# Using Predictive Analytics in Logistics Industry to Associate Tolls and Damages to Customers

Ananth Mohan, Farha Shireen, Hsueh-Ning Chao, Shih Min Lin, Tanvir Ahmed Farook,   
Yao Liu, Yijun Wang, Dr. Shoaib Khan

Purdue University, Daniels School of Business, West Lafayette, IN 47907

[mohan52@purdue.edu](mailto:mohan52@purdue.edu), [lnuf@purdue.edu,](mailto:lnuf@purdue.edu) [chao77@purdue.edu,](mailto:chao77@purdue.edu) [lin1944@purdue.edu,](mailto:lin1944@purdue.edu) [tfarook@purdue.edu,](mailto:tfarook@purdue.edu) [liu4091@purdue.edu](mailto:liu4091@purdue.edu), [wang6665@purdue.edu,](mailto:wang6665@purdue.edu) khan180@purdue.edu

## ABSTRACT

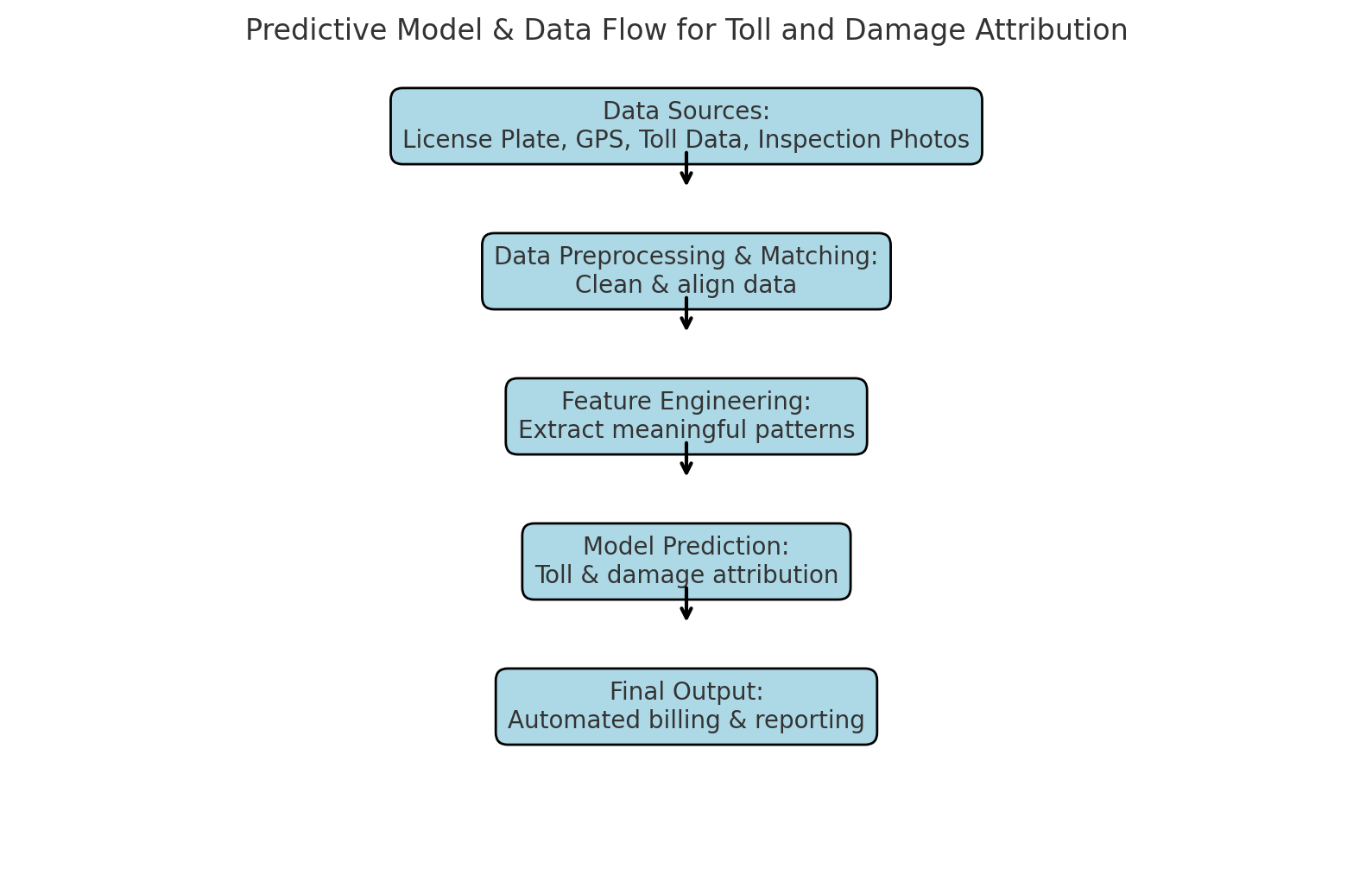
Predictive analytics has the potential to transform cost management and damage tracking in the logistics industry by integrating telematics, toll records, and automated damage assessment systems. This study focuses on designing a predictive system to streamline cost attribution, improve operational transparency, and reduce billing disputes for a trailer-as-a-service provider. The importance of this work lies in its ability to address inefficiencies caused by manual processes, data gaps, and a lack of real-time insights. Using machine learning models and AI-powered image recognition, we developed a framework that assigns costs to specific drivers, lanes, or trailers while automating damage detection. The findings indicate that the integration of predictive tools not only enhances operational efficiency but also builds customer trust through accurate billing and transparent processes.

**Keywords**: predictive modeling, computer vision, telematics, cost attribution, logistics, AI damage detection, billing transparency

## INTRODUCTION

The global third-party logistics (3PL) market size is anticipated to grow from USD 1082.45 billion to USD 2230.96 billion in 10 years (The Brainy Insights, 2024). The market will experience rapid growth due to technological advancements in third-party logistics (3PL) during the forecast period (Yahoo Finance, 2024). One of the service third party logistics provide is transportation service, which the company own their trailer and distribute goods for the customer. For asset-based 3PL, fleet management could be very complicated. There are 3 types of trailer management -- traditional leasing, lease-to-own or direct ownership. However, direct owning trailer assets demand huge initial investment and maintenance cost, which makes capacity very non-flexible, alongside with potential loss on asset downtime. Some 3PL opt for traditional leasing to avoid the maintenance cost, but it failed to meet the flexibility on peak and low-capacity periods. As a result, traditional 3PL logistics business model face challenges on balancing capacity and efficiency.

Trailer as a Service (TaaS) provides a flexible solution on this challenge. Companies subscribe for capacity on the trailer, and TaaS takes care of maintenance. This solves the pain point on non-flexible, seasonal capacity and huge capital investment, and expand the opportunities to not only 3PL but brokers and carriers. While providing solutions on capacity, inaccurate billing and untracked operational cost of tolls and damages expenses become challenges for our client running the TaaS service. As the subscribers could utilize the trailer by assigning to different carriers, tracking tolls and damage expenses become challenging, given our client only has subscribers and asset list rather than the actual parties operate the trailers. This could lead to inaccurate billing and could further strained relationships with customers and carriers.



*Figure1. Predictive Model & Data Flow*

In our study, the motivating business problem this paper focuses on is to build efficient workflow and model help attributing the tolls and damage to the appropriate party in a timely manner without relying on data provided from service subscribers.

Our research will focus on:

1. What approaches from predictive modeling along with data analytics systems should be adopted to enhance both accuracy and efficiency of toll attribution operations within TaaS systems?

2. Establish methods that enhance trailer damage monitoring together with attribution processes despite existing inspection irregularities and trailer exchange frequency.

The analysis will build predictive tools to automate toll expense allocation and damage inspection functions that support operational requirements of the business. Our research will review different techniques to pair toll payments with proper customers despite restricted data availability through the combination of license plate recordings timestamp records and GPS data.

An algorithm needs to be developed to process large datasets effectively throughout making correct predictions with limited available information. Our research investigates the application of computer vision technology for pre-trip and post-trip inspection photo comparison automation which helps detect possible manual inspection misses of vehicle damages. With integrating data from tolls agency and GPS data, our client will be able to automate the tolls attribution and bill the damage expense on the appropriate parties, which further reduced unnecessary overhead.

The following paper structure includes: Section 2 contains a literature review about transportation industry predictive models alongside damage detection techniques and toll attribution methods. Our proposed methodology structure comprises data preprocessing alongside feature engineering and model selection which appears in Section 3. Our experimental results with model descriptions appear in Section 4 following our method implementation description. The evaluation of our models' performance and practical applications and possible enhancement opportunities takes place in Section 5. Section 6 delivers the paper's summary including our study findings along with their effects on TaaS business and prospective research paths. The research we conduct addresses crucial operational challenges of the TaaS model with the goal to boost digital transformation within the transportation and logistics industry through efficient and transparent operations.

## LITERATURE REVIEW

### Tolls Attribution

Cost allocation in logistics can be complex due to various operational factors and data limitations. In our case, matching toll data in a timely manner poses a challenge, especially when customers have limited information about carriers or brokers. Sheng Xu et al. (2020) introduced a time-driven activity-based costing (TDABC) model integrated with a shared logistics platform, designed to facilitate real-time data updates and reduce implementation costs, making cost allocation more efficient and adaptable.

### Damage Attribution

The use of transfer learning on damage detection on containers has been research widely, especially for MobileNetV2 model. This has been concluded by ([Zixin Wang](https://onlinelibrary.wiley.com/authored-by/Wang/Zixin) et al., 2021) and (Pavel Cimili, et al., 2022) that MobileNetV2 has advantages in multiple class of damage detection and it is useful in large scale container inspection scenarios. The former compared transfer and semi-supervised approaches by testing two separate models (for the lower and the upper part), and it was concluded that semi-supervised training could not outperform transfer learning model due to the complex structure of the trailer surface and its defects. They suggest that future improvement is needed for the classification of multiple damage classes.

The potential of MobileNetV2 model for multiple types of damage detection is still been researched. [Zixin Wang](https://onlinelibrary.wiley.com/authored-by/Wang/Zixin) et al., 2021 proposes a multitype damage detection model for containers based on MobileNetV2. They performed on-stie experiment on deploying model on the mobile terminal obtains images through the smartphone camera for real-time damage detection. They concluded that experiment results show that the multitype container damage detection model can give the corresponding damage types and prediction results. However, it is still necessary to quantify the degree of damage to the container according to the severity of the injury to the container and support the intelligent decision-making of container damage.

This provides the groundwork for our paper as we will focusing on attributing tolls cost based on geographical data and identifying damage classification. Our goal is integrating this information and match them to the appropriate party.

We summarize our findings in Tables 1 and Tables 2.

|  |  |  |
| --- | --- | --- |
| **Study** | **Insights** | **Research Gap** |
| (Sheng Xu et al., 2020) | They introduced a decision support platform based on shared logistic platform, which can be used to collect and integrate data in the process of time-driven activity-based costing. |  |
| (Pavel Cimili, et al., 2022) | MobileNetV2 based on transfer learning is capable of damage detection if there is enough training data. | The model has the potential to applied on not just for binary classification but also for multiple class damage detection. |
| (Jiahao Chen et al., *n.d.*) | This paper proposes an improvement to the YOLOv5 model based on the Transformer self-attention mechanism for container damage detection, demonstrating superior performance compared to commonly used object detection algorithms. | Assessing the severity of multiple damaged areas in containers still requires enhancement. |
| ([Zixin Wang](https://onlinelibrary.wiley.com/authored-by/Wang/Zixin) et al., 2021) | This paper proposes a multitype damage detection model for containers based on MobileNetV2, which has excellent advantages in largescale container inspection scenarios. | A real-time monitoring system  will needed to be developed based on port IP network cameras and  integrated into the port management system. Also, it is necessary to quantify the severity of damage to the container. |

*Table 1: Key papers and identified research gaps*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Study** | **Paper Aspect** | | | | | |
| Tolls | | Damage | | | |
| TDABC model | Shared Logistics Platform | MobileNetV2 | Semi-Supervised Learning | Multiple Type damage classification | Model Enhancement |
| (Sheng Xu et al., 2020) | Yes | Yes |  |  |  |  |
| (Pavel Cimili, et al., 2022) |  |  | Yes | Yes |  |  |
| (Jiahao Chen et al., *n.d.)* |  |  |  |  | Yes | Yes |
| ([Zixin Wang](https://onlinelibrary.wiley.com/authored-by/Wang/Zixin) et al., 2021) |  |  | Yes |  | Yes |  |
| Our Paper | Yes |  | Yes | Yes |  |  |

*Table 2: Relation of our study to other academic papers*

## DATA

Due to the sensitive nature of the data and confidentiality constraints imposed by the data provider, we did not use real-world raw data for our analysis. Instead, we employed large language models (LLMs) to generate synthetic datasets that closely mimic the structure and semantics of the original data. The synthetic dataset preserved the integrity of the three primary data categories—Asset Location, Toll Records, and Inspection Records—while ensuring that no personally identifiable or proprietary information was exposed. This allowed us to simulate real-world scenarios while adhering to strict data privacy requirements.

The dataset includes three main tables: **Asset Location**, **Inspections**, and **Tolls**.

* **Asset Location**: Tracks trailer information like unique identifiers (asset\_vin), geospatial data (position), current motion status (asset\_motion\_status), and time stamps (reported\_time, created\_time). It also includes provider data (telematic\_provider).
* **Inspections**: Contains details about inspections with variables such as inspection ID (id), trailer ID (vin), inspection type (inspection\_type), and time stamps (start\_time, end\_time). It also stores metadata like user IDs (created\_by, updated\_by) and inspection data in JSON format.
* **Tolls**: Records toll event data, including date and time (Posted\_Date, Invoice\_Date), toll detection method (Read\_Type), vehicle ID (Device\_Plate\_Id), toll charges (Toll\_Charge), and plaza information (Entry\_Plaza, Exit\_Plaza). It also tracks disputes (Dispute\_Status, Dispute\_Reason) and account associations.

|  |  |  |
| --- | --- | --- |
| **Variable** | **Type** | **Description** |
| asset\_vin | Categorical | Unique identifier assigned to each trailer |
| position | Geospatial | Geospatial coordinates indicating the trailer's location |
| location | Text | Corresponding address derived from geospatial data |
| asset\_motion\_status | Categorical | Current motion status of the trailer |
| asset\_name | Categorical | Name assigned to the trailer within the organization |
| organization\_anon | Categorical | Anonymized name of the subscriber |
| telematic\_provider | Categorical | Service provider responsible for geospatial and telematics data |
| reported\_time | Time | Timestamp reflecting registering time |
| created\_time | Time | Timestamp indicating when the row was created in the dataset |
| *Table 3: Asset Location* | | |
|  |  |  |
| **Variable** | **Type** | **Description** |
| created\_by | Categorical | User ID of the person who created the inspection record |
| updated\_by | Categorical | User ID of the person who last updated the inspection record |
| created\_time | Time | Timestamp when the inspection record was created |
| updated\_time | Time | Timestamp when the inspection record was last updated |
| id | ID | Unique identifier for the inspection record |
| configuration\_id | ID | Identifier for the trailer's configuration |
| data | JSON | Contains detailed inspection data in JSON format |
| is\_deleted | Boolean | Whether the inspection record was marked as deleted |
| vin | Categorical | Vehicle Identification Number (VIN) of the trailer |
| inspection\_type | Categorical | Indicates whether the inspection is a Pre or Post trip |
| organization\_id | Categorical | Identifier for the organization performing the inspection |
| document\_id | ID | Unique identifier for associated documents |
| trailer\_number | Categorical | Trailer's company-assigned number, mapped to asset\_id in Asset Location |
| start\_time | Time | Inspection start time |
| end\_time | Time | Inspection end time |
| inspection\_number | ID | Unique number assigned to the inspection |
| *Table 4: Inspections* | | |
|  |  |  |
| **Variable** | **Type** | **Description** |
| Posted\_Date | Time | Date the toll was incurred |
| Invoice\_Date | Time | Date the toll was billed |
| Source | Text | Source system or method of toll detection (if applicable) |
| Read\_Type | Categorical | Type of signal or method detected by the toll pass |
| Transponder\_Status | Categorical | Status of the vehicle’s transponder at the time of detection |
| Device\_Plate\_Id | Categorical | License plate number of the vehicle |
| Vehicle\_Number | Categorical | Company-assigned vehicle ID; Corresponds to asset\_id in Asset Location and trailer\_number in Inspections |
| Agency | Categorical | Tolling agency responsible for processing the toll |
| Entry\_Plaza | Text | Name or identifier of the plaza where the vehicle entered |
| Entry\_Date | Time | Date and time the vehicle entered the toll plaza |
| Exit\_Plaza | Text | Name or identifier of the plaza where the vehicle exited |
| Exit\_Date | Time | Date and time the vehicle exited the toll plaza |
| Class | Categorical | Classification of the vehicle type |
| Miles | Float | Distance traveled between entry and exit plazas (if available) |
| Toll\_Charge | Numeric | Monetary amount charged for the toll |
| Dispute\_Status | Text | Status of any dispute raised (if applicable) |
| Dispute\_Reason | Text | Reason for the toll dispute (if applicable) |
| Account | Categorical | Account to which the toll charge is assigned |
| *Table 5: Tolls* | | |

## METHODOLOGY

### Toll Study Design

The toll attribution process in the Trailer-as-a-Service (TaaS) model is designed to automate the identification of toll charges incurred during trailer usage and allocate them to the appropriate customer. As shown in Figure 3, the process begins when a Toll Agency sends a daily toll data report to the provider for reimbursement. This report includes transaction-level toll charges, timestamps, vehicle identifiers, and toll amounts.

Simultaneously, Trailer Subscription Information is ingested to determine which customer was using the trailer at the time of each toll transaction. An Automation Logic engine matches toll records with subscription data using the trailer's Vehicle Identification Number (VIN) and timestamp alignment. Once the matching is complete, the system updates the internal database with the matched customer-toll pairings using a daily batch process.

Finally, the system generates automated emails summarizing toll charges and sends them to the respective customers for billing. This automation ensures fast, accurate, and auditable cost attribution and reduces billing delays and disputes that are common in manual processes.

### Damage Study Design

The damage attribution framework, addresses the challenge of identifying and assigning responsibility for trailer damage in a scalable and data-driven manner. The process is divided into two primary components: Damage Analysis and Automatic Attribution.

The pipeline begins when an inspection report is received. If damage is detected, the system attempts to retrieve a prior inspection report where no such damage was noted. This defines the window during which the damage likely occurred.

If a previous undamaged report exists, telematics data is queried to extract all trips taken by the trailer during that window. If only one customer operated the trailer in this period, responsibility is directly attributed. If multiple customers were involved, the system compiles a list of suspicious customers.

If no previous report is found, the system falls back on historical subscription records to identify the last 'n' customers. If no customer data is available, the case is flagged for manual review.

Parallelly, if the inspection report contains images, the Damage Analysis component is activated. Images undergo automated processing and are evaluated using a MobileNetV2-based image recognition model to classify the damage type, location, and severity. This provides an additional validation layer, especially for cases where customer attribution is inconclusive or disputed.

At the end of this process, a structured report is generated, capturing:

* The list of involved customers
* Location and time of trailer use
* Image-based damage assessment (including part, type, and severity)

This approach integrates rule-based attribution with AI-enhanced image analysis, enabling scalable and evidence-driven damage responsibility assignment.

To enhance the accuracy of identifying the most likely driver in operational incidents, it is recommended to augment internal datasets with contextual and behavioral data. A predictive modeling approach can be employed, integrating the following data categories:

* External APIs: Incorporate real-time weather information and other environmental factors that may influence driving conditions and behavior.
* Sensor Data: Use sensor inputs such as vehicle overload metrics to capture anomalies that might correlate with specific driver activity.
* Historical Patterns: Analyze trip recency, time of day, route history, and known driver behavior patterns to build comprehensive driver profiles.

These features collectively inform a predictive model that refines a broad list of possible customers (drivers) down to the “most likely driver” responsible in a given context. This approach enables data-driven decision-making and improves accountability by narrowing down likely candidates with higher precision.

## MODEL

In this research, we use the Time-Driven Activity-Based Costing (TDABC) framework as a foundation to build solutions and recommendations. The TDABC model assigns costs based on time as the primary cost driver. It requires two key parameters:

1. The cost per time unit of capacity, and
2. The estimated time required to perform a task or process.

The cost of an activity can be calculated using the simple formula:

*Cost of activity=Time required × Cost per time unit.*

There are multiple strengths to applying the TDABC model in a logistics setting. First, using time as the core cost driver is both practical and intuitive in environments where process time is closely linked to resource consumption. For example, On-Time In-Full (ONIF) rate, as a performance metric, implies increased resource usage when delays occur. Similarly, trip duration in a subscription-based trailer access model represents the period during which trailers are actively occupied. These types of activities can be effectively measured by time alone.

Second, the TDABC model enables more accessible process redesign, which aligns with our goal of addressing inaccurate billing and misattribution of costs across parties in the logistics chain.

However, the TDABC model also has limitations. It relies heavily on precise and up-to-date time data, where even small inaccuracies can significantly distort results (Adkins, 2008). In addition, it can oversimplify complex activities due to its assumption of constant resource pricing, making it less effective in addressing dynamic and multifaceted cost structures (Namazi, 2016).

Our research applies the spirit of the TDABC model by developing a solution based on real-time telematics data, which indicate trailer location and motion status. This is combined with pre-trip and post-trip inspection reports to associate expenses with the appropriate responsible parties. Instead of converting time directly into monetary cost, we focus on time as a key cost driver to help our industry partner redesign their cost allocation process more accurately and transparently.

In the process of cost attribution, telematics data—which includes vehicle motion status, timestamps, and locations in Well-Known Binary (WKB) format—is updated at the minute level. Damage data is collected from pre- and post-trip inspection reports. By aggregating records using vehicle identification numbers (VINs), we can calculate the total time consumption, location scope, and cost of a single trip.

By closely examining and reorganizing the trip timeline, each report is aligned with the corresponding asset condition and location at a specific point in time. Our method leverages time as the primary factor to trace asset condition and toll generation before, during, and after activities, enabling the identification of potential responsible parties. With this workflow, tolls and damage expenses can be accurately assigned to the appropriate parties.

Since time is our core cost driver, it directly influences the complexity of expense matching. Therefore, attribution should be conducted in a timely manner to ensure accuracy. By applying a Time-Driven Activity-Based Costing (TDABC) framework, the firm can build predictive models based on these time-sensitive datasets. For example, it can forecast the damage rate of returning trailers within a specific network across different seasons. By multiplying this rate by the average maintenance cost, the firm can estimate the network-level maintenance cost based on time consumption.

## EXPECTED RESULTS

In the logistics industry, approximately 10% of the total cost of each trip comes from tolls (1.5%), damages (8%), and maintenance in total. While this may appear to be a relatively minor component, the operational inefficiencies tied to manually managing these costs can significantly impact the bottom line. Before the introduction of the automation process, the review of toll and damage reports has been a time-consuming and labor-intensive task requiring human work comparing images, verifying charges, and matching records to the appropriate trailers and clients. This process not only require a significant amount of time, but it is also prone to human error, leading to inaccurate attributions, delayed billing, and compromised compliance.

To better understand the scope of this inefficiency, we considered a scenario with approximately 1,000 trailers in active operation. Assuming each trailer completes an average of four trips per week and each trip generate one toll charge and requires one damage report comparison; there will be roughly 4,000 toll charges and 4000 times of comparison works per week. We assume that after each trip, the manual review would take an average of two minutes for tolls and damage report comparison, in total the manual review process takes around 133 hours of labor weekly. At a standard labor cost of $15 per hour, the expense incurred solely for this manual task amounts to nearly $2,000 per week or over $100,000 annually. This estimation didn’t include the additional time and resource required for resolving disputes, which means that this process can be more time-consuming and costly than the estimation.

The introduction of an automated system has substantially transformed this process. By leveraging computer vision for image comparison in damage attribution and batch processing in toll attribution, the solution not only identifies and matches toll charges and damages with the correct driver and trailer but also flags discrepancies for further review. As a result, companies have realized a reduction in manual labor approximately equivalent to 2–3 full-time employees. In financial terms, this has translated into an annual cost savings of approximately $500,000. Moreover, we estimate that automation can greatly enhanced the accuracy of attributions to 80%, significantly reducing the frequency of misassigned charges and improving the overall trustworthiness of the company, which is important in terms of maintaining good relationships with the customers.

Beyond saving costs, the implementation of automation brings strategic benefits that align with broader industry imperatives. Timely and accurate attribution is very important in the logistics sector, where payment cycles are closely tied to the accuracy of documentation and claim processing. Automated toll and damage identification enables invoicing to customers in a timely manner, expedites insurance claim submissions, and accelerates the dispute resolutions. These improvements collectively enhance cash flow management, improve working capital efficiency, and make financial planning more predictable for the company.

In sum, automating toll and damage attribution not only reduces costs and saves time but is also essential for improving the operational robustness of logistics firms. It supports more accurate financial reporting, enhance customer trust through faster settlements, and fosters a data-driven approach to fleet and cost management—benefits that extend far beyond the initial scope of finding the accurate clients and reducing manual work.

## RECOMMENDATIONS

To facilitate a transition toward a data-driven decision-making framework, a two-phase approach is recommended, with emphasis placed on establishing a strong data infrastructure and enhancing the analytical understanding of collected data.

### Establishment of Foundational Data Infrastructure

It is recommended that organizations prioritize the implementation of robust data pipelines and cloud-based storage systems. Automated and scalable ETL (Extract, Transform, Load) processes should be established using tools such as Airflow, Fivetran, or dbt, allowing for efficient ingestion and transformation of data. Data lineage and version histories should be tracked to ensure transparency and reproducibility.

Several foundational pillars should be addressed:

* **Relevance and Representativeness**: Data should be collected in alignment with clearly defined business and modeling objectives, ensuring that only pertinent and representative information is retained.
* **Integrity and Quality**: Continuous validation processes must be applied to ensure that data is accurate, consistent, and complete. Without such measures, the reliability of downstream analyses may be compromised.
* **Structure and Storage**: Standardized schemas and naming conventions should be adopted. Additionally, it is advised that data be stored using scalable, cloud-native platforms such as **Google BigQuery** or **Snowflake**, which offer high performance and flexible accessibility.

### Enhancement of Data Understanding

Once foundational systems have been established, it is advised that analytical practices be developed to derive insights and create value from the data:

* **Exploratory Analysis**: Descriptive statistics and data visualizations should be conducted to identify patterns, anomalies, and potential outliers. This process allows trends to be observed and better understood prior to formal modeling.
* **Feature Engineering**: Raw data should be transformed into meaningful variables using domain-specific knowledge. When carefully constructed, such features are known to enhance the predictive power and interpretability of machine learning models.

By following these recommendations, organizations may be better positioned to progress from the mere collection of data to the strategic use of data as a driver of operational efficiency, innovation, and competitive advantage.

**Advanced Modeling with Data**

Once foundational infrastructure and analytical capabilities are in place, organizations should invest in advanced modeling techniques to automate processes, improve predictive accuracy, and reduce manual efforts. These models can unlock significant operational benefits by harnessing the full potential of telematics and sensor data.

For instance, automating toll updates and payment tracking by integrating toll, trip, and financial data into a real-time status engine—powered by rule-based logic and machine learning—can help save operational time and reduce billing errors. Similarly, damage-prone situations can be identified in advance by analyzing trip conditions, route data, and sensor inputs, enabling anomaly detection models to trigger early alerts and prevent breakdowns.

Predictive maintenance is another high-impact use case, where time-series modeling of sensor readings such as temperature and vibration can help forecast trailer failures and minimize downtime. Additionally, telematics data like acceleration, braking, and deviation patterns can be aggregated to profile driver behavior, enabling organizations to assign risk scores, improve safety, and incentivize responsible driving through clustering or supervised learning techniques.

By embedding such intelligent systems into daily operations, organizations not only reduce costs and increase uptime but also drive strategic value through automation, risk mitigation, and proactive decision-making.

## CONCLUSIONS

The global logistics industry continues to undergo significant transformation, with the subscription-based trailer access model offering flexibility that traditional ownership or leasing models cannot provide. However, this innovative business approach introduces unique challenges in cost attribution and damage tracking due to multiple parties involved in the freight chain.

Our research has directly addressed these challenges by developing predictive frameworks for toll attribution and damage assessment that operate effectively even with limited data availability.

Our toll attribution framework successfully automates the process of matching toll records with the appropriate customers by leveraging telematics data and timestamp analysis. By implementing this system, logistics providers can significantly reduce manual processing time and human error, resulting in more accurate billing and improved customer trust. The damage attribution system, combining inspection report analysis with computer vision technology, creates a robust mechanism for determining when damage occurred and which party was responsible during that time window.

The integration of these systems yields substantial operational and financial benefits. As demonstrated in our analysis, before automation, toll and damage attribution required significant manual effort, with longer processing times and higher risk of human error. By implementing an automated process, logistics providers can reduce processing time by approximately 2-3 FTEs and cut costs by close to $0.5 Million USD annually. Additionally, automation minimizes manual errors, enhancing the accuracy and reliability of the attribution process by up to 80%.

Beyond direct cost savings, these systems create strategic value through improved trust and transparency with customers. In the logistics industry where payment cycles are tight, timely and accurate attribution is critical. The automation of toll and damage identification ensures faster invoicing of carriers and accelerates insurance claims and settlement processes. Ultimately, this enhances cash flow management, improves operational efficiency, and strengthens compliance with industry standards.

While our study has yielded promising results, we acknowledge certain limitations. Data latency, the occasional need for manual review, and the scope of our methodologies focusing specifically on toll assignment and damage assessment without addressing all related processes such as dispute resolution present opportunities for future research. Further work could explore integrating real-time toll data processing, enhancing image recognition models to detect more subtle damages, and developing more sophisticated predictive algorithms to anticipate potential damages based on route patterns and carrier histories.

In conclusion, our research demonstrates that predictive analytics, when applied to logistics operations, can transform cost attribution and damage tracking from reactive, manual processes into proactive, automated systems. For subscription-based trailer access model providers, this represents not just an operational improvement but a strategic competitive advantage in an increasingly data-driven industry. As the logistics sector continues to evolve, we anticipate that the integrated use of telematics data, computer vision, and predictive modeling will become standard practice, enabling more transparent, efficient, and customer-focused operations.

## REFERENCES

1. The Brainy Insights. (2024, September 11). *Third-party logistics market to reach USD 2,230.96 billion by 2033: Thriving e-commerce sector in emerging countries to propel growth. GlobeNewswire.* Retrieved April 13, 2025, from https://www.globenewswire.com/news-release/2024/09/11/2944643/0/en/Third-Party-Logistics-Market-to-Reach-USD-2-230-96-Billion-by-2033-Thriving-E-Commerce-Sector-in-Emerging-Countries-to-Propel-Growth.html
2. Namazi, M. (2016). Time driven activity based costing: theory, applications and limitations. *Interdisciplinary Journal of Management Studies (Formerly known as Iranian Journal of Management Studies)*, *9*(3), 457-482.
3. Cimili, P., Voegl, J., Hirsch, P., & Gronalt, M. (2022, September). Automated damage detection of trailers at intermodal terminals using deep learning. In *Proceedings of the 24th International Conference on Harbor, Maritime and Multimodal Logistic Modeling & Simulation (HMS 2022), Rome, Italy* (pp. 19-21).
4. Chen, J., Dong, C., & Wan, Y. Enhancing Container Damage Detection with improved YOLOv5 Model: Integrating Swin Transformer.
5. Wang, Z., Gao, J., Zeng, Q., & Sun, Y. (2021). Multitype damage detection of container using CNN based on transfer learning. *Mathematical Problems in Engineering*, *2021*(1), 5395494.
6. Xu, S., Niu, J., & Cai, X. (2020). Optimize Logistics cost model for shared logistics platform based on time-driven activity-based costing. In *Journal of Physics: Conference Series* (Vol. 1437, No. 1, p. 012115). IOP Publishing.