access

SCHEDULED TRIP DEMAND FORECASTING FY 2027 – FY 2036

PREPARED FOR

ACCESS SERVICES

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Hollingsworth Consulting

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1. Executive Summary

The scheduled trip demand and the number of new applicants drive the need for funding and resources at Access Services. Reliable forecasts and projections are essential to plan sufficient budgets and adequate operational resources to fully fund the expected demand as required by ADA regulations. Through an initial analysis and the review of results from previous testing for explanatory variables, followed by training, validation, and testing, the best fit forecasting models were selected and used to develop projections for fiscal years 2027 through 2036.

The historical analysis reveals insights into the scheduled trip demand and paratransit ridership nationwide. The pre-pandemic data, however, does not reflect current behavior causing uncertainty about whether, or when, pre-pandemic patterns will re-emerge. Models to forecast scheduled trip demand need to have the capacity to predict, with a limited amount of historical data.

Explanatory variables provide insight into demand and thoughtful consideration given during forecasting model selection. Several variables were considered and analyzed in the previous report as a potential cause in a cause-and-effect relationship with scheduled trip demand including household income and gasoline prices, adjusted for inflation. These variables lack value for predicting the number of scheduled trips and were not incorporated into the current forecasting models.

An assessment of FY2025 projections demonstrates favorable results for scheduled trip demand. Projections submitted to Access Services for FY 2025 scheduled trip demand aligned very well with the actual number of scheduled trips with a slight variance of 1.21%.

Different methodologies were utilized to perform experiments for the current forecasting period to identify the parameters for the Long Short-Term Memory (LSTM) model that produced projections even closer to scheduled trip demand than the previous parameters. Adjustments to parameters of the LSTM model produced projections of scheduled trip demand for the most recent 12 months with much better results than the previous forecast with only a 0.004% variance. The Meta Prophet model was also explored to further refine long term projections.

Occasionally, scheduled trips are canceled by the rider, or the rider is a no-show. An analysis of the completed trip ratio indicates that 80.01% of scheduled trips are completed. This ratio appears to be stationary, constant, and stable.

Projections submitted to Access Services for the number of new applicants for FY 2025 exhibit a 6.31% error. The level of error initiated further evaluation of the data, which revealed it is now stationary and stable. This discovery led to the identification and selection of a model focused on the mean average. An initial analysis along with preliminary projections on the number of In-Person Evaluations, a subset of the number of new applicants.

Characteristics of the Los Angeles County population such as age and the number of people reporting a disability provide insight into long-term scheduled trip demand and the number of new applicants. The population of individuals aged 55 years and older has increased by 67% since 2000 and the number of people reporting a disability increased by 21% since 2010. Continued growth of individuals reporting disability and individuals ages 55 years and older indicates the likelihood of growth for the number of eligible riders.

2. Introduction

Access Services provides Americans with Disabilities Act (ADA) mandated paratransit service for eligible persons in Los Angeles County, California. Its services are available to any location within three quarters of a mile of any public bus fixed route and the same distance around Metro rail stations during its operating hours. Its service area is divided into six regions and extends into portions of the surrounding counties of San Bernardino, Orange, and Ventura. Independent ridership estimates are necessary to fully fund the expected ADA paratransit demand. Reliable forecasts and projections are essential to plan sufficient budgets and adequate operational resources for these critical services.

The first step to developing the projections includes an initial analysis, a peer review, an assessment of lingering pandemic effects, and an assessment of the prior projections. It is necessary to understand the state of paratransit, internally and nationally, to guide the course of projections for scheduled trip demand and new applicants.

The second step is to identify potential tools, models, and parameters to create forecasts. Training and testing prospective models reveal the best choice to select for projections. The selected model(s) and parameters are then applied to develop forecasts of scheduled trip demand and new applicants.

The third step is an evaluation to understand prediction errors associated with the forecasted values and the confidence in utilizing the values. The final step of the approach includes reflection on the steps, and evaluation of them, to identify ways to improve the forecasting model for projections in the next iteration.

2.1. Purpose

Paratransit demand forecasting has traditionally relied on historical ridership data analyzed under relatively stable conditions, where predictable patterns in scheduled trips and the number of new applicant growth could be identified and extrapolated. Under such circumstances, trend-based forecasting methods were effective in capturing gradual shifts and cyclical changes in demand over time. However, a large-scale global disruption (COVID-19 pandemic) fundamentally altered behavior rendering long-standing demand patterns unstable and less reliable. As a result, historical data generated prior to this disruption no longer provides sufficient value for informing current or future projections.

In the post-disruption environment, paratransit demand exhibits increased volatility and structural change, necessitating a more robust and adaptive forecasting framework. The purpose of this project is to develop a systematic approach for training, testing, and comparing prospective forecasting models that can dynamically identify the most appropriate model or set of models for annual projections. This approach is designed to improve the reliability and sustainability of projections used to support critical planning, resource allocation, and budgetary decisions essential to meeting the needs of paratransit riders, their families, and the broader region.

Ongoing evaluation of model performance for both scheduled trip demand and new applicant volumes provides insight into forecast error, uncertainty, and confidence in projected values for operational decision-making. Continuous reflection and refinement of the forecasting approach establish an iterative improvement cycle, increasing the relevance and precision of projections over time. Future enhancements to machine learning techniques and advanced time-series methods further position Access Services to strengthen analytical rigor and maximize the long-term value of demand forecasting.

3. Scheduled Trip Demand

3.1. Initial Analysis – Scheduled Trip Demand

Patterns of the past foster planning for the uncertainty of the future. Essential factors that provide insight into the paratransit needs in Los Angeles County, California, include the scheduled trip demand. A review of peer paratransit services also provides an opportunity for insights on services in other regions of the country.

The focus of the initial analysis includes a historical analysis on scheduled trip demand, a brief evaluation of the global pandemic effect, a peer review, and an assessment of the most recent projections. Together, the historical analysis, pandemic evaluation, peer review, and assessment of the most recent projections provide direction for the types of forecasting models to consider and evaluate.

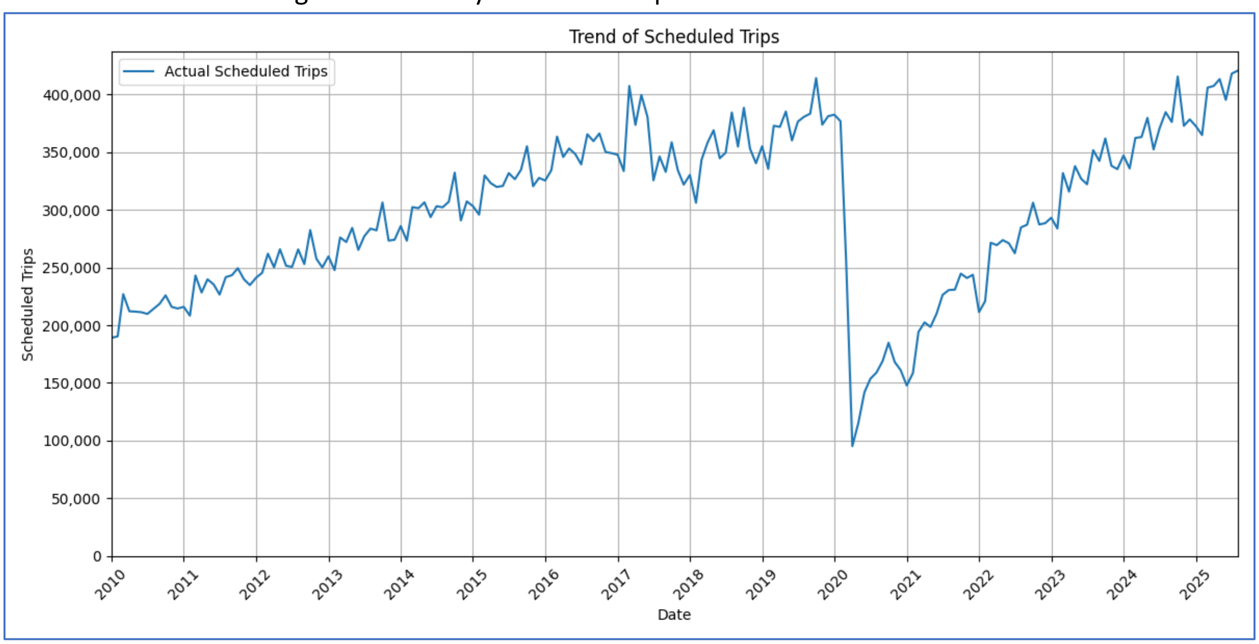
3.1.1. Historical Analysis – Scheduled Trip Demand

The examination of evidence from the past helps form a more coherent story. The focus of this examination includes an analysis of events in time series to identify patterns, trends, and changes over time. The analysis identifies the presence of (or lack of) seasonal patterns, cyclical patterns, stationarity, and autocorrelation along with trends. These components are key for model identification and selection.

Access Services needs to understand ridership to develop an accurate, effective budget and plan future fiscal year(s). The historical analysis includes scheduled trip demand and actual trip demand.

The initial data for the historical analysis of scheduled trip demand includes the number of trip requests from January 2010 through August 2025. The data file provided to Hollingsworth Consulting included the count of trip requests per month for each service region and the count of trip requests per month system-wide. The time-series plot for the monthly scheduled trip demand is shown below in Figure 1.

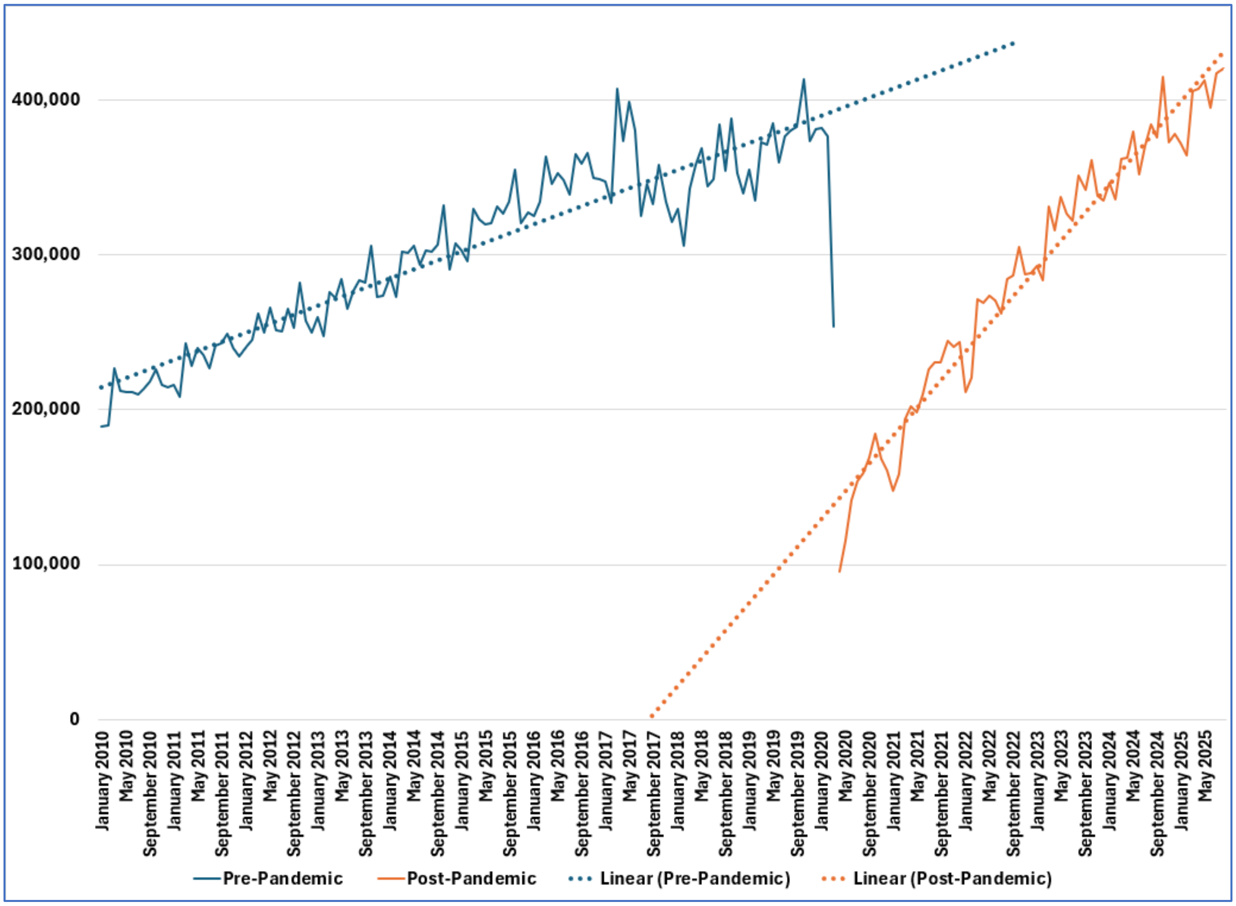
Figure 1: Monthly Scheduled Trip Demand Time-Series Plot



The graph reveals a story with a twist. There is a 75% drop in the number of trip requests per month from February 2020 to April 2020, equal to 281,522 fewer scheduled trips per month. The scheduled trip demand does not return to calendar year 2019 levels until October 2024.

The intercept and the slope of the scheduled trip demand appear to be different when comparing February 2020 and the months prior to it with April 2020 and the months following. The time-series plot shown in Figure 2 displays monthly scheduled trip demand prior to the pandemic with its trendline compared to the trendline of the demand after the pandemic began through August 2025.

Figure 2: Monthly Scheduled Trip Demand Time-Series Plot – Pre and Post-pandemic



Visual inspection of Figure 2 illustrates a clear difference in the observed values. There are only two (2) pre-pandemic observations below the value of 200,000 trip requests while there are thirteen (13) post-pandemic observations below the same amount. The slope of the lines in each figure looks different. The trend analysis in the Scheduled Trip Demand Forecasting FY 2026 (Appendix A-2) report indicated a mathematical difference between the trend for the monthly scheduled trip demand before the pandemic and after the pandemic. This is important because pre-pandemic scheduled trip demand does not reflect current scheduled trip demand limiting its value to forecast scheduled trips. Visual inspection of Figure 2 illustrates the difference between the trends persists.

3.1.2. Global Pandemic Effect

A new disease, COVID-19 (coronavirus disease 2019), spread worldwide causing a global pandemic. The World Health Organization (WHO) declared the virus a pandemic on March 11, 2020. State shutdowns began in March 2020 to prevent the spread of the virus. The virus and the shutdowns along with risk mitigation tactics such as requiring face coverings and social distancing changed the behaviors and consumption choices of consumers in the United States.

"The COVID-19 pandemic has disrupted everything from consumer behavior to supply chains, and the economic fallout is causing further changes," reported Sara Brown in a webinar hosted by MIT Sloan Management Review in January 2021 (para 1).

Several data sources document the disruption and change in behavior patterns that continue across the United States with uncertainty about whether and when pre-pandemic patterns will re-emerge. One example is related to retail sales, which increased as much as 30% (inflation adjusted) from Quarter 4 in 2019 to Quarter 4 of 2022. Restaurant visits in 2022 were down 12.2% compared to 2019, while grocery store visits increased 5% during the same period. Telehealth, an alternative to in-person healthcare, is double the pre-pandemic levels for Medicare recipients (Gilbert, et al., 2022).

"Pre-pandemic data is now unreliable, or even obsolete in predicting new trends," according to Seddik Cherif, Strategic Insights Manager at Google (2021, para 1). Examples from *The Washington Post* provide evidence to support this theory (Gilbert, et al., 2022).

"The simplest predictive model is what happened yesterday," Jeffrey Camm, a professor and associate dean of business analytics at Wake Forest University, posits. "That's what we're going to use to predict what's going to happen today" (Camm, 2020). The pandemic changed the paradigm for utilizing historical data to the point where pre-pandemic data only provides value in certain, limited context (Ivy Professional School, 2022). Further, there is evidence the pandemic changed the dynamics of demand at this time. However, it is plausible the demand dynamics will revert to original values and patterns (Ahmed & Sarkodie, 2021).

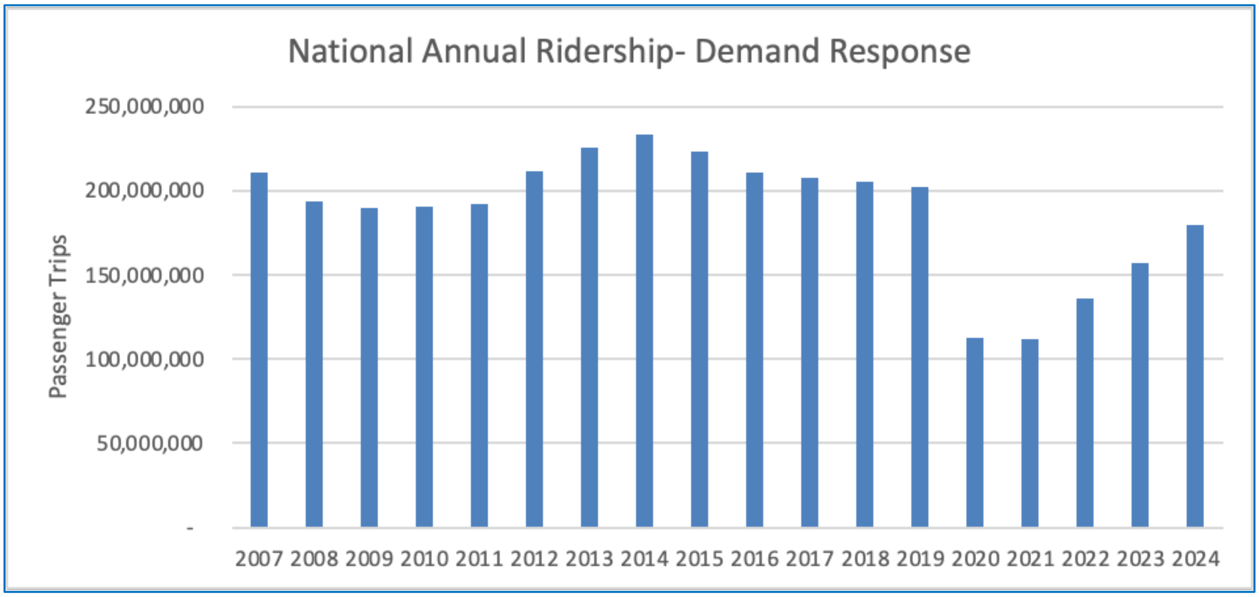
3.1.3. Peer Review

It is always important to understand practices and the trends that result or occur. This project includes a brief peer review that considers an overview of national trends and practices along with a review of comparable agencies.

The focus of the peer review is the demand response mode of service that reflects the Access Services model. The data analysis and comparisons in the review are based on calendar year data and quarterly data from two primary sources, the American Public Transportation Association (APTA) and the Florida Transit Information System (FTIS). These sources primarily use the National Transit Database (NTD) to collect and compile data. These sources provide the calendar year data up through 2024, with partial data for 2025, limiting the ability to analyze annual post-pandemic trends and patterns.

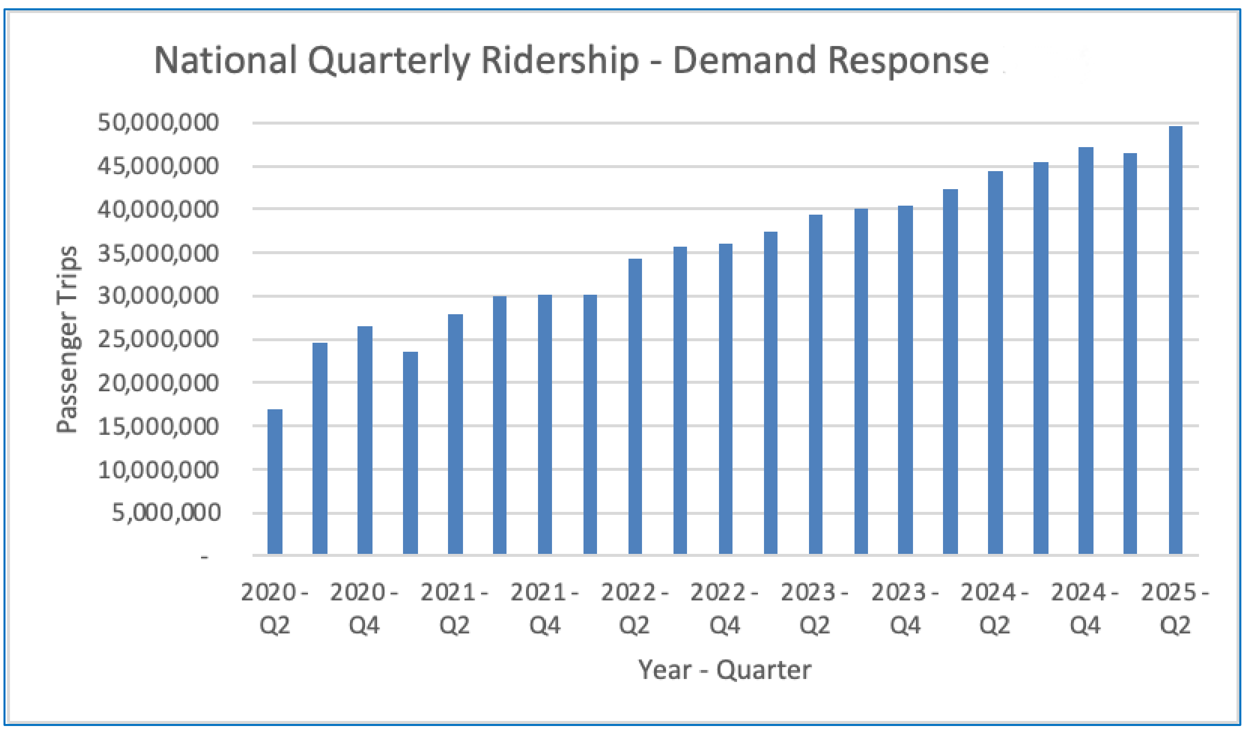
The APTA ridership report calculates ridership based upon the number of unlinked passenger trips. The bar graph in Figure 3 shows the national annual ridership for the most recent 18 years.

Figure 3: National Annual Ridership – Demand Response Model



The national annual ridership does not reveal specific patterns or trends other than the significant decrease in ridership after the COVID-19 pandemic followed by an upward trajectory. The APTA also compiles national quarterly ridership data. Figure 4 displays the national quarterly ridership for the post-pandemic period.

Figure 4: National Quarterly Ridership – Demand Response Mode



The national quarterly ridership indicates a clear upward trend in the number of demand response passengers for the post-pandemic period. The trend analysis tool in Minitab Statistical Software (version 21.4.2) was used to examine the national quarterly ridership. The analysis, shown in Appendix A-3, illustrates the number of demand response trips increases by more than 1.4 million every quarter based upon the liner trend post-pandemic. Access Services is experiencing a similar trend of increasing passenger trips as the national post-pandemic trend.

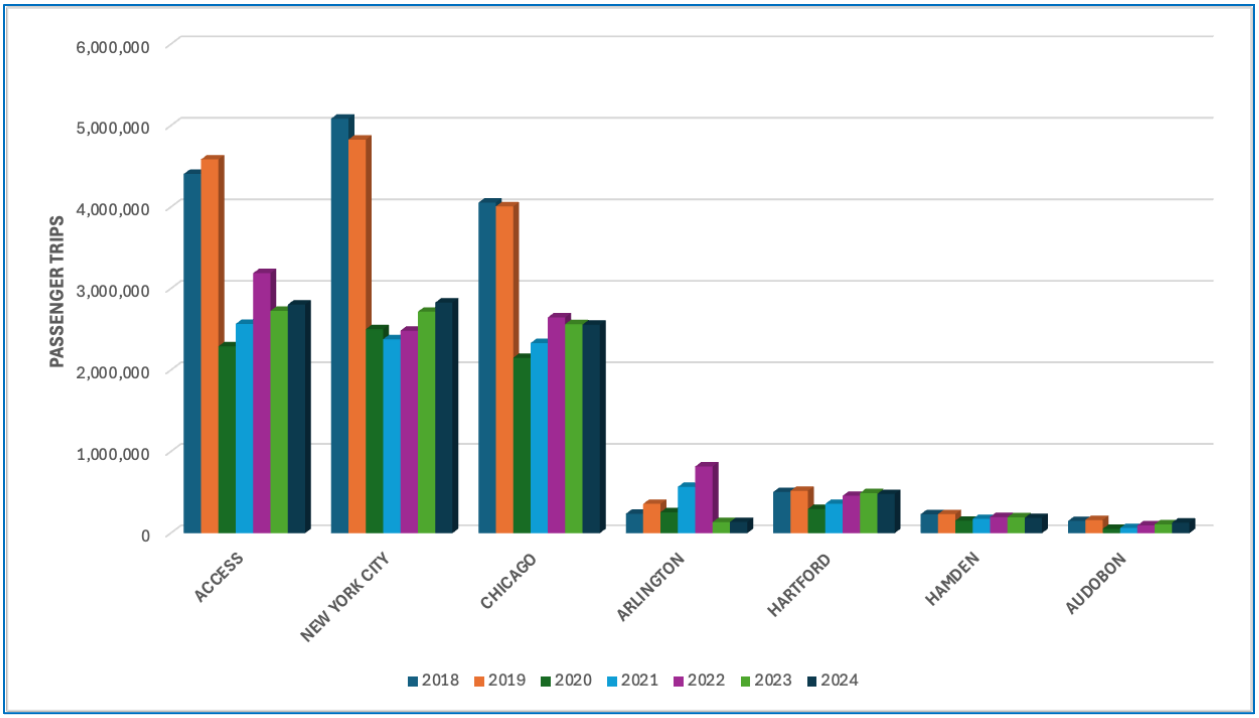
The Florida Transit Information System (FTIS) uses a likeness score to identify similar transit agency peers. Population, service type, and percent demand response, are among the factors used for the calculations found in the Guide to FTIS Peer Selection, https://ftis.org/iNTD-Urban/quickguidev2.0.pdf. The FTIS Peer Selection tool helped identify six (6) peers[1] of Access Services:

- MTA New York City Transit, New York, NY (New York City)
- Pace-Suburban Bus Division, ADA Paratransit Services, Arlington Heights, IL (Chicago)
- City of Arlington, Arlington, TX (Arlington)
- Greater Hartford Transit District, Hartford, CT (Hartford)
- Greater New Haven Transit District, Hamden, CT (Hamden)
- Senior Citizens United Community Services of Camden County, Inc., Audubon, NJ (Audubon)

The Complete Monthly Ridership (with adjustments and estimates) report in the National Transit Database (NTD) was used to collect the annual ridership to compare Access Services with its peers. The annual ridership, passenger trips, are shown in Figure 5 for seven (7) calendar years, 2018 through 2024.

[1] All six peers have identical scores to Access Services of 1.0 for the “Percent Service Demand Response” in the FTIS Peer Selection tool.

Figure 5: Peer Comparison – Annual Ridership 2018-2024



Five of the six peers experienced a similar decline in annual ridership as Access Services at the onset of the pandemic. All peers experienced a similar increase in annual demand response ridership post-pandemic except Arlington.

FTIS provides reports to compare peers on both efficiency and effectiveness measures. Table 1 shows the operating expense per passenger trip and the passenger trips per revenue hour for Access Services and its peers in 2024.

Table 1: Peer Comparison – Efficiency and Effectiveness

MEASURES	ACCESS	NYC	CHICAGO	ARLINGTON	HARTFORD	HAMDEN	AUDOBON
Operating Expense Per Passenger Trip	$59.72	$96.01	$72.76	$32.11	$48.93	$69.13	$44.32
Passenger Trips Per Revenue Hour	1.69	1.22	1.56	3.73	1.86	1.48	1.90

A brief analysis of Table 1 indicates that Access Services' operating expenses are lower than the average of its peers. Access Services' passenger trips per revenue hour are similar to the median value of its peers indicating its effectiveness is on par or better than the peers.

3.1.4. Initial Analysis Summary – Scheduled Trip Demand

The historical analysis reveals insights into the scheduled trip demand and paratransit ridership nationwide. The results provide guidance on the types of models to select, and the periods of data used to forecast these variables.

The results document that there is a difference in trends for scheduled trip demand pre-pandemic and post-pandemic. The pandemic disrupted consumer behavior including paratransit trip requests. A review of the results of the historical analysis with Access Services validated the findings based on agency knowledge and experience with day-to-day operations.

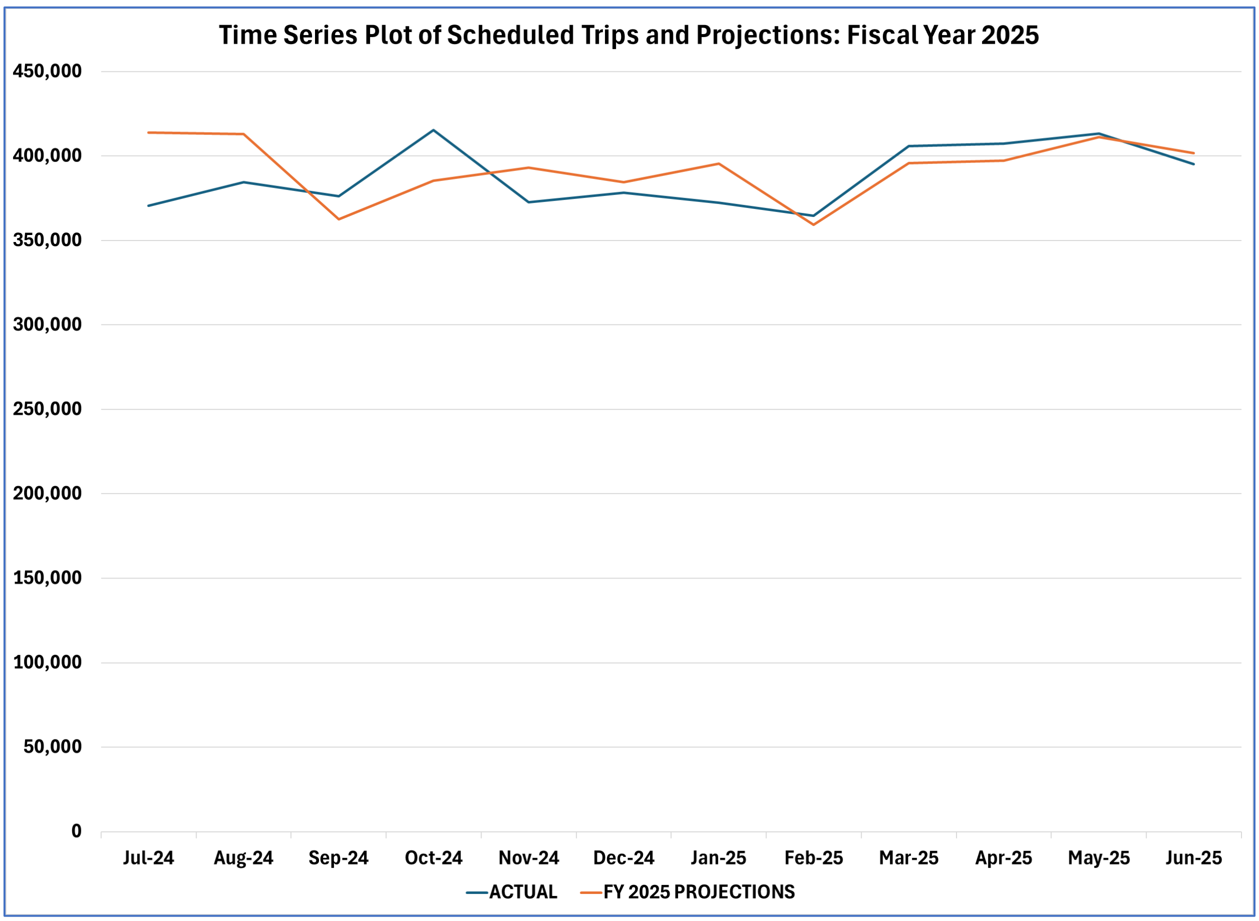
The pre-pandemic data does not reflect current behavior; post-pandemic data captures the altered dynamics more accurately. Forecasting models need to use post-pandemic data to ensure relevance to the current economic, social, and environmental context and to generate projections.

There is uncertainty about whether, or when, pre-pandemic patterns will re-emerge. Models to forecast scheduled trip demand need to have the capacity to predict accurately, with a limited amount of historical data, and must be able to respond quickly to changes given the anticipated uncertainty.

3.1.5. Assessment: Fiscal Year 2025 Projections

The projections of scheduled trip demand for Fiscal Year (FY) 2025 were generated from a Long Short-Term Memory (LSTM) model described in the Conceptual Models. The time-series chart of the actual scheduled trips along with the projections are shown in Figure 6.

Figure 6: FY 2025 Comparison of Actual Schedule Trips and Projections



A total of 4,713,014 scheduled trips were projected for FY 2025 while a total of 4,656,747 were observed. The forecast projected a cumulative total of 56,267 more trips than observed. The assessment of the FY

2025 scheduled trip demand projections demonstrates low prediction error with the overall forecast being 1.21% higher than actual observations. This is the equivalent of an average of 4,689 projected scheduled trips more than the actual scheduled trips per month. The low prediction error of the FY 2025 projections ensures Access Services has an appropriate and reasonable budget and operational resources to meet the demand for ADA mandated paratransit service.

3.2. Conceptual Models

3.2.1. Overview of model selection

There are several models that can be utilized to forecast the time-series data for trip requests of the potential Access Services customers. There are several phenomena that data (particularly time series) can exhibit, and any model should take these phenomena into account including:

- Trend, which occurs when the data has increasing or decreasing values as time progresses from one period to another;
- Seasonality, which refers to recurring patterns that follow a regular and predictable interval, often associated with calendar seasons or other periodic occurrences;
- Cyclicality, which encompasses fluctuations that occur over an extended duration, typically not as rigidly defined as seasonal patterns, and often are influenced by economic or external factors; and
- Autocorrelation, which happens when the next value of data item is dependent on some previous data point, either an immediate predecessor or a predecessor with some lag (distance between related data items).

Making a model from real data, to be able to predict the future behavior of the time series, is critical. Such a model should account for all the mentioned phenomena. Traditional models use statistical analysis to predict model parameters, such that some measure of mean square error between the data and the model will be minimized. This is explained in the description of linear regression (Appendix A-1). From the linear regression, as the simplest model for time-series prediction, many other models were developed in classical statistical analysis, and other models were developed utilizing neural networks.

Several methods were explored to provide a reliable estimate of data trends in the future for this project including the Long Short-Term Memory (LSTM) and the Meta Prophet model. Following is a description of methods that were utilized to develop the trip request estimates: LSTM and Prophet.

3.2.2. Long Short-Term Memory (LSTM) Model

LSTM model is the type of recurrent neural network (RNN) model that was developed by Hochreiter and Schmidhuber (1997) to address the problem of vanishing gradient in traditional RNN models, which were sensitive to the gap length when modeling seasonal data. LSTM model, like other neural network models, consists of one input layer, several internal (hidden) layers, and one output layer, as shown in the example on Figure 7 (Surakhi et al., 2021). The LSTM builds its neuronal units as sets of cells, controlled by input gates, output gates, and forget gates all built with appropriate sigmoid functions (see Figure 8, Calzone, 2022). The cell remembers values over any time intervals, while gates regulate the flow of information into the cell and from the cell to other cells. The forget gates are responsible for a decision if the information from a previous state will be forgotten or not. All these selections allow the LSTM model to maintain long-term dependencies while propagating short-term variations between consecutive states.

Figure 7: Layered Architecture of the LSTM Model (Surakhi et al., 2021)

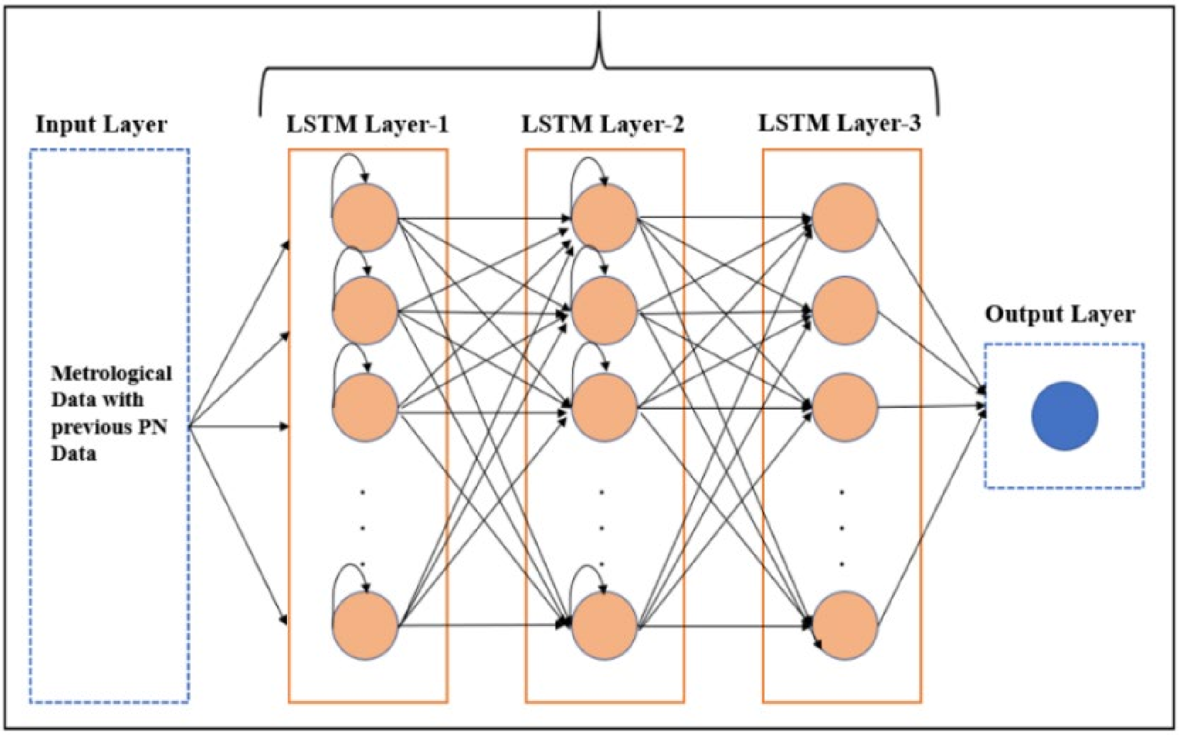
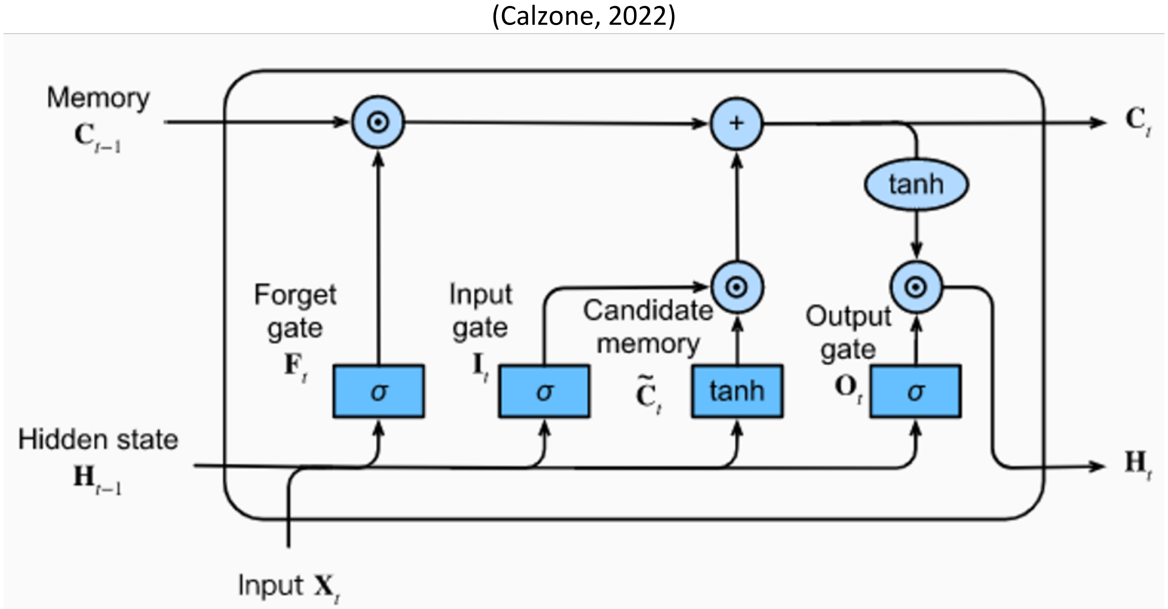


Figure 8: The Structure of the LSTM Cell with Three Gates: Input Gate, Forget Gate, and Output Gate (Calzone, 2022)



The dynamics of an LSTM cell can be described by the following equations, from Bedi and Toshniwal (2019) and Bordoni and Giagu (2023):

$$i_t = \sigma\left(x_t U^i + h_{t-1} W^i\right)$$

$$f_t = \sigma\left(x_t U^f + h_{t-1} W^f\right)$$

$$o_t = \sigma(x_t U^o + h_{t-1} W^o)$$

$$\tilde{c} = Tanh(x_t U^g + h_{t-1} W^g)$$

$$c_t = \sigma\left(f_t \otimes c_{\{t-1\}} \oplus i_t \otimes \tilde{c}_t\right)$$

$$h_t = Tanh(c_t) \otimes o_t$$

Where

x_t is the input vector at time step t,

h_t is the output vector at time step t,

c_t is the cell state vector at time step t,

c~ is a candidate cell state that is computed based on the current input and the previous hidden state,

U is the weight matrix that connects the inputs to the hidden layer,

W is the recurrent connection between the previously hidden layer and current hidden layer,

i_t, f_t, and o_t are the input gate, forget gate, and output gate vectors respectively.

Input to the LSTM model is a time-series data set (for this project actual trip requests from the past, either monthly or daily), which is used for both training and testing of the model to minimize statistical errors. Usually 70-80% of the data set is used for training, while the remaining 20-30% is used for testing the model. Once an appropriate model is obtained through training and testing, it is then utilized to predict the future data in the continuation of the time series.

Python Libraries was employed to perform LSTM model utilizing the LSTM model three stages:

Transformation, which is the preparation of the data set for the LSTM model that first removes trend in the data (detrending), then removes seasonality, and finally normalizes the data into the range of (0,…1), which is suitable for the next stage, forecasting.

Forecasting, which is the essence of the LSTM Recurrent Neural Net learning model with specifying necessary parameters for the model, such as number of *epochs*, *lag* specification (layers in the model), and number of *units* (cells in the model).

Revert, which is the last phase used to revert the normalized data (in testing and in the prediction) to actual values and to reintroduce trend and seasonality into predicted values.

The model is trained and tested on real data (past observations) and then used to predict time series into the future periods. For the trained and tested models, daily and monthly data are utilized to make the LSTM model of trip requests, as will be explained later.

The linear, quadratic, and cubic forms refer to different ways in which the cell state and hidden state transformations are modeled.

The **Linear Form** involves simple linear combinations of inputs and past hidden states followed by non-linear activation functions (sigmoid and tanh). This is the most common form of LSTM used in time-series forecasting. This form is simpler to implement and train as well as computationally efficient. However, this form struggles with highly nonlinear dependencies in time series.

The **Quadratic Form** introduces quadratic interactions between the input and previous states to capture second-order dependencies. This form is more expressive than the Linear form and captures second-order dependencies (squared effects) in time-series data.

The **Cubic Form** captures even more complex dependencies in time-series data than the Quadratic form. This form may help in modeling highly nonlinear relationships however it is prone to overfitting with limited data.

The Linear Form works well for most real-world forecasting, but when data exhibits strong nonlinear patterns, a Quadratic form might improve the prediction.

An activation function in an LSTM model controls information flow through the network. It helps regulate neuron activations, ensuring that the model learns meaningful patterns from time-series data. This control includes the amount of past information retained or forgotten at each time step. The activation function helps model nonlinear patterns (seasonal trends, sudden spikes, etc.). The activation function provides the model with the ability to capture complex time-dependent patterns. Three common activation functions for time-series forecasting include tanh, ReLU, and sigmoid (Brownlee, 2021).

The important part of the LSTM model utilization is the quality (or metric) of its prediction (similar to other models). There are four metrics to evaluate the quality of LSTM models:

1. RMSE: root mean square error, also known as mean squared error
2. MAPE: mean absolute percent error
3. MAE: mean absolute error, also known as mean absolute deviation
4. Coefficient of determination, commonly referred to as R^2

Definitions for these metrics are given in Appendix A-1.

The R^2 metric describes the percentage of variation of the dependent variable the model explains. The greater the R^2 value, the better the model performs at predicting future values. The other three metrics are measures of error meaning the smaller the value for these, the better the model performs. The LSTM model reports all four metrics during testing and forecasting. The R^2 and MAPE were identified as the preferred metrics to aid the selection and verification of the best model parameters.

3.2.3. Meta Prophet Model

Taylor and Letham (2018) describe Prophet as an additive time-series model that decomposes data into trend, seasonality, and holiday effects. The Meta Prophet model is a time-series forecasting framework designed to generate reliable projections in environments characterized by trend changes, seasonality, and irregular disruptions. Developed to support operational and planning decisions, Prophet is particularly well suited for applied forecasting contexts where interpretability, adaptability, and robustness are critical.

Prophet models a time series as the additive combination of several distinct components: long-term trend, seasonal patterns, and event-driven effects. Each element is estimated and adjusted independently. This structure enables the model to respond effectively to changing demand conditions while remaining transparent and explainable to non-technical stakeholders.

Model Framework and Core Components

At a high level, Prophet represents a time series using the following formulation: $y(t)=g(t)+s(t)+h(t)+\varepsilon t$

Each term captures a different underlying driver of demand:

1. Trend Component: g(t)

The trend component models the long-term trajectory of demand over time. Prophet supports both linear and logistic growth trends and allows for changepoints, which are moments where the growth rate shifts. Changepoints are either automatically detected or specified by the analyst and are essential for capturing structural changes in demand patterns.

This capability is particularly important when historical trends are disrupted by external events or policy changes, as it allows the model to adapt without relying on outdated assumptions.

2. Seasonality Component: s(t)

Seasonality captures recurring patterns that repeat over fixed intervals, such as weekly, monthly, or annual cycles. Prophet models seasonality using Fourier series, which provides flexibility in representing both smooth and complex seasonal effects.

Multiple seasonal patterns can be included simultaneously, enabling the model to account for overlapping demand cycles (e.g., weekday vs. weekend behavior and annual fluctuations).

3. Event and Holiday Effects: h(t)

Prophet allows for the explicit inclusion of known events or calendar effects that influence demand. These may include holidays, service changes, policy implementations, or other discrete occurrences that create temporary or sustained deviations from normal patterns.

Incorporating event effects improves forecast accuracy by ensuring that known external influences are treated as structural inputs rather than unexplained noise.

4. Error Term: εt

The error term represents random variation not explained by the model components. Prophet assumes this noise follows a normal distribution and uses it to quantify uncertainty in the forecasts.

Summary

The Meta Prophet model provides a flexible, interpretable, and robust framework for time-series forecasting. By decomposing demand into trend, seasonal, and event-based components, the model captures both long-term structural behavior and short-term variability. Its Bayesian foundation supports uncertainty estimation, enabling more informed decision making when projections are used for resource allocation, service planning, and budget development.

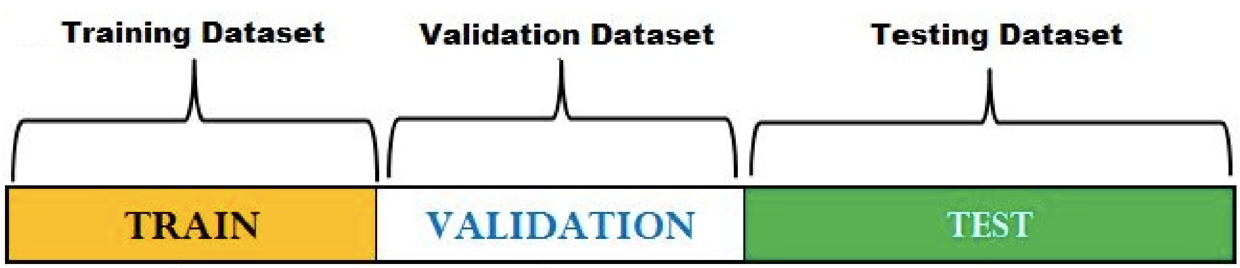
As a result, Prophet serves as a reliable forecasting approach in dynamic environments where demand patterns evolve and traditional trend-based methods may be insufficient.

3.3. Tests and Results – Scheduled Trip Demand

The assessment of the prior year (FY 2025) projections reveals the LSTM forecasting model creates projections with low prediction error.

Several parameters with the LSTM model were tested to evaluate the results and select the parameter(s) with the best likelihood to produce accurate forecasts. Common practice in data science is to separate historical data into three (3) data sets shown in Figure 9. The data is split, in chronological sequence for time series data sets, with the first 70% designated for training, 10% allocated for validation, and the remaining 20% set aside for testing.

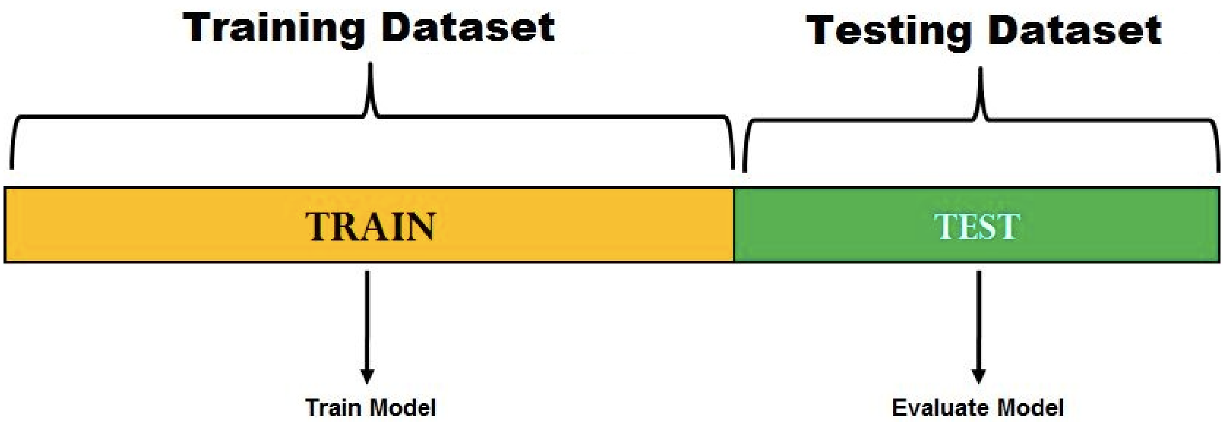
Figure 9: Training Validation Testing Model



* *Image credit to Analytics Yogi, https://vitalflux.com/hold-out-method-for-training-machine-learning-model/*

The historical analysis reveals the need to utilize post-pandemic data to reflect current trends most accurately. There is a limited amount of post-pandemic data available, especially considering potential seasonality and day-to-day variation. The hold-out method is common practice in data science and machine learning when there is too little data to break it into three (3) traditional sets. Figure 10 provides a visual representation of the hold-out method.

Figure 10: The Hold-Out Method Data Sets



* *Image credit to Analytics Yogi, https://vitalflux.com/hold-out-method-for-training-machine-learning-model/*

For the hold-out method, the data is grouped into the training set (70%) and the test set (30%) in chronological sequence for time-series data. The training set is used to create the model. The test set is compared to the results of the model trained on the training data set to evaluate the model performance.

3.3.1. Training, Testing, and Results Summary – Scheduled Trip Demand

Access Services identified the projected values aligning with actual outcomes of FY 2027 projections as the highest priority for the scheduled trip demand forecasting. The most recent 12 months provides an evaluation period with sufficient post-pandemic data for training and testing the LSTM with various parameters. These parameters include the:

- Form (linear, quadratic, cubic)
- Activation Function (tanh, ReLU, and sigmoid)
- Units (number of cells in the model)
- Lags (number of layers)
- Epochs (number of complete passes through dataset during the learning process)

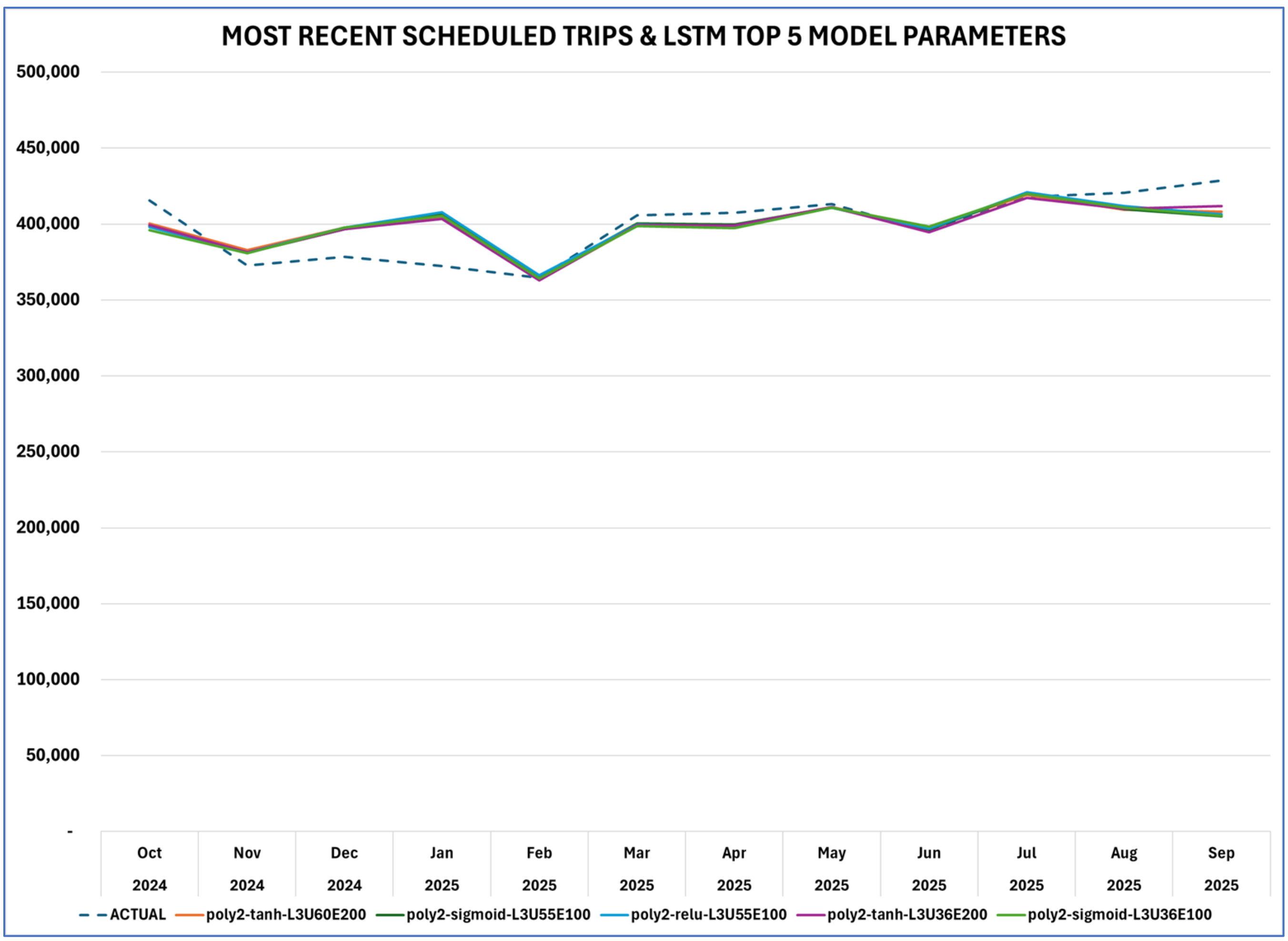
Experiments were performed testing hundreds of combinations of these parameters to identify those that best predict the most recent 12 months. The LSTM forecasting model analyzed the number of scheduled trips daily from January 1, 2021, through September 30, 2024 as the training set. Based on the patterns of this historical data the model generated daily predictions for the number of scheduled trips for the testing set, October 1, 2024, through September 30, 2025. Parameters were evaluated both on the daily performance (RMSE, R^2, MAPE) along with the aggregate annual performance. Parameters of the best five (5) models are shown in Table 2.

Table 2: Top Five Model Parameters

Parameters	RMSE	R^2	MAPE Daily	Annual Difference	MAPE Annual
poly2-tanh-L3U60E200	2383.977864	0.768008802	15.367%	214	0.004%
poly2-sigmoid-L3U55E100	2385.776205	0.778852143	15.378%	927	0.019%
poly2-relu-L3U55E100	2372.13981	0.764466117	15.290%	3,957	0.083%
poly2-tanh-L3U36E200	2409.29493	0.785099826	15.530%	5,097	0.106%
poly2-sigmoid-L3U36E100	2400.833313	0.766539272	15.475%	6,516	0.136%

The coefficient of determination, R^2, values of the best models demonstrate they provide good predictive performance as they explain 76% to 78% of the variation in the number of scheduled trips daily. The top 5 model parameters were identified based upon their aggregate annual performance. The annual difference between the projections and the actual observations range from 214 scheduled trips to 6,516 as shown in Table 2. The top 5 model parameters all exhibit error at or lower than 0.136% for the 12 month period overall. The testing results are shown in Figure 11.

Figure 11: Model Comparison for Most Recent 12 Months



The model that best predicts the most recent 12 months uses the parameters of quadratic form, an activation function tanh, 3 lags (layers), 60 units (cells), and 200 epochs.

3.4. Methodology

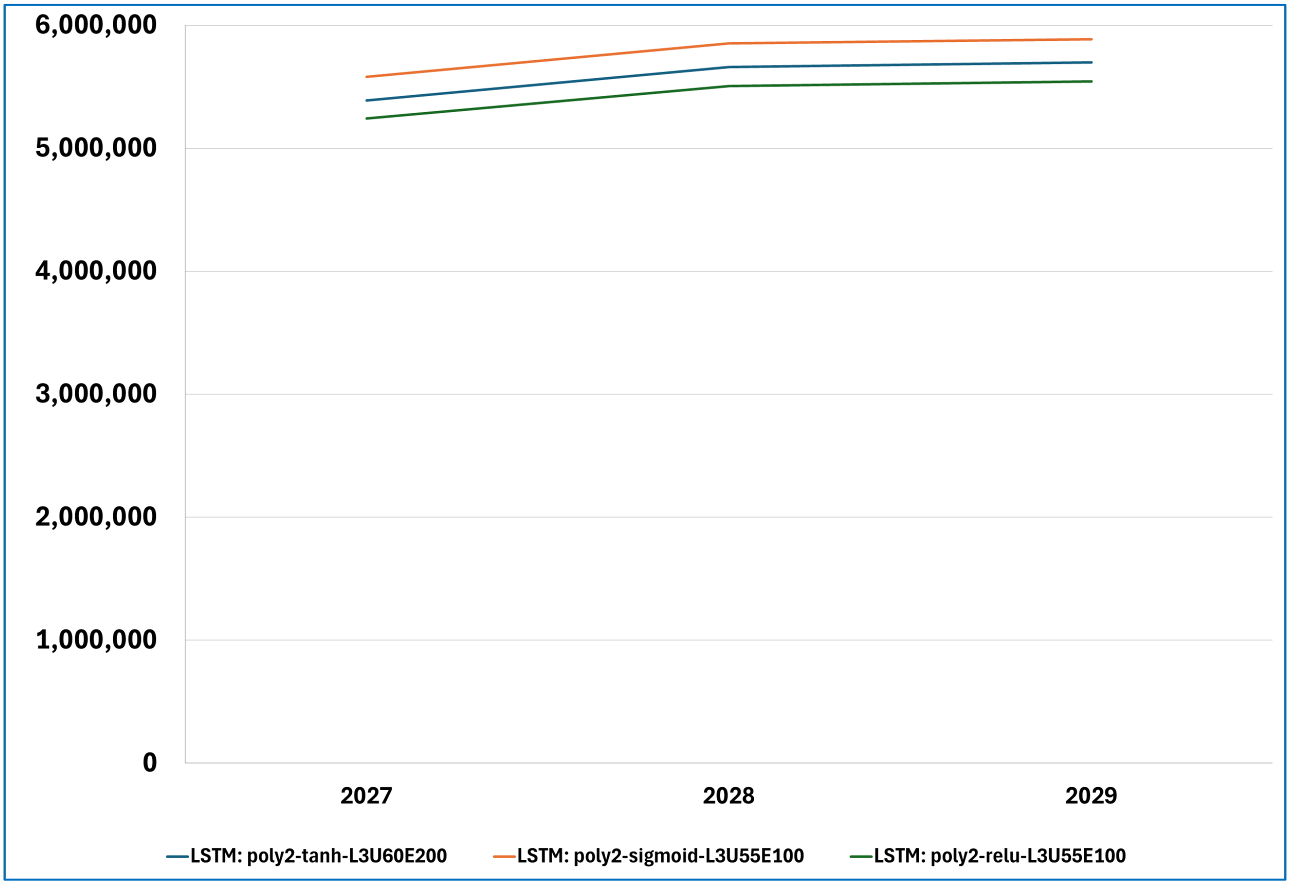
The Quadratic form of the LSTM model best fits the most recent 12 months of the actual number of scheduled trips. This suggests scheduled trip demand is currently increasing based on a squared effect, potentially due to response to the pandemic. The demand has increased exponentially since the pandemic instead of growing at a steady, additive or multiplicative, rate as shown in Table 3.

Table 3: The Increase of Scheduled Trips in the Post-Pandemic Period

Fiscal Year	Scheduled Trips	Increase	Percentage Increase
2021	2,107,392	-	-
2022	2,934,929	827,537	39.27%
2023	3,604,831	669,902	22.83%
2024	4,191,267	586,436	16.27%
2025	4,656,747	465,480	11.11%

While the Quadratic form models the current exponential growth well, it also assumes the demand will reach a peak and then begin declining. Pre-pandemic demand along with feedback from Access Services suggests that demand will continue to increase. The projections for the Quadratic form of the LSTM model begin to reach the peak and plateau in Fiscal Year 2029. The peak or plateau is shown in Figure 12.

Figure 12: LSTM Quadratic Form Projections for FY 2027-2029

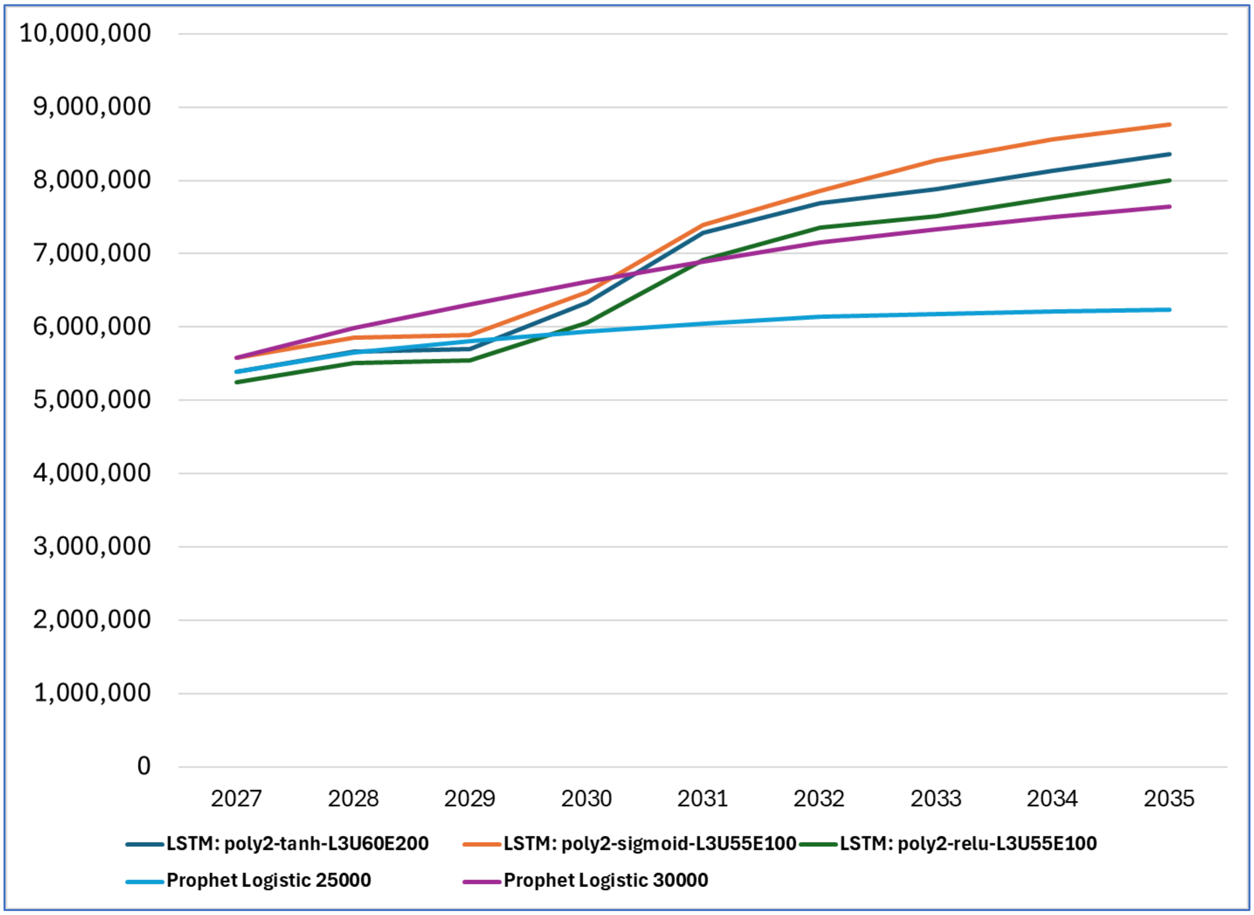


The projections from the LSTM quadratic model begin to level off in FY 2028 and reach a peak or plateau in FY 2029. It is possible for demand to reach a market saturation. However, a peak or plateau in demand is not anticipated based on the pre-pandemic and the post-pandemic trends.

The quadratic form of the LSTM model lacks the ability to estimate the increase in the number of scheduled trips for Fiscal Year 2029 and following years. The linear form of the LSTM model and the Meta Prophet model were tested to address the long-term forecast beyond Fiscal Year 2028.

The three (3) best sets of parameters for the projections for the most recent 12 months, shown in Table 2, were selected to use for the linear form of the LSTM model. Projections of the number of scheduled trips were created for Fiscal Year 2029 through 2035 using the linear form. These projections are shown in Figure 13. This time period selected was due to limitations in the LSTM model with the number of historical data points necessary to create projections. It should be noted that projections for Fiscal Years 2027 and 2028 are from the quadratic form of LSTM, which demonstrates the lowest error in the most recent 12 months.

Figure 13: FY 2029 through 2035 Scheduled Trip Demand Comparison – Linear LSTM and Meta Prophet



The linear LSTM model suggests the number of trips per month would grow more than 62% over the most recent fiscal year (2025). It also suggests Access Services would experience a month with over 753,000 scheduled trips, 76% greater than any month in the most recent fiscal year.

A brief study on the population in Los Angeles County (Figure 14) reveals a steady upward trend for people ages 55 and older, approximately 2.79% per year. An analysis on the population reporting a disability (Figure 15) shows a steady upward trend, increasing approximately 1.62% per year. These trends illustrate steady growth but lack evidence to suggest the levels of growth (62% to 76%) projected by the linear LSTM models.

The projections for Fiscal Year 2029 through 2035 shown in Figure 13 also include those for two capacity levels from the Meta Prophet model. In the Meta Prophet forecasting model, capacity represents a realistic upper limit on how high the projected values can grow over time. You can think of it as a ceiling that reflects real-world constraints. Capacity in the Meta Prophet model is the model's way of recognizing that real systems have limits. It allows growth to continue, but at a slowing rate as those limits are approached. This results in forecasts that are more realistic, more stable, and more useful for long-term planning and budgeting.

The capacity levels of 25,000 and 30,000 were chosen based upon analysis of the historical number of scheduled trips per day (post-pandemic). The analysis of the number of scheduled trips compared to the two capacity levels are shown in Appendix A-4. The capacity level of 25,000 scheduled trips per day is 71% greater than the median and 40% greater than the largest number of trips scheduled in a day. The capacity level of 30,000 scheduled trips per day is 106% greater than the median and 67% greater than the largest number of trips scheduled in a day.

The graph in Figure 13 illustrates the capacity level of 25,000 trips per day limits the long-term growth. The number of scheduled trips appears to plateau at Fiscal Year 2033 and beyond. However, a peak or plateau in demand is not anticipated based on the pre-pandemic and the post-pandemic trends.

A capacity level of 30,000 trips per day removes the constraints that caused the plateau observed with the level of 25,000. The graph in Figure 13 illustrates the capacity level of 30,000 trips per day, which demonstrates a steady growth throughout the long-term forecast.

The quadratic form of the LSTM model (an activation function tanh, 3 lags (layers), 60 units (cells), 200 epochs) is recommended for projecting the number of scheduled trips Fiscal Years 2027 and 2028 along with the Meta Prophet model using a capacity level of 30,000 trips per day for Fiscal Year 2029 through 2036.

3.5. Forecasting Assumptions and Error Analysis – Scheduled Trip Demand

There are different approaches to evaluate error for the results of forecasting models. Predictors used to evaluate the error of the model during the testing phase include the coefficient of determination (R^2), Mean Average Percentage Error (MAPE), and the Mean Squared Error (MSE). Definitions and formulas for these metrics are shown in Appendix A-1: Definitions. The values for the quadratic form of the LSTM model parameters are shown in Table 2.

The coefficient of determination, R^2, values of the best models demonstrate they provide good predictive performance as they explain 77% of the variation in the number of scheduled trips per day.

The value of the error is an inverse relationship to the difference between projected values and actual outcomes in the model. The lower the value of the result of the error formula, the closer the projected values are to the actual outcomes in the model. The MAPE values are higher than desirable, however this is a measure of the model's ability to predict the number of scheduled trips on a given day. The error of these projections decreases significantly when they are aggregated into monthly and annual values.

Another approach to evaluate error is comparing the forecasting results of the model parameters with the most recent observed values. The quadratic LSTM model parameters selected demonstrated a high level of alignment with the demand with a minimal variance of 0.004%.

3.5.1. Assumptions – Scheduled Trip Demand

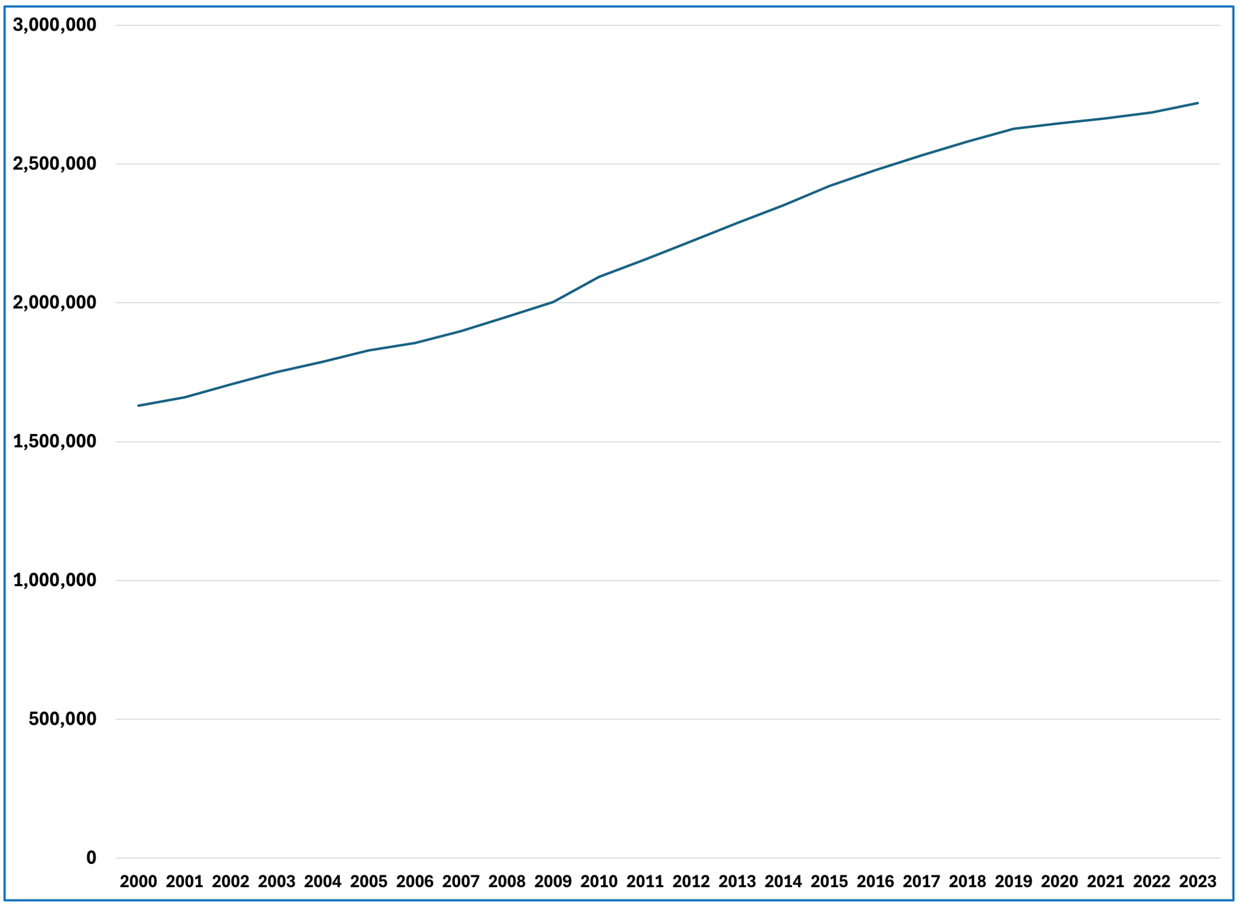
Projections for scheduled trip demand have inherent uncertainty, which is typical of any predictions. The forecasted values one (1), five (5), and ten (10) fiscal years into the future are greater than the most recently completed fiscal year, 2025 (4,857,458). Several factors explain the feasibility of these projections and the possibility of actual observations reaching these values.

The relationship between the scheduled trip demand and the median age of Los Angeles County does not adequately predict the increase (or decrease) in demand nor does it explain the month-to-month variation of demand. However, the age of the population in Los Angeles County does provide insight into the long-term scheduled trip demand.

The Access Services 2024 Biennial Customer Satisfaction Survey reveals that 61.6% of eligible riders are 55 years of age and older. Essentially 3 out of 5 eligible riders are 55 and up. More than 42% of eligible riders are 65 years of age and older. The age of the population potentially influences the need for paratransit service.

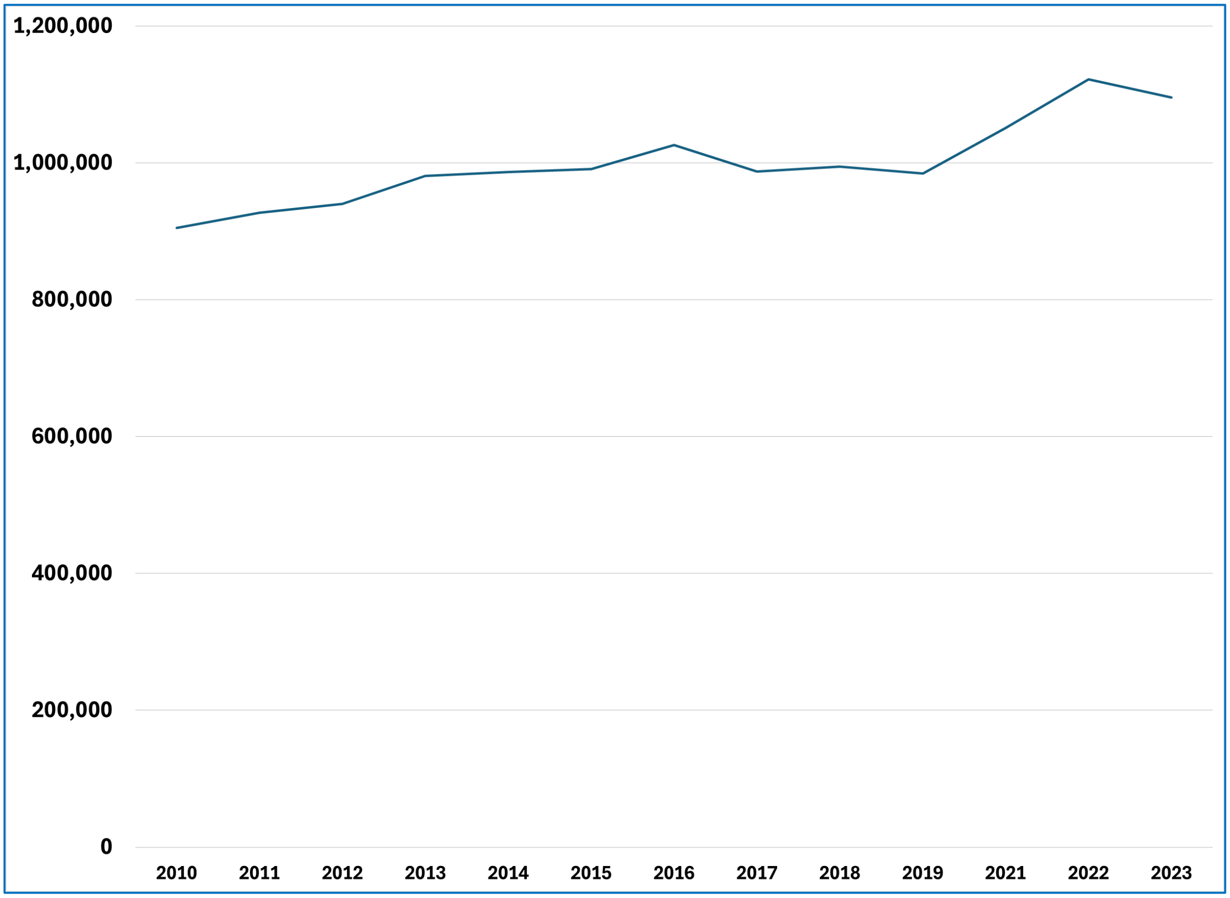
According to the US Census Bureau, the population of 55 and older category has increased by 1,090,120 people since 2000. This represents a 67% increase in this age category. The population data for 23 consecutive recent years available demonstrates a steady upward trend in Figure 14. The steady, continued growth of this age group indicates the likelihood of growth for the number of eligible riders.

Figure 14: Los Angeles County Population Ages 55+



A disability is generally one of the requirements for an individual to become an eligible rider. The Census Bureau collects data on the number of individuals in Los Angeles County reporting a disability annually. According to the US Census Bureau, the population reporting a disability has increased by 190,725 individuals since 2010. This represents a 21% increase. The population data for 13 recent years demonstrates a steady upward trend in Figure 15. The steady, continued growth of individuals reporting a disability indicates the likelihood of growth for the number of eligible riders.

Figure 15: Individuals Reporting a Disability in Los Angeles County



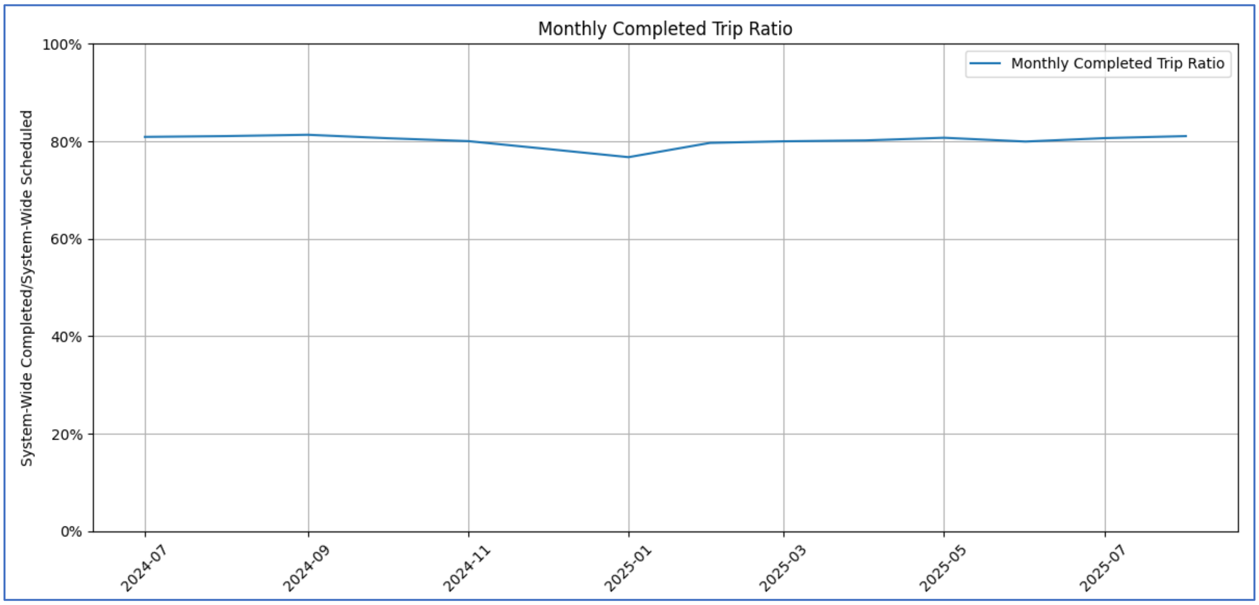
These trends suggest growth in the need for paratransit service and the number of eligible riders, which leads to an increase in scheduled trip demand.

3.5.2. Scheduled Trip Cancellation

Scheduled trip demand reflects the number of trip requests from eligible riders. As with any reservation or appointment, there are cancellations by the rider and rider no-shows. An analysis of the number of trip requests, scheduled trip demand, provides guidance to Access Services for translating the scheduled trip demand into the number of completed trips.

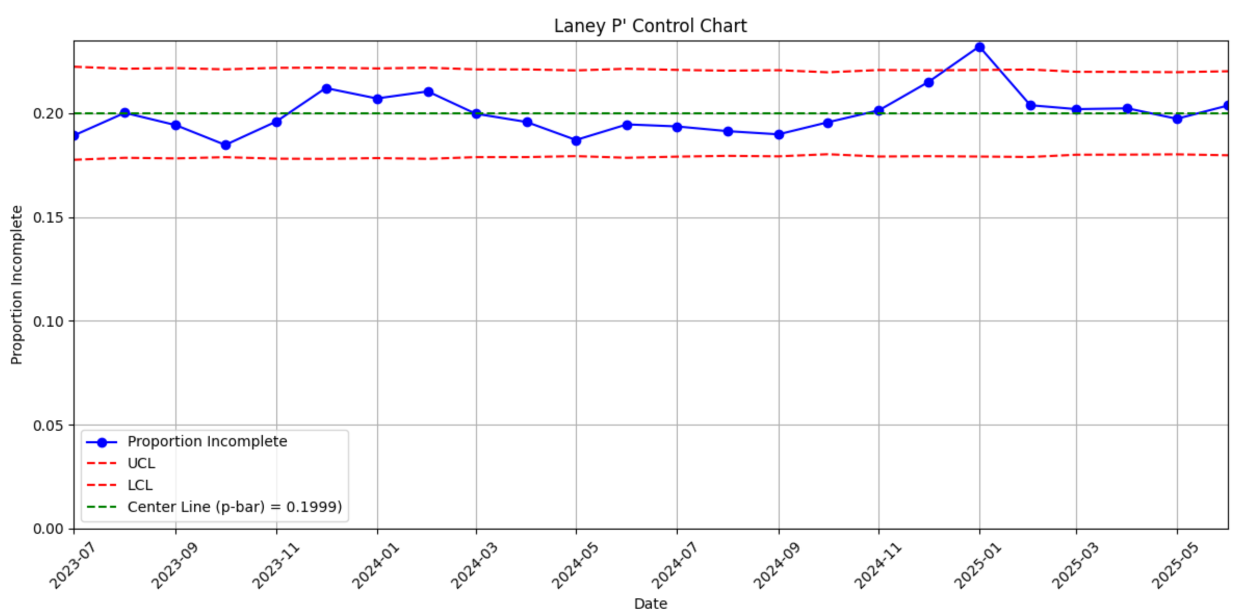
The completed trip analysis uses monthly data for the period from July 2023 through August 2025. The completed trip ratio is the number of completed trips divided by the number of scheduled trips (trip requests) during the month. This ratio is the percentage (%) complete. While it experiences slight fluctuation month to month, the ratio of completed trips is relatively constant as shown in the time series graph in Figure 15.

Figure 15: Time Series Plot – Completed Trip Ratio



The time series chart shows slight variation from month to month. The Laney P' statistical process control (process behavior) chart in Figure 16 illustrates the stability of the percentage of incomplete trips. With one exception, the monthly observations from Fiscal Years 2024 and 2025 pass all the tests for special causes including: (1) one point above or below the control limit, (2) nine points in a row on the same side of the center line, (3) six points in a row (all increasing or decreasing), and (4) fourteen points in a row, alternating up and down.

Figure 16: Incomplete Trips - Laney P' Statistical Process Control Chart



The exception to the rules for a special cause is January 2025, the month of the wildfires in Altadena and the Palisades. This cause is known and assignable. It is not the type of event that is expected to occur on a regular basis and does not reflect the stability of the completed trip ratio. Passing all tests on this chart indicates the percentage of incomplete trips is stable. This means the inverse, the completed trip ratio, is also stable. The completed trip ratio is 80.01%.

The scheduled trip demand forecast, along with the completed trip ratio analysis, provides Access Services with insight for planning budgets and operational resources along with confident long-range planning for the next ten (10) fiscal years.

3.6. Conclusion and Next Steps – Scheduled Trip Demand

The initial analysis of the scheduled trip demand reveals essential insight into current trends. The trend is significantly different after the COVID-19 pandemic than the trend prior to the pandemic. Forecasting models utilize post-pandemic historical data for projections to reflect current trends.

Training and testing of several parameters of the Long Short-Term Memory (LSTM) model led to the selection of the parameters that best fit current trends for the scheduled trip demand.

Due to the nonlinear behavior of the demand and the use of a quadratic form in the forecasting model, a hybrid approach between the quadratic form of the LSTM model and the Meta Prophet model were used to forecast scheduled trip demand for Fiscal Years 2029 through 2036.

An analysis of the completed trip ratio, the percentage of scheduled trips completed, is stable with an average value of 80.01%.

The national trend exhibits increasing demand response trips as discovered in the peer review for this project. The steady, upward trend of the population in Los Angeles County in the 55 and older age group along with upward trend for individuals reporting a disability also illustrate a growing need and potential demand. These trends indicate Access Services' scheduled trip demand will increase in the future, supporting the projections provided in this report.

Next steps include exploring additional machine learning models and testing them as appropriate. Models such as the Koopman Operator may help identify various signals to further understand and predict the number of scheduled trips. Monitoring the demand dynamics on future iterations will continue to determine if the data sets revert to pre-pandemic values and patterns.

4. New Applicants

4.1. Initial Analysis – New Applicants

Patterns of the past help plan for the uncertainty of the future. Essential factors that provide insight into the paratransit needs in Los Angeles County, California, include the number of new applicants for paratransit service. A study on the COVID-19 pandemic, shown in Section 3.1.2, provides further insight. A review of peer paratransit services, shown in Section 3.1.3, also provides an opportunity for insights on services in other regions of the country.

The focus of the initial analysis includes a historical analysis on the number of new applicants for paratransit service, a brief evaluation of the global pandemic effect, and peer review. Together, the historical analysis, pandemic evaluation, and peer review provide direction for the types of forecasting models and the variables to include (exclude), consider and evaluate.

4.1.1. Historical Analysis – New Applicants

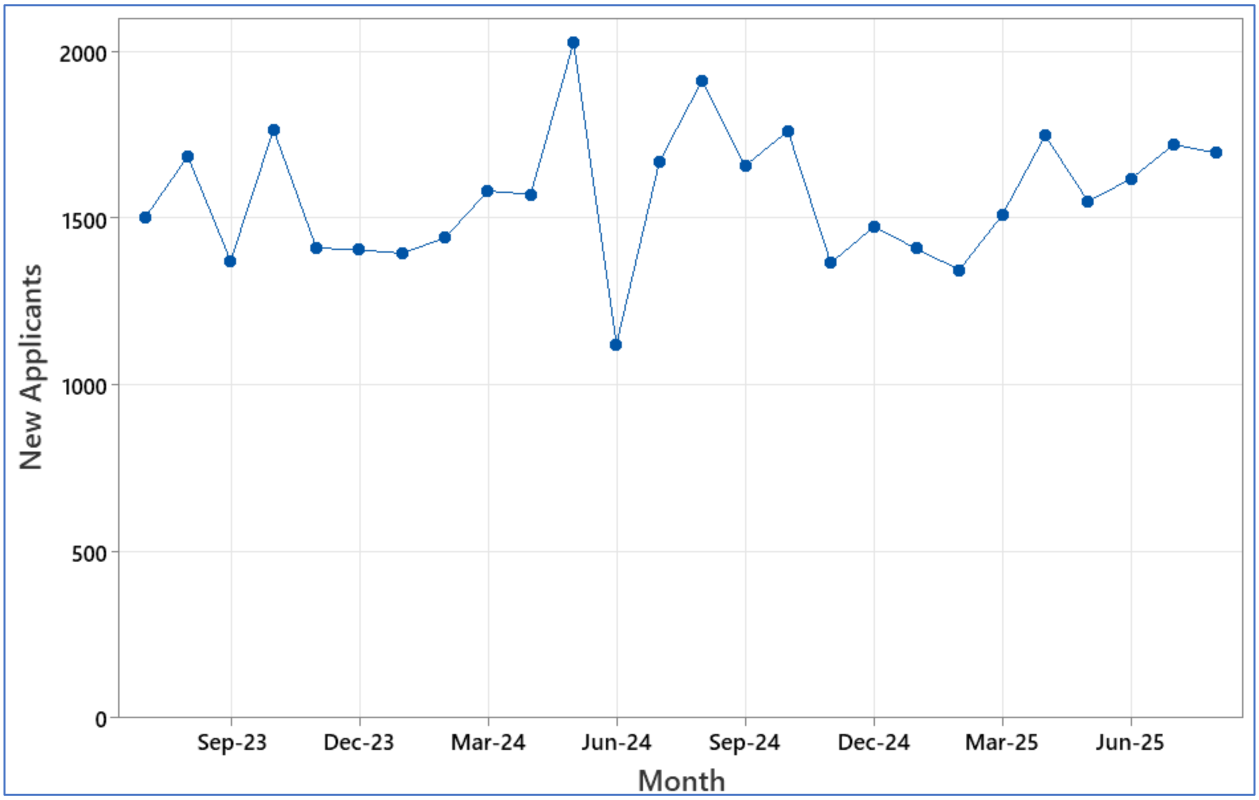
The examination of evidence from the past informs a more coherent story. The focus of this examination includes an analysis of events in time series to identify patterns, trends, and changes over time. The analysis identifies the presence of (or lack of) seasonal patterns, cyclical patterns, stationarity, and autocorrelation along with trends. These components are key for model identification and selection.

Access Services needs to understand the number of eligible customers to develop an accurate, effective budget and plan future fiscal year(s). The historical analysis includes the number of new applicants.

The initial data for the historical analysis of new applicants to become eligible customers for Access Services includes the number of new applicants, from July 2004 through August 2025. The data file provided to Hollingsworth Consulting included a count of certification evaluations (new applicants) per month for each service region[2]. Visualization was the first step to begin to understand this variable. The time-series plot for monthly new applicants between July 2023 and August 2025 is shown in Figure17.

[2] Recertification evaluations were excluded since these are for existing eligible riders.

Figure 17: Monthly New Applicants Time Series Plot – July 2023 through August 2025



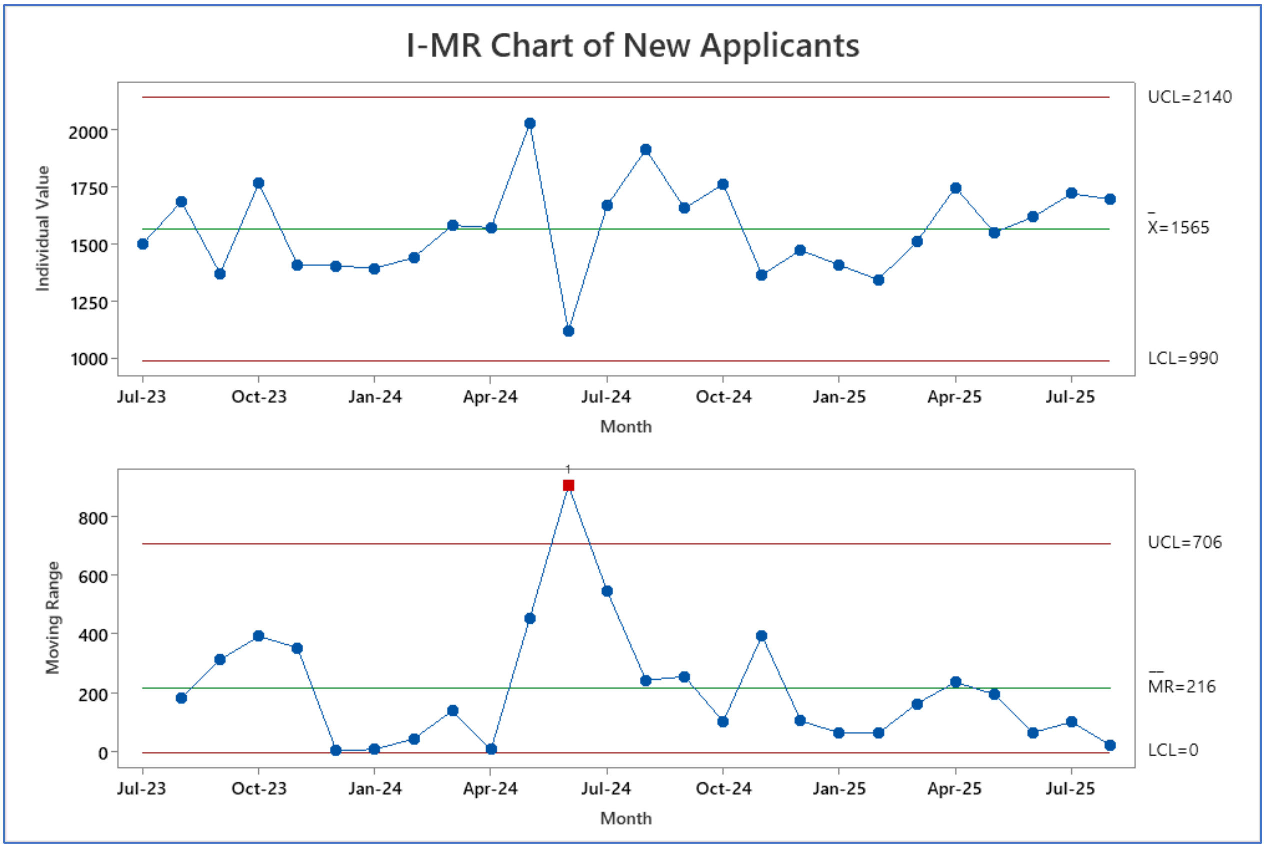
The time-series plot reveals minimal fluctuations during the most recent two (2) year period. Visual inspection of the plot illustrates the number of new applicants primarily hovers around 1,500 each month with some months slightly higher and other months slightly lower.

Two tools were used to further examine the most recent number of new applicants every month. The Augmented Dickey-Fuller Test is a statistical test used to determine whether the number of new applicants is stationary. The I-MR chart is a statistical process control chart used to evaluate process stability and detect variations in the process.

Time-series forecasting models such as ARIMA rely on the assumption that the data is stationary where the statistical properties do not change over time. Stationary data is easier to model because its statistical properties remain constant over time, making predictions more reliable. Non-stationary data can cause models to generate biased, unreliable, or misleading results. The results of the Augmented Dickey-Fuller Test shown in Appendix A-5 reveal that the new applicant data is stationary.

Fiscal years 2024 and 2025 were selected to create an I-MR chart along with the first month of FY 2026. The I-MR chart shown in Figure 18 identified one (1) occurrence of a special cause, an unusual variation in the process, in June 2024. Further investigation revealed that Access Services switched to a different electronic system for processing evaluations during this month, which likely led to this isolated occurrence of unusual variation. Otherwise, the monthly observations pass all the tests for special causes indicating the monthly number of new applicants is stable.

Figure 18: I-MR Chart New Applicants



The results of the historical analysis indicate the number of new applicants is stationary, meaning it lacks a detectable trend, and it is stable. The historical data for new applicants is based upon the number of monthly evaluations for certifications. Forecasts for the number of new applicants provide Access Services with the knowledge to plan budgets and operational resources necessary to perform certification evaluations.

4.1.2. Assessment of Projections – New Applicants

The projections provided to Access Services were aggregated by the fiscal year. This limits the ability to assess the performance of past projections to Fiscal Year 2025 along with the most recent 21 months or this assessment. The model used to generate the annual projections provides monthly forecasts. The assessment of the projections uses both Fiscal Year 2025 along with the most recent twenty-one months, December 2023 through August 2025.

The times series plot in Figure 19 illustrates the actual number of new applicants per month along with the forecasted values for each month. Table 4 provides a summary of the performance of the projections for both time periods. The forecast for the most recent twenty-one months experienced a 5.31% error, meaning the projections were 1,751 greater than the actual number of new applicants. The forecast for

Fiscal Year 2025 experienced a 6.13% error, meaning the projections were 1,165 greater than the actual number of new applicants.

Figure 19: New Applicants December 2023 – August 2025

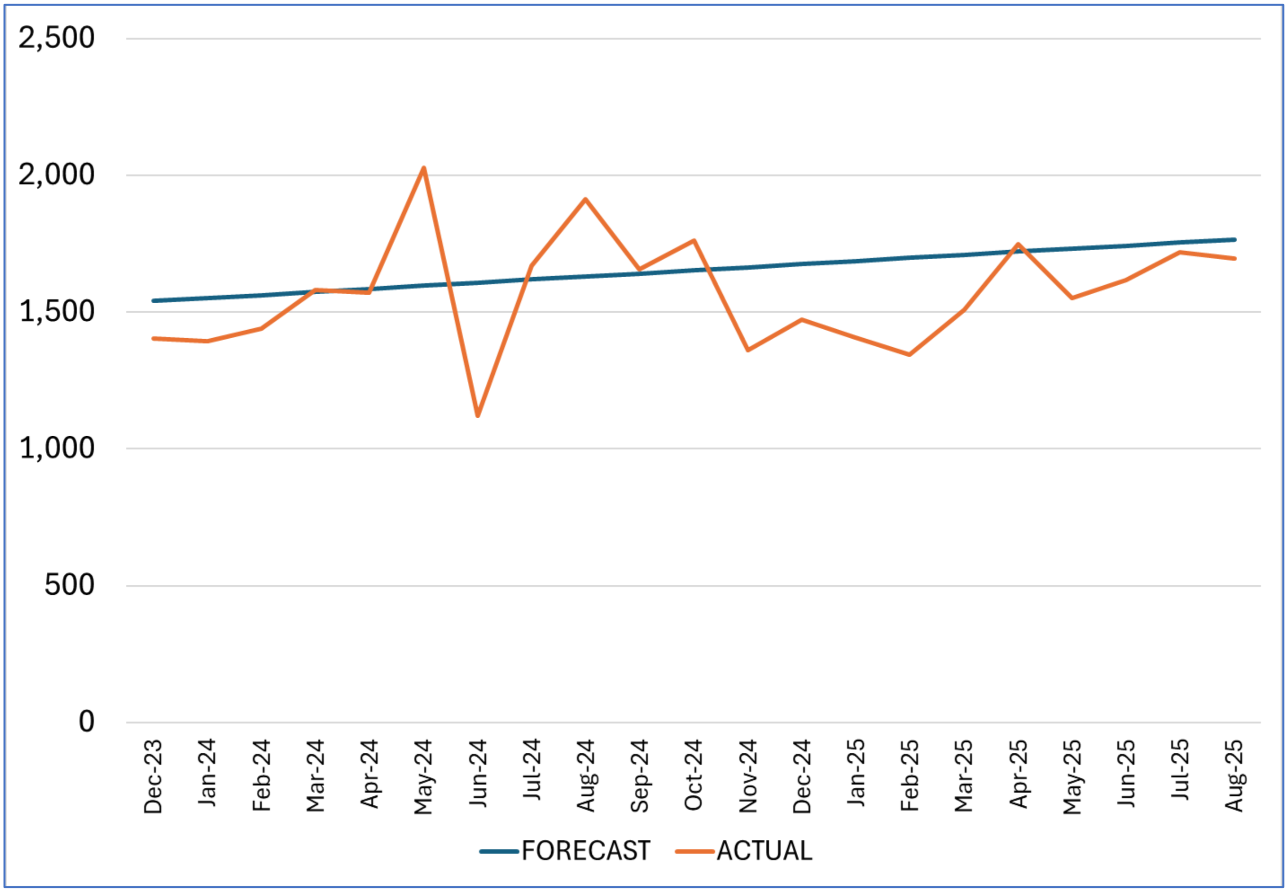


Table 4: New Applicants –Projections Assessment

TIME PERIOD	FORECAST	ACTUAL	ERROR	PERCENT ERROR
December 2023 - August 2025	34,711	32,960	1,751	5.31%
FY 2025	20,173	19,008	1,165	6.13%

The prediction error for the number of new applicants is greater than desired. The error experienced illustrates the need to re-evaluate the selection of the model and the parameters.

4.2. Model and Parameter Selection – New Applicants

The assessment of the FY 2025 projections along with the most recent 21 months revealed that the forecasting model, ARIMA, and the parameters used to create them experiences more prediction error than desired.

The historical analysis of the number of new applicants demonstrates this demand is both stationary and stable. The Autocorrelation Function chart (ACF) in Appendix A-5 shows there is no autocorrelation present in the number of new applicants.

Hyndman and Athanasopoulos (2021) explain that when a time series is stable, stationary, and exhibits zero autocorrelation, it can be treated as a white noise process with a constant mean and variance. In this situation, past observations contain no systematic information about future values beyond the overall average level of the series. Simple forecasting approaches, such as using the historical mean (or an equivalent constant-level model), perform best. Methods like ARIMA and other trend-based models do not necessarily reduce forecast error and may instead overfit random variation. The focus with time-series data exhibiting these characteristics is estimating the mean accurately.

The historical analysis revealed the mean (average) number of new applicants per month is 1,566. The standard deviation, a measure of variation, is 198 new applicants. The mean multiplied by twelve (12), for 12 months in a year, equals 18,792.

Probability plots were generated to test the historical data to determine if it follows the normal distribution. The plots and results are shown in Appendix A-6. The “p-value” for the Anderson-Darling is greater than 0.05 indicating there is a lack of evidence to suggest the data does not follow the normal distribution. The Ryan-Joiner score of 0.985 is very close to 1, indicating an excellent fit between the historical data and a theoretical normal distribution, which demonstrates the data closely follows a normal distribution.

The normal distribution describes the probability (likelihood) of experiencing a future value of the number of new applicants in any given month. The mean average and the standard deviation are the two key variables for a normal distribution.

The mean average of 1,566 new applicants per month and the standard deviation of 198 were entered into a random number generator tool designed for a normal distribution. The tool created a random number representing an expected value of new applicants for each month in the forecast through Fiscal Year 2036. The process was repeated for ten (10) replications. The results of the random number generation are shown in Appendix A-7.

The median is the middle value in a data set ordered from smallest to largest. For the 10 replications, the median value for each month was identified and selected to minimize the amount of fluctuation in the projections. The median values for each month were compiled to create the annual projections shown in the new applicant forecasts.

4.3. Forecasting Assumptions and Error Analysis – New Applicants

The historical analysis determined that the number of new applicants is both stationary and stable with no autocorrelation. The statistical properties for the number of new applicants do not change over time and the likelihood of unusual variation is low.

4.4. Conclusion and Next Steps – New Applicants

The model selected best reflects the stationary, stable, and lack of trend characteristics for the number of new applicants. The error in the projections is expected to be low due to the low likelihood of unusual variation.

Monitoring the demand dynamics on future iterations will continue to determine the data set's characteristics such as stationarity, stability, and trends (or the lack thereof). This includes checking to see if the data set reverts to pre-pandemic values and patterns. The monitoring will also identify the need to consider and evaluate other forecasting models.

4.5. New Applicants and In-Person Evaluations

In-Person Evaluations are a subset of the number of new applicants. The In-Person Evaluation is performed to determine if an individual, a new applicant, is eligible for services. In-Person Evaluations are for new applicants that have never been an eligible rider with Access Services.

The In-Person Evaluations are resource intensive as they require a trip to transport the individual to the evaluation appointment followed by a return trip to their home. Access Services needs to be able to plan a budget and operations to meet the demand for In-Person Evaluations. This is a substantial budget item for the agency.

The need to forecast and project the number of In-Person Evaluations arose at the end of the current cycle for Ridership Demand projections. Hollingsworth Consulting performed an initial analysis of the historical number of In-Person Evaluations along with the identification and selection of a model to create projections for Fiscal Year 2027.

The initial analysis of the In-Person Evaluations followed a similar approach to that of the number of new applicants. Time-series charts were created followed by tests of the historical data for stationarity, stability, and autocorrelation.

Time-series charts were created for three different periods of time to further understand the demand for In-Person Evaluations. The first time-series chart, shown in Figure 20, illustrates the demand every month for over a nine (9) year period. The second time-series chart narrows the focus to the post pandemic demand, shown in Figure 21. The most recent two (2) fiscal years of new applicants is stationary and stable. A third time-series chart was created to focus on this period, shown in Figure 22.

Figure 20: Time Series Chart – In Person Evaluations FY 2017 through 2025

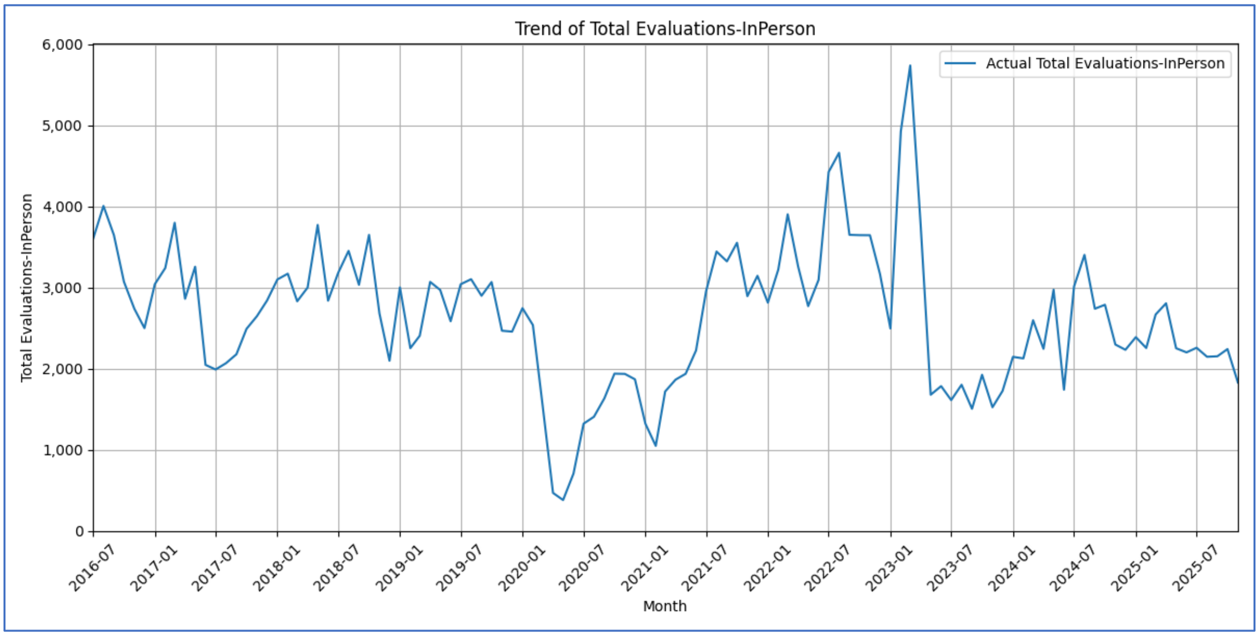


Figure 21: Time Series Chart – In Person Evaluations Post Pandemic

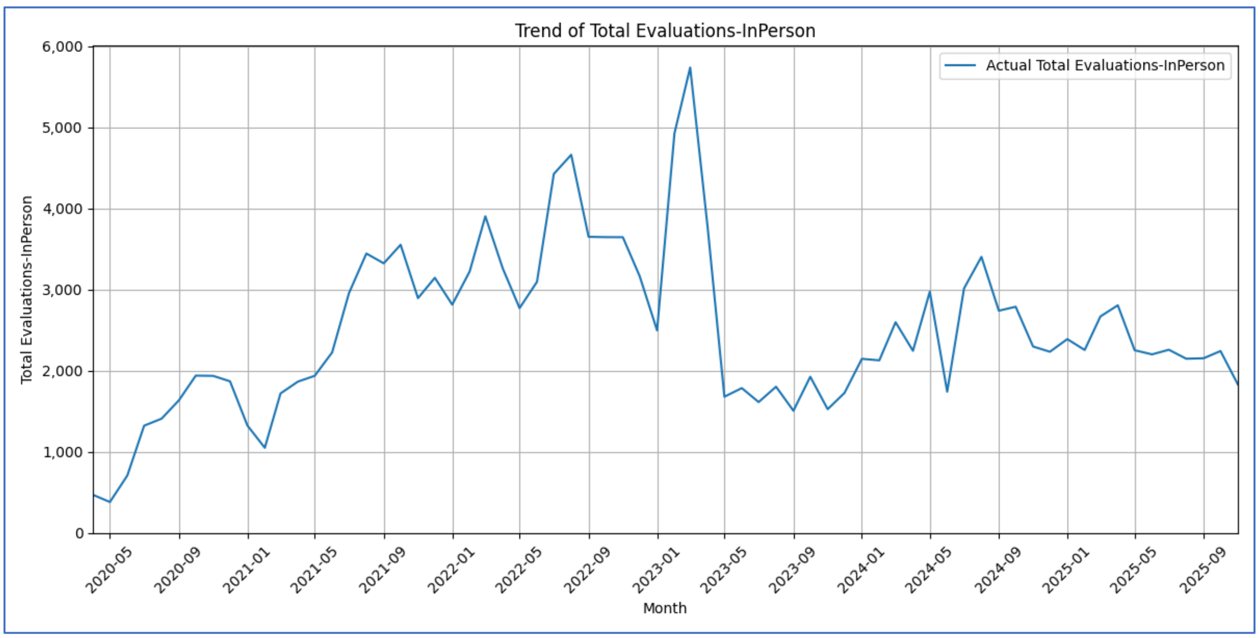
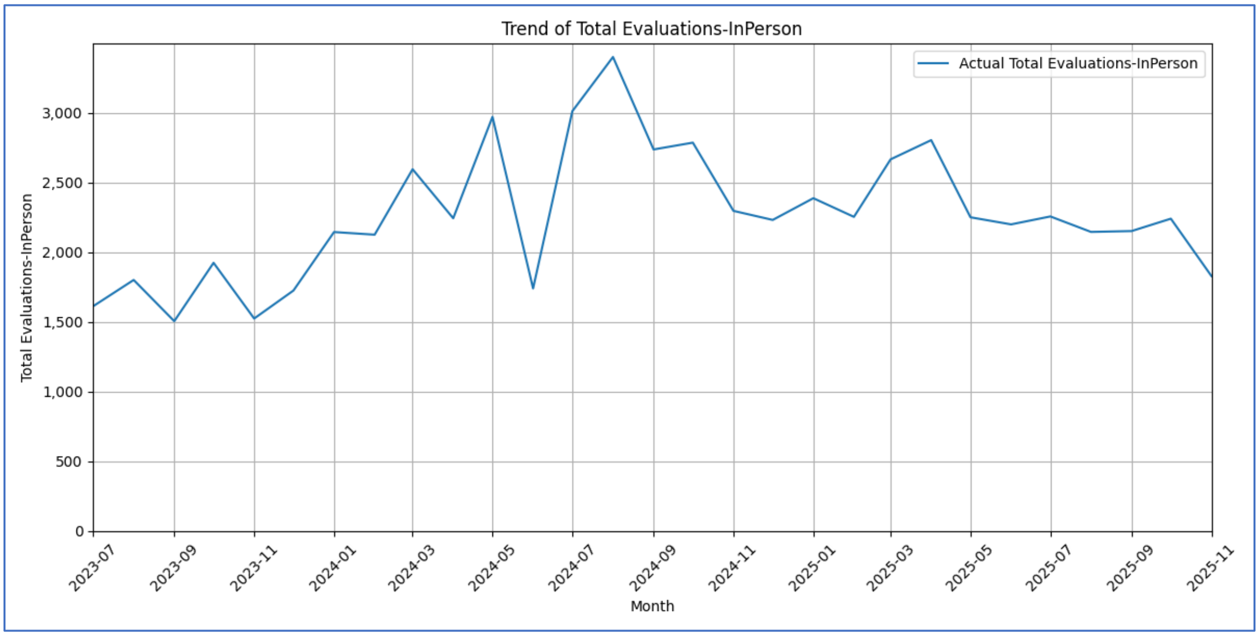
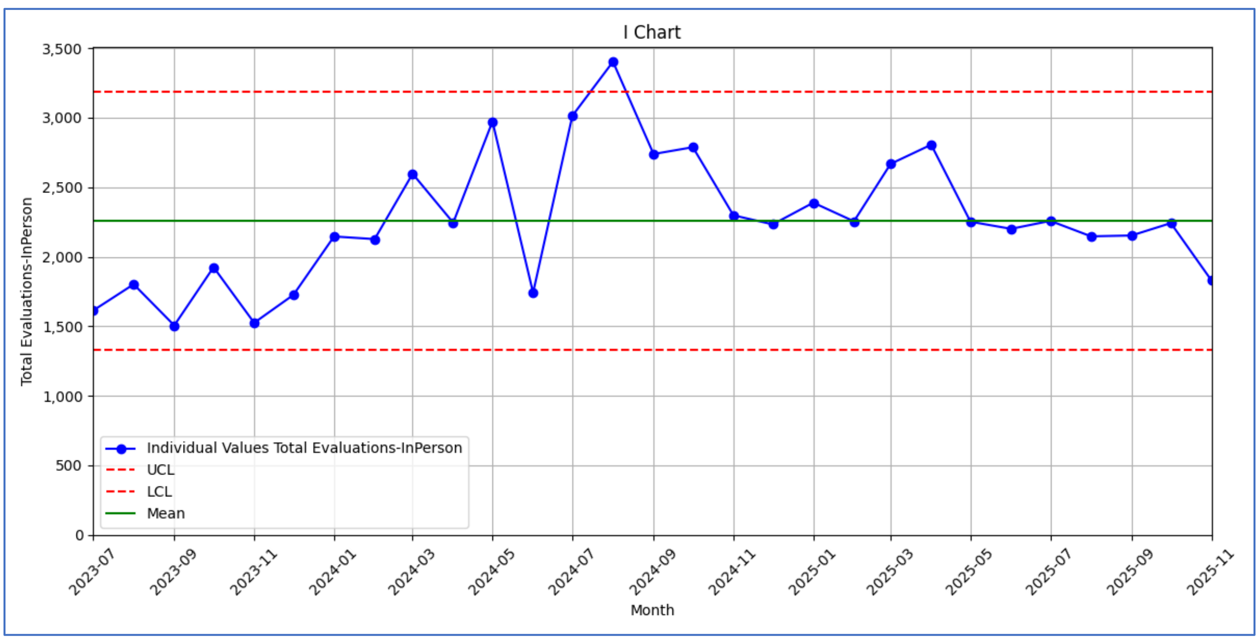


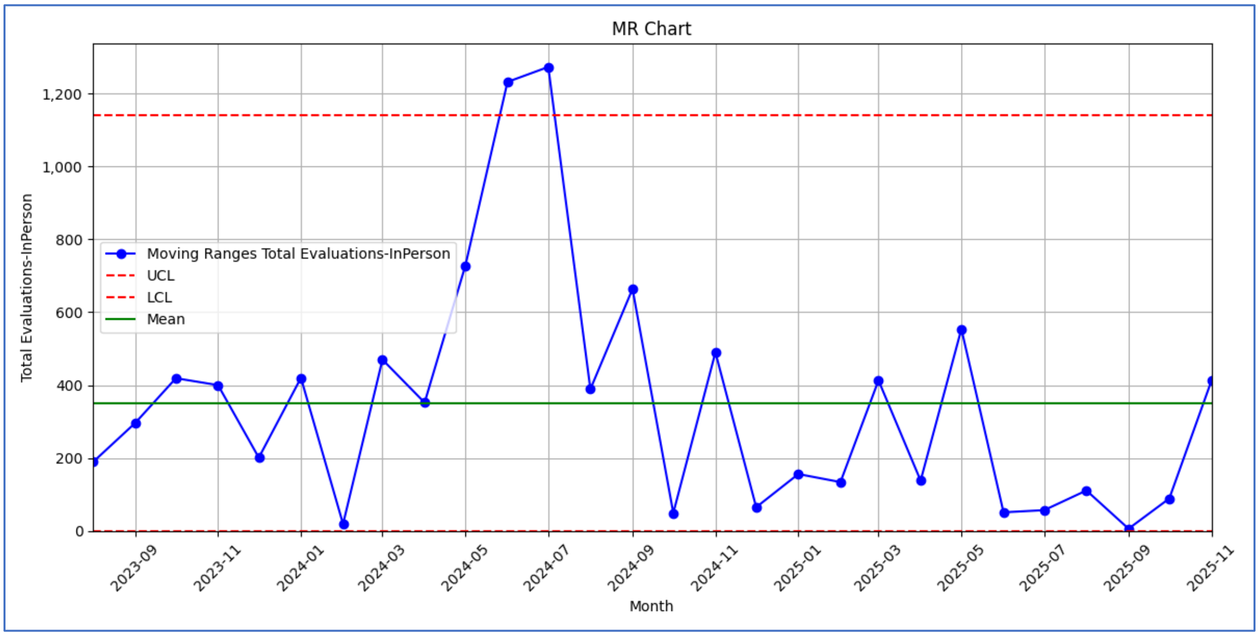
Figure 22: Time Series Chart – In Person Evaluations FY 2024 through 2025



The time-series charts reveal the behavior for the number of In-Person Evaluations in the most recent two (2) years appear different than the past. The Dickey-Fuller test was performed on the number of In-Person Evaluations for Fiscal Years 2024 through the present. The p-value of 0.019 is less than 0.05 (5%), which indicates the data is stationary. The I-MR statistical process control chart was performed on the most recent two (2) years to test for stability.

Figure 23: I-MR Chart for In-Person Evaluations FY 2024 to Present





Three data points in the I-MR chart appear as special causes. One of these points is above the upper control limit on the "I" portion of the chart while two (2) data points are above (outside) of the upper control limit on the moving range (MR) portion of the chart. The source of these special (exceptional) causes is not known meaning they are unassignable. With the lack of ability to assign a reason for these data points, it is unclear if the data is stable.

Autocorrelation is another important characteristic to understand to select an appropriate model to create projections. Autocorrelation measures the correlation between a time series and a lagged (delayed) version of itself, showing how similar a variable is to its past values at different time intervals (lags). The analysis of the autocorrelation is shown in Appendix A-8. There is autocorrelation present at the lag value of two (2), referring to 2 months in the past. However, there is no autocorrelation present for any other lag values indicating autocorrelation for the number of In-Person Evaluations is minimal and weak.

The lack of known stability and the slight autocorrelation limit the feasibility of using the historical mean average to predict the number of In-Person Evaluations. Single Exponential Smoothing method is suited for data that does not exhibit a trend or pattern, Hyndman, R.J., & Athanasopoulos, G. (2021). This method produces a constant projection with upper and lower prediction intervals.

The results of the Single Exponential Smoothing including a graph of the projections are shown in Appendix A-9. The projections for the number of In-Person Evaluations in the remainder of Fiscal Year 2026 and Fiscal Year 2027 are shown in Table 5. The projections total 37,763 for Fiscal Year 2027.

Table 5: Fiscal Year 2027 Projections for the Number of In Person Evaluations

Fiscal Year	Period	Lower Prediction Interval (95%)	Forecast	Upper Prediction Interval (95%)
2026	Dec-25	1,298	2,052	2,806
2026	Jan-26	1,298	2,052	2,806
2026	Feb-26	1,298	2,052	2,806
2026	Mar-26	1,298	2,052	2,806
2026	Apr-26	1,298	2,052	2,806
2026	May-26	1,298	2,052	2,806
2026	Jun-26	1,298	2,052	2,806
2027	Jul-26	1,298	2,052	2,806
2027	Aug-26	1,298	2,052	2,806
2027	Sep-26	1,298	2,052	2,806
2027	Oct-26	1,298	2,052	2,806
2027	Nov-26	1,298	2,052	2,806
2027	Dec-26	1,298	2,052	2,806
2027	Jan-27	1,298	2,052	2,806
2027	Feb-27	1,298	2,052	2,806
2027	Mar-27	1,298	2,052	2,806
2027	Apr-27	1,298	2,052	2,806
2027	May-27	1,298	2,052	2,806
2027	Jun-27	1,298	2,052	2,806

The forecasting assumptions and error risk will be further explored in the next cycle of Ridership Demand projections. Monitoring the demand dynamics on future iterations will continue to determine the data set’s characteristics such as stationarity, stability, trends (or the lack thereof), and autocorrelation. The monitoring will also identify the need to consider and evaluate other forecasting models.

5. Scheduled Trip Demand Forecasts

Access Services uses scheduled trip demand to plan budgets and operations for upcoming fiscal years. Table 6 shows the monthly forecasts through Fiscal Year 2027.

Table 6: Scheduled Trip Demand Monthly Forecast - Fiscal Years 2025 through 2027

MONTH	TOTAL	Antelope Valley	Eastern	Santa Clarita	SF Valley	Southern	West/ Central
Jul-24	370,494	16,514	105,796	3,657	59,109	124,661	60,757
Aug-24	384,622	17,702	110,764	3,669	61,242	128,923	62,322
Sep-24	376,075	17,142	108,611	3,415	60,440	124,967	61,500
Oct-24	415,473	19,400	120,576	3,911	66,267	138,227	67,092
Nov-24	372,790	16,765	108,784	3,300	59,545	122,283	62,113
Dec-24	378,362	16,717	111,240	60,827	3,426	124,465	61,687
Jan-25	372,410	16,372	107,256	59,684	3,324	125,052	60,722
Feb-25	364,790	16,484	105,244	58,649	3,279	122,730	58,404
Mar-25	405,879	17,711	117,032	64,916	3,538	138,354	64,328
Apr-25	407,342	17,504	118,715	65,741	3,644	138,030	63,708
May-25	413,281	18,087	121,152	66,972	3,470	139,038	64,562
Jun-25	395,230	17,357	114,096	65,128	3,356	133,081	62,212
Jul-25	418,005	17,498	121,291	68,977	3,541	140,172	66,526
Aug-25	420,684	18,221	121,676	70,170	3,818	141,566	65,233
Sep-25	428,576	18,079	124,824	71,519	3,598	144,013	66,543
Oct-25	417,836	18,845	120,666	3,834	65,168	140,540	68,782
Nov-25	397,066	17,909	114,668	3,644	61,928	133,554	65,363
Dec-25	429,518	19,372	124,039	3,942	66,990	144,470	70,705
Jan-26	429,061	19,352	123,908	3,937	66,919	144,316	70,630
Feb-26	387,306	17,468	111,849	3,554	60,406	130,271	63,756
Mar-26	423,909	19,119	122,420	3,890	66,115	142,583	69,782
Apr-26	415,802	18,754	120,078	3,816	64,851	139,856	68,447
May-26	428,618	19,332	123,780	3,933	66,849	144,167	70,557
Jun-26	427,669	19,289	123,505	3,925	66,701	143,848	70,401
Jul-26	453,377	20,800	129,464	4,209	69,650	154,880	74,374
Aug-26	441,303	20,246	126,016	4,097	67,795	150,756	72,393
Sep-26	437,004	20,048	124,789	4,057	67,135	149,287	71,688
Oct-26	448,764	20,588	128,147	4,166	68,941	153,305	73,617
Nov-26	431,448	19,794	123,202	4,005	66,281	147,389	70,777
Dec-26	460,445	21,124	131,482	4,274	70,736	157,295	75,534
Jan-27	456,196	20,929	130,269	4,235	70,083	155,844	74,837
Feb-27	420,002	19,268	119,934	3,899	64,523	143,479	68,899
Mar-27	470,064	21,565	134,229	4,364	72,214	160,581	77,112
Apr-27	453,907	20,824	129,615	4,214	69,731	155,061	74,461
May-27	458,671	21,042	130,976	4,258	70,463	156,689	75,243
Jun-27	456,592	20,947	130,382	4,239	70,144	155,979	74,902

Shaded rows represent Actual Scheduled Trips (Trip Requests)

Access Services uses ten (10) year projections for scheduled trip demand for long-range planning activities such as strategic planning, capital purchase planning, and other operational decisions. The scheduled trip demand annual forecasts through Fiscal Year 2036 are shown in Table 7.

Table 7: Scheduled Trip Demand Annual Forecast - Fiscal Years 2026 through 2036

Fiscal Year	TOTAL	Antelope Valley	Eastern	Santa Clarita	SF Valley	Southern	West/ Central
2025*	4,857,458	237,126	1,321,500	54,635	676,516	1,752,553	815,127
2026**	5,004,748	225,727	1,445,309	45,927	780,566	1,683,362	823,857
2027	5,387,773	247,175	1,538,507	50,015	827,695	1,840,545	883,836
2028	5,660,780	259,699	1,616,465	52,549	869,636	1,933,809	928,622
2029	6,312,131	289,581	1,802,462	58,596	969,700	2,156,320	1,035,473
2030	6,620,652	303,735	1,890,561	61,460	1,017,096	2,261,715	1,086,084
2031	6,894,797	316,312	1,968,845	64,005	1,059,212	2,355,367	1,131,056
2032	7,151,625	328,095	2,042,184	66,389	1,098,667	2,443,104	1,173,187
2033	7,331,236	336,335	2,093,472	68,056	1,126,259	2,504,461	1,202,652
2034	7,501,935	344,166	2,142,216	69,641	1,152,483	2,562,775	1,230,654
2035	7,641,720	350,579	2,182,133	70,938	1,173,957	2,610,528	1,253,585
2036	7,784,743	357,140	2,222,974	72,266	1,195,929	2,659,386	1,277,047

* Actual Scheduled Trips (Trip Requests)
** Original Projections for FY 2026 (no actual trip requests, observations, included)

Scheduled trip demand has a positive trend as the demand increases from one fiscal year to the next. The percentage increase (or decrease) for the scheduled trip demand from one year to the next is shown in Table 8.

Table 8: Scheduled Trip Demand Annual Forecast % Increase (Decrease) From Prior Year

Fiscal Year	TOTAL	Antelope Valley	Eastern	Santa Clarita	SF Valley	Southern	West/ Central
2025*	-	-	-	-	-	-	-
2026**	3.0%	-4.8%	9.4%	-15.9%	15.4%	-3.9%	1.1%
2027	7.7%	9.5%	6.4%	8.9%	6.0%	9.3%	7.3%
2028	5.1%	5.1%	5.1%	5.1%	5.1%	5.1%	5.1%
2029	11.5%	11.5%	11.5%	11.5%	11.5%	11.5%	11.5%
2030	4.9%	4.9%	4.9%	4.9%	4.9%	4.9%	4.9%
2031	4.1%	4.1%	4.1%	4.1%	4.1%	4.1%	4.1%
2032	3.7%	3.7%	3.7%	3.7%	3.7%	3.7%	3.7%
2033	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%
2034	2.3%	2.3%	2.3%	2.3%	2.3%	2.3%	2.3%
2035	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%
2036	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%	1.9%

* Actual Trip Requests

** Original Projections for FY 2026 (no actual trip requests, observations, included)

6. New Applicant Forecasts

Projections for the annual number of new applicants are shown in Table 9. These projections include ten (10) fiscal years from Fiscal Year 2027 through 2036.

Table 9: New Applicant Annual Forecast - Fiscal Years 2026 through 2036

Fiscal Year	TOTAL	Antelope Valley	Eastern	Santa Clarita	SF Valley	Southern	West/ Central
2025*	18,749	787	6,094	211	2,785	6,130	2,742
2026**	18,835	758	6,084	206	2,741	6,221	2,825
2027	18,908	761	6,108	207	2,752	6,245	2,836
2028	18,627	750	6,017	204	2,711	6,152	2,793
2029	18,499	744	5,976	202	2,692	6,110	2,774
2030	19,085	768	6,165	209	2,777	6,303	2,862
2031	18,775	756	6,065	205	2,732	6,201	2,816
2032	18,811	757	6,076	206	2,738	6,213	2,821
2033	18,635	750	6,019	204	2,712	6,155	2,795
2034	19,177	772	6,194	210	2,791	6,334	2,876
2035	18,880	760	6,099	206	2,748	6,236	2,831
2036	18,427	742	5,952	202	2,682	6,086	2,763

* Actual New Applicants
** Projections for FY 2026 (no actual new applicants, observations, included)

The annual number of new applicants lacks the presence of a trend in the demand from one fiscal year to the next. The percentage increase (or decrease) for the number of new applicants from one year to the next is shown in Table 10.

Table 10: New Applicant Annual Forecast % Increase (Decrease) From Prior Year

Fiscal Year	TOTAL	Antelope Valley	Eastern	Santa Clarita	SF Valley	Southern	West/ Central
2025*							
2026	0.5%	-3.7%	-0.2%	-2.4%	-1.6%	1.5%	3.0%
2027	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%	0.4%
2028	-1.5%	-1.5%	-1.5%	-1.5%	-1.5%	-1.5%	-1.5%
2029	-0.7%	-0.7%	-0.7%	-0.7%	-0.7%	-0.7%	-0.7%
2030	3.2%	3.2%	3.2%	3.2%	3.2%	3.2%	3.2%
2031	-1.6%	-1.6%	-1.6%	-1.6%	-1.6%	-1.6%	-1.6%
2032	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%
2033	-0.9%	-0.9%	-0.9%	-0.9%	-0.9%	-0.9%	-0.9%
2034	2.9%	2.9%	2.9%	2.9%	2.9%	2.9%	2.9%
2035	-1.5%	-1.5%	-1.5%	-1.5%	-1.5%	-1.5%	-1.5%
2036	-2.4%	-2.4%	-2.4%	-2.4%	-2.4%	-2.4%	-2.4%

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8. Appendices

8.1.Appendix A-1: Definitions

Dependent variable A dependent variable is what happens as a result of the independent variable. In other words, a variable (often denoted by y) whose value depends on that of another.

Exponential Growth Trend A time series where values increase by a consistent relative rate (eg. 10% per year on previous year value).

Generalized linear model (**GLM**) Flexible generalization of ordinary linear regression. The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value.

Independent Variable A variable that stands on its own and is not affected by anything that you do. A variable (often denoted by x) whose variation does not depend on that of another.

For example, the weather (rain, snow, temperature, etc.) is independent of fares. Regardless of any increases or decreases in the fare, the temperature will not be affected.

Intercept The distance from the origin to a point where a graph crosses a *y* coordinate axis.

Lags Number of layers in an LSTM model.

Linear regression Linear approach for modeling the relationship between a scalar response and one or more explanatory variables (also known as dependent and independent variables). The case of one explanatory variable is called simple linear regression.

Linear Trend A time series where each data point increases (decreases) by a consistent value and forms a straight line.

Mean absolute deviation (MAD) The absolute difference between the observed and forecasted values.

$$\text{MAD} = \frac{\sum \left| y_i - \hat{y}_i \right|}{N}$$

Mean absolute percent error (MAPE) The average error for the absolute difference between the observed and forecasted values.

$$\text{MAPE} = \frac{\sum \left| \frac{y_i - \hat{y}_i}{y_i} \right|}{N}$$

Mean squared error (MSD) The average squared difference between the observed and forecasted values.

$$\frac{\sum_{t=1}^{n} \left| y_t - \hat{y}_t \right|^2}{n}$$

Multivariate analysis of variance (**MANOVA**) extends the analysis of variance to cover cases where there is more than one dependent variable to be analyzed simultaneously; see also Multivariate analysis of covariance (MANCOVA).

Multivariate regression attempts to determine a formula that can describe how elements in a vector of variables respond simultaneously to changes in others. For linear relations, regression analyses here are based on forms of the general linear model. Some suggest that multivariate regression is distinct from multivariable regression, however, that is debated and not consistently true across scientific fields.

Polynomial equation An equation comprised of variables, exponents, and coefficients. The degree of the equation is the value of the largest exponent.

Polynomial regression A form of regression analysis in which the relationship between the independent variable x and the dependent variable y is modeled as an n^{th} degree polynomial in x.

Quadratic Trend A time series where values increase (decrease) at a rate that is not constant.

S-Curve (Pearl-Reed Logistic) Trend A time series where values increase exponentially until the saturation causes growth to switch to a linear trend and growth stops at maturity.

Slope A number that describes both the direction and steepness of a line.

Trend An upwards or downwards shift in a data set over time.

Units The number of cells in an LSTM model.

Equation Terms

y_i	i^{th} observed response value
$\bar{y}$	mean response
$\hat{y}_i$	i^{th} fitted response
N	number of rows

8.2. Appendix A-2: Trend Analysis – Scheduled Trip Demand

Using the trend analysis tool in Minitab Statistical Software (version 21.4.2) to examine the monthly scheduled trip demand, four (4) different trend models were identified and utilized to compare time-series data and determine the general trend model that best fit the observations. The four trend models include: (1) linear, (2) quadratic, (3) exponential growth (or decay), and (4) the S-curve. The tool calculates three metrics to identify and choose the model that fits best: (1) Mean Absolute Percent Error (MAPE), (2) Mean Absolute Deviation (MAD), and (3) Mean Standard Deviation (MSD). The definitions and equations for the metrics are shown in Appendix A-1: Definitions. The lower the value for the metric the better the observations fit the model compared to the other models.

The quadratic model is the best fit of a general trend model for the monthly scheduled trip demand prior to the pandemic as shown in Figure 24. The quadratic model scored a lower MAPE, MAD, and MSD than the linear and exponential growth (or decay) trend models while tying the S-curve model for MAPE but outperforming it on MAD and MSD as shown in Table 11.

Figure 24: Trend Analysis Monthly Scheduled Trip Demand – Pre-Pandemic

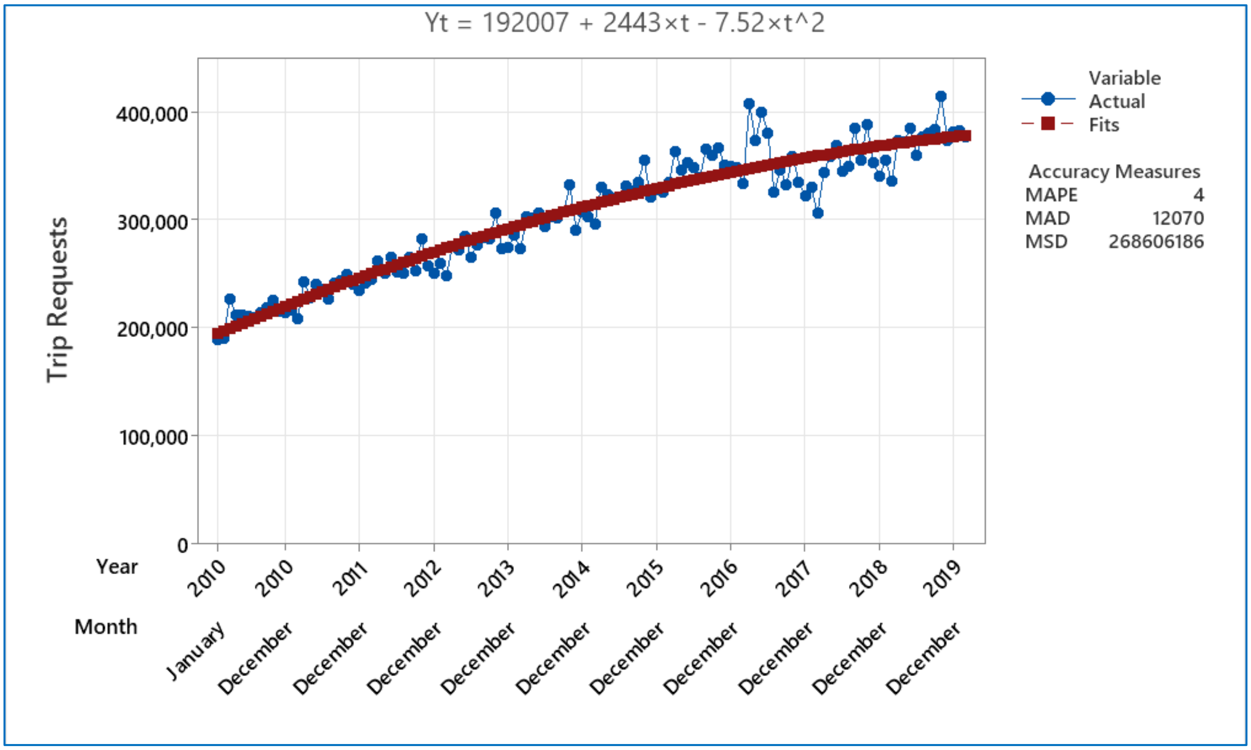


Table 11: Pre-Pandemic Scheduled Trip Demand Trend Model Scores

TREND MODEL	MAPE	MAD	MSD
Linear	5	14,292	338,159,170
Quadratic	4	12,070	268,606,186
Exponential Growth (Decay)	5	16,766	438,473,616
S-Curve	4	12,370	271,225,954

The quadratic model is the best fit of a general trend model for the monthly scheduled trip demand after the pandemic as shown in Figure 25. The quadratic model tied the linear and S-curve models for MAPE but scored (better) on all three other models for both MAD and MSD for this data set as shown in Table 12.

Figure 25: Trend Analysis Monthly Scheduled Trip Demand – Post-Pandemic

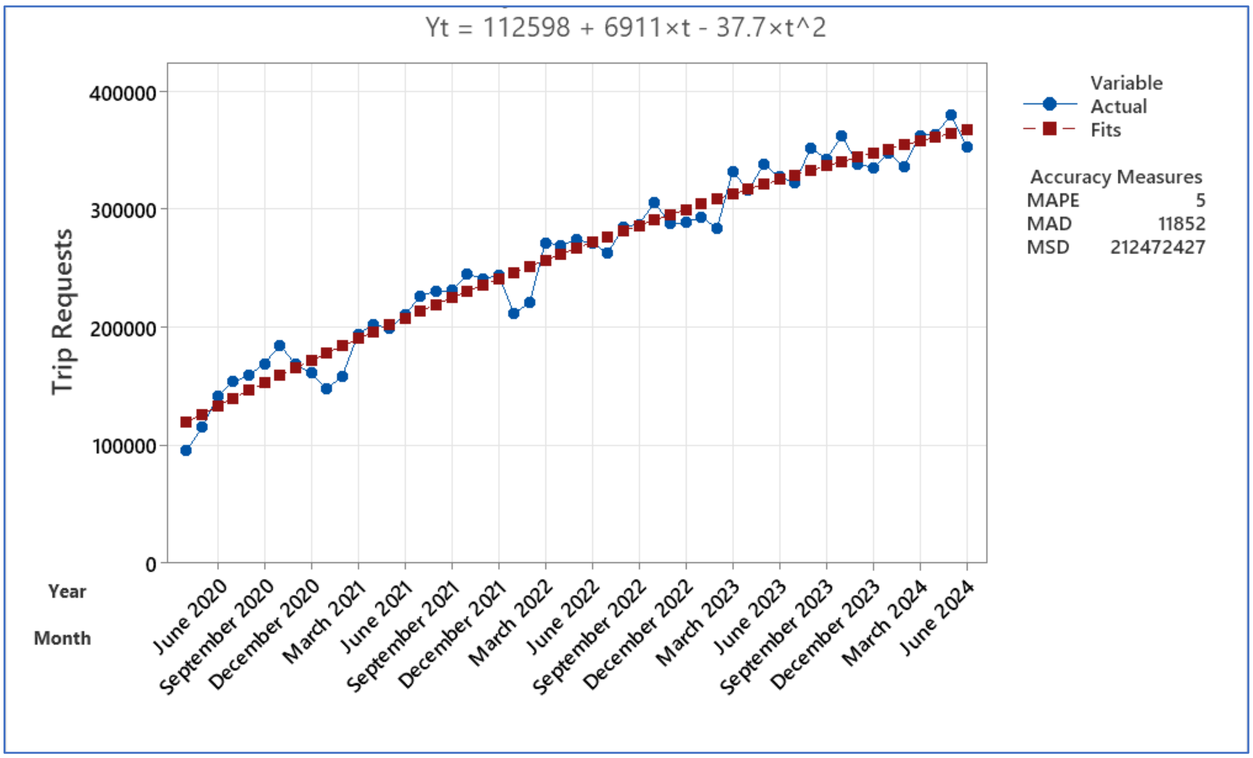
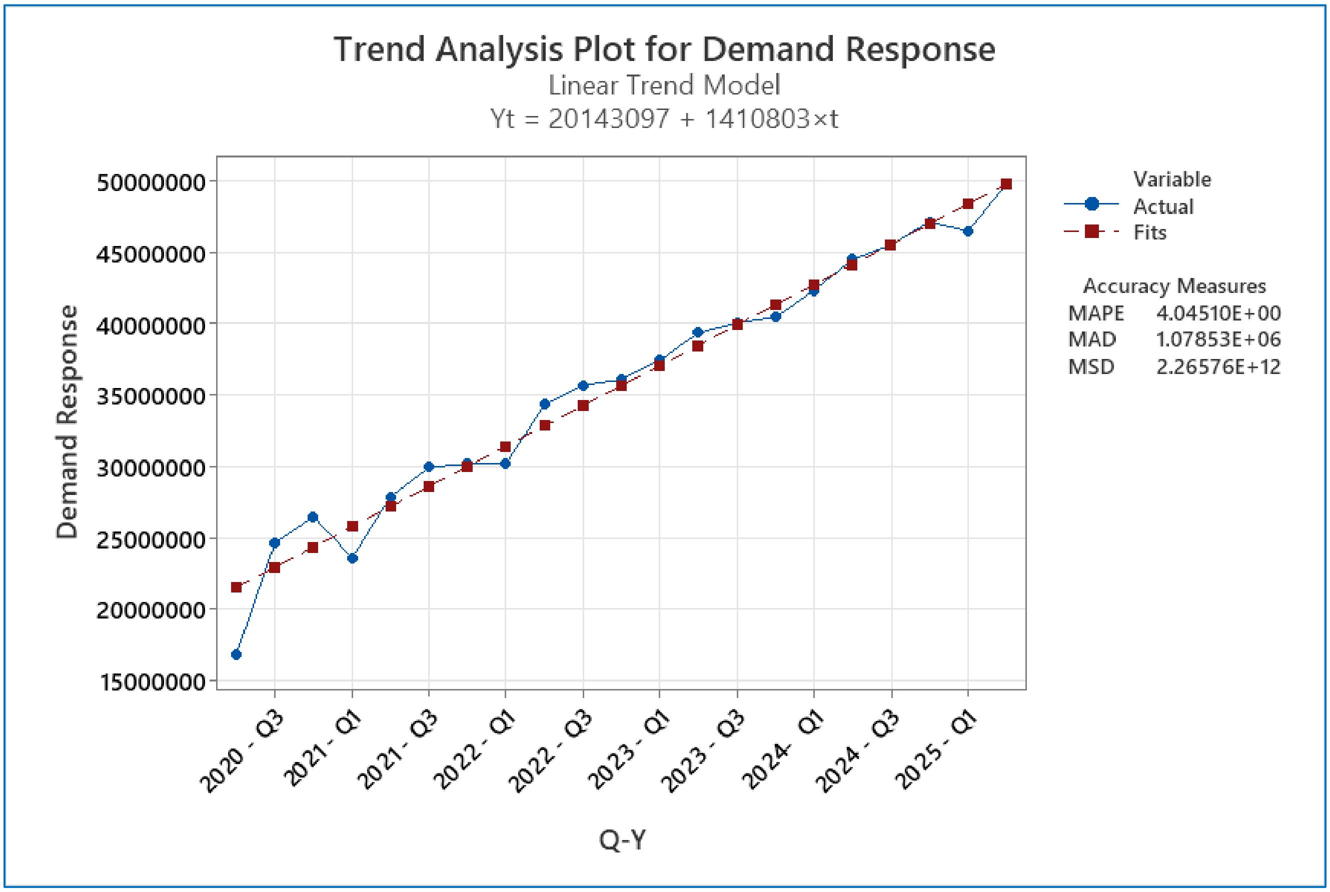


Table 12: Post-Pandemic Scheduled Trip Demand Trend Model Scores

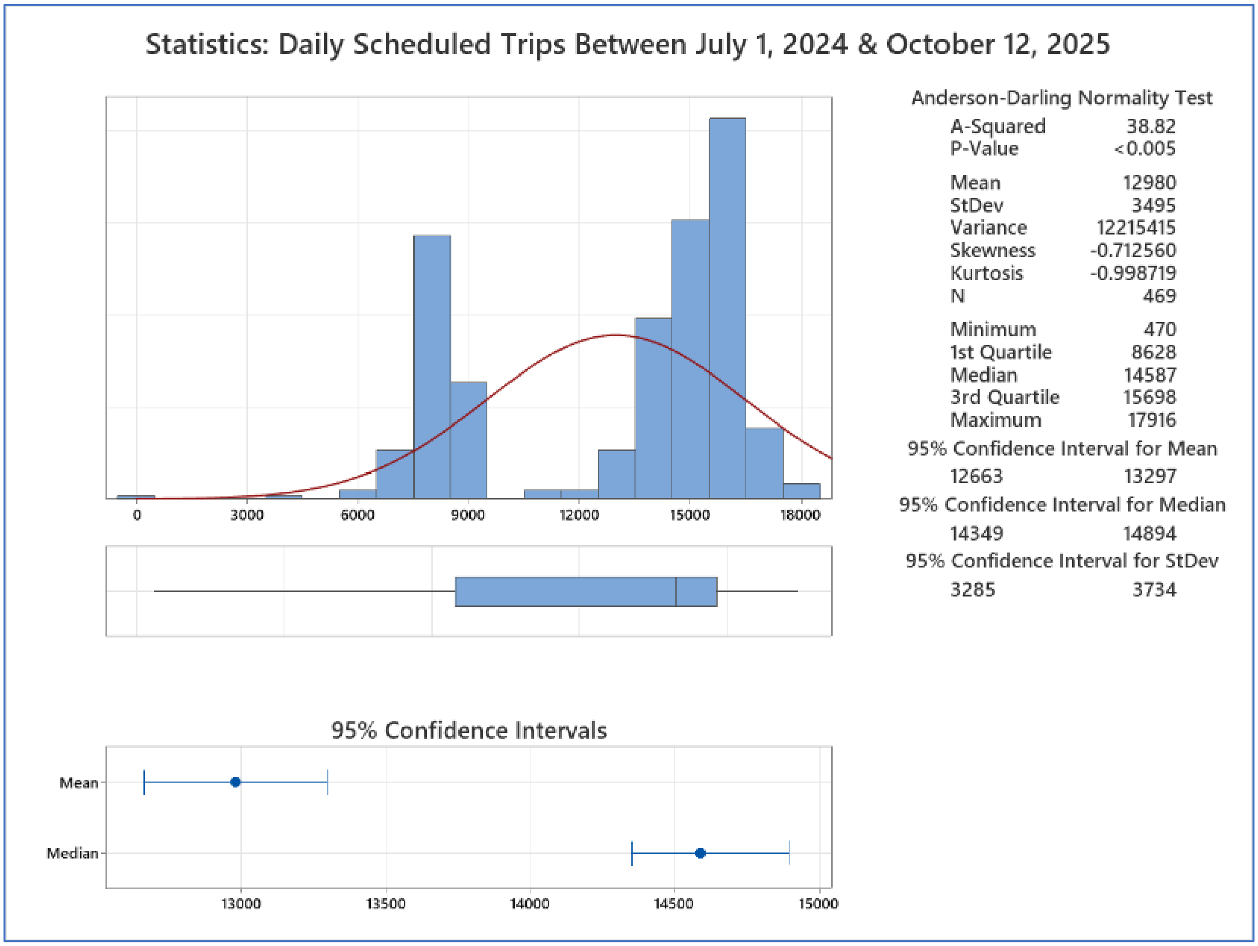
TREND MODEL	MAPE	MAD	MSD
Linear	6	13,424	265,757,996
Quadratic	5	11,852	212,472,427
Exponential Growth (Decay)	8	19,691	568,515,968
S-Curve	6	12,871	225,547,701

Figure 24 illustrates the polynomial equation representing the trend of the monthly scheduled trip demand prior to the pandemic, Y_t = 192,007 + 2,443t – 7.52t^2. The equation illustrated in Figure 25, Y_t = 112,598 + 6.,911t – 37.7t^2, represents the trend post-pandemic. The equations in Figure 24 and Figure 25 are different indicating there is a mathematical difference between the trend for the monthly scheduled trip demand before the pandemic and after the pandemic. This is important because pre-pandemic scheduled trip demand does not reflect current scheduled trip demand limiting its value to forecast scheduled trips.

8.3. Appendix A-3: National Quarterly Ridership Trend Analysis



8.4. Appendix A-4: Meta Prophet Capacity Level Analysis and Selection



	Current Value	Meta Prophet Capacity Level	Difference	% of Capacity that is Greater than Current Value
Mean (Average)	12,980	25,000	12,020	93%
Median	14,587	25,000	10,413	71%
75th Percentile	15,698	25,000	9,302	59%
Maximum	17,916	25,000	7,084	40%
	Current Value	**Meta Prophet Capacity Level**	**Difference**	**% of Capacity that is Greater than Current Value**
Mean (Average)	12,980	30,000	17,020	131%
Median	14,587	30,000	15,413	106%
75th Percentile	15,698	30,000	14,302	91%
Maximum	17,916	30,000	12,084	67%

8.5.Appendix A-5: Augmented Dickey-Fuller Test - New Applicants

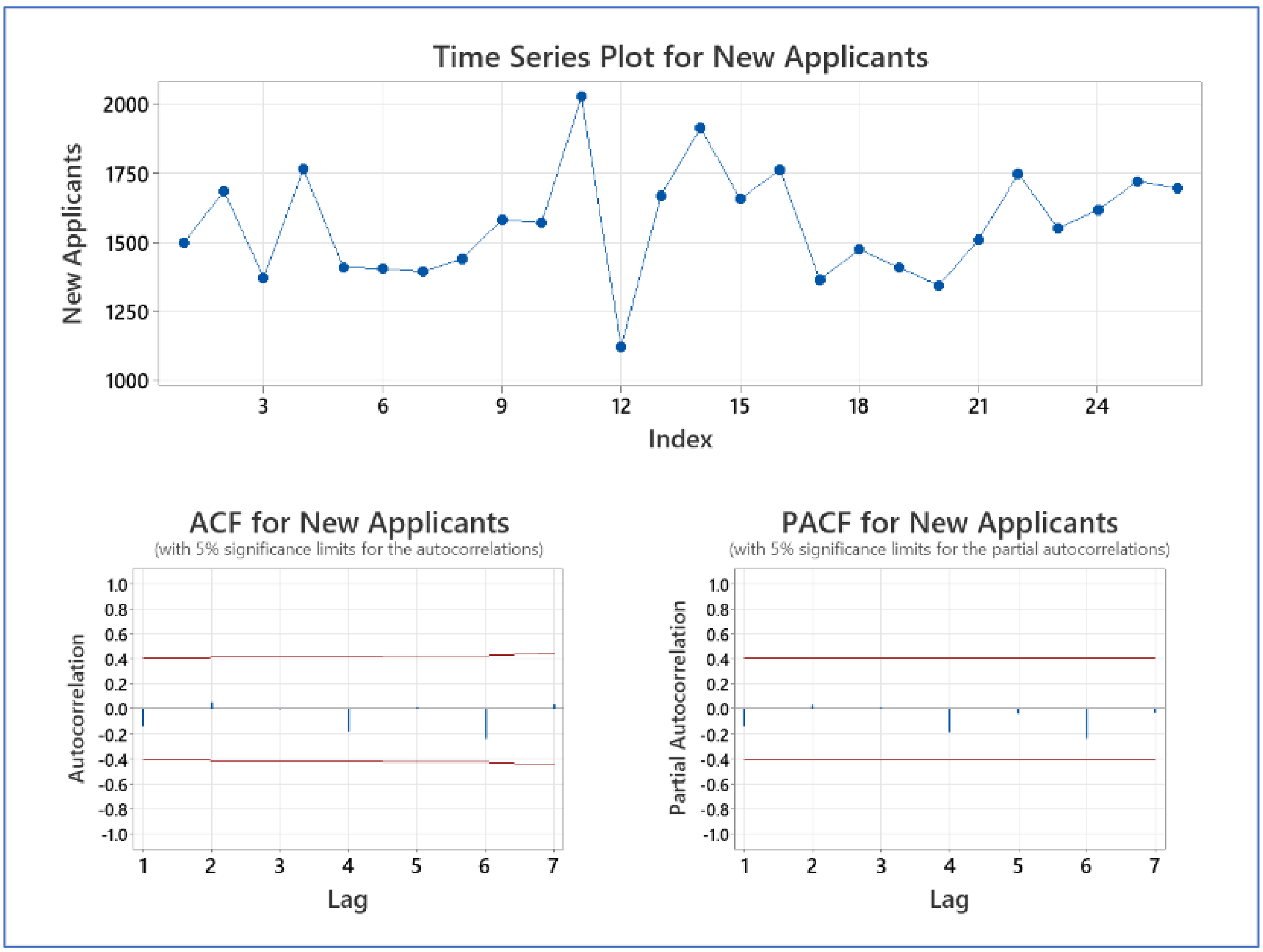
Method

Maximum lag order for terms in the regression model	9
Criterion for selecting lag order	Minimum AIC
Additional terms	Constant
Selected lag order	0
Rows used	26

Augmented Dickey-Fuller Test

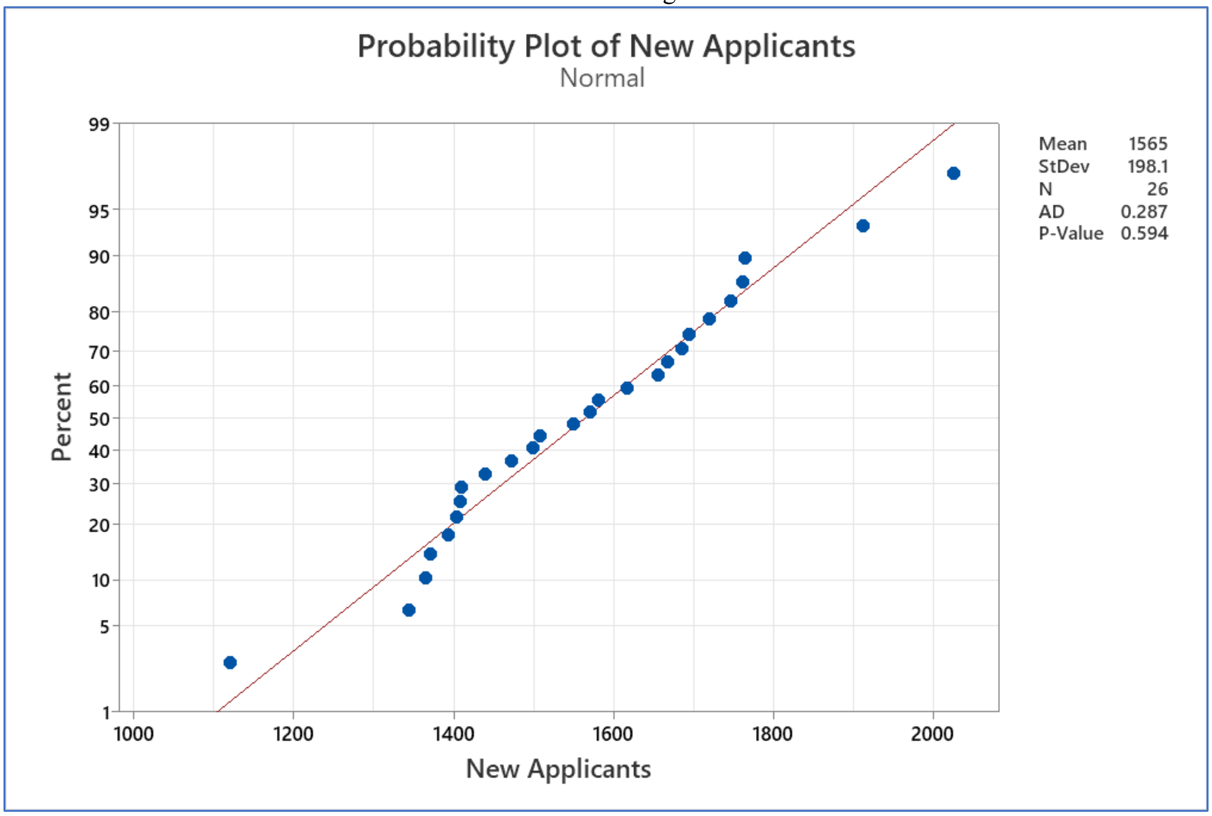
Null hypothesis:	Data are non-stationary
Alternative hypothesis:	Data are stationary

Test Statistic	P-Value	Recommendation
-5.48774	0.000	Test statistic <= critical value of -2.98649. Significance level = 0.05 Reject null hypothesis. Data appears to be stationary, not supporting differencing.

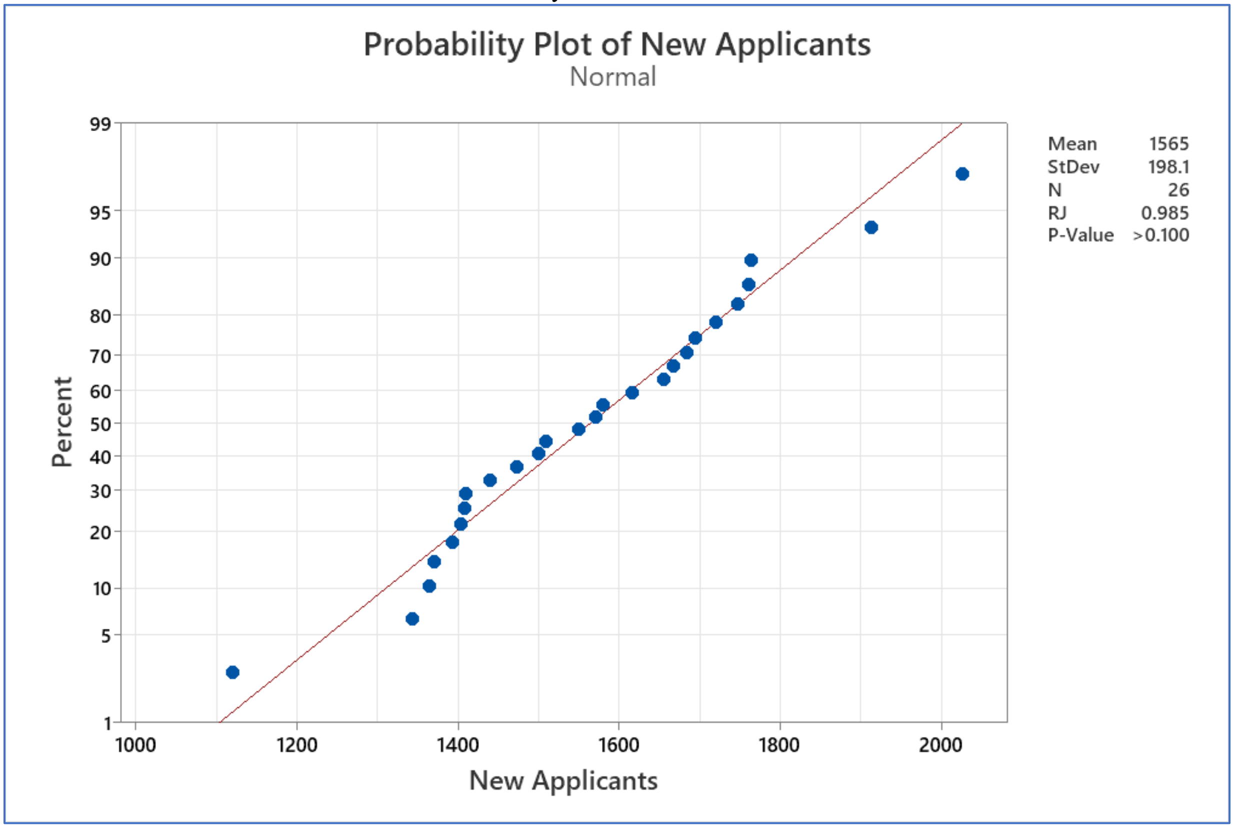


8.6. Appendix A-6: New Applicants Test for Normality

Anderson-Darling Test



Ryan-Joiner Test



8.7. Appendix A-7: New Applicants Random Number Generation Values

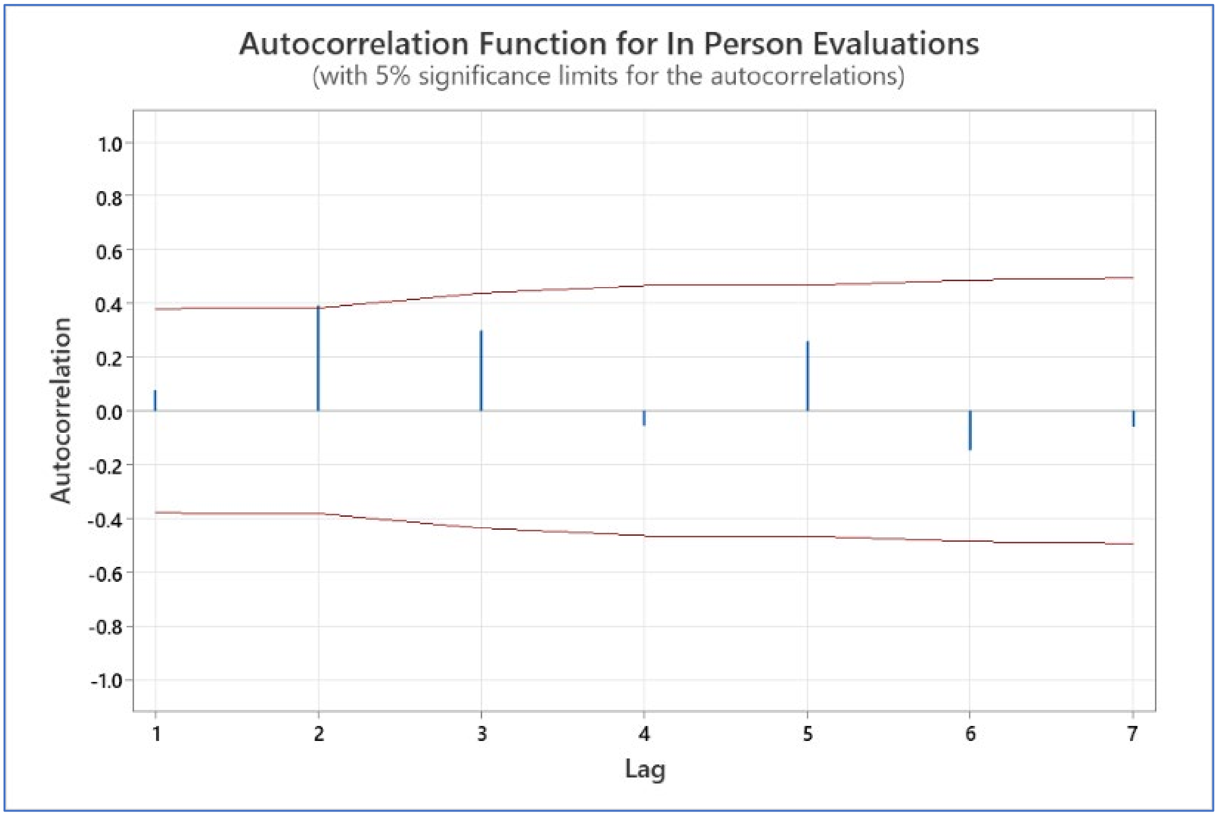
		Replication										
Month	Fiscal Year	1	2	3	4	5	6	7	8	9	10	Median
Jul-26	2027	1,558	1,789	1,529	1,351	1,564	1,564	1,299	1,618	1,570	1,928	1,564
Aug-26	2027	1,478	1,095	1,492	1,445	1,076	1,712	1,742	1,559	1,330	1,598	1,485
Sep-26	2027	1,674	1,763	1,709	1,512	1,760	1,532	1,649	1,210	1,790	1,590	1,662
Oct-26	2027	1,821	1,470	1,279	1,709	1,782	1,478	1,477	1,642	1,670	1,273	1,560
Nov-26	2027	1,651	1,362	1,610	1,934	1,178	2,017	1,267	1,476	1,506	1,427	1,491
Dec-26	2027	1,748	1,537	1,526	1,560	1,587	1,480	1,526	1,481	1,821	1,429	1,532
Jan-27	2027	1,222	1,654	1,694	1,727	1,546	1,687	1,504	1,672	1,564	1,593	1,624
Feb-27	2027	1,681	1,457	1,394	1,323	1,373	1,312	1,864	1,403	1,567	1,553	1,430
Mar-27	2027	2,083	1,784	1,609	1,754	1,340	1,807	1,871	1,512	1,817	1,409	1,769
Apr-27	2027	1,696	1,893	1,662	1,350	1,759	2,094	1,204	1,198	1,395	1,436	1,549
May-27	2027	1,693	1,763	1,097	1,600	1,678	1,427	1,837	1,385	1,840	1,540	1,639
Jun-27	2027	1,626	1,293	1,619	1,814	1,607	1,993	1,551	1,392	1,437	1,601	1,604
Jul-27	2028	1,293	968	1,486	1,676	1,206	1,527	1,728	1,705	1,258	1,723	1,507
Aug-27	2028	1,726	1,595	1,485	1,461	1,400	1,638	1,962	1,373	1,229	1,579	1,532
Sep-27	2028	1,639	1,771	1,644	1,368	1,676	1,798	1,461	1,609	1,641	1,562	1,640
Oct-27	2028	1,768	1,908	1,765	1,183	1,523	1,597	1,454	1,722	1,436	1,565	1,581
Nov-27	2028	1,510	1,624	1,713	1,374	1,711	1,072	1,538	1,481	1,609	1,849	1,574
Dec-27	2028	1,567	1,583	1,638	1,608	1,376	1,278	1,410	1,434	1,365	1,652	1,501
Jan-28	2028	1,801	1,389	1,734	1,905	1,558	1,524	1,291	1,375	1,715	1,568	1,563
Feb-28	2028	1,421	1,686	1,325	1,522	1,746	1,381	1,515	1,474	1,765	1,677	1,519
Mar-28	2028	1,443	1,513	1,388	1,643	1,418	1,630	1,506	1,699	1,724	1,636	1,572
Apr-28	2028	1,687	1,575	1,293	1,690	1,490	1,562	1,568	1,532	1,538	1,545	1,554
May-28	2028	1,640	1,540	1,477	1,728	1,642	1,356	1,555	1,565	1,523	1,302	1,548
Jun-28	2028	1,555	1,417	1,580	1,523	1,340	1,336	1,574	1,489	1,762	1,752	1,539
Jul-28	2029	1,448	1,691	1,367	1,622	1,276	1,733	1,270	1,313	1,517	1,292	1,408
Aug-28	2029	1,494	1,524	1,505	1,740	1,536	1,643	1,612	1,874	1,414	1,511	1,530
Sep-28	2029	1,327	1,490	1,060	1,339	1,074	1,657	1,306	1,851	1,591	1,710	1,415
Oct-28	2029	1,222	1,100	1,609	1,584	1,490	1,447	1,759	1,502	1,907	1,575	1,539
Nov-28	2029	1,618	1,648	1,891	1,749	1,764	1,769	1,407	1,705	1,483	2,035	1,727
Dec-28	2029	1,633	1,383	1,700	1,542	1,323	1,449	1,591	1,448	1,476	1,532	1,504
Jan-29	2029	1,630	1,297	1,570	1,646	1,708	1,837	1,371	1,555	1,503	1,589	1,580
Feb-29	2029	1,387	1,694	1,645	1,273	1,832	2,052	1,804	1,529	1,675	1,843	1,685
Mar-29	2029	1,263	1,458	1,378	977	1,399	1,729	1,387	1,692	1,656	1,447	1,423
Apr-29	2029	1,738	1,327	1,605	1,240	1,300	1,951	1,688	1,552	1,903	1,625	1,615
May-29	2029	1,760	1,340	1,367	1,683	1,581	1,665	1,659	1,304	1,744	1,090	1,620
Jun-29	2029	1,400	1,348	1,725	1,730	1,342	1,719	1,418	1,341	1,785	1,493	1,456
Jul-29	2030	1,581	1,407	1,768	1,446	1,671	1,661	1,423	1,653	1,777	1,265	1,617
Aug-29	2030	1,543	1,873	1,863	1,449	1,402	1,402	1,501	1,489	1,568	1,665	1,522
Sep-29	2030	1,851	1,917	1,752	1,396	1,680	1,393	1,501	1,488	1,506	1,492	1,504
Oct-29	2030	1,497	1,778	1,623	1,536	1,576	1,593	1,436	1,502	1,983	1,829	1,585
Nov-29	2030	1,432	1,550	1,572	1,551	1,137	1,591	1,653	1,841	1,562	1,885	1,567
Dec-29	2030	1,378	1,364	1,164	1,794	1,650	1,607	1,531	1,394	1,376	1,519	1,457
Jan-30	2030	1,607	1,739	1,834	1,394	1,585	1,600	1,780	1,602	1,036	1,587	1,601
Feb-30	2030	1,618	1,474	1,614	1,077	1,513	1,887	1,831	1,486	1,201	1,626	1,564
Mar-30	2030	1,827	1,572	1,585	1,746	1,933	1,796	1,627	1,770	1,642	1,672	1,709
Apr-30	2030	1,069	1,914	1,293	1,283	1,502	1,241	1,624	1,693	1,622	1,646	1,562
May-30	2030	1,830	1,776	1,717	1,504	1,423	1,834	1,930	1,595	1,129	1,892	1,747
Jun-30	2030	1,549	1,704	1,539	1,648	1,741	1,590	1,597	1,892	1,656	1,759	1,652
Jul-30	2031	1,784	1,773	1,460	1,224	1,501	1,715	1,621	1,742	1,249	1,479	1,561
Aug-30	2031	1,478	1,486	1,713	1,628	1,589	1,366	1,404	1,804	1,547	1,307	1,517
Sep-30	2031	1,770	1,132	1,603	1,341	1,668	2,039	1,593	1,656	1,851	1,654	1,655
Oct-30	2031	1,507	1,548	1,948	1,482	1,533	1,569	1,799	1,515	1,391	1,577	1,541
Nov-30	2031	1,565	1,663	1,489	1,524	2,002	1,675	1,573	1,764	1,330	1,616	1,595
Dec-30	2031	1,567	1,558	1,577	1,690	1,522	1,268	1,638	1,162	1,877	1,511	1,563
Jan-31	2031	1,503	1,711	1,764	1,490	1,343	1,801	1,736	1,653	1,373	1,884	1,682
Feb-31	2031	1,717	1,659	1,341	1,658	1,454	1,495	1,835	1,187	1,613	1,103	1,554
Mar-31	2031	1,077	1,486	1,474	1,732	1,589	1,184	1,339	1,619	1,371	1,961	1,480
Apr-31	2031	1,261	1,373	2,140	1,897	1,458	1,546	1,535	1,513	1,505	1,733	1,524
May-31	2031	1,228	1,334	1,727	1,426	1,865	1,935	1,478	1,843	1,526	1,692	1,609
Jun-31	2031	1,208	1,862	1,601	1,578	1,916	1,589	1,413	1,254	1,182	1,196	1,496

		Replication										
Month	Fiscal Year	1	2	3	4	5	6	7	8	9	10	Median
Jul-31	2032	1,616	1,692	1,612	1,378	1,453	1,244	1,876	1,661	1,736	1,351	1,614
Aug-31	2032	1,684	1,462	1,268	1,450	1,752	2,057	1,550	1,531	1,849	1,377	1,541
Sep-31	2032	1,265	1,374	1,677	1,687	1,534	1,490	1,255	1,536	1,700	1,190	1,512
Oct-31	2032	1,798	1,462	1,555	1,586	1,464	1,545	1,464	1,529	1,758	1,566	1,550
Nov-31	2032	1,579	1,667	1,552	1,678	1,727	1,290	1,483	1,625	1,760	1,833	1,646
Dec-31	2032	1,169	1,458	1,523	1,567	1,624	1,533	1,324	1,498	1,397	1,279	1,478
Jan-32	2032	1,608	1,485	1,485	1,914	1,643	1,412	1,435	1,527	1,339	1,753	1,506
Feb-32	2032	1,384	1,568	1,890	1,404	1,330	1,559	1,335	1,500	1,569	1,829	1,530
Mar-32	2032	1,705	1,509	1,201	1,935	1,665	1,124	1,748	1,773	1,604	1,790	1,685
Apr-32	2032	1,725	1,473	1,449	1,325	1,326	1,403	1,478	1,379	1,413	1,398	1,408
May-32	2032	1,464	1,783	1,655	1,567	1,667	1,394	1,631	1,592	1,585	1,541	1,589
Jun-32	2032	1,678	1,401	1,669	1,716	1,806	1,860	1,963	1,790	1,821	1,699	1,753
Jul-32	2033	1,753	1,649	1,417	1,293	2,203	1,817	1,538	1,243	1,239	1,527	1,533
Aug-32	2033	1,483	1,427	1,487	1,678	1,938	1,514	1,395	1,318	1,480	1,652	1,485
Sep-32	2033	1,304	1,518	1,271	1,645	1,256	1,379	1,813	1,902	1,496	1,293	1,438
Oct-32	2033	1,871	1,525	1,528	1,503	1,315	1,397	1,592	1,663	1,745	1,815	1,560
Nov-32	2033	1,641	1,596	1,548	1,681	1,596	1,420	1,332	1,747	1,843	1,622	1,609
Dec-32	2033	1,602	1,452	1,491	1,502	1,659	2,008	1,794	1,762	1,540	1,534	1,571
Jan-33	2033	1,718	1,578	1,287	1,600	1,482	1,690	1,674	1,927	1,311	1,375	1,589
Feb-33	2033	1,444	1,566	1,579	1,845	1,372	1,383	1,507	1,266	1,555	1,467	1,487
Mar-33	2033	1,723	1,731	1,467	1,613	1,572	1,406	1,854	1,509	1,611	1,551	1,592
Apr-33	2033	1,757	1,343	1,524	1,695	1,721	1,502	1,644	1,598	1,505	1,531	1,565
May-33	2033	1,689	1,802	1,848	1,559	1,628	1,614	1,522	1,611	1,373	1,639	1,621
Jun-33	2033	1,868	1,583	1,588	1,915	1,531	1,425	1,585	1,741	1,840	1,110	1,587
Jul-33	2034	1,240	1,555	1,528	1,432	1,354	1,721	1,321	1,436	1,495	1,373	1,434
Aug-33	2034	1,696	1,617	1,625	1,533	1,507	1,835	1,968	1,918	1,582	1,597	1,621
Sep-33	2034	1,532	1,729	1,922	1,819	1,398	1,389	1,537	1,794	1,819	1,607	1,668
Oct-33	2034	1,824	1,604	1,190	1,370	1,534	1,670	1,727	1,827	1,732	1,672	1,671
Nov-33	2034	1,739	1,775	1,546	1,166	1,250	1,703	1,804	1,503	1,250	1,686	1,616
Dec-33	2034	1,789	1,606	1,795	1,570	1,466	1,598	1,282	1,547	1,711	1,476	1,584
Jan-34	2034	1,649	1,334	1,359	1,788	1,647	1,771	1,756	2,067	1,525	1,410	1,648
Feb-34	2034	1,862	1,647	1,384	1,583	1,735	1,417	1,284	1,437	1,697	1,941	1,615
Mar-34	2034	1,954	1,503	1,137	1,729	1,281	1,682	1,709	1,762	1,192	1,652	1,667
Apr-34	2034	1,526	1,465	1,646	1,567	1,652	1,507	1,389	1,664	1,652	1,245	1,547
May-34	2034	1,554	1,247	1,724	1,473	1,386	1,679	1,692	1,477	1,567	1,865	1,561
Jun-34	2034	1,449	1,878	927	1,318	1,794	1,197	1,564	1,745	1,642	1,527	1,546
Jul-34	2035	1,077	1,754	1,476	1,582	1,710	1,340	1,563	1,652	1,914	1,418	1,573
Aug-34	2035	1,755	1,693	1,579	1,803	1,290	1,841	1,842	1,574	1,238	1,603	1,648
Sep-34	2035	1,627	1,741	1,604	1,604	1,201	1,711	1,498	1,478	1,347	1,435	1,551
Oct-34	2035	1,278	1,880	1,433	1,360	1,627	1,466	1,651	1,645	1,211	1,698	1,547
Nov-34	2035	1,813	1,776	1,787	1,348	2,028	1,418	1,460	1,667	1,476	1,598	1,633
Dec-34	2035	1,544	1,340	1,286	1,499	1,504	1,437	1,718	1,612	1,856	1,505	1,505
Jan-35	2035	1,586	1,727	1,460	1,851	1,128	1,350	1,395	1,530	1,820	1,458	1,495
Feb-35	2035	1,856	1,415	1,121	1,655	1,752	1,720	1,658	1,398	970	1,188	1,535
Mar-35	2035	1,560	1,622	1,557	1,640	1,511	1,422	1,608	1,280	1,965	1,647	1,584
Apr-35	2035	1,403	1,524	1,463	1,975	1,205	1,757	1,513	1,740	1,737	1,867	1,631
May-35	2035	1,634	1,389	1,250	1,551	2,011	1,369	1,876	1,730	1,762	1,727	1,681
Jun-35	2035	1,712	1,544	1,290	1,455	1,318	1,727	1,552	1,438	1,697	1,429	1,500
Jul-35	2036	1,319	1,781	1,417	1,489	1,435	1,518	1,713	1,551	1,682	1,402	1,504
Aug-35	2036	1,489	1,673	1,795	1,441	1,358	1,631	1,549	1,602	1,554	1,495	1,552
Sep-35	2036	1,874	1,626	1,573	1,321	1,348	1,416	1,355	1,400	1,946	1,399	1,408
Oct-35	2036	1,544	1,452	1,264	1,337	1,708	1,750	1,792	1,147	1,437	1,513	1,483
Nov-35	2036	1,733	1,451	1,603	1,720	1,605	1,520	1,490	1,534	1,462	1,449	1,527
Dec-35	2036	1,476	1,492	1,542	1,606	1,402	1,066	1,967	1,450	1,393	1,287	1,463
Jan-36	2036	1,769	1,752	2,063	1,757	1,324	1,877	1,720	1,727	1,309	1,793	1,755
Feb-36	2036	1,403	1,773	1,492	1,901	1,250	1,795	1,323	1,621	1,349	1,303	1,448
Mar-36	2036	1,416	1,444	1,358	1,390	1,761	1,661	1,824	1,165	1,665	1,267	1,430
Apr-36	2036	1,722	1,860	1,538	1,773	1,539	1,681	1,670	1,873	1,530	1,617	1,676
May-36	2036	1,278	1,812	1,769	1,416	1,691	1,647	1,755	1,239	1,269	1,829	1,669
Jun-36	2036	1,488	1,542	1,789	1,390	1,768	1,608	1,266	1,568	1,356	1,288	1,515

8.8.Appendix A-8: Autocorrelation Test for In Person Evaluations

Autocorrelations

Lag	ACF	T	LBQ
1	0.078186	0.42	0.20
2	0.391896	2.10	5.31
3	0.297818	1.40	8.38
4	-0.056790	-0.25	8.49
5	0.258757	1.14	11.00
6	-0.148503	-0.63	11.86
7	-0.059749	-0.25	12.01



8.9. Appendix A-9: Single Exponential Smoothing for In Person Evaluations