	26.1655	0.0000*
	Midday			**Night**		
TTR Index	– 0.0151	– 6.2455	0.9999	– 0.0150	– 10.4855	1.0000
LOTTR	– 0.0071	– 9.1466	1.0000	– 0.0064	– 28.3572	1.0000
Median travel time	4.0810	55.9075	0.0000*	3.9500	58.6835	0.0000*
95th percentile	3.4019	18.6888	0.0000*	3.2175	30.0868	0.0000*
	Weekend					
TTR Index	0.0155	7.6579	0.0000			
LOTTR	0.0063	7.8296	0.0000			
Median travel time	4.8778	59.3155	0.0000			
95th percentile	6.3399	37.7770	0.0000*			

LOTTR = level of travel time reliability; TTR = travel time reliability. *Significant at 0.01 level; **Significant at 0.05 level.

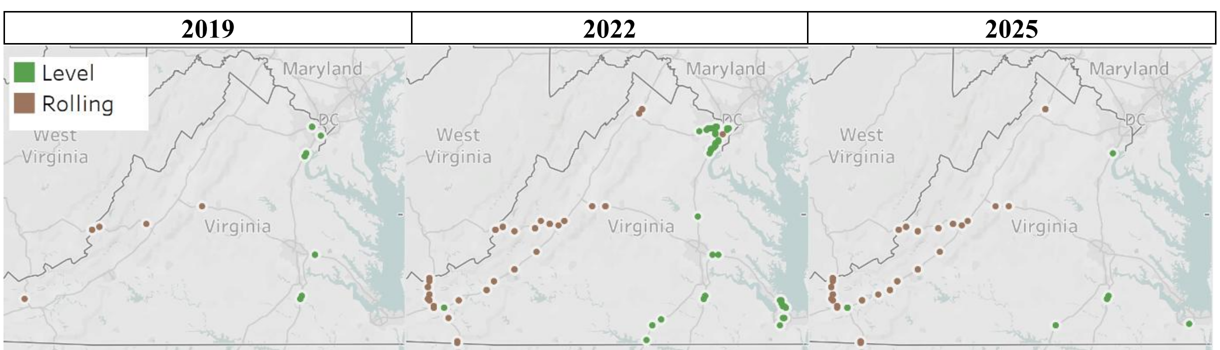
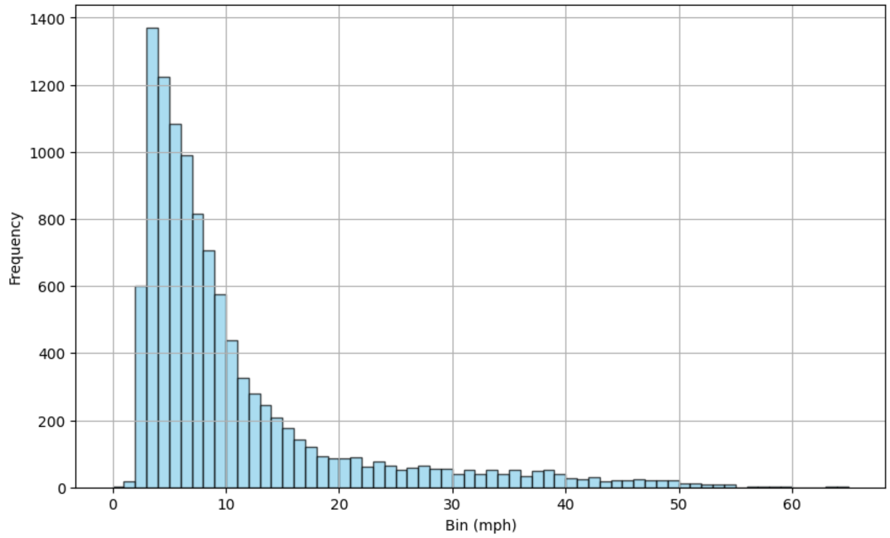
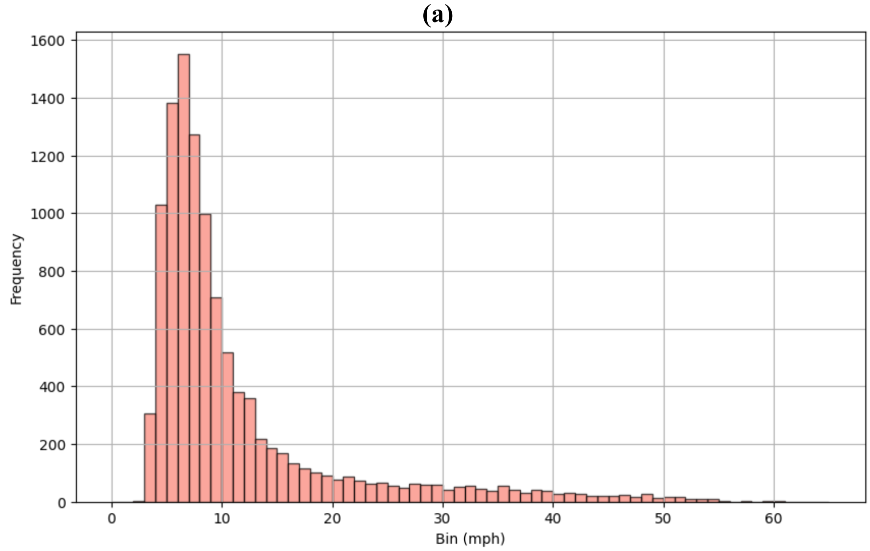


Figure 18. Locations Where Truck Median Speed and Passenger Vehicle Median Speed > 10 mph



(a)



(b)

Figure 19. Distribution of Differences Between the 5th and 50th Percentile Speeds for (a) Trucks and (b) Passenger Vehicles

During the evening peak period, when traffic is congested for all types of flows, especially during stop-and-go traffic, trucks are less adaptable to the more dynamic traffic conditions. This inadaptability is mainly attributed to their operational characteristics, such as slower acceleration and deceleration, requiring larger gaps for lane maneuvers, and being less likely to use the left lane. Consequently, trucks experience greater variability in travel times during this period.

During the course of the 7 study years, 96 occurrences were observed in which the truck TTR index was more than twice that of passenger vehicles on the same segment. These locations, shown in Figure 20, are on urban interstates, in mountainous areas, or at tunnel entrances. For these instances, the difference between the 5th and 50th percentile truck speeds ranges from 22 to 55 mph. About 38% of these instances took place during weekend hours, but many of these locations are known for heavy congestion on weekends, including I-95 between north of Richmond and Fredericksburg, as well as I-664 and I-64 near the tunnels in Hampton Roads. Nearly 80% of these instances were observed in 2022, which was the transition year between two distinct traffic patterns and a year that experienced more variability (Table 7). In addition, this variability may also be related to changes in the composition of the NPMRDS source data because of a data provider interruption during that year.

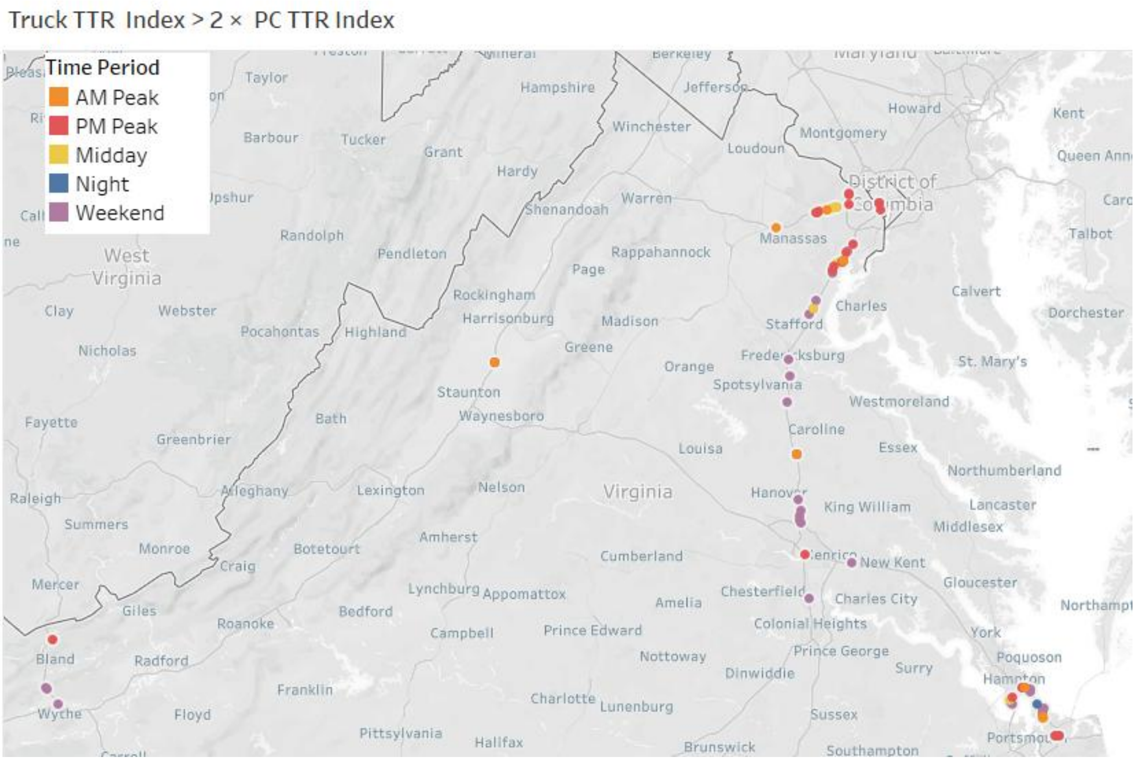


Figure 20. Locations with Large Differences Between Truck and Passenger Vehicle Travel Time Reliability Index. PC = passenger car; TTR = travel time reliability.

Table 7. Count of Instances with Large Differences Between Truck and Passenger Vehicle Trave Time Reliability Indexes

	AM Peak	PM Peak	Midday	Night	Weekend
2019	2	5	5	2	4
2020	0	0	0	0	0
2021	0	0	0	1	0
2022	5	23	12	3	33
2023	0	0	0	0	0
2024	2	0	1	0	0
2025	0	0	0	0	0

Figure 21 compares LOTTR calculated using truck and passenger vehicle travel times separately. Based on the trendlines in Figure 21, passenger vehicle LOTTR is likely slightly less than truck LOTTR in 2019, nearly identical in 2020, and then increasingly higher from 2021 to 2025. This trend reflects the major shifts in travel patterns, freight operations, and traffic conditions before, during, and after the COVID-19 pandemic. In 2019, peak commute-hour congestion resulted in unreliability for passenger vehicles, whereas truck travel times remained relatively stable. In 2020, the statewide reduction in traffic volumes and the collapse of peak-period traffic made both modes similarly reliable. After 2021, passenger vehicle reliability degraded more than truck reliability. Truck traffic was less affected by the pandemic than passenger vehicle travel, experiencing smaller reductions in volume. In addition, truck trips are often scheduled to avoid peak period congestion, during which idling carries a cost for shippers. Therefore, truck traffic patterns differ from passenger vehicle patterns and respond differently to disruptions. In addition, the major VDOT interstate improvement projects in the past several years, especially those designed to improve TTTR, like the I-81 Corridor Improvement Program, could benefit TTTR more than passenger traffic.

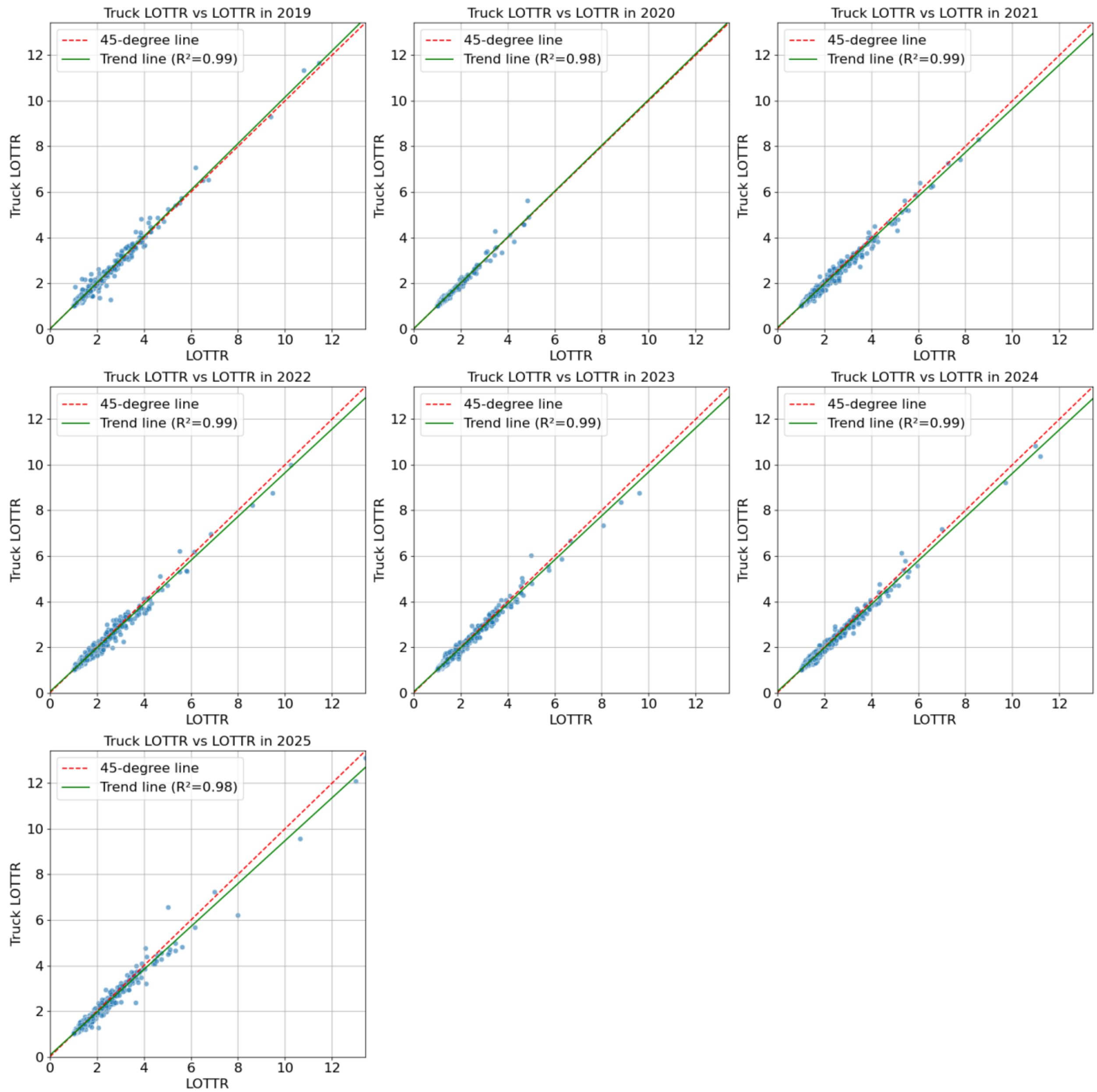


Figure 21. Comparison of LOTTR Calculated Using Respective Truck and Passenger Vehicle Data. LOTTR = level of travel time reliability.

It should be noted that the NPMRDS source data composition can affect the trends described in this section. As previously discussed, the availability of NPMRDS travel time data has been increasing since 2021, with data completeness in and after 2023 being significantly higher than in previous years. The primary source of the probe samples was commercial truck fleets. With the increased adoption of truck telematics technologies, the volume of truck probe samples has increased, resulting in a more representative and less noisy dataset for truck travel times and, therefore, increased consistency of the 80th percentile truck travel times.

Locations with Unreliable Truck Travel Times

TMC segments with a TTTR index greater than 10 in any time period were identified to study the location of highly unreliable conditions. TTTR equal to 10 means that the 95th percentile is 10 times the normal travel time, representing extremely poor conditions. These segments are all on urban interstates with posted speed limits of 55 or 60 mph. The median speeds at most of these locations are slightly below the posted speed limit but relatively stable across the years. Figure 22 shows the truck speed cumulative distribution functions for the highly unreliable segments in 2024 and 2025. The highly unreliable segments were more in 2024 compared with all other years. In this year, three segments with a posted speed limit of 55 experienced higher 10th to 50th percentile speeds than those with a posted speed limit of 60, indicating shorter median and 80th percentile travel times. This observation is significantly different from all other years. The curves' rise near 0 (1st–5th percentile) is slower in 2025, indicating fewer low-speed and longer travel time samples compared with 2024.

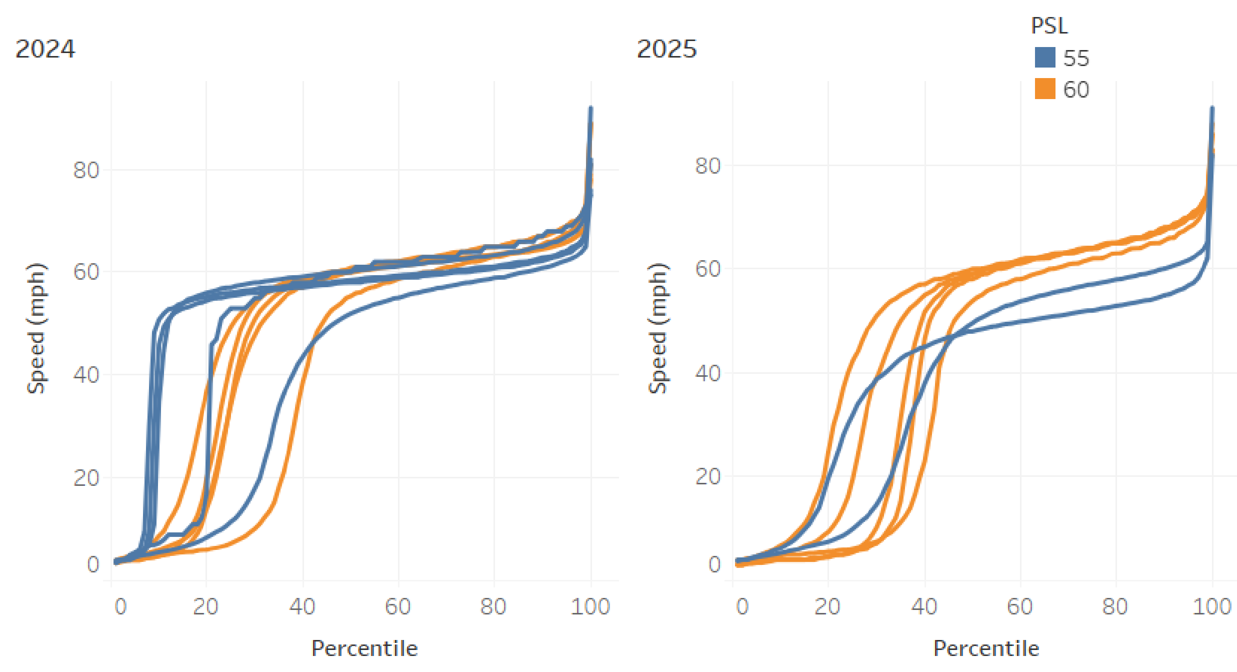


Figure 22. Cumulative Distribution Functions for Highly Unreliable Segments. PSL = posted speed limit.

Throughout the 7 study years, the following three locations were consistently at the top of the list of most unreliable segments:

- I-664 East in Newport News between Exits 6 and 5, about 0.5 mile upstream of Monitor Merrimac Bridge Tunnel (Figure 23).

* I-495 North in Northern Virginia between Exit 47 (VA-3) and Exit 45 (VA-267), about 3 miles upstream of the American Legion Memorial Bridge (Figure 24).
* I-395 North in Northern Virginia between Exits 8 and 10, about 0.5 mile upstream of George Mason Memorial Bridge (Figure 25).

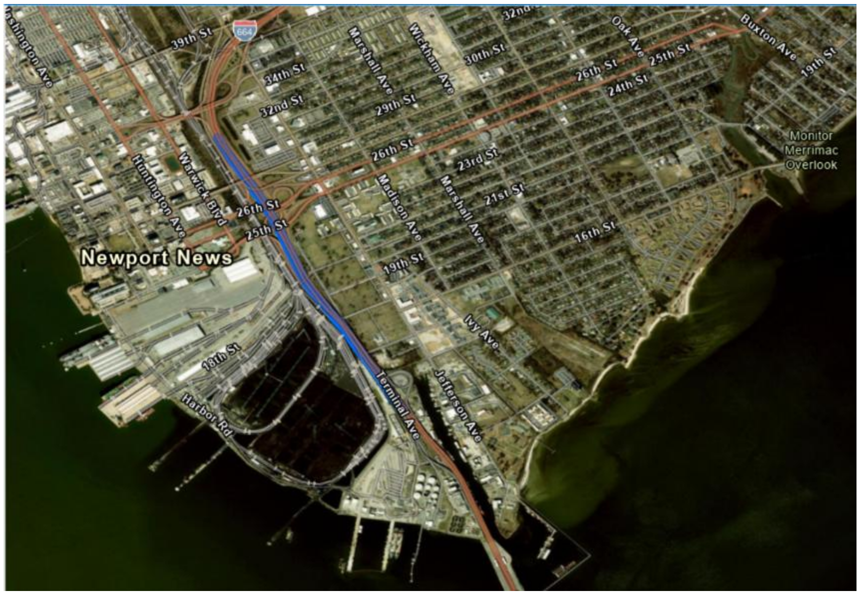


Figure 23. Highly Unreliable Segments on I-664 East

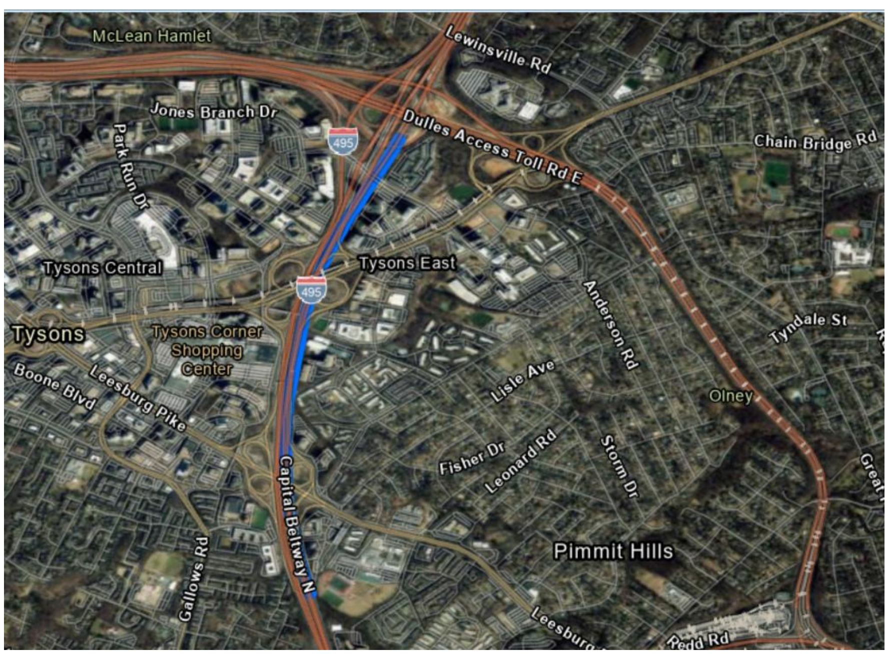


Figure 24. Highly Unreliable Segments on I-495 North

Figure 25. Highly Unreliable Segments on I-395 North

The segments on I-664 East, especially the two TMCs between the 26th Street and 35th Street exits, had the highest TTTR indexes during the years. Table 8 lists the TTTR metrics for these segments. This location has an AADT of 30,000, with 6% trucks on average and posted speed limit of 60 mph. Although the truck travel time data availability was high, the percentage of density A data was also higher. Segment 110-04737 was only 0.08 miles long, and more fluctuations could occur in probe speeds than in the longer segments. Based on LOTTR, this location was unreliable for all flow types. The highest TTTR index of 17.20 was observed on segment 110N04738 during the evening peak period of 2025.

Table 8. Travel Time Reliability Metrics and Data Availability for I-664 East Segments

TMC Code	Year	Period	Maximum TTTR	LOTTR	% Time with Data	% Imputed Data	% Density A Data	Length
110-04737	2019	PM Peak	16.32	11.43	96.60	23.00	88.72	0.08
	2020	PM Peak	6.92	1.08	97.07	20.37	86.21	0.08
	2021	PM Peak	14.95	8.56	98.40	12.05	67.29	0.08
	2022	PM Peak	15.01	10.26	98.61	16.67	69.43	0.08
	2023	PM Peak	15.01	9.60	95.84	12.34	92.90	0.08
	2024	Midday	14.98	4.70	98.47	1.97	58.53	0.08
	2025	PM Peak	15.47	13.00	96.79	14.82	92.16	0.08
110N04738	2019	PM Peak	16.55	10.79	97.51	19.62	86.62	0.22
	2020	PM Peak	5.42	1.07	97.40	19.50	85.30	0.22
	2021	PM Peak	15.00	7.78	98.66	10.90	65.24	0.22
	2022	PM Peak	15.12	9.46	98.75	14.92	67.70	0.22
	2023	PM Peak	15.10	8.07	96.27	11.34	92.88	0.22
	2024	Midday	15.12	3.44	98.87	1.75	56.67	0.22
	2025	PM Peak	**17.20**	13.42	97.10	13.19	91.12	0.22

LOTTR = level of travel time reliability; TMC = Traffic Message Channel; TTTR = truck travel time reliability.

The median travel speeds on segment 110N04738 have remained consistent during the analysis years. Thus, the extreme TTTR index observed in 2025 was attributed to the extremely high 95th percentile travel time. A review of all 15-minute intervals with travel times close to the 95th percentile (5th percentile speed = 3.43 mph) found that no incidents or adverse weather conditions occurred during these intervals on this segment. However, tunnel stoppage events were observed downstream of this segment. It is likely that congestion from the Monitor Merrimac Bridge Tunnel contributed to the significantly high travel times. The propagation of uncertainty presents a challenge in modeling travel time reliability. Existing studies use complex link cost functions and route choice models to assess the effect of an incident source on adjacent links and the network. These methods are often computationally demanding and not designed to simultaneously analyze a large number of events in a statewide network.

The I-495 and I-395 sites are also unreliable for both truck and passenger traffic. These three most unreliable locations share several common characteristics that contribute to consistently poor TTTR. All sites are on urban interstates and experience heavy traffic throughout the day, especially during peak periods. These locations also have high crash frequencies for both trucks and passenger vehicles, which increase the likelihood of severe incidents that disrupt traffic flow and create unpredictable delays. In addition, all three locations have multiple complicated interchanges within a short range, resulting in frequent merging and weaving movements and shockwaves into the traffic stream. Their proximity to major capacity-limited facilities, such as bridges and tunnels, further limits operational flexibility and slows recovery from congestion or incidents. Together, these conditions create traffic conditions in which even minor disruptions can propagate quickly, leading to substantial variability in travel times. Because of their unique operating characteristics, it is challenging for trucks to maintain speed after slowdowns and merge and change lanes efficiently at these locations, which significantly reduces TTTR.

Development of Models to Analyze and Predict Truck Travel Time Reliability

A hierarchical Bayesian model and an RF model were developed to analyze and predict the TTTR index. The dataset used included 10 variables for 1,743 TMC segments. Table 9 provides the variables and summary statistics.

Table 9. Summary Statistics

Variable	Mean	Minimum	Maximum
Segment length (miles)	1.25	0.01	9.04
Number of lanes	2.6	1	6
Posted speed limit (mph)	62.5	55	70
Traffic volume (vehicles/hour)	1975	65	9524
Trucks (%)	13.38	0.01	39.31
Weather impact risk (× 100)	0.06	0	0.97
Terrain (1 = Level, 0 = Rolling)	0.71	0	1
Segment type (1 = Mainline, 0 = Interchange area)	0.51	0	1
Crash frequency (per 100 hour-miles)	0.20	0.00	15.67
TTTR Index (Ratio of 95th percentile to 50th percentile truck travel time)	1.34	1.01	17.20

TTTR = truck travel time reliability.

Bayesian Analysis and Results

The Bayesian results are based on analyses of 4,000 posterior samples of each model parameter obtained using the *PyMC* Python^{TM} library.

Factors Affecting Truck Travel Time Reliability

Table 10 summarizes the posterior means and 95% credible intervals for the segment-level covariates. These estimates provide useful insights into factors influencing TTTR. In particular, the results suggest that higher traffic volumes and crash frequencies increase variability, and segments with more lanes and segments with higher speed limits tend to be more reliable. Other variables studied in this research—truck percentage, terrain, weather, and segment type—had relative contributions to the TTTR prediction totaling less than 2.5% and were not used in the final model.

Table 10. Posterior Means of Model Covariates

Covariate	Posterior Mean	95% Credible Interval	Interpretation
Log (Traffic Volume)	0.049	[0.039, 0.059]	1 SD increase increases TTTR by 5.0%
Number of Lanes	– 0.057	[– 0.068, – 0.046]	Additional lane reduces variability
Segment Length	– 0.005	[– 0.012, 0.003]	Very small negative effect
Speed Limit	– 0.044	[– 0.058, – 0.031]	1 SD increase reduces TTTR by 4.3%
Crash Frequency	0.034	[0.032, 0.037]	1 SD increase increases TTTR by 3.5%

SD = standard deviation; TTTR = truck travel time reliability.

Corridor-Level Trends

The corridor-level analysis quantified the temporal evolution of TTTR across corridors. Table 11 summarizes the average baseline and average shifts in TTTR growth due to the 2020 and 2022 structural breaks across all study corridors. The results show that the 2020 break caused sharp increases in TTTR, indicating heightened variability, whereas the 2022 break reflects a general trend reversal.

Table 11. Posterior Means and Credible Intervals of Slope Components

	Baseline	2020 Shift	2022 Shift
AM Peak	– 0.041 [– 0.054, – 0.03]	0.045 [0.031, 0.057]	0.007 [– 0.005, 0.019]
Midday	– 0.043 [– 0.053, – 0.032]	0.069 [0.053, 0.085]	– 0.026 [– 0.042, – 0.008]
PM Peak	– 0.066 [– 0.078, – 0.054]	0.092 [0.074, 0.109]	– 0.024 [– 0.039, – 0.009]
Weekend	– 0.052 [– 0.062, – 0.041]	0.086 [0.071, 0.102]	– 0.037 [– 0.051, – 0.024]
Night	– 0.064 [– 0.073, – 0.055]	0.093 [0.081, 0.105]	– 0.031 [– 0.041, – 0.021]

Deterioration probabilities, $P(\beta > 0)$, were calculated for every corridor and every period at each breakpoint, which Figure 26 shows as a risk map across all 225 corridors. The plot shows vertical red stripes across all five time periods for the "2020 shift," suggesting that after 2020, a systemic, statewide increase was observed in unreliability compared with the 2019–2020 period, with the effects more pronounced for the overnight and weekend periods. The "2022 Shift" columns also have several red cells, denoting post-pandemic warning flags where reliability was actively worsening.

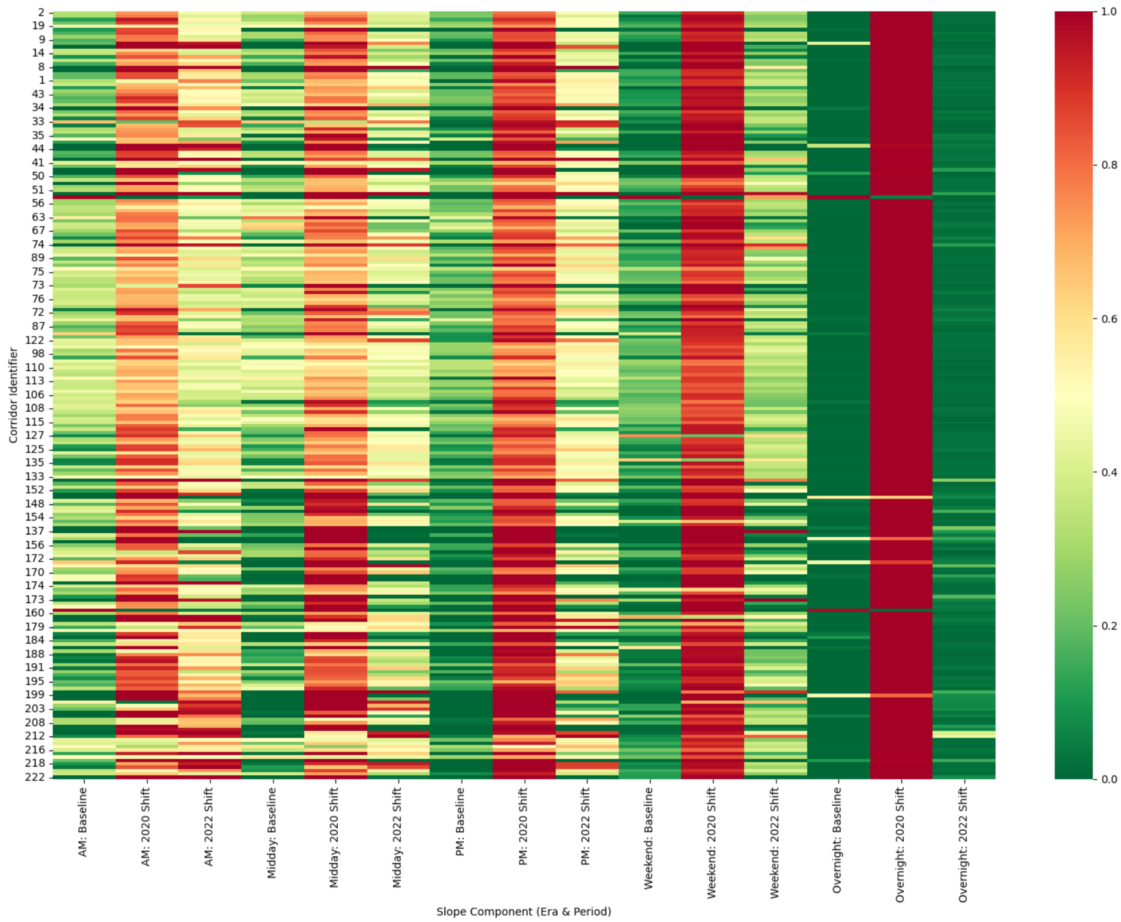


Figure 26. Truck Travel Time Reliability Deterioration Risk Map

A transition matrix was calculated to demonstrate the overall network shift by counting how many corridors moved from a "stable/improving" state ($P < 0.90$) in the pre-pandemic baseline to a "deteriorating" state ($P \geq 0.90$) in the "current" 2022–2024 era. Because the study included five time periods, a corridor was defined as deteriorating if any of its five periods met the $P(Slope > 0) \geq 0.90$ threshold for that era. Table 12 summarizes the results.

Table 12. Summary of Reliability Shifts Pre-2020 and Post-2022

	Stable: Now	**Deteriorating: Now**
Stable: 2019	175	48
Deteriorating: 2019	2	0

The results show that most corridors (175 out of 225) that were stable before 2020 remain stable. However, 48 corridors that were reliable before 2020 have now tipped into high-confidence unreliability, with the morning peak and midday periods showing the greatest systemic decrease in TTTR. Table 13 summarizes a list of the top 20 corridors with the highest risks based on their current (2022–2024) growth trajectories. These corridors are potential candidates for further investigation. Note that the transition counts are based on a threshold probability of 0.90 and may change if a different threshold were used.

Table 13. Top 20 High-Risk Corridors Based on 2022–2024 Growth Trajectories

Corridor	Primary Period of Risk	Annual Growth Rate
R-VA IS00564SB_NORFOLK (CITY)_U	Midday	13.5%
R-VA IS00066WB_ARLINGTON_U	Midday	9.4%
R-VA IS00095SB_SPOTSYLVANIA_R	Weekend	7.5%
R-VA IS00095SB_HANOVER_U	Midday	7.3%
R-VA IS00395NB_FAIRFAX_U	Midday	7.1%
R-VA IS00664WB_HAMPTON (CITY)_U	AM Peak	6.9%
R-VA IS00064EB_GOOCHLAND_U	Midday	6.1%
R-VA IS00064EB_NEWPORT NEWS (CITY)_U	Midday	5.7%
R-VA IS00095SB_CAROLINE_R	Weekend	5.6%
R-VA IS00095NB_CAROLINE_R	AM Peak	5.5%
R-VA IS00195NB_HENRICO_U	AM Peak	4.1%
R-VA IS00095SB_CHESTERFIELD_U	AM Peak	3.6%
R-VA IS00664EB_NEWPORT NEWS (CITY)_U	AM Peak	2.2%
R-VA IS00064WB_AUGUSTA_U	AM Peak	2.2%
R-VA IS00095NB_HENRICO_U	AM Peak	3.3%
R-VA IS00395SB_ALEXANDRIA (CITY)_U	Midday	3.2%
R-VA IS00664EB_CHESAPEAKE (CITY)_U	AM Peak	2.6%
R-VA IS00495NB_FAIRFAX_U	Weekend	1.6%
R-VA IS00395SB_ARLINGTON_U	Midday	5.7%
R-VA IS00664WB_CHESAPEAKE (CITY)_U	AM Peak	3.5%

R = rural; U = urban.

Segment-Level Forecasts

The model was trained on 2019 to 2024 data and used to forecast the 2025 TTTR index. The forecasts include credible intervals for uncertainty quantification and are essential for effective operational planning and corridor management. Table 14 provides a summary of median TTTR index forecasts and credible intervals for select segments.

Table 14. Median Truck Travel Time Reliability Index Forecasts for Select Segments

Segment	Corridor	Period	Median	5th Percentile	95th Percentile
110N04707	R-VA IS00264WB_VIRGINIA BEACH (CITY)_U	PM Peak	1.39	1.11	1.73
110+04612	R-VA IS00495NB_FAIRFAX_U	Midday	3.35	2.69	4.22
110N04168	R-VA IS00066EB_ARLINGTON_U	Midday	1.67	1.33	2.08
110P04734	R-VA IS00664WB_SUFFOLK (CITY)_U	Weekend	1.48	1.15	1.89
110P04157	R-VA IS00095NB_FAIRFAX_U	Weekend	1.54	1.23	1.93
110-04127	R-VA IS00395SB_ARLINGTON_U	Weekend	1.32	1.05	1.66
110P04879	R-VA IS00064WB_HAMPTON (CITY)_U	Night	1.25	1.02	1.53
110+04926	R-VA IS00095NB_SPOTSYLVANIA_U	PM Peak	1.36	1.03	1.79
110P04817	R-VA IS00095NB_RICHMOND (CITY)_U	Night	1.67	1.35	2.04
110+04913	R-VA IS00464NB_CHESAPEAKE (CITY)_U	Night	1.15	1.00	1.43

R = rural; U = urban.

Network-Level Forecast

The posterior forecasts from the segment-level were aggregated to produce the distribution of the network TTTR index for 2025 (Figure 27). The predicted TTTR index is

1.463, with a 95% credible interval (1.456, 1.494). For planning purposes, a distribution of forecasts is desirable because it quantifies uncertainty, providing a range of potential outcomes and their probabilities, rather than a single number.

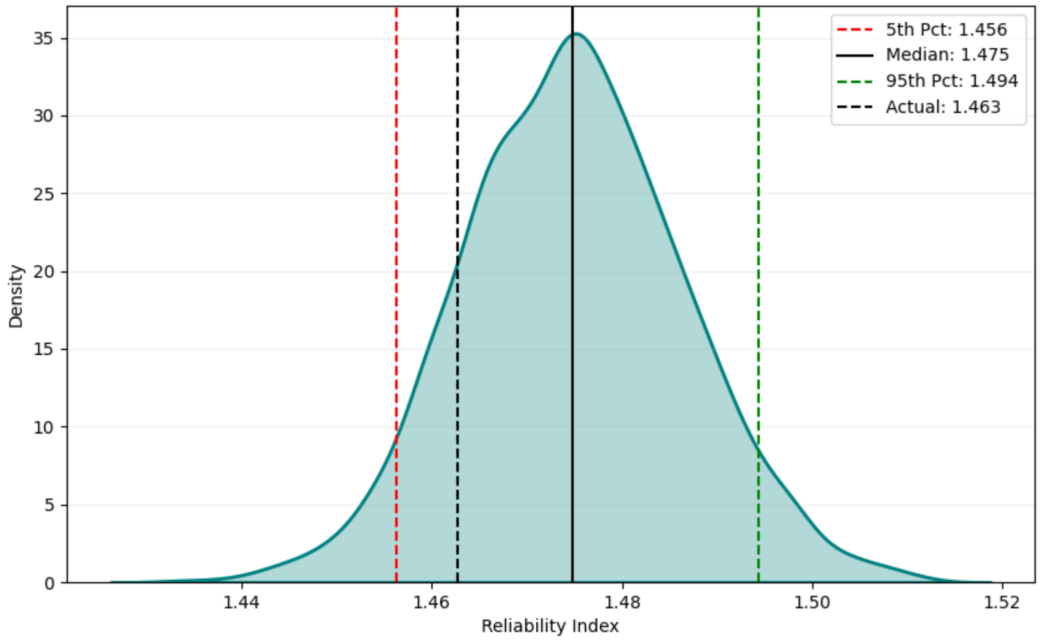


Figure 27. Posterior Predictive Distribution of Truck Travel Time Reliability Index. Pct = percentile.

Model Evaluation

Table 15 summarizes the model evaluation results. Performance was better on the training data than on the test data, which was expected. Nevertheless, the error metrics remain within an acceptable range for the test data. The credible interval coverage of 85.1% compared with the target of 90% suggests the model is relatively well calibrated. Overall, the model retains predictive utility on unseen data. Although the *R*-squared dropped noticeably, the error rates (MAPE = 10.8%) and credible interval coverage remain within operationally acceptable limits.

Table 15. Prediction Performance of Bayesian Model

Metric	Training Data	Testing Data
Mean Absolute Error	0.119	0.206
Root Mean Squared Error	0.348	0.549
R-Squared	0.818	0.584
Bias	– 0.031	– 0.045
Mean Absolute Percentage Error	6.3%	10.8%
90% Credible Interval Coverage Probability	89.7%	85.1%
90% Credible Interval Average Width	0.42	0.62

Random Forest Models

Five RF models were created, one for each study period. Variables in the RF models were selected based on prediction accuracy metrics and variable importance scores. Eight variables were used in the final models, including the encoded corridor variable, average 15-

minute volume, truck percentage, crash count, segment length, posted speed limit, the number of through lanes, and an indicator for an interchange segment. Unlike the Bayesian model, the RF models use crash count instead of crash frequency because it produced better results. This outcome is probably because the segment length is sufficient for RF to account for the uncertainty accumulation on segments with various lengths. In addition, the 15-minute volume (expressed as an hourly rate) was used directly rather than log-transformed as in the Bayesian model. Segment type (interchange or mainline) and truck percentage were not significant in the Bayesian model but were used in the RF model. The ablation experiments found that removing these two variables reduced prediction accuracy, although their variable importance scores were not the highest. Similar to the Bayesian model, the weather terrain indicators showed limited predictive power and were therefore not included in the final models. Also, adding non-crash lane-impacting incidents did not improve prediction accuracy during the ablation experiments, likely because crash events better capture changes in the 95th percentile truck travel times.

Table 16 shows the prediction accuracy for the testing data. The prediction error is lowest for nighttime and highest during the evening peak period, likely because of the relatively stable traffic conditions at night and the more variable conditions during the evening peak period. The average of the MAPEs of the five RF models is 8%.

Table 16. Random Forest Prediction Performance

	MAE	RMSE	MAPE	R^2
AM Model	0.1663	0.4504	8.09%	0.6552
PM Model	0.2361	0.6345	11.16%	0.7029
Midday Model	0.2097	0.5742	10.20%	0.7206
Weekend Model	0.1696	0.6220	8.29%	0.4197
Night Model	0.0561	0.1500	3.92%	0.3602

MAE = mean absolute error; MAPE = mean absolute percentage error; RMSE = root mean square error.

Figure 28 shows the variable importance scores for the evening peak and nighttime models. The GLMM encoded corridor variable dominates variable importance in all five RF models. The GLMM encoding process replaced each corridor category with an estimate of its effect on the target, that is, the cross effect of county and city, route, and urban or rural designation on the TTTR index, so the encoded variable directly reflects the expected TTTR index per category. RF models will assign high importance to a variable that already aligns strongly with the target. Traffic volume, truck percentage, segment length, and crash count are the variables with the strongest prediction power in all five RF models.

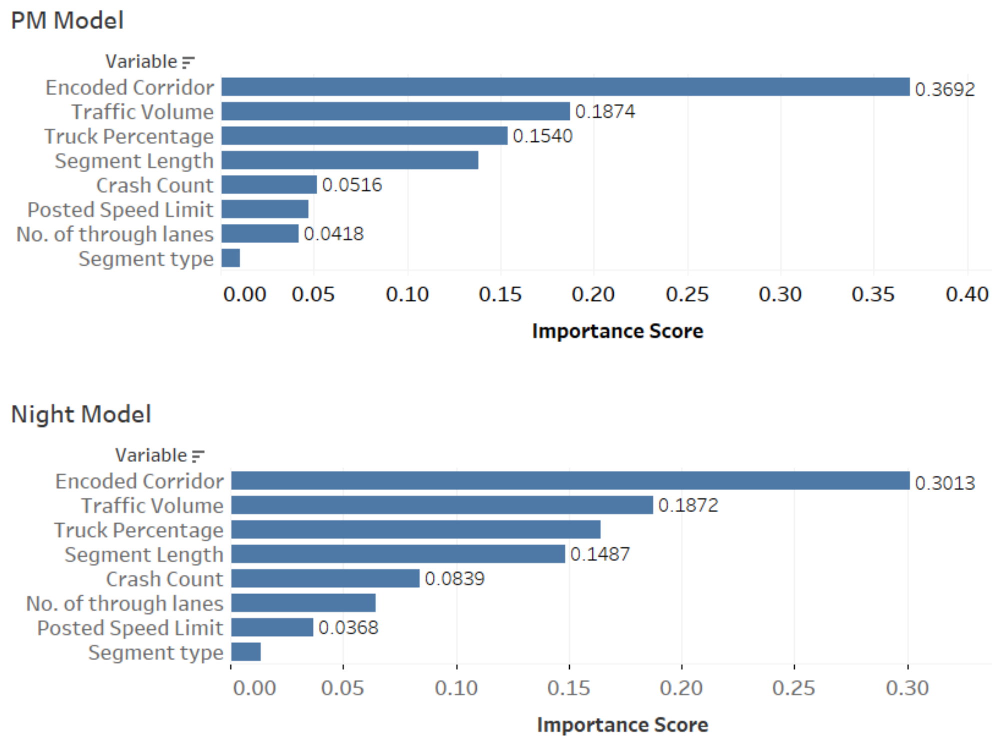


Figure 28. Random Forest Models Variable Importance Scores

Linear Trend Model

Linear trend models were fit for each TMC-analysis period combination (~1,743 × 5 = 8,715 models) using year as the independent variable. Table 17 summarizes the prediction errors and uncertainty metrics for both the training and test datasets. The results show that the linear trend model performs excellently on the training data (MAPE 2.0%, MAE 0.037, R-squared 0.975), but its performance degrades sharply on test data (MAPE and MAE each increase by ~290% and R-squared drops to 0.623), suggesting severe overfitting. The model also appears "over confident" in training (100% coverage), but coverage drops to 86.7% on test data. Although this percentage is still close to the 90% coverage target, the prediction window is wide (1.554 compared with a mean TTTR index of 1.34), likely making the predictions less useful for uncertainty quantification. The next section discusses the tradeoffs between the three models.

Table 17. Prediction Performance of Linear Trend Model

Metric	Training Data	Testing Data
Mean Absolute Error	0.037	0.145
Root Mean Squared Error	0.133	0.522
R-Squared	0.975	0.623
Bias	0.000	0.001
Mean Absolute Percentage Error	2.0%	7.8%
90% Credible Interval Coverage Probability	100%	86.7%
90% Credible Interval Average Width	1.096	1.554

Summary of Findings

Analyses of Unreliable Truck Travel Times

Descriptive and regression analyses were conducted to discover TTTR trends at state and route levels. A more in-depth analysis using a hierarchical Bayesian model was performed to characterize the pattern at the statewide, corridor, and segment levels and to quantify the factors influencing TTTR.

The descriptive and Bayesian analyses found that the COVID-19 pandemic disruptions led to a systemic, statewide increase in the unreliability of truck travel times, with the effects being more pronounced overnight and on weekends. TTTR generally degraded at the corridor, route, and statewide levels in 2021 compared with 2020 and slowly recovered after 2022.

TTTR on interstate routes in the Eastern and Northern regions fluctuated more widely across different routes during the years, and those in the Northwestern and Southwestern regions showed more consistency. Throughout the study period, statistically significant increases in TTTR index (decreased reliability) were observed on I-564 southbound in the Eastern region, I-295 and I-195 northbound in the Central region, I-95 northbound in the Northern region, I-77 southbound and I-81 southbound in the Southwestern region, and I-81 and I-64 eastbound in the Northwestern region. Increased reliability, as indicated by a reduction in TTTR index, was observed for several routes (e.g., I-66 eastbound in the Northern region where new express lanes were opened). However, the evidence is insufficient to confirm that the increased reliability is statistically significant. At the corridor level, 21% (48) of the 225 corridors studied experienced decreased TTTR during 2022 through 2024 compared with 2019, mostly during morning peak and weekend periods.

On rural interstates, the maximum TTTR index for a segment generally occurs at night, and these segments are the most reliable, with TTTR indexes of less than 1.5. For segments in urban areas with higher traffic volumes, the maximum TTTR index is more likely to occur during peak or midday periods. For unreliable segments with a maximum TTTR index greater than or equal to 2, the indexes were generally high in only one or two specific time periods rather than being consistently high across all periods.

TTTR can capture the unreliability in truck travel times at locations with consistent commuter traffic. During project planning and evaluation, it is important to analyze LOTTR for all traffic in conjunction with TTTR to ensure that the effect on truck flow is not neglected.

One-tailed paired *t*-tests using statewide data found that the 50th and 95th truck travel times were higher than those for passenger vehicles, but the travel time reliability index (95th/50th) was lower during the morning peak, night, and weekend periods. This result is probably attributed to the relatively smaller difference between the 50th and 95th percentile travel times for trucks, as observed in the data from 2019 to 2025. The findings regarding the travel time reliability index may not be applicable at the route or corridor level, because studies in the literature found that the consistency between travel time reliability metrics (e.g., 95th and

50th, planning time index, buffer time index, and LOTTR) calculated using passenger vehicle and truck data, respectively, varies by location, facility type, and time of day.

All the TTTR indexes greater than 10 were observed on urban interstates with posted speed limits of 55 or 60 mph and complex traffic dynamics. Most of these segments had unreliable passenger travel time as well, but several did not. This observation indicates that several locations were less challenging for passenger vehicles to navigate than for trucks. Congestion propagation from downstream was found to be one of the main causes of high unreliability, but a research gap exists in the literature regarding the integration of incident impact propagation into statewide travel time reliability analysis and prediction.

From both the Bayesian and RF models, traffic volume, crash frequency, the number of through lanes, and posted speed limit are the most significant factors affecting TTTR. Increased traffic volumes and crash frequencies contribute to lower reliability. Segments with more lanes (higher capacity) and those with higher posted speed limits tend to have higher reliability. With a few exceptions in 2022 and 2023, the historical pattern of crashes generally aligns with TTTR.

Since 2021, truck travel times have been available in more than 90% of the time on average for all interstate segments during peak and midday periods and reach nearly 100% after imputation with all traffic data. Truck data availability for night and weekend periods was slightly lower at 70% before imputation. It should be noted that, like all other probe datasets, the composition of probe samples in NPMRDS can affect the interpretation of historical trends. For example, the earlier data are relatively sparse and possibly biased toward segments with more samples. Later, as the probe sample increases over time, the data become denser and more representative, which can make it seem like the travel times are improving. The 50th and 95th percentile truck travel times are generally higher than those for passenger vehicles. The changes in sample vehicle type composition may make the general travel time reliability look better or worse artificially. This observation also highlights the need to analyze trucks and passenger vehicles separately.

Prediction of Truck Travel Time Reliability

Hierarchical Bayesian model and RF models were developed to predict the TTTR index, using linear trend models as a baseline. RF models were created separately for each study period to predict the TTTR index for each TMC segment. Extra steps are needed to identify the maximum TTTR index for each TMC and aggregate the values of all segments to calculate the statewide TTTR performance required by FHWA. The Bayesian model computed a posterior distribution that can account for the time-of-day effect. The model produced posterior forecasts of the TTTR index at the segment level and generated a posterior predictive distribution at the network level that represents the statewide TTTR measure.

Traffic volume and crashes were the most significant variables for both the RF and Bayesian models, but they were used in different forms. RF directly used volume and crash count, because RF is not sensitive to the scales of the variables. The Bayesian model, on the other hand, used the log-transformed volume and crash frequency. Terrain and weather variables were not significant in either model. Segment type and truck percentage were included in the RF models but not in the Bayesian model. Segment type had the lowest importance score among all RF variables, but truck percentage was of higher importance.

The RF models achieved the best prediction accuracy for the night period, with an MAPE of 3.92%, and the worst accuracy for the evening peak period, with an MAPE of 11.16%. The average of all five models was 8.3%, which is comparable with the 10.2% of the Bayesian model. However, the Bayesian model has significant advantages in producing a distribution of segment- and network-level TTTR forecasts rather than point estimates. The distribution and credible intervals of the predicted network-level TTTR index provide a range of potential outcomes and their probabilities that can help planners better address uncertainties during target setting.

The Bayesian model also shows significantly better generalization and calibration when compared with the baseline linear trend models. Although the linear model achieved an impressive training R-squared of 0.975 and a low MAPE of 2.0%, these metrics degraded sharply on the test set (MAPE increased by 290%), signaling severe overfitting. In contrast, the Bayesian model maintained a more stable performance profile between training and test sets, suggesting it captured the underlying data patterns rather than "memorizing" training noise. Although it had a higher MAPE on the test data, its behavior is more predictable and reliable for unseen data. Furthermore, the Bayesian model demonstrates greater predictive efficiency than the baseline, regarding uncertainty. It achieved a 90% interval coverage of 85.1% on the test data using an interval width of 0.616, whereas the baseline required a much wider, less precise interval of 1.554 to achieve a similar coverage of 86.7%. The Bayesian model's ability to provide tighter, well-calibrated prediction windows makes it a more attractive model for decision-making than the high-variance nature of the baseline model.

In addition to PM3 truck travel time performance target setting, the Bayesian and RF models developed in this study can be applied in performance-based project screening to estimate the TTTR benefit from planned projects. However, case studies are needed to evaluate the sensitivity and adaptability of these models for different types of interstate improvement projects. In addition, as OIPI and VDOT's TMPD and Traffic Operations Division increasingly use the more granular INRIX XD (eXtreme Definition) instead of TMC data for interstate performance analysis, further research is needed, when truck travel time is available on the XD network, to study the prediction performance of the Bayesian and RF methods for much shorter (0.1 mile long in general) XD segments and a much larger network in terms of the number of segments.

CONCLUSIONS

- *NPMRDS truck travel times have decent coverage on interstates in Virginia, with data available for more than 90% of the time during peak and midday periods on average*. After imputation with all-vehicle travel time data, the availability reached nearly 100% during these periods. For night and weekend periods, truck data availability was slightly lower at 70% before imputation.

- *The disruption caused by the COVID-19 pandemic led to a systemic, statewide increase in unreliability of truck travel times*. Approximately 21% of interstate corridors that were stable before 2020 now show clear signs of worsening TTTR. The degree of degradation varies by route and corridor. Interstates in the Northern and Eastern regions of Virginia displayed the most volatility, whereas the Western regions remain more stable.

- *Unreliable truck travel times generally occurred in one or two specific times of day for a given segment, rather than constantly present across all times of day*. On most of the TMC segments with a maximum TTTR index greater than or equal to 2, the high indexes (low reliability) were observed in only one or two of the five analysis periods.

- *Highly unreliable truck travel times were exclusively observed on high-volume urban interstates with posted speed limits of 55 or 60 mph and complex traffic dynamics*. The instances with the TTTR index greater than 10 observed during the study years were all on urban interstates with heavy traffic throughout the day and high crash frequencies. These locations have heavy traffic, frequent crashes, and downstream constraints, which amplify delays. They also feature complex roadway geometry and frequent merging and weaving movements that are more challenging for trucks to navigate.

- *Across all analyses, the factors most strongly associated with decreased TTTR were high traffic volumes and crash frequency; more travel lanes and higher posted speed limits were associated with more reliable truck travel times*. Traffic volume and crashes showed the strongest prediction power for both the Bayesian and RF models, followed by the number of through lanes and posted speed limit. Other variables studied, such as terrain and weather risk, had relatively low contributions to the TTTR prediction.

- *The hierarchical Bayesian model and RF models achieved comparable accuracy in predicting the TTTR index, but the Bayesian model provides a credible interval to help planners better account for the uncertainty in setting performance targets*. The RF models predicted the TTTR index for each TMC, and the prediction accuracy varied by analysis period, with the best MAPE accuracy of 3.92%. The average of the five RF models was 8.3%, which was close to the Bayesian model's MAPE of 10.2%. The Bayesian model provides predictions for individual segments and the statewide network, along with the distribution of predictions. The Bayesian model also demonstrates significantly more robust generalization and calibration compared with the baseline linear trend models.

RECOMMENDATION

1. *VDOT's Traffic Operations Division (TOD) should adopt the Bayesian model to support PM3 truck travel time reliability activities*. TOD should use the results from this study to supplement the current method, based on time-series estimation and project benefit scores, to set performance targets and communicate progress toward the targets. Where applicable, the findings may be used to identify locations for TTTR improvement and performance-based project planning.

IMPLEMENTATION AND BENEFITS

The researcher and the technical review panel (listed in the Acknowledgments) for the project collaborate to craft a plan to implement the study recommendations and determine the benefits of doing so. This process is to ensure that the implementation plan is developed and approved with the participation and support of those involved with VDOT operations. The implementation plan and the accompanying benefits are provided here.

Implementation

Regarding Recommendation 1, within 2 years of the publication of this report, TOD will apply the findings from this study to develop truck travel time reliability performance targets for the 2026 -2029 performance cycle. The findings will be used to establish 2- and 4-year TTTR targets for the PM3 Performance Report or to assess the need for an adjustment to the 4-year target for the Mid Performance Period Progress Report.

In support of implementation, by July 1, 2026, VTRC will develop predictions for 2- and 4-year TTTR targets and provide prediction results and code script to the VDOT MAP-21 Team. VTRC will provide technical assistance as needed to support target setting and will organize a meeting with the Assistant Division Administrator for Operations Planning and Performance or their designee to discuss the assistance needed to implement this study's findings.

Benefits

Implementing the Recommendation will help VDOT set more reasonable TTTR targets and track the progress toward that achievement. This process will reduce the risk of missing targets and prevent additional time and manpower VDOT would otherwise need to identify and document the actions necessary to achieve the targets.

In addition, accurate prediction of TTTR can capture the expected changes in TTTR more precisely and thus help identify and prioritize sites with high potential for TTTR improvements and quantify the project benefit better. NCHRP Research Report 925 recommended monetizing reliability improvements alongside other project benefits (Guerrero et al., 2019). A case study on a hypothetical improvement project presented in that report showed that incorporating TTTR in project evaluation nearly doubled the estimated benefits for freight users, highlighting the importance of including TTTR in planning.

Using a 1.4-mile-long segment (110+04683) on I-81 North between Exits 313 and 315 near Winchester as an example:

- TTTR index = 2.00 for the evening period in 2025, that is, 95th percentile travel time is twice the normal travel time.
- 50th percentile truck travel time = 0.0216 hour.
- Average truck volume during the evening peak = 528 trucks.

Based on the estimation method and the value of TTTR of $159.90 per truck-hour suggested in NCHRP Research Report 925 (Guerrero et al., 2019), the TTTR cost on this segment during all evening peak hours in 2025 would be:

- (TTTR index – 1) × 50th percentile truck travel time × hourly truck volume × value of TTTR per truck-hour × number of hours in the evening peak period × number of weekdays per year.

- = (2 – 1) × 0.0216 hour × 528 trucks × $159.90 per truck-hour × 4 hour/period × 260 weekdays/year = $1,890,925/year.

A 10 to 25% error in the prediction of the TTTR index will translate to an overestimate or underestimate of TTTR cost in a range between $384,962 and $953,934 for all evening peak hours in 2025.

In addition, LOTTR for this segment during the same period was 1.09, which is considered reliable in terms of the NHS performance metric for general traffic. If only the LOTTR but not the TTTR index were used as a reliability measure for investment screening, this site would be overlooked. However, because freight carriers value reliability more than the savings in normal travel time (Guerrero et al., 2019), this site could incur high costs for truck flow.

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APPENDIX

District Level Analysis Results

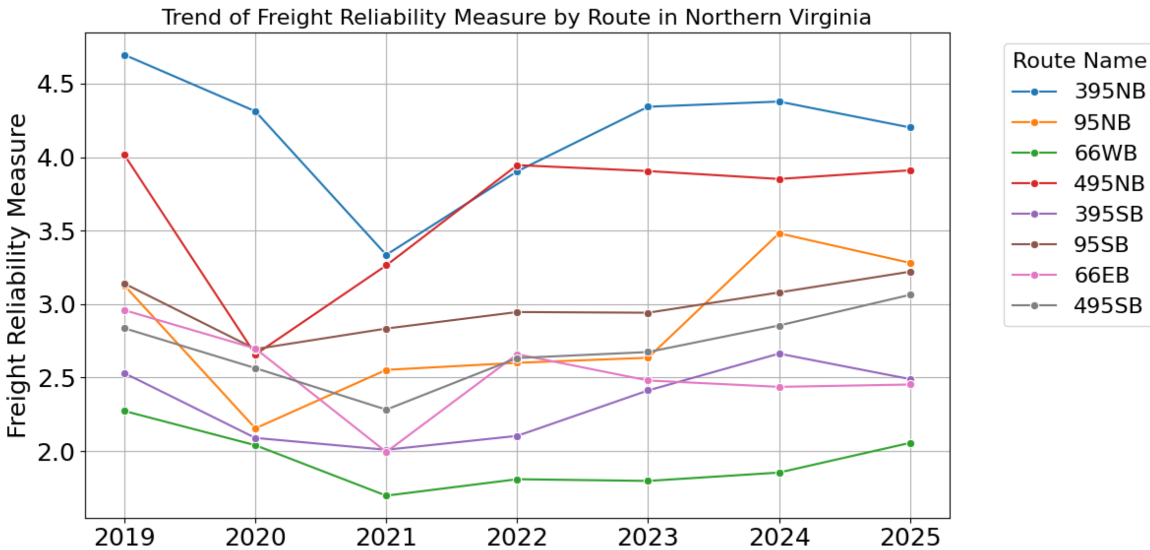

Figure A1. Truck Travel Time Reliability Measure in the Northern Virginia District

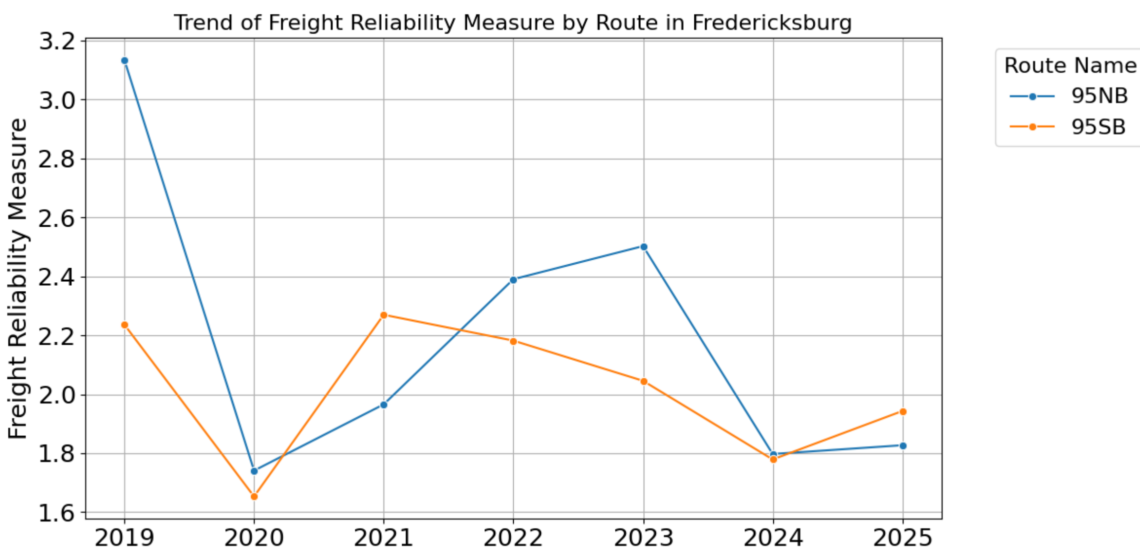

Figure A2. Truck Travel Time Reliability Measure in the Fredericksburg District

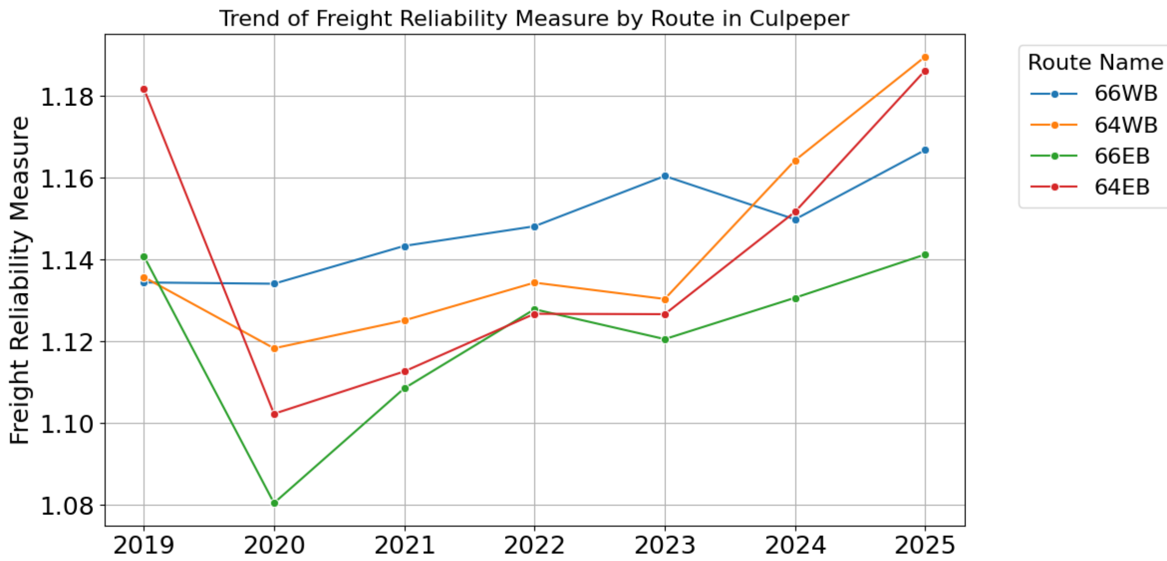

Figure A3. Truck Travel Time Reliability Measure in the Culpeper District

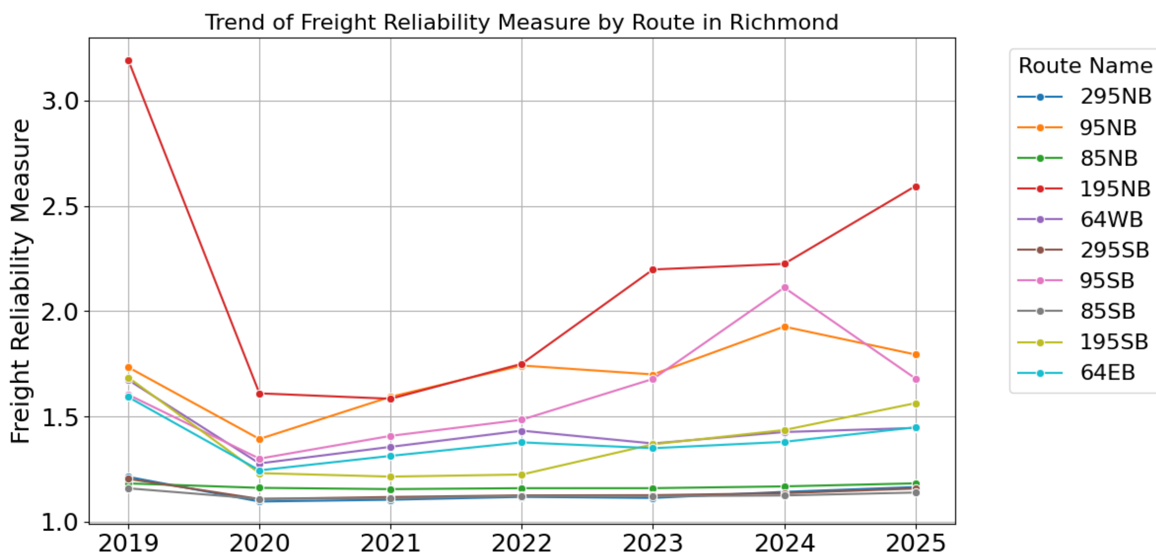

Figure A4. Truck Travel Time Reliability Measure in the Richmond District

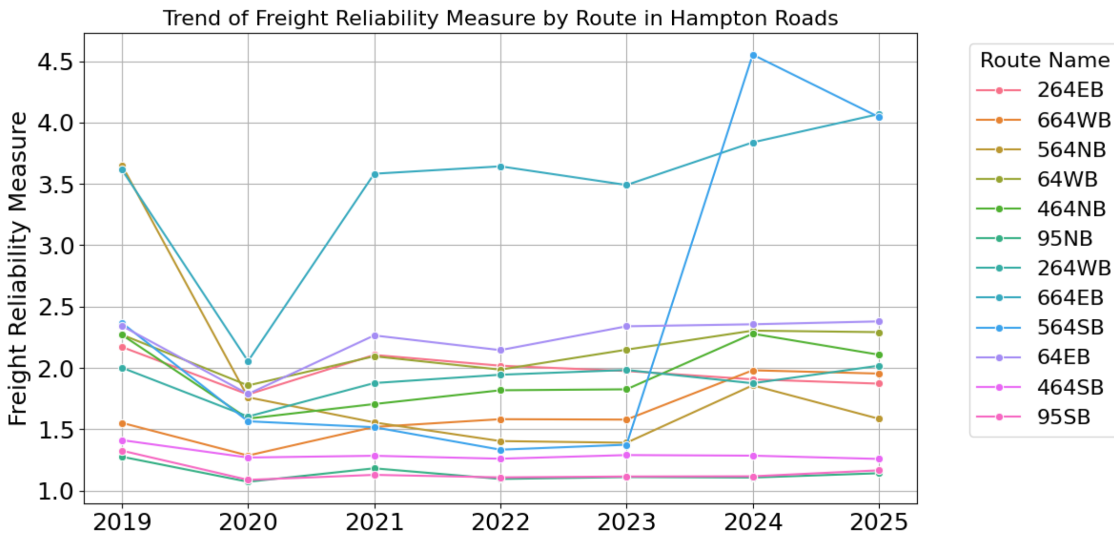

Figure A5. Truck Travel Time Reliability Measure in the Hampton Roads District

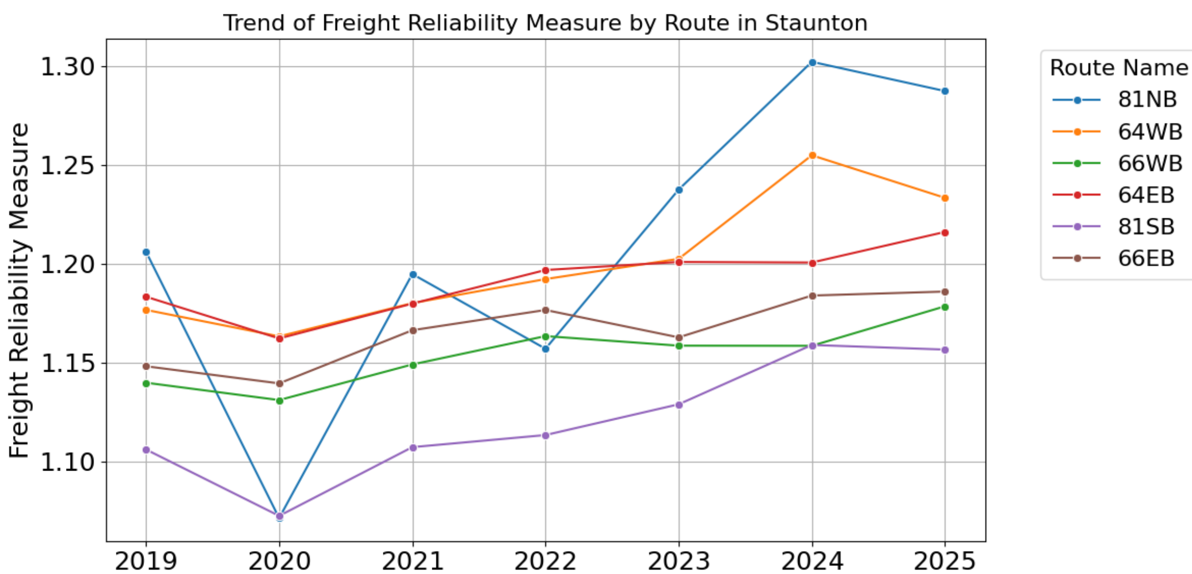

Figure A6. Truck Travel Time Reliability Measure in the Staunton District

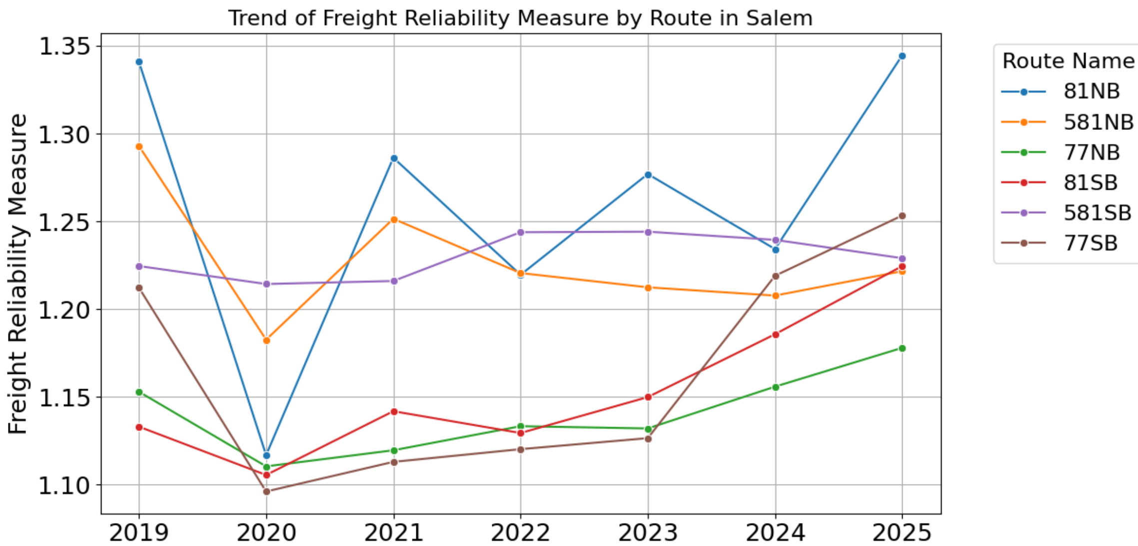

Figure A7. Truck Travel Time Reliability Measure in the Salem District.

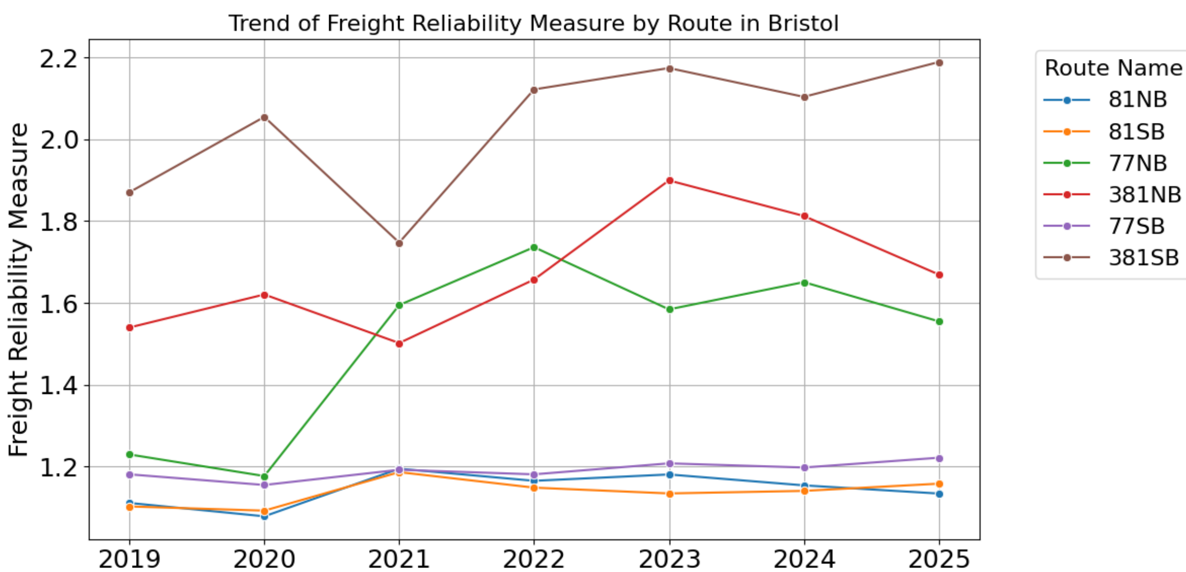

Figure A8. Truck Travel Time Reliability Measure in the Bristol District

Table A1. Trends of Truck Travel Time Reliability Measure Values by District and Route

District	Route	Slope	*p*-Value	Route	Slope	*p*-Value
Northern Virginia	395NB	0.0931	0.6954	395SB	0.1410	0.1628
Northern Virginia	95NB	0.2887	0.0083*	95SB	0.0962	0.2835
Northern Virginia	66EB	– 0.0645	0.4190	66WB	0.0815	0.1652
Northern Virginia	495NB	– 0.0159	0.9532	495SB	0.1470	0.1613
Fredericksburg	95NB	– 0.2380	0.0284**	95SB	– 0.0918	0.4945
Culpeper	66EB	0.0050	0.0868	66WB	0.0045	0.3739
Culpeper	64EB	0.0204	0.0003*	64WB	0.0200	0.0033*
Staunton	81NB	0.0454	0.0057*	81SB	0.0159	0.0066*
Staunton	64EB	0.0058	0.1889	64WB	0.0176	0.2298
Staunton	66EB	0.0049	0.5696	66WB	0.0045	0.5771
Hampton Roads	264EB	– 0.0506	0.5715	264WB	0.0113	0.8936
Hampton Roads	664EB	0.1625	0.6269	664WB	0.1518	0.1319
Hampton Roads	564NB	0.1013	0.2837	564SB	1.1313	0.0012*
Hampton Roads	64EB	0.0719	0.4680	64WB	0.1072	0.2160
Hampton Roads	464NB	0.1323	0.2728	464SB	– 0.0011	0.9150
Hampton Roads	95NB	0.0136	0.0573	95SB	0.0173	0.0895
Richmond	295NB	0.0168	0.0003*	295SB	0.0107	0.0096*
Richmond	95NB	0.0384	0.5163	95SB	0.1021	0.0716
Richmond	85NB	0.0077	0.6205	85SB	0.0052	0.3192
Richmond	195NB	0.2557	0.0545	195SB	0.1084	0.0009*
Richmond	64EB	0.0245	0.4009	64WB	0.0094	0.8335
Salem	81NB	0.0333	0.2122	81SB	0.0321	0.0054*
Salem	581NB	– 0.0001	0.9895	581SB	– 0.0049	0.7936
Salem	77NB	0.0158	0.0116**	77SB	0.0492	0.0086*
Bristol	81NB	– 0.0120	0.3363	81SB	0.0036	0.5688
Bristol	77NB	– 0.0477	0.5612	77SB	0.0112	0.2305
Bristol	381NB	– 0.0050	0.9699	381SB	0.0130	0.9457

*Significant at 0.01 level; **Significant at 0.05 level.