Who Are You Gonna Call?:

A Smart Recommendation System for Carrier-Shipper Matching

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ABSTRACT

For a broker in the transportation industry, one of the most critical decisions for the carrier representatives within the company is determining which carrier to select for a customer load. In order to determine which carrier would be the best for a shipment, certain criteria need to be selected in order to align and develop a scorecard ranking system. To decide which carrier should be selected from its database for a shipment, GlobalTranz is seeking a strategic scorecard system that would complement its current carrier-shipper matching platform. In this capstone project, a customized ranking system was developed that would allow the carrier representatives to make strategic decisions. A narrowed down list of criteria was created that encompassed three major metrics including geographical fit, level of service, and financial fit. The prototype recommendation system will enable the carrier representative's decision to be more objective. This solution will standardize the current decision process and facilitate efficiency in the future.

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1. Introduction

GlobalTranz is a third-party logistics company (3PL) founded in 2003 that specializes in freight transportation. The company is a brokerage company that works with numerous customers to ship products all over the world via various modes of transportation. GlobalTranz has become an innovative leader in transportation by utilizing advanced technological systems and decisional analysis to create a more efficient end-to-end supply chain for customers. In less than two decades, GlobalTranz has become a billion-dollar company and most recently reported 40% growth in sales specifically for Q4 of 2020 (*GlobalTranz*, 2022). The company continues to grow year over year by remaining on the cutting edge of the market and by acquiring various smaller entities to enhance its market footprint. GlobalTranz currently does business with over 50,000 truckload carriers and 120 less-than-truckload carriers, moving an average of 40,000 loads per week (*GlobalTranz*, 2022).

1.1 Problem Statement: The What

GlobalTranz utilizes multiple modes of transportation to ship their products; however, the scope of this project will solely focus on the company's one-billion-dollar truckload transportation business. GlobalTranz is interested in adopting a carrier recommendation system for its carrier representatives. Specifically, the proposed system will help the carrier representatives prioritize potential carriers based on financial data, level of service, geographical fit, and other factors.

The company's current strategy utilizes carrier representatives whose responsibility is to obtain a carrier for a specific load received from a shipper. When the representative receives the load request, they select a carrier that they believe will accept the load, obtain a price quote, enter the quote into the system, and then wait for potential approval by account management. At this point, the quote is approved or rejected by an upper-level employee. If rejected, the representative then has to begin the process all over again with a different carrier quote. This occurs when the price quote was rejected by a GlobalTranz employee. The current decision process is cumbersome and inefficient**.** It can lead to unsatisfactory customer service levels and time-consuming tasks. To optimize the process and improve efficiency, GlobalTranz is interested in a recommendation system that will enhance and streamline this process. Such a recommendation system should help to accurately and expeditiously assist them in narrowing the list of potential carriers that they can utilize for a requested load or for a lane for longer term contracting. An integrated recommendation system such as this should decrease the representatives' time spent during the decision process and improve the current process flow.

To address this crucial need, we developed a customized ranking recommendation system using an algorithm that supports and guides the representatives, thus making their decision process more efficient and more precise. Coded in Python and tested with various training data sets for fitness examinations, the recommendation system should alleviate significant bottlenecks in the current decision process. It is important to note that this recommendation system was designed to be utilized as a strategic tool for the carrier representatives, not to be used on a load-by-load basis, using real-time vehicle location or other real-time data.

1.2 Motivation: The Why

GlobalTranz is in need of a standardized tool that will enhance its current carrier selection process. This project aims to develop a smart carrier selection recommendation system that would complement its current carrier-shipper matching platform, which matches based solely on price. Most would agree that the matching process should be based on more than ranking carriers by their price since there are other critical factors to consider such as service level and geographical coverage. Various recommendation algorithms have been previously developed to more precisely cater to a customer's taste in movie streaming, music, fashion, and other areas. These algorithms typically provide users with more personalized recommendations by evaluating users' profiles, historical browsing data, and searching criteria.

GlobalTranz has observed a similar need in the trucking business. The company would like to implement a scorecard recommendation system to differentiate itself from competitors by providing a higher level of service to its customers. Therefore, in addition to the current real-time matching platform, GlobalTranz aspires, in the long-run, to be able to provide more strategic matching recommendations by taking into account not only price but other carrier-specific metrics. Such metrics could include active geographical regions, truck driver experiences, and on-time loading and unloading percentages. There is a large opportunity to create and implement a structured recommendation system in order to help GlobalTranz strategically choose carriers for customer truckload shipments in a focused, efficient, and customer tailored manner.

2. Literature Review

Recommendation systems are utilized in many industries and everyday life in order to create a sense of personalization for the user. Some of us may have finished watching a movie on a streaming service, noticing it then recommending a similar option to watch next. Similarly, others may have purchased a pair of sunglasses on Amazon, and then a list of sunglass cases that could be purchased was provided. Although some may not be aware of it at first because this after purchase sequence has become “the norm” when utilizing popular data-based sites, these are all examples of recommendation systems.

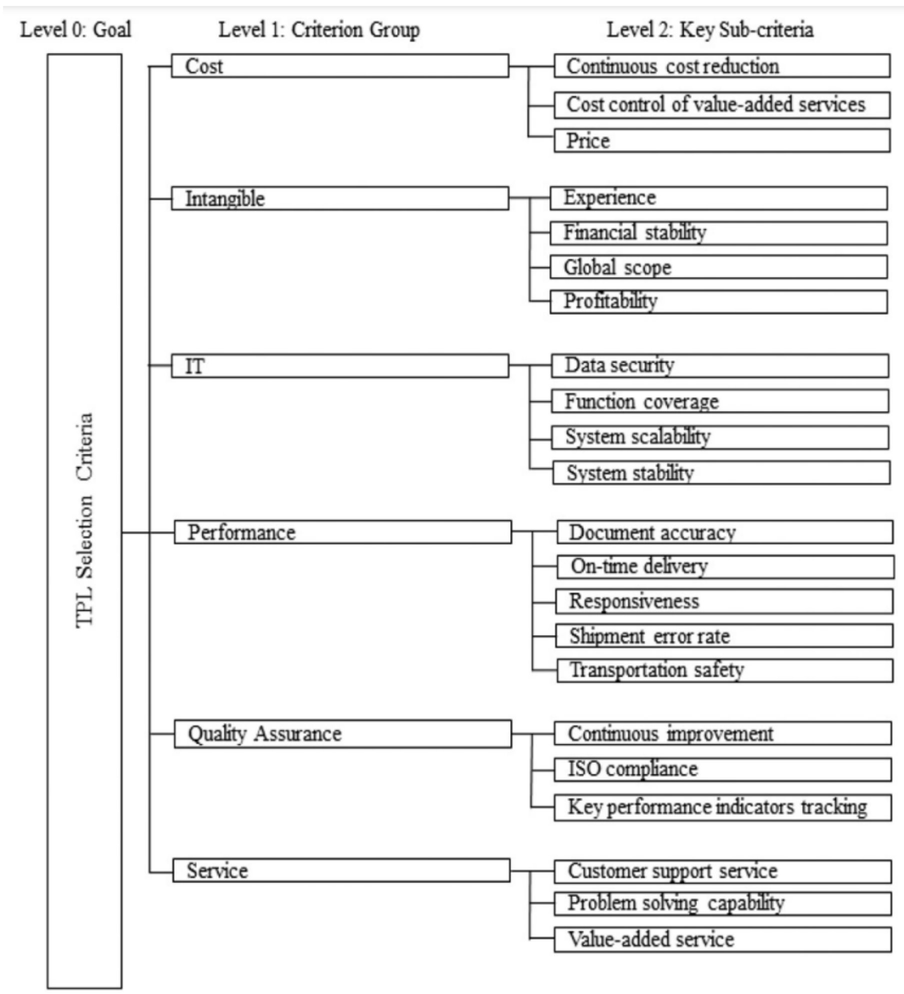
Currently, GlobalTranz manually chooses a carrier for a specific load when it receives an order from a customer. However, GlobalTranz employees informed us that the decision data informing that choice is currently not tracked, collected, or monitored. Saving and later mining that decision data could help make the next decision easier for the next load which may have similar characteristics or requirements. The current manual selection process is time-consuming and redundant. In our project, we are developing a recommendation tool that will algorithmically help the transportation representatives narrow down their list of carriers and more efficiently recommend an appropriate carrier that will most likely accept the load.

In this literature review, we will explore current strategies and recommendation systems of other broker carriers and transportation companies similar to that of GlobalTranz. We will also investigate recommendation systems that are used in other consumer industries such as cinema streaming and retail, which may hold value in developing a better decision system for GlobalTranz. This process will give us a more holistic view of the available strategies and principal qualities that other recommendation systems utilize, which in turn will help us devise an algorithmic approach for GlobalTranz’s carrier choice system.

2.1 The Transportation Industry: Carrier/3PL Selection Criteria

Maras (2015) notes that in the food and beverage (F&B) industry, it is often through trial and error that shippers finally realized what factors, other than price, would help in selecting which carriers to work with. Partnering with appropriate carriers and maintaining strong interactions could potentially help foster expansion and growth for companies. Similarly, in the integrated circuit manufacturing industry, an appropriate carrier partner is considered a competitive advantage in today's supply chain environment. According to an article about the manufacturing industry, carrier selection criteria play a critical role, more than just a cost reduction strategy to assess whether a carrier is a good fit or not. For example, as shown in **Figure 1** (Hwang et al., 2016), a two-level logic tree with 5 additional metrics other than cost is utilized to assess carriers. While the first level created high level metrics, the second level dove deep into each metric to assess a carrier's "goodness of fit" in more detail.

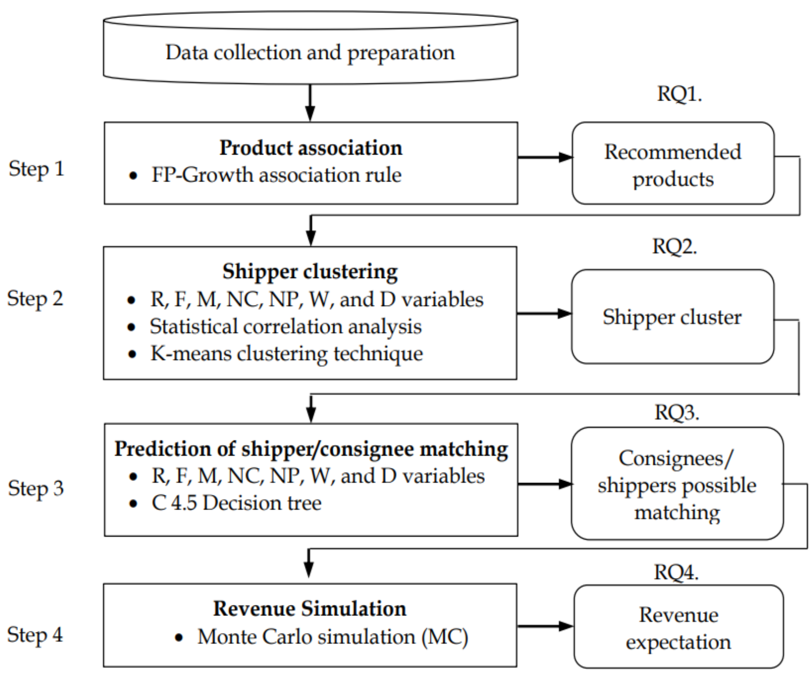
Figure 1 *Two-level Hierarchy of Carrier Selection Criteria (Hwang et al., 2016)*



2.2 The Transportation Industry: Adoption of Technology and Data Analytics

Once the carrier selection criteria are in place, the next step would be to automate the process and start leveraging the analysis of both the historical and real-time data to continuously improve carrier-shipper matching. The use of data analytics tools has recently become more popular, and it has been realized that this could drive better results of carrier selection. In a recent example that applied an FP-Growth (Frequent Pattern-Growth) association rule as shown in **Figure 2**, (Jintana et al., 2020) to local courier companies in Thailand, a 36% increase in revenue was achieved for a local business environment consisting of 8 consignees and 56 shippers when it comes to matching consignees and shippers.

Figure 2 *Research Methodology (Jintana et al., 2020)*



The FP-Growth association rule is also known as frequent itemset mining or basket analysis. It is used to in Step 1 to determine what products / items from shippers have been frequently delivered together to consignees by couriers. Step 2 uses K-means clustering to identify which shippers and consignees are more valuable through analyzing R, F, M, NC, W, and D variables (see **Table 1** for definitions). The results of step 2 are used for predicting potential shipper-consignee matching by a C 4.5 decision tree that identifies consignee's R, F, M, NC, W, and D variables. Step 4 runs Monte Carlo simulation to examine whether a shipper-consignee matching really generates revenues.

Table 1 *Definition of R, F, M, NC, NP, W, and D Variables*

Variables	Definition	Calculation
R (Recency)	Period of time between previous service and set date	Set date—last transaction date
F (Frequency)	Total number of service users within a particular period of time	Count of sale transactions
M (Monetary)	Total THB generated by customer's service within a particular period of time	Sum of money for each customer
NC (Number of customers)	Number of consignees/shippers	Count of total consignee/shipper customer numbers
NP (Number of product items)	Number of product items	Count of consignee/shipper product items
W (Weight)	Average weight per transaction (kg)	Average weight per transaction (kg)
D (Day)	Interval between transactions (day)	Average number of days between transactions

In terms of exploiting data analysis to assign scores to carriers, a balanced scorecard system and the Delphi method were considered to be candidate frameworks for us to explore. The balanced scorecard, which was first developed by Arthur M. Schneiderman in 1987 at Analog Devices, integrated four perspectives: financial, customer, internal business processes and learning and growth, to identify and track the implementation of strategy. On the other hand, a generic framework was created by (Rajesh et al., 2012) using the Delphi method for evaluating various functions of carriers at different stages of collaborations with shippers. The Delphi method provided a process flow that could be used to reach a group agreement by surveying industrial experts, who were GlobalTranz's carrier representatives in this case.

This research will aid us in the development of GlobalTranz's own carrier selection methodology/recommendation system. Our creation is based on historical data extracted from their Transportation Management System (TMS) and incorporates the concepts of a scorecard system which is composed of multi-stage filtering mechanisms. We expect that the carrier-shipper recommendation system will automate GlobalTranz's internal manual process of the supplier preference ranking process.

2.3 Outside of the Industry: Other Recommendation Systems

Netflix, the widely used subscription-based television and movie streaming service is a good example of a recommendation systems outside of the transportation industry. Netflix's show recommendation system was developed by data mining subscriber star ratings of shows or movies they watched. The system's algorithm subsequently recommends another show of similar content or genre based on that ranking. As data accumulated and its system evolved, Netflix can now recommend content very specifically to each of its 40 million subscribers (Madrigal, 2014). Netflix's personal suggestions to each user makes the subscriber feel as if the system knows them personally by how accurately it suggests content to watch that each user may enjoy, based on their prior content selections.

Although surprising and at times uncanny on how accurately Netflix predicts an individual's potential choices, the process is based completely on an algorithm formulated from both human and artificial intelligence. The Netflix database is composed of 76,987 unique combinations of descriptive content known as "micro-genres" (Madrigal, 2014). Netflix refers to the humans behind the scenes of helping develop the system as "taggers" (Madrigal, 2014). These trained individuals are paid to watch movies and provide an in-depth analysis on specific characteristics of the genre, characters, plot etc. With this in-depth analysis, Netflix creates an enormous database that houses all of this metadata from the content review by the taggers. The process results in almost 77,000 unique and extremely specific genres. In order to then provide specific suggestions to its users, Netflix utilizes specific grammar compositions through its machine generated computational algorithm. A grammar composition is a compiled set of adjectives that can be used to describe a movie or show title. The algorithm takes into account past individual user history similar to what has been watched in order to construct and devise a specific proposal. Although this current algorithm was not the first way that Netflix recommended content to its users, it has found a niche and competitive advantage in the specificities it takes into account (Madrigal, 2014). According to Netflix 80% of all of its streaming corresponds to its recommendation system (Chong, 2020).

Amazon started as an online book retailer less than thirty years ago and is now one of the largest companies in the world with over 350 million products of various types ranging from fashion to food & drink (Curry, 2021). No matter what product one is searching for, it or a similar item can most likely be located on Amazon's site. Amazon recorded $386 billion in revenue in 2020 alone (Curry, 2021). Additionally, there are currently more than 200 million active Amazon Prime subscribers (Curry, 2021). Amazon Prime subscribers pay for services and benefits such as faster shipping and other perks on an annual basis. However, it is important to note that there are many other users who shop on Amazon that are unaccounted for in this statistic since they do not subscribe to the Prime service.

To suggest items to a consumer, the recommendation systems tend to focus on three major categories: purchasing history, browsing history, and user profile data (Mitra et al., 2016). To keep up with its growth and vast product offerings, as well as remain ahead of its competitors, Amazon has had to continually revamp and revitalize its recommendation system since its inception. Amazon mainly focuses on collaborative filtering. This method remembers and builds on certain criteria that allows the system to filter behaviors and patterns and algorithmically provide suggestions. Before the improved system, Amazon used collaborative filtering specifically based on the customer. Collaborative filtering is a data analysis method that utilizes preferences or similarities between something to recommend something else (*Collaborative Filtering | Recommendation Systems*, n.d.). With this method, Amazon reads the user and notes its behavior and searches, matching it with a similar consumer and their buying patterns to recommend products. System analysts then refined this method and found it to be more accurate and successful if they transitioned to "item-to-item collaborative filtering" (Hardesty, 2019). This technique then based its algorithm on items similar to or related to items previously purchased to recommend other items to the user. Amazon continues to add even more nuances in its algorithm to add in more and more personalization to the user. More recently, Amazon has characterized and personalized such user styles and brands, thus providing even more specific recommendations based on these niche characteristics (Hardesty, 2019). To gain even more specificity in the recommendation, Amazon has also explored taking into account timing for orders or products. For example, their recommendation system may know when it's around the time a customer needs to reorder a certain product. Additionally, potentially connecting different users and their purchases on the same account has also been considered (Hardesty, 2019).

In its continuous improvement of the recommendation system, Amazon adopted the use of a matrix completion method. This tool deploys ones and zeros into a constructed matrix to easily track historical customer data and ultimately obtain probabilities of certain behavior (Hardesty, 2019). They also used an autoencoder in which the system uses iterations and learnings in order to synthesize the data to provide more discrete and distinct recommendations. In this development, the analysts realized that there are certain details that need to be included when making recommendation systems that are key for the system to be successful. For example, Amazon found that how recent or new a product was played a role into a more accurate recommendation using the matrix completion method (Hardesty, 2019). As a continually expanding business, Amazon continues to innovate and create new additions to algorithms to further enhance their recommendation systems (Hardesty, 2019).

Currently, GlobalTranz focuses their current real-time matching system predominantly on price. To have as successful a recommendation system as Amazon, GlobalTranz needs a system that incorporates various carrier profiling data and potentially updates it on a regular basis in order to capture the dynamics of this trucking brokerage environment. Our goal is to develop a value-added algorithmic prototype for GlobalTranz in order for the representatives to recommend carriers.

2.4 Applicability of other Recommendation Systems to GlobalTranz

As we dove deeper into the data and learned more about the company and the current way it functions, we realized that the recommendation systems mentioned above for Amazon and Netflix are not suitable for this project. Although collaborative filtering does utilize historical data which is what we used to design our recommendation system, other factors are essential to this method. Previous preferences weigh heavily in collaborative filtering for B2C recommendation systems. For GlobalTranz, we did not want to strictly rely on carrier representatives' historical preferences in the design of the scorecard. Therefore, if we utilized the process of collaborative filtering for our algorithm, we would be basing our system solely off of the past preferences of the carrier representatives which could potentially incur bias and lead to worse solutions. Furthermore, using collaborative filtering could also reinforce past incorrect or poor decisions and selections. We did find it helpful to learn about other recommendation systems in various sectors; however, after further review, we did not find it applicable and usable for the construction of our carrier recommendation system.

For our recommendation system for carrier-shipper matching, we do not want to predominantly favor the carrier representatives' incumbent selection of carriers. This is because carrier representatives may not have worked with the most appropriate carriers. In order to avoid this mishap and not reinforce the incumbency effect, we do not want to base our recommendation system off of the current selection process.

2.5 Summary

Recommendation systems are widely used across industries ranging from the transportation sector to movie streaming services and online retail shopping. Most current B2C recommendation systems take specific data and key characteristics crucial to the overall decision-making process and create an algorithm that suggests an option or options that best fit the question or situation at hand. All of these systems use some version of collaborative filtering that includes specific details that are important to target a certain market for which recommendations are required. This is because they base their recommendations and suggestions on customer preferences or similarities between other customers that seem to be alike.

As discussed in the literature review, this approach would not work when building our recommendation system as it focuses on previous preferences. We would not want to solely focus on carrier representatives' preferences as the static foundation of our recommendation system since this could potentially lead to subjective bias and worse solutions when choosing a carrier. Recommendation systems need to be dynamic and equipped to keep up with advances in technology in order to be fully functional and performing at its best ability for the user. Reviewing both current recommendation systems and strategies within the transportation sector as well as those utilized in other industries helped us formulate our proposed system for GlobalTranz. It is reasoned these systems and strategies would not effectively transfer to the transportation industry.

3. Data and Methodology

One of the core components of GlobalTranz's business is matching a shipper's requirements to an appropriate carrier by its agents. From multiple conversations with the GlobalTranz team, it appears that they do not currently have a strategic system for selecting carriers. Our project focused on creating a recommendation system that will help the agents more efficiently and effectively narrow down the list of possible carriers that are best suited for a shipper's specific load, lane, or set of lanes.

Section 3.1 discusses the basic components of the algorithm, while section 3.2 examines the data provided to us by GlobalTranz. Section 3.3 describes how we cleaned the data and prepared it to use in our proposed algorithm. We explain how we assembled and developed our code for the recommendation system. Finally, we describe our proposed algorithm, how it works, why it would be useful, and how GlobalTranz could benefit from utilizing a tool like this in the future.

3.1 The Structure of the Proposed Recommendation System

One of the main objectives of our project is to define a "goodness of fit" for carriers. Deciding what characteristics are most important for a carrier to be successful for a load or a lane was imperative for developing our prototype algorithm. In speaking with GlobalTranz, we learned that, in addition to price, the relationship that they have currently with each carrier is extremely important to them. A more stable and long-term relationship between a carrier and agent leads to a higher service level for clients. However, quantifying and forcibly assigning scores to a relationship is not the most user-friendly approach for agents. Therefore, to capture carrier attributes that were not numeric values, we incorporated the feature labels such as drop-trailer capability, high-value insurance, and hazardous material handling license. Numeric metrics acted as filters to restrict some carriers from consideration while non-numeric feature labels helped filter out carriers that did not meet certain criteria.

Our algorithm consists of two primary parts: a recommended list of carriers and the associated carrier feature labels. The former acts as the backbone of the entire recommendation system, while the latter helps provide additional insights about a carrier's operational attributes. We used 34 months' worth of data (January 2019 – October 2021) to evaluate the "goodness of fit" of a carrier. In each iteration, we added more metrics and invited GlobalTranz to evaluate the change in the relational rankings of the recommended carriers. Multiple iterations were conducted to help enrich and incorporate more metrics into the recommended list. More metrics were added to test the "fitness" in each iteration. The carrier profile data, on the other hand, was developed through interviewing internal stakeholders of GlobalTranz. We identified critical departments to help determine tagging mechanisms, including procurement teams, account managers, and data analytics teams. Each department articulated what they considered important when it came to selecting carriers according to carrier profiling data.

Combining the quantitative recommended list of carrier rankings and profile data, we captured most of the dynamics in the carrier-shipper matching process. We discussed perceptions of "fitness" with GlobalTranz.

3.2 The Provided Datasets

We were provided data for business out of the Chicago office from January 2019 to October 2021. Five different csv datasets were pulled and provided. Each dataset specifically categorized data about the following: Movements, Carriers, Locations, Offers, and Stops. The Movements dataset encompassed the load operations data, recording only origins and destinations. The Carriers dataset detailed carrier profile data. The Locations dataset included pickup and drop-off sites data. The Offers dataset encompassed historical records of each rejected and accepted load or movement. Finally, the Stops dataset delineated records of all locations included in the load.

The project focuses solely on truckload data with single origins and destinations. After data scrubbing, we decided to use the Movements, Carriers, and Locations datasets for our proposed algorithm. We examined but eliminated the Offers and Stops datasets provided since these included less-than-truckload (LTL) and intermodal (IM) loads, which were outside the scope of our project.

With the load-by-load information database being maintained – the historical performance metrics for carriers associated with different lanes – we were able to aggregate the information for an optimized and efficient strategy. Therefore, we decided to utilize the load-by-load data in order to gain insights on GlobalTranz's current loads shipped and carriers' performances.

3.3 Data Cleaning Process

All of the data utilized was from the Chicago business, although GlobalTranz had hubs located in Chicago, Illinois, Salt Lake City, Utah, as well as Phoenix, Arizona. We solely built our algorithm using the Chicago data that we were provided. This is because the other locations utilize different TMS systems and the data is not standardized through all of these locations. Standardizing these three TMS systems was outside the scope of our project; therefore, we were limited to working with only the data provided by the Chicago office.

Next, we joined the three tabs of data that we felt were critical for the construction of our recommendation system. These included Carriers dataset, Moves dataset, and Locations dataset. Next, we filtered out all of the customer shipments that were less than 250 miles in order to solely focus our efforts on long-haul full truckloads. We also were provided multiple modes of shipments but in order to narrow the focus, we filtered out all other shipment types except Dry-Van and Temp-Controlled. Also, because there were some international moves within the data, we determined that focusing on domestic moves within the United States would be acceptable for our prototype recommendation system.

3.4 The Metrics and Labels for the Proposed Recommendation System

Geographically, we examined load-by-load data from both the Movements and Locations datasets to understand carriers' geographical patterns (e.g., from where carriers usually sent their trucks to and how recent those loads were). This information helped us understand the big picture of how active and geographically proximate carriers were, given a set of different origins and destinations for GlobalTranz.

The complete list of metrics is shown below in **Table 2** for an enquiry to match carriers for a requested lane (origin-destination).

Table 2 *Geographical Fit Metrics*

<u>**Metric**</u>	<u>**Explanation**</u>
Number of loads hauled historically on the requested lane	It was the most critical indicator to examine and be compared against the other metrics. The more loads hauled, the more "fit" a carrier was anticipated to be.
Number of recent loads hauled for the past 30/60/90 days on the requested lane	It implied how frequently and recently a carrier shipped loads for a specific route, maintaining an active status or not.
Number of outbound loads hauled historically from the requested origin to ANY destination	To compensate for the bias that some carriers may have shifted their volume with GlobalTranz from one route to another but still maintain a healthy total load shipped in general.
Number of inbound loads hauled historically from ANY origin to the requested destination	
Historical imbalance on the requested lane	$\frac{Number\ of\ backhauls}{Number\ of\ headhauls + Number\ of\ backhauls}$ <u>*Headhaul:</u> Loads shipped from the requested origin to the destination <u>*Backhaul:</u> Loads shipped from the origin to the requested destination A carrier that has more reverse volume could potentially offer more forward volume.

The level of service dictates the efficiency of trucking operations and namely shipper customers' satisfaction. We assessed the level of service using the Movements, Offers and Carriers datasets to capture service level-related metrics. By relating these metrics to each carrier, GlobalTranz would be able to evaluate each carrier's service performance in more detail. The **Table 3** below listed the metrics with specific explanations. We calculated the metrics for both on the requested lane only and across all lanes.

The across all lanes' metrics provided a broader overview of a carrier's overall level of service, reducing the potential bias resulted from lane specific performance.

Table 3 *Level of Service Metrics*

<table>
<tr><th><u>Metric</u></th><th><u>Explanation</u></th></tr>
<tr><td>Average OTP
(Ontime-To-Pickup) performance
on the requested lane</td><td rowspan="2">One carrier could have totally different performances on different lanes. This could be in part due to the drivers, lane condition, etc.

<u>*Unit: percentage</u></td></tr>
<tr><td>Average OTD
(Ontime-To-Delivery) performance
on the requested lane</td></tr>
<tr><td>Overall average OTP
(Ontime-To-Pickup) performance
across all lanes</td><td rowspan="2">Compared to the above lane-specific metrics, these metrics provided a broader and relatively unbiased view of a carrier's overall performance.

<u>*Unit: percentage</u></td></tr>
<tr><td>Overall average OTD
(Ontime-To-Delivery) performance
across all lanes</td></tr>
</table>

Finally, we pulled the data from the Movements and Offers datasets to obtain the profit and cost information. Furthermore, by benchmarking the cost, the actual amount paid to carriers, against the DAT Freight & Analytics (a freight exchange service and provider of transportation information) spot market rate, how each requested load performed financially compared to the market was disclosed. The **Table 4** below listed the metrics with their respective explanations.

Table 4 *Financial Fit Metrics*

<u>Metric</u>	<u>Explanation</u>
Average profit per load on the requested lane	It was critical for GlobalTranz to know how much net margin they actually earned.
Average cost per load on the requested lane	The actual amount that GlobalTranz paid to a carrier for each load hauled.
Average ratio of cost per load to DAT spot rate on the requested lane	This metric provided a good indicator of how much GlobalTranz could have saved.

However, not all derived metrics could be evaluated independently as some are correlated. GlobalTranz would need to determine which carriers to call at its discretion, after weighing the pros and cons from the recommendation system-generated carrier rankings of “goodness of fit”. Therefore, to compensate for the bias that may have been caused by the historical performance data, we also recommended extending GlobalTranz’s current carrier profile database to capture more unbiased carrier census data.

The broader carrier profile data was extracted from an external database (FMCSA - Federal Motor Carrier Safety Administration) and incorporated into the recommendation system. It provides an overall snapshot of a carrier’s extensive capabilities and commitment to compliance. In addition, it also served as an indicator of whether they were the capable and appropriate carriers that could grow with GlobalTranz as demands increase, one of the key components that could not be derived from GlobalTranz’s existing databases. The metrics that were found relevant to the analysis are listed in **Table 5** below.

Table 5 *Carrier Labels (Source: FMCSA, Federal Motor Carrier Safety Administration)*

<table>
<tr><th><u>Carrier Attribute</u></th><th><u>Data Type</u></th><th><u>Definition</u></th></tr>
<tr><td>PHY_STATE
PHY_ZIP</td><td>Categorical</td><td>Physical state of a carrier
Physical zip code of a carrier

Knowing a carrier's base station may help increase the geographical fit.</td></tr>
<tr><td>Carrier Operations</td><td>Categorical</td><td>Codes identifying carriers' type of Operation:
A = Interstate;
B = Intrastate Hazmat;
C = Intrastate Non-Hazmat</td></tr>
<tr><td>Number of power units</td><td>Numeric</td><td rowspan="2">Number of power units / drivers reported.

These indicated whether a carrier may have enough capacity to grow with GlobalTranz.</td></tr>
<tr><td>Number of drivers</td><td>Numeric</td></tr>
<tr><td>Driver_OOS_Total</td><td>Numeric</td><td rowspan="2">Number of Out-Of-Service violations related to Driver / Vehicle

GlobalTranz has a zero-tolerance rule that stops the collaborations with carriers that violated any of the left inspections.</td></tr>
<tr><td>Vehicle_OOS_Total</td><td>Numeric</td></tr>
<tr><td>HM_FLAG</td><td>Binary</td><td>Hazardous material handling capability

Carrier is subject to placardable hazardous material threshold (Y = Yes, N = No). Certain clients request this capability on specific lanes.</td></tr>
</table>

3.5 The Prototype Recommendation System

The user interface for the prototype system has five steps:

Step 1: Entering data

User (GlobalTranz's carrier representative) enters the requested origin and destination, which can be state, zip code, zone ID, etc., along with the optimal filters such as desired minimum loads hauled, minimum average OTD ratio, etc.

Step 2: Obtaining database-wide metrics

The system first calculates all database-wide metrics, across all origins and destinations, for carriers across the historical data.

Step 3: Obtaining lane-specific metrics

The system then calculates all metrics for the requested origin and destination in question, this includes overall OTD, overall OTP, imbalance, etc.

Step 4: Returning the qualified carriers

The system finally returns all carriers that match the given filters. They can be ranked by each metric or by a "goodness of fit" score. The feature labels are also displayed next to the qualified carriers for GlobalTranz's reference.

Step 5: Data interpretation

As shown in **Figure 3**, the filter – desired minimum number of loads shipped – was used for the purpose of demonstration to act as a threshold to help narrow down and obtain a condensed recommendation list of carriers. Other filters could be applied. An example list of recommended carriers from CA to TX was exported from the prototype system and can be found in **Figure 4**. The carriers were sorted by the volume of headhauls, however, the carriers could be ranked using other metrics (e.g., the volume of backhauls, profitability per load, etc.). Different GlobalTranz's carrier representatives may rank by other metrics. The tool is designed to provide a pool of qualified carriers for carrier representatives to refer to rather than a single carrier.

Figure 3 *Input User Interface of The Prototype Recommendation system*

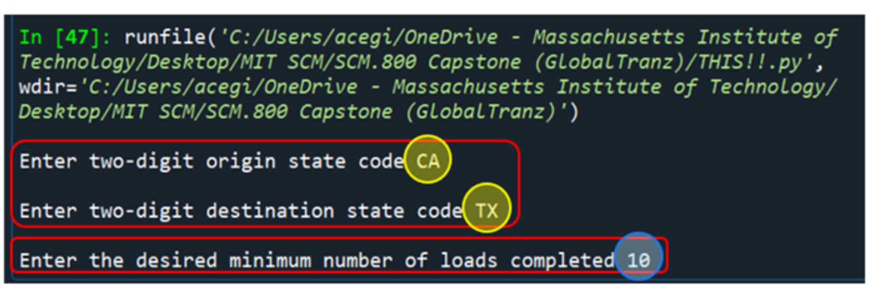


Figure 4 *Example List of Recommended Carriers Ranked By The Number of Headhauls (Lane CA to TX)*

	Carrier_ID	Geographical Fit									Level of Service				Financial Fit		
		CA:TX #loads	TX:CA #loads	Imbalance #loads	Imbalance%	<30days #loads	30-60days #loads	60-90days #loads	CA:Any D #loads	TX:Any O #loads	OTP%	Overall OTP%	OTD%	Overall OTD%	A(Cost) per load	A(Pft) per load	A(Cost/DAT) per load
Most Volume Headhaul	Carrier A	501	1	-500	0	33	30	33	503	1880	83%	81%	94%	92%	3305	734	95%
	Carrier B	380	94	-286	0.2	20	13	24	2499	405	98%	97%	96%	95%	4303	706	125%
Most Volume Backhaul	Carrier C	322	308	-14	0.49	40	29	21	2136	326	93%	91%	91%	88%	4397	542	125%
	Carrier D	273	1	-272	0	2	0	1	280	386	83%	88%	93%	92%	2481	336	102%
	Carrier E	255	74	-181	0.22	0	0	0	411	255	100%	99%	88%	93%	3324	93	141%
	Carrier F	168	161	-7	0.49	0	0	0	180	168	100%	99%	88%	92%	3250	129	138%
Most Profitable per Load	Carrier G	139	42	-97	0.23	1	1	0	518	161	97%	95%	90%	92%	3947	1208	109%
	Carrier H	135	0	0	0	0	0	0	143	161	96%	93%	83%	94%	3226	67	148%
	Carrier I	72	26	-46	0.27	0	0	0	72	72	100%	100%	90%	93%	3318	131	142%
	Carrier J	64	1	-63	0.02	0	1	0	99	209	92%	94%	89%	90%	4397	732	117%
	Carrier K	58	1	-57	0.02	0	0	0	59	73	100%	87%	72%	89%	3113	116	146%
	Carrier L	58	0	0	0	1	2	3	136	62	95%	97%	98%	97%	4152	-246	123%
	Carrier M	49	7	-42	0.12	1	3	0	140	170	84%	88%	80%	87%	2796	303	106%
	Carrier N	47	15	-32	0.24	0	1	9	1863	52	89%	84%	81%	88%	4774	995	119%
	Carrier O	44	0	0	0	0	0	0	45	45	84%	85%	95%	92%	2824	398	134%
Best OTD Service	Carrier P	41	10	-31	0.2	0	0	4	54	42	93%	93%	98%	99%	5013	568	122%
	Carrier Q	40	0	0	0	0	0	0	74	49	90%	93%	55%	85%	2871	157	127%
	Carrier R	35	5	-30	0.12	0	1	0	55	35	97%	98%	97%	98%	3548	187	94%
	Carrier S	35	0	0	0	0	0	16	35	35	91%	91%	94%	94%	5357	1171	112%
	Carrier T	34	13	-21	0.28	0	2	11	34	34	97%	96%	94%	96%	4973	1040	109%
	Carrier U	33	0	0	0	0	0	0	116	49	91%	91%	97%	88%	2045	142	96%

3.6 The Underlying Calculating Mechanism

To generate the carrier performance metrics, multiple queries were used to aggregate the load-by-load performance data on the carrier level, both across all lanes (database-wide) and on the requested lane. The headhaul metrics were first obtained by performing division over the number of loads hauled per carrier. With the headhaul metrics available, the backhaul metric, imbalance, could then be calculated. To derive the imbalance, i.e., the ratio of the number of backhauls to the number of headhauls and backhauls combined, the same queries were utilized again but with a reverse origin and destination setup. The pseudocode is presented below. Refer to **Appendix 1** for the complete Python code.

Calculate the database-wide metrics

Create a data frame df1 that groups the data by the distinct carrier ID #across of lanes

    Aggregate ({count the number of distinct loads,
               sum up OTP, OTD})

Calculate the desired metrics and add new columns to the data frame

    "Overall average OTP% across all lanes" = sum of OTP divided by the number of loads
    "Overall average OTD% across all lanes" = sum of OTD divided by the number of loads

#data frame df1 was then kept for later merge use

Calculate the inbound and outbound loads hauled
Create a data frame df2 that only keeps the loads hauled from the requested origin
Group the data frame by the distinct carrier ID

Aggregate ({count the number of distinct loads})

Add a new column “Number of outbound loads hauled” = count the number of distinct loads #from the requested origin to ANY destination”

Create a data frame df3 that only keeps the loads hauled back from the requested destination
Group the data frame by the distinct carrier ID

Aggregate ({count the number of distinct loads,})

Add a new column “Number of inbound loads hauled” = count the number of distinct loads #from ANY origin to the requested destination”

#data frame df2 & 3 were then kept for later merge use

Calculate the headhaul metrics
Create a data frame df4 that only keeps the loads hauled on the requested lane
Group the data frame by the distinct carrier ID

Aggregate ({count the number of distinct loads,
sum up length of hauled, costs, profits, DAT spot rates, OTP, OTD})

Calculate the desired metrics and add new columns to the data frame

“Number of headhaul loads” = count the number of distinct loads

Divide the above summed values by the number of distinct loads respectively to obtain the below metrics:

Average cost per load,
Average profit per load,
Average DAT spot rate per load,
Average OTP%,
Average OTD%,
Average ratio of cost per load to DAT spot rate
= “Average cost per load” divided by “Average DAT spot rate per load”

Calculate the number of recent loads metrics
Use time.time() to obtain the current UNIX timestamp

#this function ensures that the past 30/60/90 days are moving time windows in real time and carrier representatives will always be provide the most recent past 30/60/90 days’ information when using the recommendation system

for i in range (the number of distinct loads)

Loop over year, month and day to convert all times to UNIX timestamps #unit: seconds

Create a column “timeDiff” to record the difference between “NOW” and the desired past X days

for j in range (3) #looking back three months worth of data
    86400*30*(j-1) <= timeDiff <= 86400*30*j
    Group the data frame by the distinct carrier ID
        Aggregate ({count the number of distinct loads})
        Add the new columns to record the "number of loads hauled for the past 30/60/90 days loads hauled" respectively

#data frame df4 was then kept for later merge use

Calculate the backhaul metrics

Create a data frame df5 that only keeps the reverse loads hauled on the requested lane
Group the data frame by the distinct carrier ID
    Aggregate ({count the number of distinct loads})
    Add a new column "Number of backhaul loads" = count the number of distinct loads #from the requested destination back to the requested origin"
    Add a new column "Imbalance" = "Number of backhaul loads" divided by the sum of "Number of headhaul loads" and "Number of backhaul loads"

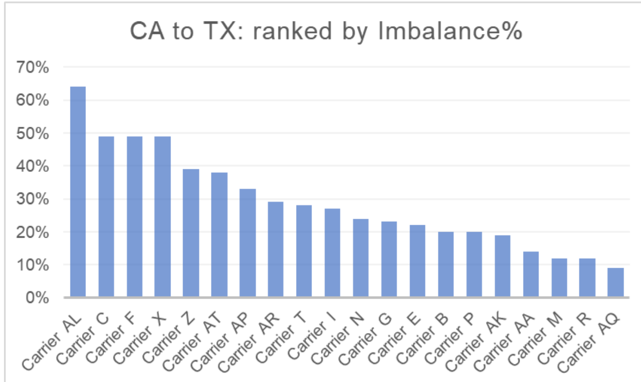
#data frame df5 was then kept for later merge use

Merge data frames, filter carriers and generate the recommendation list

Create the final data frame dfFINAL that merges(df1, df2, df3, df4, df5, on carrier ID)
Filter out carriers that meet the desired filtering criteria
Export dfFINAL according to the default desired ranking preferences

In our example, CA to TX was the requested headhaul lane. This obviously makes TX to CA the backhaul lane, **Figure 5** shows the top 20 carriers with the largest imbalance percentage. These carriers were noticeably different from the ones in **Figure 4** which ranked the carriers by the number of headhauls. The difference was expected as different metrics were used for ranking carriers. A higher number of headhauls indicated more frequently a carrier had been selected by GlobalTranz, which could be seen as preferred or incumbent carriers. However, these kinds of carriers did not automatically equate to good carriers, neither did the carriers who had the largest imbalance percentage. Therefore, a score of "goodness of fit" may be useful for helping GlobalTranz select carriers from a more objective perspective, which was covered in the next section.

Figure 5 *Example List of Imbalances for The Lane CA to TX*



$$* \, Imbalance \quad = \frac{Backhaul}{Headhaul \, + \, Backhaul}$$
$$= \frac{number \ of \ loads \ shipped \ TX \ to \ CA}{number \ of \ loads \ shipped \ TX \ to \ CA \ + \ number \ of \ loads \ shipped \ CA \ to \ TX)}$$

When ranking carriers by different metrics, GlobalTranz's carrier representatives could easily bring in their own subjective biases. Some may favor the lane specific OTD while some others may put more emphasis on the backhaul headhaul imbalance. The subjective biases could be perceived positively or negatively. It could be viewed as years of experience and industry knowledge that enabled GlobalTranz to select the appropriate carriers. On the other hand, it might be a vicious cycle that nudges GlobalTranz to keep selecting the suboptimal carriers. Striking a balance between the subjective biases and objective metrics is critical. The next section discussed how a survey, score of "goodness of fit", and sensitivity analysis may help further improve the carrier ranking process.

3.7 The Use of a Utility Function vs a "Goodness of Fit" Score

In addition to simply ranking carriers by different individual metrics such as the headhaul volume, we created a utility function to generate a "goodness of fit" score. To generate a "goodness of fit" score, each individual level-2 metric was converted to be between 0% and 100% by comparing with the minimum and maximum values within each level-2 metric itself. Each level-2 metric was then multiplied with equal weight, generating the uniform "goodness of fit" score. In addition to the uniform score, three extreme cases were developed. This illustrates how sensitive the change in carrier rankings could be. Lastly, to further understand whether the uniform "goodness of fit" score reflects GlobalTranz's preferences, a survey was sent to GlobalTranz as shown in **Appendix 2**. The survey received only 6 responses. In the survey, GlobalTranz managers as well as carrier representatives were asked to allocate 100 points to the three level-1 metrics. Although six responses is not statistically sufficient to make a general assumption, this survey provided a glimpse of how GlobalTranz employees weighed different metrics. The GlobalTranz Survey Results Score was generated based on the averages of the three metrics. The summary of weight assignment can be found in **Table 6** and the scores of all six scenarios, on a scale 0-100%, are shown in **Table 7**.

- GlobalTranz Survey Results Score:
    - Assigned 48% weight to geographical fit; 33% to level of service; 19% to financial fit.
- Uniform "goodness of fit" Score:
    - Each of the three level-1 metrics was assigned an equal weight
- 100% Geographical Fit: Assigned 100% weight to geographical fit while 0% to the other two.
- 100% Level of Service: Assigned 100% weight to level of service while 0% to the other two.
- 100% Financial Fit: Assigned 100% weight to financial fit while 0% to the other two.
- Headhaul loads: The number of headhauls shipped.

Table 6 *Weight Assignment of The Six Scenarios*

Score	**Weight**		
	Geographical Fit	Level of Service	Financial Fit
GlobalTranz Survey Results	**0.48**	**0.33**	**0.19**
Uniform Score	**0.33**	**0.33**	**0.33**
100% Geographical Fit	**1**	**0**	**0**
100% Level of Service	**0**	**1**	**0**
100% Financial Fit	**0**	**0**	**1**
Headhaul loads	**N/A**	**N/A**	**N/A**

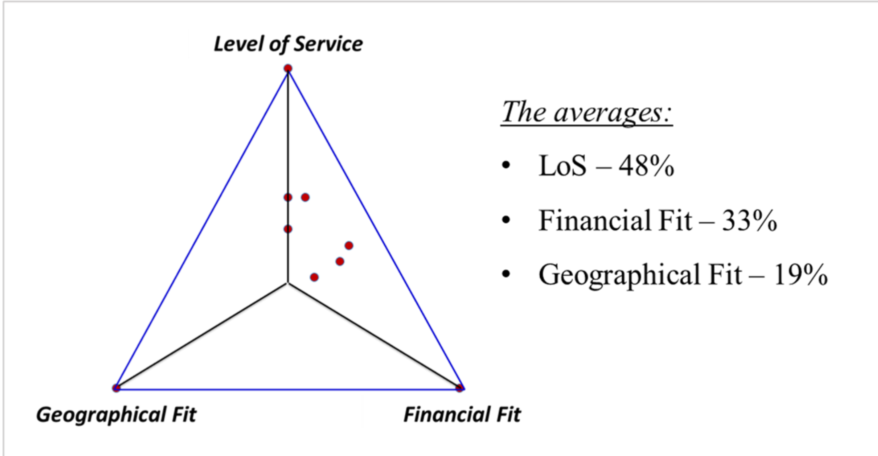
__Table__ 7 Example List of Recommended Carriers Ranked By The "GlobalTranz Survey Results Score" (Lane CA to TX)

Carrier ID	GlobalTranz Survey Results Score	Uniform Goodness of Fit Score	100% Geographical	100% Level of Service	100% Financial	Headhaul #loads
Carrier A	53.60%	4.2565188774%	100.000000000%	67.77%	6.28%	322
Carrier B	51.75%	2.9238017688%	37.890609051%	86.69%	8.90%	380
Carrier C	45.24%	0.0000000044%	0.000000085%	90.36%	5.66%	35
Carrier D	44.75%	0.0004622555%	0.000246193%	76.30%	24.62%	139
Carrier E	42.89%	0.0000036414%	0.000055979%	84.03%	7.74%	34
Carrier F	42.21%	0.0000000919%	0.000020773%	87.60%	0.50%	58
Carrier G	41.35%	0.0000003107%	0.000011399%	83.91%	3.25%	41
Carrier H	40.87%	0.0000000416%	0.000002355%	83.70%	2.11%	72
Carrier I	39.39%	0.0000059243%	0.000480012%	81.02%	1.52%	255
Carrier J	39.24%	0.0000036928%	0.000198525%	80.15%	2.32%	168
Carrier M	36.76%	0.5103209203%	3.541703567%	58.14%	24.78%	501
Carrier K	36.43%	0.0000000687%	0.000001031%	69.27%	9.62%	64
Carrier L	36.37%	0.0000000073%	0.000000140%	70.69%	7.39%	33
Carrier N	36.09%	0.0000005554%	0.000025900%	73.17%	2.93%	35
Carrier O	34.70%	0.0000186157%	0.000208878%	62.49%	14.26%	273
Carrier P	33.75%	0.0000000154%	0.000002324%	69.66%	0.95%	135
Carrier Q	33.01%	0.0000000038%	0.000000067%	62.40%	9.26%	44
Carrier R	28.42%	0.0002158880%	0.004709346%	53.29%	8.60%	47
Carrier S	28.29%	0.0000004633%	0.000008256%	51.45%	10.91%	49
Carrier T	27.36%	0.0000000019%	0.000000187%	55.75%	1.83%	58
Carrier U	20.11%	0.0000000017%	0.000000108%	39.13%	4.02%	40

While geographical fit seemed to be dominant which dictated the uniform "goodness of fit" score, it was indeed difficult for carriers to perform equally well on the other two metrics. Only Carrier B and G were able to be in the top 10 across all scenarios. With the utility function in place, GlobalTranz could start tuning the weights assigned to different metrics and generating the "goodness of fit" score that they considered would best reflect their carrier-shipper matching process.

In the survey (**Figure 6**), all 6 responses fell in the financial fit and level of service sector, and none allocated more than 25 points to geographical fit. Of the 6, 3 considered level of service the most important metric which was in general consistent with our interviews with GlobalTranz. However, although the geographical fit was emphasized multiple times during the interviews, it diminished when compared to the other two. (The datapoint would be in the middle if the three metrics had the same weight. On the other hand, when geographical fit was zero, for example, the datapoint would be on the level of service-financial fit line and closer to either metric depending upon which one had more weight.)

Figure 6 *Survey Results - The Priority Triangle Mapping*



Considering GlobalTranz put almost 50% of weight to level of service, Carrier A and D should be red-flagged. They both had below average GlobalTranz Survey Results Score (GSRS) but had hauled the most and fourth most loads. Further examination would be necessary in order to determine whether these carriers were deemed appropriate to work with in the long run. On the contrary, Carrier R, T and P had great GSRS but had not hauled a lot historically. These kinds of carriers may be potential candidates for GlobalTranz to explore further.

4. Results and Discussion

Even though **Figure 6** showed that GlobalTranz cared about the level of service the most and then the financial fit, **Table 7** disclosed a slightly different trend. Carrier A, D and M had the biggest gaps between GSRS and 100% Level of Service. To explain the below than average level of service phenomenon, we came up with two hypotheses:

1. GlobalTranz may have had less of an issue with finding carriers that were geographically fit but had difficulty increasing level of service, and thus the survey results were a reflection of what GlobalTranz wanted to improve instead of what GlobalTranz had been focusing on.
2. The possibility of not being on time may increase, reducing level of service, as a carrier hauled more loads on a given lane, which could be statistically possible.

Even though the two hypotheses regarding the low level of service could not be answered at this stage without GlobalTranz's managerial interpretation. A -0.35 correlation was observed between level of service and financial fit. When GlobalTranz received worse level of service, it historically paid less to a carrier. The dilemma was by how much more GlobalTranz would still be willing to pay to be offered good level of service. However, in the event when level of service and financial fit were comparable for two potential carriers, geographical fit could be the deciding factor for one carrier to win the other. Therefore, despite the fact that geographical fit did not score high in the survey, it was critical and could be the most controllable factor for GlobalTranz.

Nonetheless, there were few carriers that performed almost equally well across the three categories but did not make it to the top 10 carriers that had the most headhaul volume. Take "Carrier E" for example, it was the 20th in terms of headhaul volume but did not even account for 10% of "Carrier A" volume. There were several plausible reasons:

1. The lack of drivers and power units. It could be a yellow flag for GlobalTranz that this carrier may not be suitable for developing a long-term relationship as it will not grow with GlobalTranz. The carrier feature labels may help provide a good reference.
2. A carrier purposefully avoided hauling loads on specific lanes but had no issue with others. It may indicate this carrier might not be a good geographical fit on this requested lane and might treat this lane as a secondary market, eventually deteriorating its level of service in the long run. The metrics "Number of outbound loads hauled from the requested origin to ANY destination" and "Number of inbound loads hauled from ANY origin to the requested destination" would help capture this effect.
3. The worst-case scenario was that this carrier used to be good but recently violated compliance. Although there were few carriers feature labels that could bring this information to GlobalTranz's attention, the data was not updated in real-time. GlobalTranz would need to utilize other external platforms to receive instant warning.

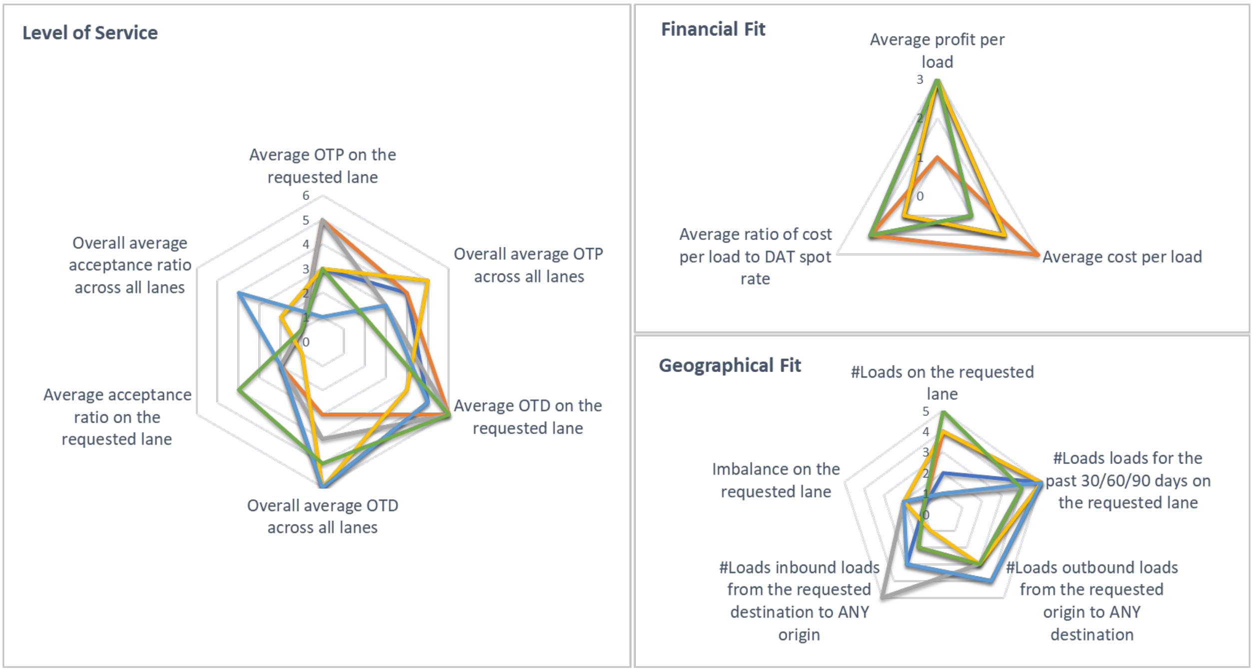
5. Conclusion

GlobalTranz was in need of a strategic recommendation system that could be utilized by the carrier representatives to standardize their current carrier-shipper matching decision process. We developed a prototype algorithm based on three major categories: geographical proximity, level of service, and cost, that could be utilized by the carrier representatives. By altering the selected criteria, the recommendation system returns a list of carriers best suited for the specific decision. After the recommendation system returns its solution, the carrier representatives could then determine which carriers to contact. They should proceed, after weighing the pros and cons of the recommendation system-generated carrier rankings, to choose a carrier based on "goodness of fit". We believe that the integration of our prototype recommendation system would further complement the current carrier-shipper matching platform. New efficiencies would be recognized by GlobalTranz that would aid in business decisions and strategy both currently and in the future.

5.1 The Next Step for Level-2 Sub Metrics

In the survey sent to GlobalTranz, the rankings of sub metrics within each major category were also collected as presented in **Figure 7**. (The higher the number, the more important the sub metrics). The preferred sub metrics were observed across the three categories. The top two metrics for level of service were average OTD on the requested lane and across all lanes. This observation was consistent with our interview with GlobalTranz. Being on-time to a delivery site, a shipper's client, is usually more critical. In terms of geographical fit, GlobalTranz carrier managers and representatives were most concerned about the number of recent loads and the number of inbound loads. The recent volume is a proxy not only for how active a carrier has been recently but also for a carrier's capacity. On the other hand, average profit per load topped the list of financial fit.

Figure 7 Survey Results for The Sub Metrics



The sub metrics could then be used as a second layer of ranking carriers. GlobalTranz may first narrow down the list of carriers by ranking carriers by the level-1 metrics and then further select those shortlisted carriers based on the sub metrics. A prototype two-level hierarchy logic tree (Hwang et al., 2016) could thus be generated. Nevertheless, in the long run, GlobalTranz would have to spread the survey to more carrier managers and representatives to acquire more datapoints for verifying the significance of the ranking of the sub metrics.

5.2 Future Opportunities

If this project was to be advanced further by GlobalTranz in the future, there is an opportunity for GlobalTranz to increase its data transparency and develop stronger data maintenance. These suggestions would significantly improve consistency and clarity when analyzing the data. Currently, GlobalTranz utilizes three transportation management systems (TMS) nationally. If GlobalTranz integrated all of these systems to functionally record and update data in the same exact manner, our recommendation would then become scalable to the entire national business. Therefore, our recommendation system would be able to be used throughout the entire business.

Second, our recommendation system was designed as a strategic tool for supporting decision-making process due to the limited data available for analysis. However, with the inclusion of more enhanced data, especially in regard to real time vehicle positioning, GlobalTranz would be able to utilize our recommendation system on a load-by-load basis. This would be extremely beneficial to the carrier representatives. It would make the daily decision process for the carrier representatives much more efficient and effective.

Last, looking at the methodology of the current selection process, it seems as though there is a competitive nature within the carrier representatives' teams, we feel that utilizing the prototype recommendation system will alleviate some of this competitiveness by easily providing the best suited carriers for shippers which will allow for further efficiency for GlobalTranz.

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APPENDICES

Appendix 1: Python Code

```
import pandas as pd
pd.set_option('display.max_columns', 10)
import time
import datetime
import matplotlib.pyplot as plt
```

```
df = pd.read_csv("GTZ_data.csv")

## Conditions
df = df.loc[df['LOH'] >= 250]
Origin = "CA" #(input("Enter two-digit origin state code "))
Destination = "TX" #str(input("Enter two-digit destination state code "))
MIN_loads = 10 #int(input("Enter the desired minimum number of loads completed "))
days = 30
```

Database-wide metrics

```
## Overall average OTP & OTD across all lanes
All_OTP_OTD = df.groupby(by = ["Carrier_ID"],
                         as_index=False).agg({"Load_ID":"count",
                                              "OTP":"sum",
                                              "OTD":"sum"})

All_OTP_OTD["Overall_OTP%"] = round((All_OTP_OTD["OTP"] / All_OTP_OTD["Load_ID"]),2)
All_OTP_OTD["Overall_OTD%"] = round((All_OTP_OTD["OTD"] / All_OTP_OTD["Load_ID"]),2)

All_OTP_OTD = All_OTP_OTD[["Carrier_ID", "Overall_OTP%", "Overall_OTD%"]]
```

```
## Calcuate the requested origin to any destination
O_to_any = df[(df['O_state'].str.contains(Origin))]

O_to_any = O_to_any.groupby(by = ["Carrier_ID"],
                            as_index=False).agg({"Load_ID":"count"})

O_to_any.rename(columns={"Load_ID": Origin + ": Any D #loads"}, inplace=True)
```

```
## Calcuate the requested destination to any origin
Des_to_any = df[(df['D_state'].str.contains(Destination))]

Des_to_any = Des_to_any.groupby(by = ["Carrier_ID"],
                            as_index=False).agg({"Load_ID":"count"})

Des_to_any.rename(columns={"Load_ID": Destination + ": Any O #loads"}, inplace=True)
```

The requested origin and destination

```
########################################
########  FORWARD SHIPPING  ###########
## Origin state to destination state ##
########################################


test1 = df[(df['O_state'].str.contains(Origin))
           & df['D_state'].str.contains(Destination)]

test1["timeNOW"] = 1635220800  ### use time.time() for the real system
test1["timeDiff"] = test1["timeNOW"] - test1["unix"]


## Calculating < 30-day loads
test_30D = test1[test1["timeDiff"] <= (86400*1*days)]
test_30D = test_30D.groupby(by = ["Carrier_ID"], as_index=False).agg({"Load_ID":"count"})
test_30D["<30D #loads"] = test_30D["Load_ID"]
test_30D = test_30D[["Carrier_ID", "<30D #loads"]]


## Calculating < 60-day loads
test_60D = test1[test1["timeDiff"] <= (86400*2*days)]
test_60D = test_60D.groupby(by = ["Carrier_ID"], as_index=False).agg({"Load_ID":"count"})
test_60D["30-60D #loads"] = test_60D["Load_ID"]
test_60D = test_60D[["Carrier_ID", "30-60D #loads"]]


## Calculating < 90-day loads
test_90D = test1[test1["timeDiff"] <= (86400*3*days)]
test_90D = test_90D.groupby(by = ["Carrier_ID"], as_index=False).agg({"Load_ID":"count"})
test_90D["60-90D #loads"] = test_90D["Load_ID"]
test_90D = test_90D[["Carrier_ID", "60-90D #loads"]]
```

```
# Group by carrier_id and aggregate the attributes of interest
test1 = test1.groupby(by = ["Carrier_ID"],
                      as_index=False).agg({"Load_ID":"count",
                                           "LOH":"sum",
                                           "OTP":"sum",
                                           "OTD":"sum",
                                           "Revenue":"sum",
                                           "Cost":"sum",
                                           "Mkt_linehaul":"sum",
                                           "Profit":"sum"})
```

```
# Calculate average values per load
test1["A(Rev)/load"] = (test1["Revenue"] / test1["Load_ID"]).astype(int)
test1["A(Cost)/load"] = (test1["Cost"] / test1["Load_ID"]).astype(int)
test1["A(Pft)/load"] = (test1["Profit"] / test1["Load_ID"]).astype(int)
test1["A(Mkt)/load"] = (test1["Mkt_linehaul"] / test1["Load_ID"]).astype(int)
test1["A(LOH)"] = (test1["LOH"] / test1["Load_ID"]).astype(int)
test1["OTP%"] = round((test1["OTP"] / test1["Load_ID"]),2)
test1["OTD%"] = round((test1["OTD"] / test1["Load_ID"]),2)


# Filter out the necessary info
test11 = test1[["Carrier_ID",
                "Load_ID",
                "A(LOH)",
                "OTP%",
                "OTD%",
                "A(Rev)/load",
                "A(Cost)/load",
                "A(Pft)/load",
                "A(Mkt)/load"]

test11.columns = ["Carrier_ID",
                  "#loads",
                  "A(LOH)",
                  "OTP%",
                  "OTD%",
                  "A(Rev)/load",
                  "A(Cost)/load",
                  "A(Pft)/load",
                  "A(Mkt)/load"]
```

```
TEST = test11.merge(
    test_30D, on="Carrier_ID", how="left").merge(
        test_60D, on="Carrier_ID", how="left").merge(
            test_90D, on="Carrier_ID", how="left").merge(
                test_1Y, on="Carrier_ID", how="left")


TEST["<30D #loads"].fillna(0, inplace=True)
TEST["30-60D #loads"].fillna(0, inplace=True)
TEST["60-90D #loads"].fillna(0, inplace=True)
TEST["90D-1Y #loads"].fillna(0, inplace=True)


TEST["90D-1Y #loads"] = TEST["90D-1Y #loads"] - TEST["60-90D #loads"]
TEST["60-90D #loads"] = TEST["60-90D #loads"] - TEST["30-60D #loads"]
TEST["30-60D #loads"] = TEST["30-60D #loads"] - TEST["<30D #loads"]

TEST["(<90D/1Y)% #loads"] = ((TEST["<30D #loads"] + TEST["30-60D #loads"] + TEST["60-90D #loads"])
                              / (TEST["<30D #loads"] + TEST["30-60D #loads"] + TEST["60-90D #loads"] + TEST["90D-1Y #loads"]))
```

```
#######################################
########  REVERSE SHIPPING  ###########
## Destination state to origin state ##
#######################################

test2 = df[(df['O_state'].str.contains(Destination))
           & df['D_state'].str.contains(Origin)]

# Group by carrier_id and aggregate the attributes of interest
test2 = test2.groupby(by = ["Carrier_ID"],
                      as_index=False).agg({"Load_ID":"count"})
```

```
# Filter out the necessary info
test22 = test2[["Carrier_ID",
                "Load_ID"]]

test22.columns = ["Carrier_ID",
                  "#loads"]
```

Imbalance

```
## IMBALANCE ##

test1122 = TEST.merge(test22, on='Carrier_ID', how='left')

test1122["Inbalance"] = test1122["#loads_y"] - test1122["#loads_x"]

test1122 = test1122[["Carrier_ID",
                     "#loads_x",
                     "#loads_y",
                     "Imbalance",
                     "OTP%",
                     "OTD%",
                     "A(Cost)/load",
                     "A(Pft)/load",
                     "A(Mkt)/load",
                     "<30D #loads",
                     "30-60D #loads",
                     "60-90D #loads"]]

test1122.columns = ['Carrier_ID',
                    Origin + ":" + Destination + ' #loads',
                    Destination + ":" + Origin + ' #loads',
                    'Imbalance',
                    "OTP%",
                    "OTD%",
                    "A(Cost)/load",
                    "A(Pft)/load",
                    "A(Mkt)/load",
                    "Tag",
                    "<30D #loads",
                     "30-60D #loads",
                     "60-90D #loads"]

test1122["Imbalance%"] = round(test1122[Destination + ":" + Origin + ' #loads']
                        / (test1122[Origin + ":" + Destination + ' #loads']
                           + test1122[Destination + ":" + Origin + ' #loads']),2)


test1122[Destination + ":" + Origin + ' #loads'].fillna(0, inplace=True)
test1122['Imbalance'].fillna(0, inplace=True)
test1122["Imbalance%"].fillna(0, inplace=True)
test1122["(<90D/1Y)% #loads"].fillna(0, inplace=True)
```

Merge database-wise and O-D specific metrics

```
FINAL = test1122.merge(
    All_OTP_OTD, on='Carrier_ID', how='left').merge(
    O_to_any, on="Carrier_ID", how="left").merge(
    Des_to_any, on="Carrier_ID", how="left")
```

```
## Final filtering
FINAL = FINAL.loc[FINAL[Origin + ":" + Destination + ' #loads'] >= MIN_loads]
FINAL.sort_values(by=[Origin + ":" + Destination + ' #loads'], ascending=False)
```

Appendix 2: GlobalTranz Survey and Results

Global Tranz Carrier Recommendations

Introduction

This survey is part of a project that GlobalTranz is conducting with MIT's Supply Chain Management masters program. The project is looking to better understand the preferences for selecting carriers for customer requests. These will be imbedded within a prototype decision support tool that is being developed. There are 4 quick questions that should take less than 5 minutes to complete. Thank you in advance.

1. Carriers differ in terms of Level of Service, Financial/Cost, and Geographic Fit for a lane or set of lanes. How much do you prefer each of these three criteria when selecting carriers? Please allocate 100 points across the three metrics so that they sum to 100.

Geographic Fit (e.g., prior activity on the lane, carrier headquarters, etc.)

Level of Service (e.g., on-time, acceptance ratio, etc.)

Financial (e.g., profit per load, cost per load, etc.)

2. Please rank the below "Level of Service" metrics when selecting carriers for a requested lane or lanes where 1 is most important and 6 is least important.

- Average OTP (On time-To-Pickup) performance on THIS lane
- Overall average OTP (On time-To-Pickup) performance across all lanes
- Average OTD (On time-To-Delivery) performance on THIS lane
- Overall average OTD (On time-To-Delivery) performance across all lanes
- Average acceptance ratio on THIS lane
- Overall average acceptance ratio across all lanes

3. Please rank the below "Financial/Cost" metrics when selecting carriers for a requested lane or lanes where 1 is most important and 3 is least important.

- Average profit per load
- Average cost per load (the actual amount paid to carrier)
- Average ratio of cost per load to DAT spot rate

4. Please rank the below “Geographic Fit" metrics when selecting carriers for a requested lane or lanes where 1 is most important and 5 is least important.

- Number of loads hauled historically on THIS lane
- Number of recent loads hauled for the past 30/60/90 days on THIS lane
- Number of recent outbound loads hauled for the past 30/60/90 days from the requested origin to ANY destination
- Number of recent inbound loads hauled for the past 30/60/90 days from the requested destination to ANY origin
- Historical imbalance = #backhauls / (#headhauls + #backhauls) on THIS lane

5. Any other suggestions or thoughts on the carrier selection process that we should know about?

Done