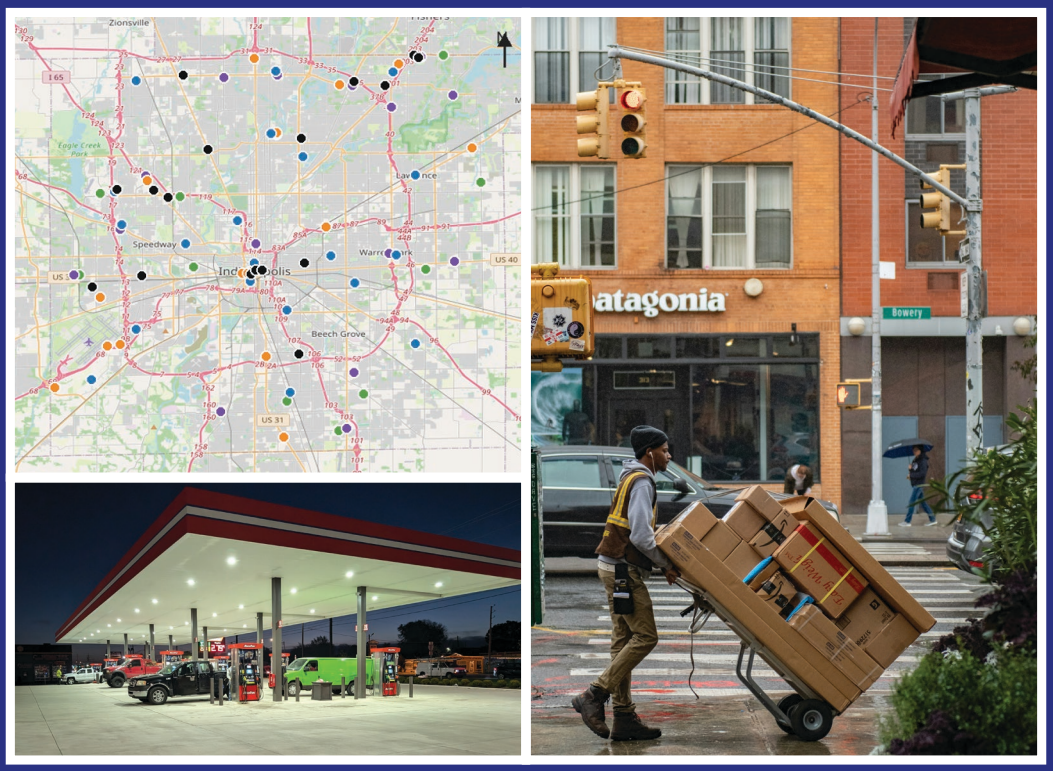
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Development of Indiana-Specific Trip Generation Procedures and Models of E-Commerce Demand: Implications for INDOT's Travel Demand Modeling and Investment Planning



Rishika Rao Tumula, Zhuoli Yin, Hua Cai, and Konstantina Gkritza

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16. Abstract

This study aims to improve Indiana's travel demand modeling practices by incorporating locally collected trip generation data and emerging e-commerce travel trends into INDOT's planning framework. The research focuses on two primary objectives. First, it enhances trip generation procedures for high-impact land uses in Indiana, including warehouses, fast-food restaurants, gas stations, and truck stops. This effort includes reviewing existing ITE land use categories, prioritizing land uses for phased data collection, and developing improved trip generation equations that incorporate Indiana-specific independent variables and adjacent traffic conditions. Second, the study develops models to capture the transportation impacts of rapidly evolving e-commerce behavior. A statewide survey of Indiana residents is used to examine online and in-store shopping patterns, delivery preferences, return behaviors, barriers to e-commerce adoption, and sociodemographic influences on consumer choices. These data support the development of agent-based models to simulate microfreight travel demand and estimate outcomes such as vehicle miles traveled and the potential benefits of alternative fuel delivery vehicles.

The study's findings will support updates to Indiana's Statewide Travel Demand Model and improve INDOT's ability to forecast traffic impacts from new developments. By integrating local land use data and e-commerce-related travel behavior, this research provides a stronger foundation for infrastructure investment decisions, more accurate travel demand forecasts, and more effective transportation planning in Indiana.

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EXECUTIVE SUMMARY

Introduction

Transportation planning and investment decisions depend on reliable estimates of travel demand. In Indiana, two emerging needs motivated this study. First, the Indiana Department of Transportation (INDOT) and local agencies frequently rely on national trip generation rates from the Institute of Transportation Engineers (ITE) Trip Generation Manual when reviewing Traffic Impact Studies. Although these rates provide a widely accepted starting point, they may not always reflect Indiana-specific land use patterns, roadway contexts, or site operating characteristics. Second, the rapid growth of e-commerce has changed how households shop, how goods are delivered, and how passenger and freight vehicle miles traveled (VMT) are generated.

This study addressed these needs through two primary tasks. The first task developed Indiana-specific trip generation procedures and statistical models for selected high-impact land uses commonly encountered in INDOT permit and Traffic Impact Study reviews. These land uses included high-cube warehouse facilities, fast-food restaurants with drive-through windows, gasoline/service stations with convenience markets, and truck stops. The second task assessed Hoosiers' attitudes toward and use of e-commerce and incorporated updated behavioral insights into an enhanced travel demand simulation framework. The study combined field data collection, permit record review, statistical modeling, statewide survey analysis, National Household Travel Survey data, motif-based trip-chain analysis, agent-based modeling, and delivery optimization.

Findings

The trip generation analysis showed that national ITE estimates do not always align with observed traffic volumes at Indiana sites. For high-cube warehouse land uses, ITE estimates generally overestimated observed traffic activity, although the magnitude of the difference varied by site and peak period. For fast-food restaurants with drive-through windows, the standard ITE LU 934 category tended to underestimate trip generation at higher-volume sites, while the newer high-volume fast-food category produced higher estimates but did not consistently improve agreement with field observations. For gasoline/service stations and truck stops, the results indicated that site-specific operating characteristics, such as parking supply and fueling capacity, can be important predictors of traffic activity.

The analysis also demonstrated the value of Indiana-specific field data. Locally calibrated models and observed directional splits provide useful supplemental information for evaluating whether submitted trip generation estimates are reasonable for Indiana conditions. However, the study also found that model reliability depends on the number of available sites, the range of site characteristics, and the stability of the relationship between trip activity and independent variables. For some land uses, small sample sizes and operational variability limited the development of robust regression equations. Therefore, the Indiana-specific procedures should be viewed as supplemental guidance rather than complete replacements for the ITE Trip Generation Manual.

The e-commerce analysis showed that online shopping affects travel demand through multiple pathways. E-commerce can reduce some in-store shopping trips, but it can also generate delivery trips, pickup trips, return trips, and modified passenger trip chains. Survey results showed that online shopping is now a common part of household shopping behavior, but its effects vary by product type, household characteristics, and consumer preferences. Respondents generally showed strong use of home delivery, while groceries, food, and returns continued to involve substantial in-person activity.

The projected full-population results showed that 2026 e-commerce adoption increased total daily VMT under both the 2017 and 2022 National Household Travel Survey (NHTS)–informed settings. Across the baseline adoption and sensitivity scenarios, projected VMT increases ranged from approximately 5.8% to 16.4% relative to the corresponding before-e-commerce scenario, depending on the NHTS data source and scenario assumptions. Although passenger VMT from nonshopping trip chains decreased slightly, this reduction was outweighed by additional passenger travel associated with online order pickup, additional in-store shopping, and product-return trips, together with delivery-related VMT. Overall, e-commerce did not simply replace passenger shopping trips with delivery travel. Instead, it reshaped passenger activity patterns while adding delivery demand, resulting in a net increase in system-level VMT.

Implementation

The Indiana-specific trip generation results can be used by INDOT as supplemental guidance during Traffic Impact Study review. The locally observed trip rates, regression equations, and directional splits can help reviewers identify cases where national ITE estimates may overstate or understate likely traffic impacts. When submitted estimates differ substantially from Indiana-specific observations, INDOT may request additional documentation, sensitivity testing, or locally collected supporting data.

In the longer term, INDOT could develop and maintain a statewide trip generation database that includes future permit applications, Traffic Impact Studies, site plans, independent variables, and postdevelopment traffic counts. This database would allow Indiana-specific trip generation procedures to be updated over time and would support more consistent review practices across districts.

The e-commerce modeling framework can be used to support scenario testing in INDOT's travel demand modeling and investment planning processes. Because e-commerce affects passenger travel, delivery activity, pickup behavior, and return behavior, future travel demand models should explicitly account for these components rather than assuming that online shopping automatically reduces VMT. The framework can also be used to evaluate alternative delivery and pickup strategies, including parcel lockers, consolidated delivery systems, coordinated delivery windows, centralized pickup locations, and improved return networks.

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1. INTRODUCTION

1.1 Background and Motivation

Transportation systems are undergoing significant transformation due to evolving land use patterns, emerging technologies, and shifting consumer behaviors. Accurate estimation of travel demand remains central to transportation planning, infrastructure investment, and operational decision making.

The first stage of traditional four-stage transportation planning is trip generation, where the total traffic demand generation and attraction is analyzed for the impact area. Trip generation estimates form the basis for Traffic Impact Studies (TIS), corridor planning analyses, and long-range forecasting efforts. However, the reliability of these estimates depends heavily on the applicability of the underlying models to local conditions. The Indiana Department of Transportation (INDOT) has historically relied on the Institute of Transportation Engineers (ITE) Trip Generation Manual for estimating development-related traffic. While the ITE models provide a nationally recognized standard, they are developed using data collected from a limited number of sites across diverse geographic contexts. As a result, discrepancies have been observed between predicted and actual traffic volumes at Indiana developments, particularly for land uses that generate high volumes of trips. These inconsistencies may lead to underestimation or overestimation of traffic impacts, potentially affecting roadway design decisions, capacity improvements, long-term maintenance costs, roadway operations, and safety considerations.

Simultaneously, the rapid growth of e-commerce has introduced new complexities into travel demand forecasting. Online purchasing, home delivery services, and evolving logistics systems have altered household shopping behaviors and freight movement patterns. Previous research conducted under SPR-4608: *Forecasting Shifts in Hoosiers' Travel Demand and Behavior* from Verma et al. (2024) examined the travel demand implications of e-commerce using 2017 data; however, travel behaviors have changed substantially in recent years, particularly following the COVID-19 pandemic. Updated data and refined modeling approaches are, therefore, necessary to capture current and emerging trends.

1.2 Research Objectives and Deliverables

In response to the above needs, this study pursues two primary objectives:

1. Develop Indiana-specific trip generation procedures and statistical models for commonly permitted land uses along state routes; and
2. Assess Hoosiers' attitudes toward and use of e-commerce and incorporate updated behavioral insights into an enhanced travel demand simulation framework.

The project integrates field data collection, statistical modeling, survey research, and agent-based simulation to produce practical tools and guidance for INDOT. The resulting models aim to improve the accuracy of TIS, enhance the Indiana Statewide Travel Demand Model (ISTDM), and support more informed infrastructure investment decisions. By grounding trip generation and e-commerce forecasting in Indiana-specific data, this research contributes to more efficient allocation of public resources, improved planning reliability, and better anticipation of future mobility trends.

1.3 Report Organization

The subsequent sections of the report delve into the two main tasks of this study. Chapter 2 describes the first task "Develop Indiana-specific trip generation procedures and statistical models." The second task, "Assess Hoosiers' attitudes towards and use of e-commerce," is explained across three chapters. Chapter 3 discusses the national trends in shopping behavior using the 2022 edition of the National Household Travel Survey (NHTS); Chapter 4 describes the survey design and descriptive statistics; and Chapter 5 goes into the details of e-commerce travel demand modeling. Lastly, Chapter 6 synthesizes key findings across the tasks, offering insights for implementation. The specific strategies and recommendations from each task are detailed in Sections 6.1 and 6.2. Additionally, the report includes a references section and an extensive appendix offering supplementary details related to each task.

2. DEVELOPMENT OF INDIANA-SPECIFIC TRIP GENERATION PROCEDURES

2.1 Overview

This chapter documents the analytical approach and findings associated with the first task, that is, the development of Indiana-specific trip generation procedures for selected land uses. The discussion in this chapter is focused on the technical considerations, data sources, and modeling decisions that underpin the proposed refinements to existing trip generation practices.

Trip generation serves as the foundation of traffic impact analysis, providing the initial estimate of vehicle trips associated with a proposed development. These estimates directly influence subsequent evaluations of roadway capacity, intersection performance, and the need for mitigation measures. As such, inaccuracies at this stage can lead to compounding errors in later analysis steps. Within the Indiana context, trip generation estimates are frequently developed using national models that may not fully capture local land-use characteristics, development patterns, or roadway environments. This chapter addresses these limitations by examining observed trip-making behavior at representative Indiana sites and by identifying model structures better aligned with local conditions.

The analysis presented here focuses on total generated trips during peak periods, consistent with INDOT's current review practices. Pass-by trips, diverted trips, and internal capture effects are intentionally excluded to maintain clarity and consistency and to isolate the relationship between land-use characteristics and observed traffic volumes. The land uses examined were selected based on their prevalence in INDOT permit records and their potential to generate substantial traffic impacts on the state highway system.

A key component of the methodology involves evaluating alternative independent variables beyond those traditionally used in national trip generation models. The analysis investigates for contextual variables that are more strongly correlated with trip-making behavior in Indiana, including building size, and service capacity indicators such as number of parking spots, fueling stations or seating capacity, depending on the land-use type. Statistical analyses are used to assess the explanatory power of candidate variables and to develop model specifications that balance predictive accuracy with practical applicability.

This chapter also includes a systematic comparison between Indiana-specific trip generation models and corresponding estimates produced using the ITE Trip Generation Manual. These comparisons are used to quantify differences in predicted trip volumes and to illustrate the potential implications for traffic impact assessments and infrastructure planning decisions. The resulting procedures are documented in a transparent, non-software-based format to facilitate consistent application by practitioners and reviewers.

2.2 Literature Review

2.2.1 ITE Trip Generation Manual

In practice, the most commonly used reference in the United States is the Trip Generation Manual published by the ITE (2025). The manual provides trip rates and regression equations for hundreds of land uses based on observed traffic counts collected across North America. Because it offers a standardized and widely accepted framework, it has become the default source for traffic engineers, consultants, and public agencies. However, studies have noted that national average rates do not always reflect local conditions, particularly when applied to communities with different land-use patterns, travel behavior, or roadway environments (R. Schneider et al., 2013). R. Schneider et al. (2015), for example, found that developments in walkable areas frequently generated fewer vehicle trips than standard ITE estimates would predict. Similar conclusions were reached in research conducted for the National Cooperative Highway Research Program, which recommended context-sensitive adjustments based on surrounding land use and accessibility (Bochner et al., 2011).

This issue has led many researchers to emphasize the importance of local calibration. National manuals provide a useful starting point, but locally observed data often produce more accurate estimates when regional conditions differ from the national sample. Studies by Clifton et al. (2015) showed that local trip generation models can substantially improve predictive performance because they better reflect regional travel patterns, demographics, and development design. In practice, several state departments of transportation (DOTs) and metropolitan planning organizations have developed supplemental guidance or adjustment factors for common land uses rather than relying exclusively on unmodified national averages (Currans & Clifton, 2015; Handy et al., 2013; Jeihani & Camilo, 2009).

The present study thus addresses the limitations imposed by national averages by collecting observed traffic data from representative Indiana sites and developing trip generation procedures that better reflect local conditions and current development patterns.

2.2.2 Independent Variables

Another important topic is the choice of independent variables used in trip generation models. Traditional models typically rely on one measure of development size, such as gross floor area, number of dwelling units, or employees. These variables are convenient because they are easy to obtain during development review. However, a question arises whether size alone always explains traffic generation. For many land uses, operational characteristics may be stronger predictors of trip-making than square footage. Industrial land uses such as distribution centers may depend more on employee shifts, loading docks, truck parking, and freight throughput than on total building size.

2.2.3 Changing Land Uses

Considering specific land uses, the growth of e-commerce has rapidly expanded fulfillment centers, parcel hubs, and transload facilities, many of which were not well represented in earlier trip generation databases. Their traffic patterns can differ substantially from conventional warehouses because they may generate concentrated truck movements, employee shift changes, and time-sensitive delivery activity. Recent freight planning studies have noted that traditional industrial trip rates may not fully capture these emerging logistics uses (Holguín-Veras et al., 2020).

A similar issue is evident in the fast-food sector, where ITE now distinguishes between a conventional fast-food restaurant with a drive-through window and a high-volume fast-food restaurant. The conventional category generally reflects a typical drive-through restaurant with carryout and short-duration dine-in activity, while the high-volume category captures more vehicle-oriented operations with multiple order and service lanes, mobile ordering, employee-assisted ordering, lane-side delivery, and active on-site queue management. This distinction recognizes that some modern fast-food restaurants can generate traffic patterns and peak-period queues that differ substantially from traditional drive-through restaurants (ITE, 2025).

2.2.4 Peak Hours

Most traffic impact studies focus on peak-hour traffic because roadway performance problems are most likely to occur during concentrated demand periods. However, the relevant peak hour may vary by land use. A commuter-oriented office building may peak during the traditional AM and PM rush periods, while a fast-food restaurant, truck stop, or fulfillment center may peak at very different times. The ITE (2025) Trip Generation Handbook, therefore, distinguishes between street peak hours and generator peak hours and recommends evaluating whichever period is most critical for the surrounding transportation system.

TABLE 2.1
Initial Land Use List Identified by INDOT.

Priority Level	Category	LU Code	LU Description
Priority 1	Industrial	150	Warehousing
		154	High-Cube Transload and Short-Term Storage Warehouse
		155	High-Cube Fulfillment Center Warehouse
		156	High-Cube Parcel Hub Warehouse
	Services	934	Fast-Food Restaurant with Drive-Through Window
		935	Fast-Food Restaurant with Drive-Through Window and No Indoor Seating
		937	Coffee/Donut Shop with Drive-Through Window
		945	Gasoline/Service Station with Convenience Market
		960	Super Convenience Market/ Gas Station
		950	Truck Stop
Priority 2	Office	710	General Office Building
	Retail	813	Free-Standing Discount Superstore
		815	Free-Standing Discount Store
		850	Supermarket
		854	Discount Supermarket
Priority 3		860	Wholesale Market
		880	Pharmacy/Drugstore without Drive-Through Window
		881	Pharmacy/Drugstore with Drive-Through Window

2.3 Data Description

The development of Indiana-specific trip generation procedures relies on the integration of administrative records, field-observed traffic data, and site-level land-use characteristics. The data assembled for this analysis were selected to reflect conditions commonly encountered in TIS reviewed by INDOT and to support the development of statistically robust yet practically applicable trip generation models.

2.3.1 Land Use Prioritization Framework

The land uses examined in this study were provided directly by INDOT and are organized into three priority levels (Table 2.1). The prioritization is based on the frequency of permit applications for a particular land use and the relative traffic operational and safety impact a given land use is expected to have, generally with higher traffic generating land uses representing more significant traffic operational and safety impacts. Each land use (LU) corresponds to classifications in the ITE Trip Generation Manual. The priority levels were used to determine the order in which land uses were addressed during data collection and analysis.

The initial land-use list was revised to reflect the availability of appropriate study sites, supporting data and the feasibility of data collection. The final set of land uses included in the analysis is provided in Table 2.2.

TABLE 2.2
Land Uses Included in the Scope of the Study.

Priority	Class	ITE LU Code	Description
1	Industrial	154	High-Cube Transload and Short-Term Storage Warehouse
		155	High-Cube Fulfillment Center Warehouse
	Services	934	Fast-Food Restaurant with Drive-Through Window
		945	Gasoline/Service Station with Convenience Market
		950	Truck Stop

2.3.2 Site Selection

INDOT and local agency permit application data serve as the primary source for identifying sites corresponding to the land uses listed in Table 2.2. INDOT permit records, including TIS documentations, provide information on permitted development types, site locations, and access characteristics, allowing the research team to assess which sites are most suitable for data collection.

To be considered for data collection, sites were required to meet several criteria:

- Located in Indiana and within a 2-hr drive from West Lafayette, allowing undergraduate data collection teams to travel to the site, complete field observations, and return the same day while still accommodating class schedules and other academic commitments.
- Operational for at least 2 years (mature land use).
- Clear site boundaries and identifiable access points.
- Geographic diversity where possible (urban, suburban, rural).
- Represent typical size and operation for each LU category.
- Availability of key land-use and contextual information required for modeling.

The sites identified through this process are presented in Table 2.3. The locations of these sites are also shown in Figure 2.1. Site 945-1 (Table 2.3) was identified as LU 853, Convenience Market with Gasoline Pumps, in the original TIS documentation. After reviewing TIS documentation for similar establishments and coordinating with INDOT, it was determined that, despite the submitted documentation, the site is more appropriately classified as LU 945.

2.3.3 Traffic Count Data

Observed trip generation data were obtained through field traffic counts conducted at each selected site. The data collection effort was designed to capture typical operating conditions and to avoid anomalous days affected by inclement weather, construction activity, or special events. Counts focused on peak periods consistent with standard TIS practice, including weekday AM and PM peak hours, depending on the land-use type. Vehicle volumes entering and exiting each site were recorded and aggregated to estimate total site-generated trips during the

TABLE 2.3
Sites Selected for Trip Generation Data Collection.

ITE LU Code	LU Description	Index	Location
154	High-Cube Transload and Short-Term Storage Warehouse	154-1	Clayton
		154-2	Mooresville
		154-3	Whitestown
		154-4	Lebanon
155	High-Cube Fulfillment Center Warehouse	155-1	Mooresville
		155-2	Mooresville
934	Fast-Food Restaurant with Drive-Through Window	934-1	Marion
		934-2	Greenfield
		934-3	Westfield
945	Gasoline/Service Station with Convenience Market	945-1	Marion
		945-2	Clarks Hill
		945-3	Huntington
950	Truck Stop	950-1	Tipton
		950-2	Lafayette
		950-3	Indianapolis

TABLE 2.4
Independent Variables Collected by ITE LU Code.

ITE LU Code	LU Description	Independent Variables Collected
154	High-Cube Transload and Short-Term Storage Warehouse	Gross floor area (GFA); car parking spaces; truck parking spaces
155	High-Cube Fulfillment Center Warehouse	GFA; car parking spaces; truck parking spaces
934	Fast-Food Restaurant with Drive-Through	GFA; car parking spaces; drive-through lanes; indoor seating; outdoor seating
945	Gasoline/Service Station with Convenience Market	GFA; car parking spaces; car fueling spots
950	Truck Stop	GFA; car parking spaces; truck parking spaces; car fueling spots; truck fueling spots

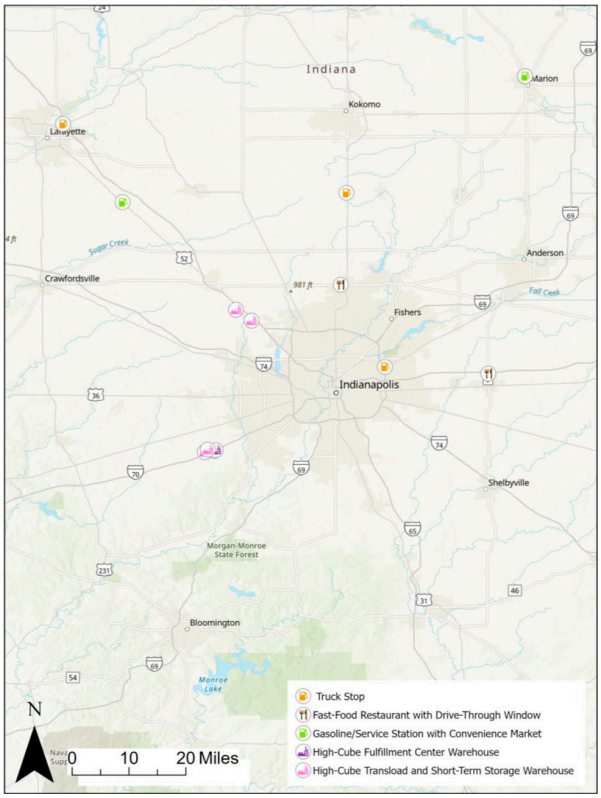


Figure 2.1 Locations of Selected Study Sites.

analysis period. The data collection methodology is discussed in detail in Section 2.4.

2.3.4 Independent Variable Data

For each study site, a set of independent variables was compiled to support trip generation modeling. These variables include commonly used land-use intensity measures such as gross floor area, or service capacity indicators such as number of parking spots, fueling stations or seating capacity, depending on the land-use type. All independent variables were selected based on two primary criteria: their hypothesized relationship with trip generation and their availability during the development review and traffic analysis process. The independent variables collected for each ITE LU code are summarized in Table 2.4.

2.3.5 Data Limitations

Several practical constraints influenced the scope and composition of the dataset used for trip generation model development. Field data collection was conducted primarily by undergraduate research assistants. As a result, study sites were limited to locations within approximately a two-hour driving distance from Purdue University West Lafayette campus. This constraint reduced the geographic coverage of the dataset and may limit the representation of conditions in more distant areas of the state.

In addition, data collection schedules were constrained by academic calendars and class commitments. Consequently, traffic data collection focused on peak-hour periods rather than continuous 24-hr counts. While peak-hour data are consistent with standard TIS practice and sufficient for evaluating development-related impacts, the absence of full-day counts limits the ability to assess daily trip patterns and temporal variability beyond peak periods.

The availability of permits and site-specific information also affected the size of the final dataset. In some cases, local agencies were unable to readily provide requested permit documentation. This further reduced the pool of candidate sites and limited the number of observations available for certain land uses.

The number of sites surveyed for each land use was guided by the recommendations of the ITE Trip Generation Handbook (2nd Edition). The Handbook indicates that, when establishing or evaluating trip generation characteristics using local data, a minimum of three sites should be surveyed, with five sites

preferred, to support stable and reliable estimates and to allow identification of potential outliers. Consistent with this guidance, the study sought to collect data from at least three sites for each land use where feasible. The final number of sites surveyed for individual land uses reflects both the availability of suitable sites and the practical constraints of field data collection. This limitation is also noted in the Handbook, as smaller sample sizes are common in trip generation studies due to site availability and resource limitations, and results should be interpreted accordingly. Thus, any differences between ITE estimates and locally observed trip volumes should not necessarily be interpreted as evidence that Indiana is inherently different from other parts of the country. Because most land-use categories were represented by only a small number of sites, the observed differences cannot establish geography as the cause of divergence from ITE estimates. Rather, the results indicate that sample composition, facility age and size, operating characteristics, and the selection of independent variables may all affect predictive performance.

Finally, the analysis is based on a finite number of sites for each land use, reflecting both the availability of suitable locations and the resources required for field data collection. As with most empirical trip generation studies, the resulting models are most applicable to developments with characteristics similar to those observed in the dataset.

2.4 Methodology

The trip generation analysis conducted as part of this study followed the procedures and guidance outlined in the ITE Trip Generation Handbook, specifically Chapters 2 through 4, which address selection of independent variables, time periods for analysis, and recommended practices for conducting local trip generation studies. The methodology was adapted as necessary to reflect the objectives of this research and the practical constraints of field data collection.

2.4.1 Study Design and Site Selection

Consistent with Chapter 4 of the Handbook, the study design included:

1. Identification of land uses to be surveyed
2. Selection of representative sites
3. Determination of appropriate survey periods
4. Identification and measurement of independent variables
5. Directional traffic counting procedures

Land uses to be analyzed were identified by INDOT; site selection process and independent variables were discussed in Section 2.3.

2.4.2 Determination of Appropriate Survey Periods

The ITE Trip Generation Handbook recommends evaluating site-generated traffic during periods when the combined effect of generator traffic and adjacent street traffic is most critical. The adjacent street peak hours were defined consistently across all land uses. A peak hour is defined as the single, consecutive 60-min period with the highest observed entering plus exiting vehicle volume within the applicable analysis window. The AM street peak hour was defined as the highest one-hour traffic volume occurring between 7:00 AM and 9:00 AM, and the PM street peak hour was defined as the highest one-hour traffic volume occurring between 4:00 PM and 6:00 PM, consistent with ITE definitions. These street peak periods were applied uniformly to all study sites.

In contrast, the generator peak hour varies by land use and reflects the hour during which a specific development generates its highest volume of trips. Generator peak hours were identified for each land use using the *ITE Trip Generation Manual*. The applicable AM and PM generator peak-hour time periods for each land use are summarized in Table 2.5. For ITE LU Code 155 (High-Cube Fulfillment Center Warehouse), generator peak-hour periods are not explicitly provided in the ITE Trip Generation Manual. Therefore, data collection for this land use was conducted during the generator peak-hour periods identified for the most similar warehouse land uses, ITE LU Code 154 (High-Cube Transload and Short-Term Storage Warehouse) and ITE LU Code 156 (High-Cube Parcel Hub Warehouse). Field observations were scheduled to capture these land-use-specific generator peak hours in addition to the standardized street peak hours.

2.4.3 Directional Traffic Counting Procedures

Traffic data collection followed the guidelines outlined in Chapter 4 of the Handbook. Manual traffic counts were conducted at all site driveways, with field staff positioned to record directional movements. Entering and exiting traffic volumes were recorded in 15-min intervals to allow identification of peak-hour conditions and calculation of total site-generated trips. Vehicles were classified into two categories: passenger vehicles and trucks. All driveways serving a site were observed concurrently to avoid double-counting and to ensure that total site activity was fully captured. Standardized ITE Trip Generation Data Forms were used to record site characteristics and traffic volumes.

2.4.4 Establishment of a Local Trip Generation Rate

Differences between observed and predicted values were evaluated to determine whether the national models reasonably represent local trip-making behavior. In addition to standard regression equations, site rates (Equation 2.1), average trip rate (Equation 2.2) and standard deviation (Equation 2.3) were also calculated to follow the representation style of the ITE Trip Generation Manual. Model performance was assessed using the coefficient of determination (R^2), percent error (Equation 2.4) and root mean square error (RMSE; Equation 2.5).

For a site i $\{i = 1,2,\ldots n\}$ belonging to land use u;

$$Site\ Rate_i = \frac{Observed\ Person\ Trips_i}{Independent\ Variable_i} \quad \text{Equation 2.1}$$

$$Average\ Trip\ Rate_u = \frac{\sum Site\ Rate_i}{n} \quad \text{Equation 2.2}$$

TABLE 2.5
Generator Peak-Hour Time Periods by LU.

ITE LU Code	LU Description	AM Peak Hour		PM Peak Hour	
		Start	End	Start	End
154	High-Cube Transload and Short-Term Storage Warehouse	9:00 AM	10:00 AM	3:00 PM	4:00 PM
155	High-Cube Parcel Hub Warehouse	8:15 AM	9:15 AM	5:15 PM	6:15 PM
934	Fast-Food Restaurant with Drive-Through Window	11:45 AM	12:45 PM	12:00 PM	1:00 PM
945	Gasoline/Service Station with Convenience Market	7:30 AM	8:30 AM	3:45 PM	4:45 PM
950	Truck Stop	11:45 AM	12:45 PM	12:15 PM	1:15 PM

$$Standard\ Deviation = \frac{\sqrt{\sum\left(Site\ Rate_i - Average\ Trip\ Rate_u\right)^2}}{n-1}$$

Equation 2.3

$$Mean\ Percent\ Error = \frac{\sum \frac{Observed\ Person\ Trips_i - Predicted\ Trips_i}{Observed\ Person\ Trips_i} \times 100}{n}$$

Equation 2.4

$$RMSE = \sqrt{\frac{\sum\left(Observed\ Person Trips_i - Predicted Trips_i\right)^2}{n}}$$

Equation 2.5

2.4.5 Comparison With ITE Estimates

Consistent with Handbook recommendations, for each land use, observed peak-hour trip volumes were compared against corresponding ITE-predicted values using the same independent variables and analysis periods. The estimates were calculated for every available independent variable with data post-2010 when feasible. Where data was deficient, all available data points were considered. The calculations were performed on the ITE Trip Gen Dashboard using the fitted regression equation where specified, and the average rate line in the absence of the former. In case of LU 950, since the curves were taken from a previous edition of the Manual, regression equations were constructed using the given data points to estimate the total number of trips.

2.5 Results

The regression analysis evaluated relationships between trip generation and several independent variables such as gross floor area (GFA), number of seats, parking spaces, and fuel pumps for all four peak periods. Only the results for the variable which gave the highest R^2 values are shown here and are organized by land use category. The alternate curves are listed in Appendix B.

2.5.1 LU 154 – High-Cube Transload and Short-Term Storage Warehouse

For LU 154 (High-Cube Transload and Short-Term Storage Warehouse), GFA was identified as the independent variable for all peak periods. Table 2.6 presents the comparison between ITE trip generation estimates for the land use and the observed field counts collected at the four study sites during generator and street peak periods.

TABLE 2.6
Comparison of ITE Trip Generation Predictions (LU 154) and Observed Field Counts Across Study Sites and Peak Periods.

		ITE Prediction			Field Counts		
		X = GFA					
Site	Peak Period	Total	In (%)	Out (%)	Total	In (%)	Out (%)
Site 1	Generator AM	170	78	22	33	45.45	54.55
	Generator PM	200	34	66	146	20.55	79.45
	Street AM	100	77	23	71	90.14	9.86
	Street PM	128	28	72	124	32.26	67.74
Site 2	Generator AM	73	78	22	27	59.26	40.74
	Generator PM	118	34	66	110	8.18	91.82
	Street AM	51	77	23	24	70.83	29.17
	Street PM	66	28	72	36	11.11	88.89
Site 3	Generator AM	16	78	22	14	42.86	57.14
	Generator PM	62	34	66	37	37.84	62.16
	Street AM	22	77	23	29	48.28	51.72
	Street PM	29	28	72	25	40.00	60.00
Site 4	Generator AM	70	78	22	6	33.33	66.67
	Generator PM	115	34	66	8	37.50	62.50
	Street AM	49	77	23	7	71.43	28.57
	Street PM	63	28	72	3	33.33	66.67

Overall, the ITE predictions show mixed agreement with the observed field counts across the study sites and peak periods. At Site 1, the generator PM prediction (approximately 199 trips) overestimates the observed total of 146 trips, while the street PM prediction (128 trips) is relatively close to the observed volume of 124 trips. In contrast, the predictions for Sites 3 and 4 generally overestimate observed traffic volumes across most peak periods, particularly during generator AM and street PM conditions.

At Site 2, the generator PM prediction (approximately 118 trips) closely matches the observed total of 110 trips. However, for other peak periods, the ITE estimates continue to overpredict observed volumes. The level of overestimation becomes more pronounced at lower-volume sites, particularly Site 4, where predicted trips substantially exceed observed counts during all peak periods.

TABLE 2.7
Calibrated Trip Generation Models, Goodness-of-Fit, and Directional Split by Peak Period.

Peak Period	Independent Variable Used	Equation	R^2	Mean Percent Error	In (%)	Out (%)
Generator AM	Number of Truck Parking Spots	T = 0.1123(X) – 3.5902	0.5961	102.23	52.04	47.96
Generator PM	Number of Truck Parking Spots	T = 0.6191(X) – 54.7627	0.6679	75.66	51.06	48.94
Street AM	Number of Truck Parking Spots	T = 0.2741(X) – 24.8029	0.7203	31.67	51.93	48.07
Street PM	Number of Truck Parking Spots	T = 0.5868(X) – 76.2261	0.8642	68.46	50.13	49.87

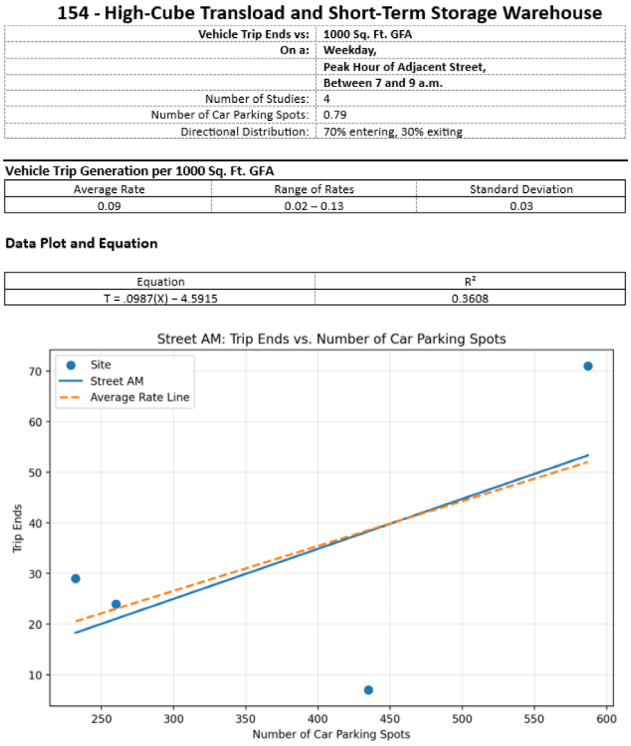


Figure 2.2 Indiana Specific Trip Generation Curves for LU 154 During the AM Peak Hour of the Generator.

Across all sites, the ITE trip generation estimates for LU 154 generally tend to overestimate observed trip volumes, although the degree of agreement varies depending on the peak period and site activity level. Street AM predictions show comparatively weaker agreement with field counts, while generator PM predictions appear to provide relatively better correspondence at selected sites.

The directional distribution of trips was also compared between ITE estimates and observed field conditions. The ITE directional splits for LU 154 indicate strongly directional flows, with inbound percentages ranging from 28% to 78% depending on the peak period. The observed field data, however, show greater variability across the study sites. For example, generator PM outbound proportions range from approximately 62% to 92%, while street AM inbound proportions vary between approximately 48% and 90%. Despite these variations, the general directional trends observed in the field are broadly consistent with the dominant inbound or outbound movements assumed by the ITE data for each peak period.

To improve predictive accuracy, regression models were developed using the observed data, as summarized in Table 2.7. An example of the Indiana-specific trip generation curves is shown in Figure 2.2.

2.5.2 LU 155 – High-Cube Parcel Hub Warehouse

For LU 155 (High-Cube Parcel Hub Warehouse), GFA was identified as the independent variable for all peak periods. Table 2.8 presents the comparison between ITE trip generation estimates for the land use and the observed field counts collected at the three study sites during generator and street peak periods.

Overall, the ITE predictions show inconsistent agreement with the observed field counts across the study sites and peak periods. At Site 1, the generator PM and street PM predictions are relatively close to the observed totals, with predicted volumes of approximately 203 and 142 trips compared to observed volumes of 152 trips. However, the generator AM and street AM predictions substantially overestimate the observed count of 60 trips.

At Site 2, the model performance varies considerably between peak periods. While the generator AM and street AM predictions are relatively close to the observed total of 106 trips, the generator PM and street PM predictions significantly overestimate the observed count of 16 trips. Similar trends are

TABLE 2.8
Comparison of ITE Trip Generation Predictions (LU 155) and Observed Field Counts Across Study Sites and Peak Periods.

		ITE Prediction			Field Counts		
		X = GFA					
Site	Peak Period	Total	In (%)	Out (%)	Total	In (%)	Out (%)
Site 1	Generator AM	132	52	48	60	76.67	23.33
	Generator PM	203	50	50	152	14.47	85.53
	Street AM	122	75	25	60	76.67	23.33
	Street PM	142	41	59	152	14.47	85.53
Site 2	Generator AM	95	52	48	106	91.51	8.49
	Generator PM	146	50	50	16	68.75	31.25
	Street AM	87	75	25	106	91.51	8.49
	Street PM	102	41	59	16	68.75	31.25
Site 3	Generator AM	132	52	48	60	76.67	23.33
	Generator PM	203	50	50	152	14.47	85.53
	Street AM	122	75	25	60	76.67	23.33
	Street PM	142	41	59	152	14.47	85.53

TABLE 2.9
Comparison of ITE Trip Generation Predictions (LU 934) and Observed Field Counts Across Study Sites and Peak Periods.

		ITE Prediction						Field Counts		
		X = GFA			X = Total Seating					
Site	Peak Period	Total	In (%)	Out (%)	Total	In (%)	Out (%)	Total	In (%)	Out (%)
Site 1	Generator AM	201	52	48	70	51	49	200	51.00	49.00
	Generator PM	236	50	50	123	50	50	205	49.27	50.73
	Street AM	153	51	49	83	52	48	205	51.22	48.78
	Street PM	142	51	49	68	53	47	150	49.33	50.67
Site 2	Generator AM	227	52	48	145	51	49	366	51.37	48.63
	Generator PM	267	50	50	172	50	50	374	50.53	49.47
	Street AM	173	51	49	145	52	48	140	52.86	47.14
	Street PM	161	51	49	119	53	47	252	51.98	48.02
Site 3	Generator AM	267	52	48	132	51	49	519	53.76	46.24
	Generator PM	314	50	50	179	50	50	517	53.38	46.62
	Street AM	203	51	49	156	52	48	261	51.72	48.28
	Street PM	189	51	49	123	53	47	271	49.08	50.92

observed at Site 3, where the predicted values generally exceed observed volumes during most peak periods.

Across all sites, the ITE trip generation estimates for LU 155 generally tend to overestimate observed traffic activity, although the magnitude of overestimation varies depending on the peak period and site characteristics. The differences between predicted and observed volumes suggest that the ITE rates may not fully reflect the operational characteristics and trip-making behavior of the surveyed developments.

The directional distribution of trips was also compared between ITE estimates and observed field conditions. The ITE directional assumptions vary considerably by peak period, ranging from approximately 41/59 to 75/25 inbound and outbound splits. The observed field data similarly demonstrate strong directional patterns, although the proportions differ substantially between sites and peak periods. For example, inbound proportions range from approximately 14% to 92% across the surveyed locations. While some peak periods exhibit directional trends similar to the ITE assumptions, the observed variability indicates that site-specific operational characteristics have a significant influence on traffic distribution patterns.

Regression analysis was not undertaken for LU 155 due to limitations in the available dataset. The observed field counts showed substantial variability between sites and peak periods, while the sample size and range of independent variable values were insufficient to establish reliable predictive relationships. In addition, repeated or closely similar observations across sites limited the statistical validity of regression modeling. As such, the development of calibrated trip generation equations for this land use was not considered appropriate based on the available data.

2.5.3 LU 934 – Fast-Food Restaurant With Drive-Through Window

Table 2.9 and Table 2.10 present a comparison between ITE trip generation estimates for LU 934 (Fast-Food Restaurant with Drive-Through Window) and LU 929 (High-Volume Fast-Food Restaurant) respectively, against the observed field counts collected at the three study sites during generator and street peak periods. Under typical practice, trip generation would be assessed using the land use code that matches the development according to its TIS documentation, which in this case is LU 934. However, with the introduction of LU 929 (High-Volume Fast-Food Restaurant), as a separate category to represent busier establishments, in the 12th edition of the ITE Trip Generation Manual, both land uses were evaluated to determine whether the newer classification better reflects observed conditions. The comparison was undertaken using GFA and, where available, total seating as independent variables.

For LU 934, the ITE predictions based on GFA generally align reasonably well with observed field counts at smaller sites, particularly during generator peak periods. At Site 1, the

TABLE 2.10
Comparison of ITE Trip Generation Predictions (LU 929) and Observed Field Counts Across Study Sites and Peak Periods.

		ITE Prediction			Field Counts		
		X = GFA					
Site	Peak Period	Total	In (%)	Out (%)	Total	In (%)	Out (%)
Site 1	Generator AM	218	50	50	200	51.00	49.00
	Generator PM	309	50	50	205	49.27	50.73
	Street AM	114	52	48	205	51.22	48.78
	Street PM	257	50	50	150	49.33	50.67
Site 2	Generator AM	246	50	50	366	51.37	48.63
	Generator PM	350	50	50	374	50.53	49.47
	Street AM	129	52	48	140	52.86	47.14
	Street PM	290	50	50	252	51.98	48.02
Site 3	Generator AM	290	50	50	519	53.76	46.24
	Generator PM	411	50	50	517	53.38	46.62
	Street AM	152	52	48	261	51.72	48.28
	Street PM	342	50	50	271	49.08	50.92

TABLE 2.11
Calibrated Trip Generation Models, Goodness-of-Fit, and Directional Split by Peak Period.

Peak Period	Independent Variable Used	Equation	R^2	Mean Percent Error	In (%)	Out (%)
Generator AM	GFA	T = 216.43(X) - 736.92	0.9805	5.51	52.04	47.96
Generator PM	GFA	T = 211.07(X) - 706.05	0.9731	6.20	51.06	48.94
Street AM	GFA	T = 211.07(X) - 706.05	0.3162	22.20	51.93	48.07
Street PM	Seats	T = 1.9422(X) + 13.925	0.9999	0.26	50.13	49.87

generator AM prediction (approximately 201 trips) closely matches the observed total (200 trips). However, the accuracy decreases with increasing site activity levels. At Site 3, the model substantially underestimates observed volumes, with predicted generator AM trips (approximately 267) compared to an observed 519 trips.

Across all sites, LU 934 tends to underestimate trip generation, particularly during generator peak periods at higher-volume locations. Predictions based on total seating are consistently lower than those based on GFA, resulting in further underestimation. During street peak periods, the variation between predicted and observed volumes is more pronounced, suggesting that external traffic influences are not fully captured by the ITE rates.

LU 929 produces higher trip estimates than LU 934, reflecting its classification as a higher-intensity fast-food land use. However, based on the observed data, LU 929 does not consistently improve agreement with field counts. At lower-volume sites (e.g., Site 1), LU 929 tends to overestimate trip generation during certain periods, particularly the generator PM peak. Conversely, at higher-volume sites (e.g., Site 3), LU 929 continues to underestimate observed trips, although the magnitude of underestimation is generally less than that of LU 934. While LU 929 shifts predictions upward, it does not fully capture the level of activity observed at the study sites and does not consistently outperform LU 934 across all conditions.

The directional distribution of trips was also compared between ITE estimates and observed field conditions. Both LU 934 and LU 929 assume generally balanced inbound and outbound splits, typically in the range of approximately 50/50 to 52/48 depending on the peak period. The observed field data show a similar pattern, with inbound proportions generally ranging from approximately 49% to 54% across all sites and peak periods. This indicates that, while there are minor variations, the ITE directional assumptions for both LU 934 and LU 929 are broadly consistent with observed traffic patterns.

To improve predictive accuracy, regression models were developed using the observed data, as summarized in Table 2.11. An example of the Indiana-specific trip generation curves is shown in Figure 2.3.

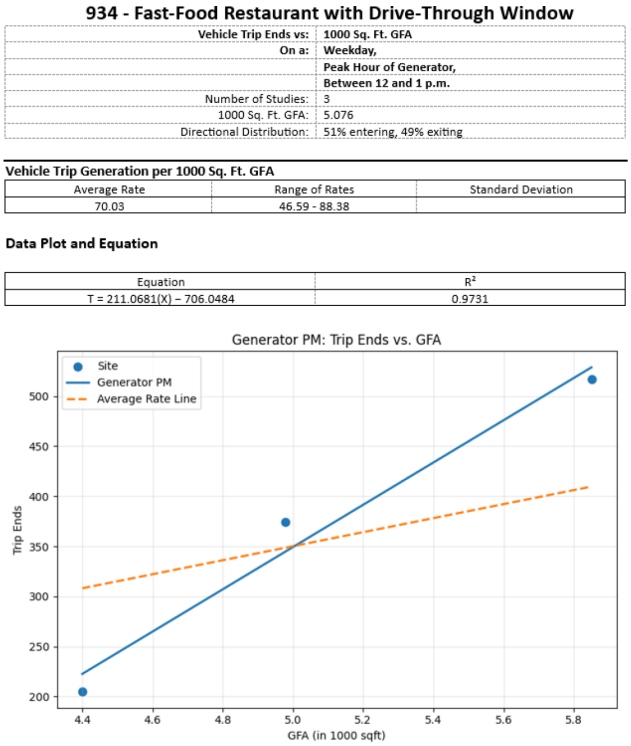


Figure 2.3 Indiana Specific Trip Generation Curves for LU 934 During the PM Peak Hour of the Generator.

2.5.4 LU 945 – Convenience Store/Gas Stations

For LU 945 (Convenience Store/Gas Stations), the number of fuel pumps was identified as the primary independent variable used in the ITE trip generation estimates. Table 2.12 presents the comparison between ITE trip generation estimates and the observed field counts collected at the three study sites during generator and street peak periods.

Overall, the ITE predictions consistently overestimate observed field counts across all study sites and peak periods. The magnitude of overestimation is particularly pronounced at Site 1, where predicted trips exceed observed volumes by a substantial margin during both generator and street peak periods. For example, the generator AM prediction is approximately 538 trips compared to an observed volume of 103 trips, while the street AM prediction is approximately 523 trips compared to the same observed count of 103 trips.

At Sites 2 and 3, the ITE estimates remain higher than the observed field counts, although the differences are less pronounced than those observed at Site 1. At Site 2, the generator PM prediction of approximately 239 trips compares relatively closely with the observed total of 198 trips. Similarly, at Site 3, the generator PM prediction of approximately 270 trips exceeds

TABLE 2.12
Comparison of ITE Trip Generation Predictions (LU 945) and Observed Field Counts Across Study Sites and Peak Periods.

		ITE Prediction			Field Counts		
		X = Number of Pumps					
Site	Peak Period	Total	In (%)	Out (%)	Total	In (%)	Out (%)
Site 1	Generator AM	538	51	49	103	60.19	39.81
	Generator PM	540	50	50	43	46.51	53.49
	Street AM	523	52	48	103	60.19	39.81
	Street PM	508	50	50	101	52.48	47.52
Site 2	Generator AM	209	50	50	179	50.28	49.72
	Generator PM	239	50	50	198	48.99	51.01
	Street AM	194	50	50	179	50.28	49.72
	Street PM	221	50	50	189	51.32	48.68
Site 3	Generator AM	269	51	49	142	50.00	50.00
	Generator PM	270	50	50	144	52.78	47.22
	Street AM	263	52	48	150	50.67	49.33
	Street PM	354	50	50	143	48.95	51.05

TABLE 2.14
Comparison of ITE Trip Generation Predictions (LU 950) and Observed Field Counts Across Study Sites and Peak Periods.

		ITE Prediction			Field Counts		
		X = GFA					
Site	Peak Period	Total	In (%)	Out (%)	Total	In (%)	Out (%)
Site 1	Generator AM	14	50	50	282	49.29	50.71
	Generator PM	120	51	49	293	50.17	49.83
	Street AM	19	50	50	266	48.12	51.88
	Street PM	351	53	47	283	48.06	51.94
Site 2	Generator AM	14	50	50	366	49.73	50.27
	Generator PM	99	51	49	382	48.43	51.57
	Street AM	-3.79	50	50	364	47.80	52.20
	Street PM	352	53	47	368	49.73	50.27
Site 3	Generator AM	14	50	50	221	51.13	48.87
	Generator PM	208	51	49	189	50.26	49.74
	Street AM	114	50	50	373	51.74	48.26
	Street PM	345	53	47	194	48.97	51.03

TABLE 2.13
Calibrated Trip Generation Models, Goodness-of-Fit, and Directional Split by Peak Period.

Peak Period	Independent Variable Used	Equation	R^2	Mean Percent Error	In (%)	Out (%)
Generator AM	GFA	T = -5.75 (X) + 241	0.763	7.79	53.49	46.51
Generator PM	GFA	T = -12.8(X) + 350.2	0.882	12.44	49.43	50.57
Street AM	GFA	T = -6.15(X) + 250.6	0.8571	5.92	53.71	46.29
Street PM	Seats	T = -6.5(X) + 257	0.7269	9.42	50.92	49.08

the observed volume of 144 trips but follows a similar relative trend across peak periods.

Across all sites, the ITE trip generation estimates generally demonstrate a tendency to overpredict observed traffic activity. The degree of overestimation varies between sites, suggesting that factors other than the number of fuel pumps may significantly influence trip generation characteristics at the surveyed developments. Despite the differences in total trip volumes, the relative variation between peak periods is reasonably consistent between predicted and observed conditions.

The directional distribution of trips was also compared between ITE estimates and observed field conditions. The ITE directional assumptions are generally balanced, ranging from approximately 50/50 to 52/48 inbound and outbound splits depending on the peak period. The observed field data similarly show relatively balanced directional distributions, with inbound proportions ranging from approximately 47% to 60% across the study sites and peak periods. While some variability is present, particularly at Site 1 during the generator AM and street AM periods, the overall directional trends are broadly consistent with the ITE assumptions.

To improve predictive accuracy, regression models were developed using the observed data, as summarized in Table 2.13. The resulting models produced moderate to strong goodness-of-fit values, with R^2 values ranging from approximately 0.73 to 0.88 depending on the peak period. However, all calibrated models yielded negative regression slopes, indicating an inverse relationship between the selected independent variable and observed trip generation. While the statistical fit of the models appears acceptable, the negative slope coefficients are not practically intuitive, as trip generation would generally be expected to increase with increasing site size or operational intensity. This outcome likely reflects limitations associated with the dataset, including the small sample size, variability between site operations, and the limited range of independent variable values across the surveyed locations. As such, the calibrated equations should be interpreted cautiously.

2.5.5 LU 950 – Truck Stops

Table 2.14 and Table 2.15 present a comparison between ITE trip generation estimates for LU 950 (Truck Stop) and LU 955 (Travel Center) respectively, against the observed field counts collected at the three study sites during generator and street peak periods. LU 950 was omitted in the 12th edition of the Trip Generation Manual, and practitioners were directed to use the 955-Travel Center curves instead. The calculations for LU 950 were performed using the 11th edition of the Trip Generation Manual, which was the last time the curves for that land use were published. The comparison was undertaken using

TABLE 2.15
Comparison of ITE Trip Generation Predictions (Land Use 955) and Observed Field Counts Across Study Sites and Peak Periods.

		ITE Prediction						Field Counts		
		X = GFA			X = Fuel Pumps					
Site	Peak Period	Total	In (%)	Out (%)	Total	In (%)	Out (%)	Total	In (%)	Out (%)
Site 1	Generator AM	No data	No data	No data	N/A	48	52	282	49.29	50.71
	Generator PM	No data	No data	No data	N/A	52	48	293	50.17	49.83
	Street AM	156.78	51	49	343.26	51	49	266	48.12	51.88
	Street PM	148.02	49	51	413.37	49	51	283	48.06	51.94
Site 2	Generator AM	No data	No data	No data	N/A	48	52	366	49.73	50.27
	Generator PM	No data	No data	No data	N/A	52	48	382	48.43	51.57
	Street AM	148.68	51	49	327.5417835	51	49	364	47.80	52.20
	Street PM	135.78	49	51	391.5223095	49	51	368	49.73	50.27
Site 3	Generator AM	13.85	50	50	No data	No data	No data	221	51.13	48.87
	Generator PM	207.69	51	49	No data	No data	No data	189	50.26	49.74
	Street AM	113.39	50	50	191.88	51	49	373	51.74	48.26
	Street PM	344.42	53	47				194	48.97	51.03

TABLE 2.16
Calibrated Trip Generation Models, Goodness-of-Fit, and Directional Split by Peak Period.

Peak Period	Independent Variable Used	Equation	R^2	Mean Percent Error	In (%)	Out (%)
Generator AM	Parking Spots	T = (X) + 181.34	0.8962	6.01	50.05	49.95
Generator PM	Parking Spots	T = 1.3758(X) + 138.96	0.9636	4.76	49.62	50.38
Street AM	GFA	T = 14.297(X) + 276.19	0.1679	12.78	49.22	50.78
Street PM	Parking Spots	T = 1.231(X) + 148.31	0.9509	4.98	48.89	51.11

GFA and, where available, fuel pumps as independent variables. There were two peak periods observed between 4:00 and 6:00 PM (PM Street Peak Hours), where in the same vehicle counts were observed but the directional distribution varied. The directional distribution for the period between 4:15 and 5:15 PM was chosen to be included in the Table 2.15 as this interval had the most overlap with the peak periods of other sites.

For LU 950, the ITE predictions based on GFA show considerable variation when compared to observed field counts. During generator AM periods, LU 950 substantially underestimates observed volumes at all three sites. For example, Site 1 has a predicted generator AM volume of approximately 14 trips compared to an observed 282 trips, and Site 2 shows a similar underestimation with approximately 14 predicted trips compared to 366 observed trips. During generator PM periods, LU 950 also underestimates Sites 1 and 2, while Site 3 is closer to the observed count. Street AM predictions generally underestimate observed traffic, including a negative prediction at Site 2, which indicates poor applicability of the GFA-based equation for that condition. Street PM predictions are closer for Site 2, but overestimate Sites 1 and 3. Overall, LU 950 does not consistently reflect the observed trip generation patterns across the study sites.

For LU 955, the comparison is limited in some peak periods because ITE predictions are not available for all independent variables and sites. Where estimates are available, LU 955 does not consistently improve agreement with field counts. During street AM periods, fuel pump–based estimates overestimate observed trips at Site 1, are closer at Site 2, and underestimate Site 3. GFA-based estimates generally underestimate observed street AM volumes. During street PM periods, fuel pump–based estimates overestimate observed trips at Sites 1 and 2, while GFA-based estimates underestimate Sites 1 and 2 but overestimate Site 3.

The directional distribution of trips was also compared between ITE estimates and observed field conditions. Both LU 950 and LU 955 generally assume balanced or near-balanced inbound and outbound splits, typically ranging from approximately 48/52 to 53/47 depending on the peak period and independent variable. The observed field data show a similar pattern with inbound proportions generally ranging from approximately 48% to 52% across all sites and peak periods. This indicates that, while the ITE directional assumptions are broadly consistent with observed traffic patterns, the total trip estimates vary substantially between the ITE land uses and the field counts.

The regression models were developed using the observed data are summarized in Table 2.16. In the case of Street AM Peak, the R^2 value was the highest when the number of fuel pumps was used as the independent variable. However, the equation had a negative slope, indicating that the number of

trips decreased with increasing size. Thus, the equation was dropped and the regression line with the next best R^2 value (with GFA as the independent variable) was chosen to be included in Table 2.16.

2.6 Summary

This chapter developed and evaluated Indiana-specific trip generation procedures for selected industrial and service land uses commonly reviewed in INDOT Traffic Impact Studies. Using field data from representative Indiana sites, the study compared observed traffic volumes with ITE Trip Generation Manual estimates and explored locally calibrated models.

The literature review showed that national ITE rates may not always reflect local conditions, particularly for newer or evolving land uses. Therefore, local calibration and context-sensitive analysis are important for improving trip generation estimates.

Traffic counts were collected during generator and adjacent street peak periods following ITE guidance. Independent variables such as gross floor area, seating capacity, parking spaces, fuel pumps, and other operational characteristics were compiled for analysis.

The comparison showed that ITE estimates varied in accuracy by land use. For warehouse land uses, ITE models generally overestimated observed traffic, with notable variation by site and peak period. For fast-food restaurants, LU 934 tended to underestimate higher-volume sites, while LU 929 produced higher estimates but did not consistently improve accuracy. For gasoline/service stations and truck stops, ITE models often showed inconsistent or inaccurate results, indicating that national variables may not fully capture local operating conditions.

Indiana-specific regression models improved predictive performance in some cases, but results were limited by small sample sizes, narrow ranges of variables, and differences in site operations. Some models were not statistically appropriate because of weak or inconsistent relationships.

Overall, the findings indicate that uncalibrated ITE rates may overestimate or underestimate traffic impacts in Indiana. However, the transferability of a trip-generation rate depends not only on geographic coverage, but also on the number, age, quality, and operational comparability of the studies used to develop it. These considerations are especially important for land uses that have changed substantially over time. For example, modern warehouse and fulfillment operations may use automation, enterprise software, revised staffing practices, and different freight-handling processes that allow substantially larger facilities to operate with fewer employees or different vehicle-activity patterns than facilities represented in older datasets. Consequently, gross floor area alone may not adequately represent the operational intensity of these developments.

Observed differences from ITE estimates should not be attributed solely to Indiana-specific geographic conditions. The Indiana-specific observations should, therefore, be used as supplemental evidence when assessing the reasonableness of submitted estimates, rather than executing a complete overhaul of the current system. Where local models perform well, they may be considered for future guidance; where results are limited, site-specific justification or additional data collection should still be required.

Finally, the Indiana field data should be preserved and submitted to ITE for possible inclusion in future Trip Generation Manual updates. This would help expand the national database and ensure that Indiana conditions, particularly for evolving land uses such as modern logistics facilities and truck-oriented service stations, are better represented in future guidance.

3. NATIONAL TRENDS IN SHOPPING RELATED TRAVEL

3.1 Overview

The NHTS provides a periodic national inventory of daily travel behavior in the United States, typically conducted every 5 years. It records trips made by households and individuals over a 24-hr period, including trip purpose, travel mode, travel time, departure time, and day-of-week information (Federal Highway Administration, 2017, 2022). This study uses the 2017 and 2022 NHTS datasets to examine how the wider adoption of e-commerce in 2022 may have influenced the way individuals carry out shopping-related travel.

NHTS is used for two primary purposes in this study. First, it serves as a major source for constructing synthetic trip chains in Indianapolis, which provide input to the trip-chain demand modeling framework developed by (Wen et al., 2020, 2025). This allows the evaluation of e-commerce on the vehicle miles traveled (VMT) changes due to e-commerce induced trips, such as in-store pickup and on-demand delivery replacing original in-store shopping. Second, NHTS is used to model return trips that were not explicitly represented in previous trip-chain generation. To do so, this study conducts motif analysis using individual-level daily trip records from NHTS and extracts shopping-related activity motifs. These motifs are grouped according to whether shopping appears as a dedicated shopping tour, a shopping stop embedded in a single tour with multipurpose stops, a multistop shopping-only tour, or shopping stops in multiple tours in a day. The resulting motif probabilities are then used to estimate the likelihood of adding a return trip in the Indianapolis synthetic trip chains. This extension allows the model developed in this study to further evaluate the VMT impacts associated with return trips generated by e-commerce-related travel behavior change.

3.2 NHTS Data Description

Table 3.1 summarizes the raw sample sizes of the NHTS datasets used in this study. The 2017 NHTS (Federal Highway Administration, 2017) contains a much larger sample, with

TABLE 3.1
NHTS Sample Size in 2017 and 2022.

Year	Households	Persons	Trips
2017	129,696	264,234	923,572
2022	7,893	16,997	31,074

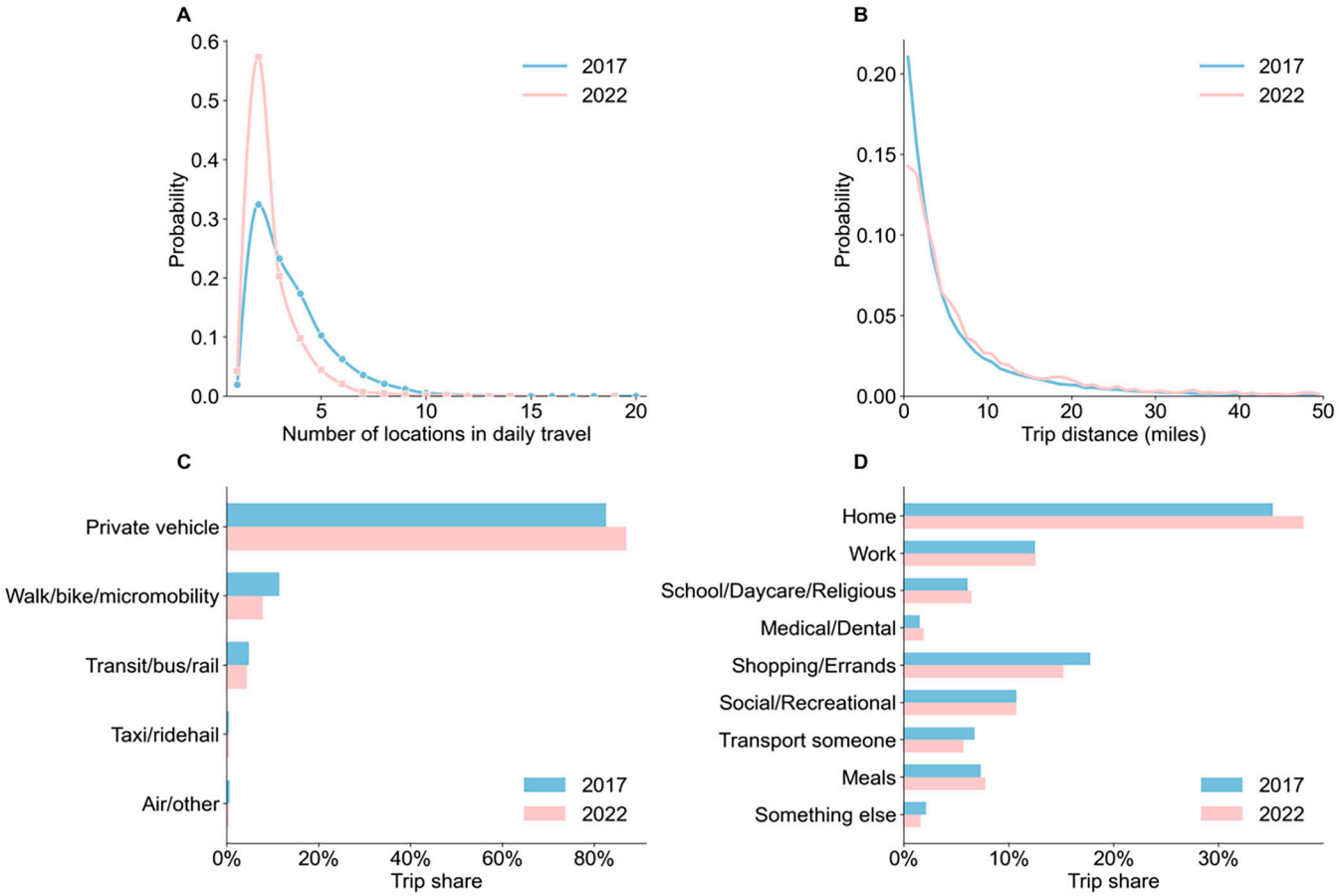


Figure 3.1 Comparison of Unweighted National-Level Travel Behavior Distributions in 2017 and 2022. (A) Distribution of the Number of Locations Visited in Individuals' Daily Trip Chains; (B) Distribution of Trip Distances Within Daily Trip Chains; (C) Trip-Level Transportation Mode Shares; and (D) Trip-Level Purpose Shares.

129,696 households, 264,234 persons, and 923,572 reported trips, while the data points of 2022 NHTS (Federal Highway Administration, 2022) reduce drastically, which includes 7,893 households, 16,997 persons, and 31,074 trips.

Figure 3.1 compares the travel behavior between 2017 and 2022. In Figure 3.1a, the distribution of the number of locations in daily travel is more concentrated at two locations in 2022 than 2017. The probability of visiting two locations increases from 32.5% in 2017 to 57.4% in 2022, while the mean number of visited locations in daily trip chains decreases from 3.64 to 2.69. Figure 3.1b shows that the trip-distance distribution changes only modestly. This suggests that the reduction in daily locations mainly reflects fewer distinct stops or chained activities. Travelers in 2022 appear to make simpler daily chains, but the remaining trips still cover comparable distances. In Figure 3.1c and Figure 3.1d, private vehicles remain the dominant travel mode and become even more prevalent in 2022, increasing from 82.6% to 87.0% of weighted trips, while walk/bike/micromobility and transit shares decline. At the same time, the purpose distribution shows a reduction in shopping/errand travel, from 17.8% to 15.2%. Together, these patterns suggest that post-2017 travel behavior is characterized less by a broad reduction in trip distance and more by a reorganization of daily activity participation: fewer stops, fewer shopping/errand activities, stronger reliance on private vehicles, and more concentrated home-based daily travel chains.

3.3 Motif Analysis

This study analyzes the motif to capture the structure of daily travel chains in the NHTS data. Motif analysis provides a data-driven way to summarize observed shopping-trip patterns and offer the basis to infer the insertion of a trip, because NHTS trip records describe personal trip purpose but do not further distinguish whether a shopping-related trip corresponds to an in-store purchase, online order pickup, or product return person-trips.

A motif is a simplified representation of a person's daily activity-travel pattern (C. Schneider et al., 2013; Yan et al., 2017). It records how many *home-based tours* a person makes during the day, how many stops are included in each tour, and where shopping stops appear in the sequence. Consequently, the motif captures the structure of the trip chain that can later be used to reconstruct possible shopping return trips. More specifically, for a trip chain record in NHTS data, we first order

TABLE 3.2
Summary of General and Shopping-Specific Travel Motif in NHTS 2017 and 2022.

Motif Type	Year	Unique Motifs	Top 20 Motif Trip-Chain Coverage
General motif	2017	858	90.87%
General motif	2022	102	97.58%
Shopping-specific motif	2017	4,482	55.44%
Shopping-specific motif	2022	261	80.12%

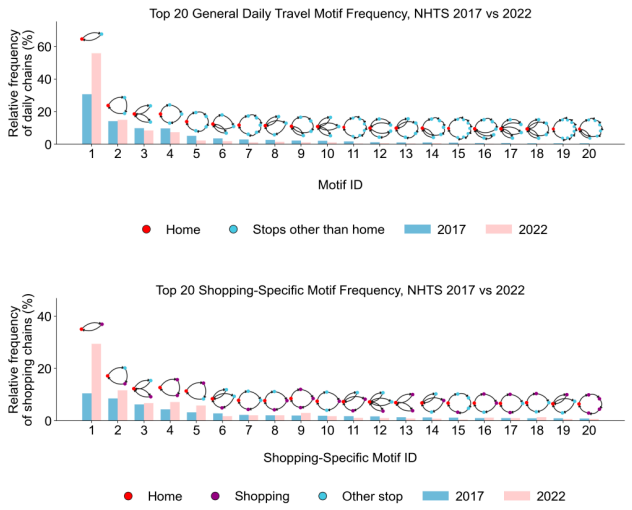


Figure 3.2 The Top 20 General and Shopping-Specific Motifs.

each person's trips within a single day by time and identify home as the anchor location. A home-based motif is defined as a sequence that starts from home, visits one or more nonhome stops, and returns home, such as "*home–stop 1–stop 2–home*". To better understand how shopping trips are embedded in travelers' daily trip chains, including whether they occur as dedicated shopping tours or as stops within multipurpose tours, as well as their sequence within the chain, we further distinguish shopping stops within each motif to construct a shopping-specific motif. This allows us to differentiate motifs by the number of shopping stops and by the position of those shopping stops within the activity sequence. Consequently, "*home–shopping–stop 1–home*" and "*home–stop 1–shopping–home*" are two unique shopping-specific motifs.

As shown in Table 3.2, for general and shopping-specific daily travel motifs, the number of unique motifs decreases sharply from 2017 to 2022. This is likely due to the smaller sample size collected in 2022, as well as changes in travel patterns associated with postpandemic work-from-home practices and the continued growth of e-commerce, which may have led to less diversified daily trip chains. The top one motif, as shown in Figure 3.2, representing the simplest home-based chain, becomes especially dominant in 2022, suggesting that a larger share of travelers made simple home-to-activity-to-home tours for both general purpose and shopping purposes. The higher frequency of the leading shopping motif indicates that dedicated shopping tours became more dominant, while complex shopping chains involving multiple stops or mixed activities became less common.

3.4 Summary

The NHTS analysis provides a national-level overview of how shopping-related travel patterns changed between 2017 and 2022. The comparison shows that the 2022 NHTS contains a much smaller sample than the 2017 survey, but it still provides useful evidence for identifying broad shifts in daily travel and shopping-chain structures as e-commerce is more adopted in 2022 than in 2017. The motif analysis further shows that a relatively small number of general daily travel motifs explain most observed trip chains.

NHTS alone is not sufficient to fully represent e-commerce-related travel behavior in Indiana. It is a national survey, and it does not directly observe online shopping frequency, return behavior, package pickup behavior, or whether a shopping-related trip was generated by e-commerce. Therefore, an Indiana-specific survey is needed to better understand how residents combine online shopping, returns, pickups, and other daily activities in the next section. Such survey data would help calibrate e-commerce behavior in the trip chains and improve the estimation of e-commerce-related VMT impacts in Indiana.

4. INDIANA SPECIFIC E-COMMERCE SURVEY

4.1 Overview

Understanding the impacts of e-commerce on shopping behavior and travel demand requires data that are both recent and sufficiently detailed at the state level. Prior research conducted under SPR-4608 (Verma et al., 2024) relied primarily on the 2017 NHTS and consumer panel data to analyze e-commerce adoption and its implications for travel behavior in Indiana. While valuable, the 2017 NHTS only contained a limited number of e-commerce–related questions, constraining the ability to analyze shopping behavior by product type, delivery mode, and sociodemographic segment.

Since 2017, shopping and travel behaviors have evolved substantially, particularly following the COVID-19 pandemic, which accelerated the adoption of online shopping, home delivery services, and hybrid shopping models. The release of the 2022 NHTS offers more recent national-level data on travel behavior and includes expanded information relevant to e-commerce use. However, despite these improvements, the 2022 NHTS still has limitations for Indiana-specific analysis, including insufficient sample sizes for detailed segmentation and a lack of granularity regarding delivery methods, pickup behavior, and attitudes toward e-commerce services.

To address these gaps, a customized survey of Indiana residents was designed and administered as part of this project. The survey complements the 2017 and 2022 NHTS by collecting Indiana-specific data on online and in-store shopping frequency, delivery and pickup choices, return behavior,

transportation modes, and attitudes toward e-commerce. The survey also captures detailed sociodemographic and technology access information that supports market segmentation and model development.

The primary purpose of this survey is to provide an updated and richer empirical foundation for analyzing e-commerce demand and its interaction with travel behavior in Indiana. The data are used in conjunction with NHTS data to support econometric analysis and to update the agent-based travel demand simulation model, enabling a more accurate assessment of how e-commerce adoption influences shopping trips, vehicle travel, and broader transportation system impacts in the state.

4.2 Literature Review

4.2.1 E-Commerce and Travel Behavior

As online shopping becomes a part of household routines, research has been focusing on how digital purchasing affects shopping trips, freight movement, land use, and long-term travel demand. While early expectations were straightforward, that is, if people bought goods online, they would make fewer trips to stores, the literature has shown that the real-world effects are far more complex. Mokhtarian (2004) argued that information and communication technologies do not create a one-directional effect on travel but instead produce multiple possible outcomes depending on the activity context. Building on that framework, later studies commonly grouped the impacts of e-commerce into four categories: substitution (an online purchase replaces an in-store trip), complementarity (online shopping generates or supports additional travel), modification (changes in trip timing, destination, or trip chaining), and neutrality (little measurable effects) (Xi et al., 2020).

Empirical findings have produced mixed evidence. For example, Cao (2009) and Cao et al. (2010) reported that e-shopping can substitute for some shopping travel, although the magnitude varies by household type and product category. Similarly, Rotem-Mindali (2010), using data from Israel, found evidence that online retailing can reduce shopping-related travel under certain conditions. At the same time, many studies show that e-commerce can complement in-store shopping rather than replace it. Farag et al. (2007) found that online and in-store shopping often coexist as part of broader consumer decision making. Weltevreden and Rietbergen (2007) similarly concluded that internet shopping did not necessarily weaken city-center retail activity but instead changed how consumers interacted with shopping environments. More recent evidence from Lisbon (Colaço & de Abreu e Silva, 2021) showed that online shopping activity during weekdays was positively associated with both online and in-store shopping on weekends, indicating a complementary relationship between channels.

4.2.2 Impact of Omnichannel Retail

The rise of omnichannel retail has further blurred the distinction between online and physical shopping. Consumers now frequently browse online before visiting stores, inspect products in stores before purchasing online, or combine online orders with pickup and return trips (Kleinlercher et al., 2020), and rely on personal attributes such as convenience (Giuliano et al., 2022). These behaviors suggest that consumers are not choosing between channels in a binary way; instead, they are selecting combinations of channels that maximize convenience, price, speed, and certainty. Thus, the question is no longer whether e-commerce substitutes for store shopping, but under what conditions different channel combinations emerge.

4.2.3 Sociodemographic Differences

A consistent finding across the literature is that e-commerce adoption is uneven across population groups. Older individuals are less likely to engage in e-commerce (Cao et al., 2012; Clemes et al., 2014; Farag, Krizek, & Dijst, 2006; Farag, Weltevreden, et al., 2006; Lee et al., 2017), while women, in general, tend to show higher levels of engagement (Ding & Lu, 2017; Saphores & Xu, 2021; Shah et al., 2021; Shi et al., 2019; Titiloye et al., 2024). Minority households exhibited lower rates of online shopping, while those with mobility-impaired members increasingly relied on online shopping compared to previous years (Saphores & Xu, 2021). Higher educational levels also showed higher delivery frequencies (Cao et al., 2013; Clemes et al., 2014; Krizek et al., 2005), just as households with more working adults, vehicles, licensed drivers, and children showed higher rates of e-commerce participation (Dias et al., 2020; Farag, Krizek, & Dijst, 2006; Farag, Weltevreden, et al., 2006; Farag et al., 2007; Spurlock et al., 2020; Zhou & Wang, 2014). Pandemic further polarized these trends, where Unnikrishnan and Figliozzi (2020) reported a surge in deliveries among households already receiving multiple deliveries per week prepandemic, full-time employees and individuals working from home. Similarly, Q. Luo et al. (2023) noted a pandemic-induced acceleration in e-commerce adoption in the Sacramento region, with generational shifts during lockdowns, particularly among older adults. Frequent internet usage, prior online shopping experience, and general tech-savviness along with urban residents have all been linked to higher e-commerce participation (Cao et al., 2012, 2013; Ding & Lu, 2017; Krizek et al., 2005; Lee et al., 2017; Ren & Kwan, 2009; Shi et al., 2019; Zhou & Wang, 2014).

Recent longitudinal analysis using the 2009, 2017, and 2022 NHTS found that females, higher-income households, and well-educated individuals remained more likely to receive online deliveries, but disparities by age and income became smaller over time (Ha, 2025). The same study also found evidence of both complementarity and substitution: online deliveries were positively associated with shopping and meal trips, yet average shopping trip rates declined across survey waves. These findings suggest that the relationship between e-commerce and travel is dynamic and evolves as digital shopping becomes mainstream.

4.2.4 Gaps

Despite substantial progress in literature, important gaps remain for state DOT applications. Much of the existing evidence comes from national surveys or studies in large metropolitan areas outside Indiana or even outside the US. These findings may not

transfer directly to Indiana as individual travel behavior as well as delivery efficiency, retail accessibility, internet quality, and household travel needs can differ substantially across geographies.

In addition, many national datasets provide only limited information on delivery methods, pickup behavior, returns, and consumer attitudes. These variables are increasingly important for forecasting travel demand because they determine whether e-commerce reduces personal trips, increases freight trips, or changes both simultaneously. For Indiana, state-specific data are, therefore, necessary to understand local shopping behavior and to update modeling tools used for planning and policy analysis. The customized survey developed in this project helps address that need by complementing NHTS data with richer behavioral information from Indiana residents.

4.3 Survey Methodology

4.3.1 Sampling Strategy

The survey targeted adult residents of Indiana (age 18 and older) and was administered using an online consumer panel. A quota-based sampling approach based on the 2020 Decennial Census was employed to improve representativeness of the Indiana population across key sociodemographic characteristics known to influence shopping and travel behavior. A target sample size of 1,070 completed surveys was established, corresponding to an approximate margin of error of ±3% at the 95% confidence level. As summarized in Table 4.1, age quotas were specified across six groups (18–24, 25–34, 35–44, 45–54, 55–64, and 65+), gender quotas targeted a distribution of 48% male and 52% female, and income quotas spanned seven household income categories ranging from less than $15,000 to $150,000 or more annually.

Survey participants were recruited through Dynata's online research panel and screened to confirm Indiana residency and age eligibility. The survey was programmed and hosted by Purdue University using the Qualtrics platform and was accessible across multiple devices, including desktop, tablet, and mobile. The average survey completion time was approximately 20 to 25 min.

TABLE 4.1
Sampling Plan and Quota Targets for the E-Commerce Survey.

Category	Quota Variable	Target Distribution
Age Quotas	18–24 years	11%
	25–34 years	17%
	35–44 years	16%
	45–54 years	16%
	55–64 years	17%
	65+ years	23%
Gender Quotas	Male	48%
	Female	52%
Household Income Quotas	Less than $15,000	12%
	$15,000–$24,999	10%
	$25,000–$49,999	23%
	$50,000–$74,999	18%
	$75,000–$99,999	12%
	$100,000–$149,999	13%
	$150,000 or more	11%

4.3.2 Data Collection

The survey was administered between December 9, 2025, and April 10, 2026, using the Qualtrics survey platform hosted by Purdue University. Respondents were recruited through Dynata's online consumer research panel and screened to confirm Indiana residency and age eligibility (18 years and older). In accordance with Dynata's standard panel policies, participants received compensation through Dynata's internal incentive structure.

The survey instrument was designed to be accessible across desktop, tablet, and mobile devices to improve participation and reduce device-related response barriers. Participation in the survey was voluntary, and all responses were collected anonymously. Institutional Review Board (IRB) approval was obtained on July 17, 2025. Respondents were required to complete all mandatory survey items before submission, and incomplete surveys were not accepted.

A total of 2,550 survey starts were recorded during the data collection period. Of these, 1,169 completed responses were obtained for further processing and quality assessment.

4.3.3 Data Cleaning and Quality Control

Several quality-control procedures were implemented to improve the reliability and consistency of the survey data. Attention-check questions were embedded throughout the survey instrument to identify inattentive respondents. Responses failing these checks were removed from the final dataset. Additional screening procedures targeted low-quality responses, including straight-lining behavior and incomplete survey submissions. Speeding behavior was also monitored through Qualtrics' automated response-quality controls.

Responses with missing key sociodemographic information, specifically gender or household income, were excluded from the final analytical dataset. Following the data cleaning process, 1,143 valid responses were retained for analysis from the original 1,169 completed surveys. Poststratification survey weights based on age and gender distributions from the 2020 Decennial Census were applied to improve the representativeness of the sample relative to the Indiana adult population. The demographics of the survey post weights are presented in Table 4.2.

To estimate the loss in precision because of weighting, the unequal weighting effect (UWE) was calculated using the following formula (Biemer & Christ, 2008).

$$UWE = 1 + \frac{Var(w_i)}{\bar{w}^2} = 1 + CV_{weights}{}^2 \quad \text{Equation 4.1}$$

Where w_i the weight of the individual i and $CV_{weights}{}^2$ is the squared coefficient of variation of weights (standard deviation/mean). A UWE of 1.35 was obtained, indicating that the magnitude that the variance of a mean will increase due to the weights is 1.35 (or 1.16 for the standard error of the mean). The low

TABLE 4.2
Demographics of the E-Commerce Survey After Weighting.

Demographic	Value	Unweighted Count	Weighted %
Age	18 to 24 years old	62	5.42%
	25 to 34 years old	223	19.51%
	35 to 44 years old	268	23.45%
	45 to 54 years old	210	18.37%
	55 to 64 years old	167	14.61%
	65 years or older	213	18.63%
Gender	Male	480	42%
	Female	663	58%
Income	Less than $25,000	190	8.75%
	$25,000-$49,999	239	15.38%
	$50,000-$99,999	338	31.81%
	Over $100,000	376	44.05%
Race	White	1003	87.82%
	Black	83	6.47%
	Asian	9	0.89%
	Other	48	4.82%
Education	Some High School or less	32	1.88%
	High School	221	17.44%
	Some College, but no degree	255	21.09%
	Associate degree	162	13.74%
	Bachelor's degree	325	30.18%
	Graduate or Professional degree (MA, MS, MBA, PhD, JD, MD, DDS etc.)	148	15.68%
Employment	Works part time	319	27.39%
	Works full time	400	38.95%
	Homemaker	86	7.29%
	Student	9	0.41%
	Currently Unemployed	62	3.85%
	Other	267	22.11%
Disability	Does not have a disability that restricts movement	851	77.15%
	Has a disability that restricts movement	292	22.85%
Driving Status	Drives	1047	93.94%
	Does not drive	96	6.06%
Vehicles per Household	Zero Vehicles	52	2.67%
	1 Vehicle per household	469	35.06%
	2 Vehicles per household	387	37.04%
	3 Vehicles per household	158	16.58%
	4+ Vehicles per household	77	8.65%

figure indicates that the gain in representativeness far outweighs the minor precision lost.

4.4 Survey Structure

The survey instrument was structured into several thematic sections, with adaptive branching used to tailor questions based on respondents' shopping behaviors. An initial screening section confirmed eligibility and obtained informed consent. Respondents were then classified into broad categories based on their frequency of online shopping (nonshoppers, infrequent shoppers, and frequent shoppers), which determined the specific sets of questions they received.

Core sections of the survey included:

- **Online shopping behavior**, covering frequency of purchases, years of experience with e-commerce, types of products purchased, delivery and pickup methods, and use of alternative delivery options such as lockers or consolidated shipping.
- **In-store shopping behavior**, including shopping frequency, trip planning, and primary transportation modes used for shopping trips.
- **Pickup and return behavior**, focusing on how online orders are picked up or returned, transportation modes used, and whether these trips are combined with other activities.
- **Attitudes and perceptions,** measured using a 5-point Likert-scale to address convenience, efficiency, trust, delivery concerns and social norms.
- **Technology access and internet use**, including access to the internet, years of internet use, and preferred payment methods.
- **Socio-demographic characteristics**, such as age, gender, employment status, race/ethnicity, housing situation, and income.

Quality control measures, including attention-check questions embedded throughout the survey, were used to enhance data validity. The full survey instrument is provided in Appendix C.

4.5 Survey Data Description

This section presents select descriptive statistics from the Indiana e-commerce survey. All results presented are weighted to better reflect the demographic composition of Indiana residents. The findings provide insight into the prevalence of online shopping, product purchasing and return behaviors, attitudes toward e-commerce, and perceived changes in shopping behavior following the adoption of online shopping. Together, these results offer an initial indication of how e-commerce may be influencing consumer travel patterns and shopping activities in Indiana.

4.5.1 Online Shopping Frequency

Figure 4.1 presents the weighted distribution of online shopping frequency among respondents. The results indicate that online shopping has become a mainstream activity among Indiana residents. More than four-fifths of respondents reported shopping online at least occasionally, while only a small proportion indicated that they never shop online. The largest share of respondents reported shopping online between one and three times per month, followed closely by those shopping online one to two times per week.

The distribution suggests that e-commerce is no longer confined to a small group of highly engaged users. Instead, online shopping appears to have been integrated into routine purchasing behavior for a broad segment of the population. While daily online purchasing remains relatively uncommon, the prevalence of weekly and monthly online shopping indicates that e-commerce now serves as a regular channel for household consumption rather than an occasional alternative to in-store shopping. From a transportation perspective, this finding suggests

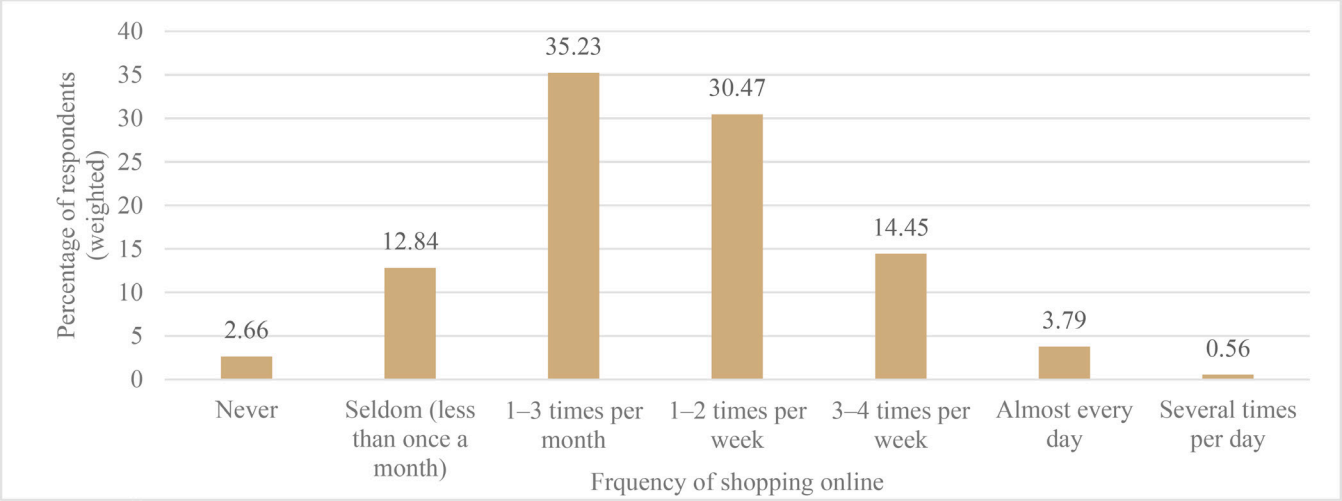


Figure 4.1 Weighted Share of Respondents' Online Shopping Frequency.

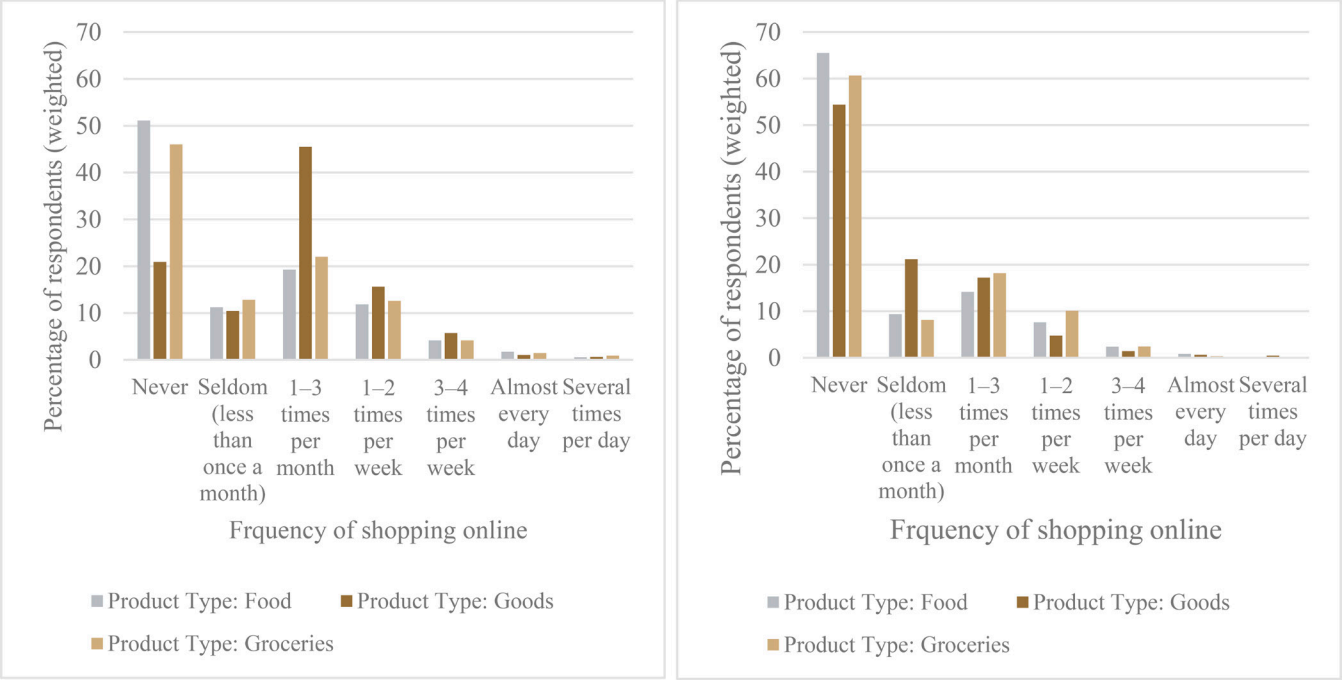


Figure 4.2 Frequency of Ordering Online for Delivery (Left) and Pickup (Right) by Product Type.

that the effects of e-commerce on travel demand are likely to be widespread rather than concentrated among a small subset of consumers.

4.5.2 Frequency of Ordering Online by Product Type

Figure 4.2 compares the frequency of online ordering for home delivery and pickup across food, groceries, and general merchandise. A clear distinction emerges between product categories. General merchandise is ordered online considerably more frequently than either groceries or prepared food, particularly through home delivery channels. The predominance of merchandise deliveries likely reflects the maturity of online retail platforms and the suitability of many consumer goods for remote purchasing. In contrast, food and grocery purchases often involve greater immediacy, perishability concerns, or preferences for in-person product selection, which may explain their lower adoption rates. Although grocery delivery and pickup services expanded substantially during and after the COVID-19 pandemic, the results suggest that they have not achieved the same level of routine use as online purchasing of consumer goods.

Another notable finding is the strong preference for home delivery over pickup across all product categories. While pickup services have received considerable attention as a means of

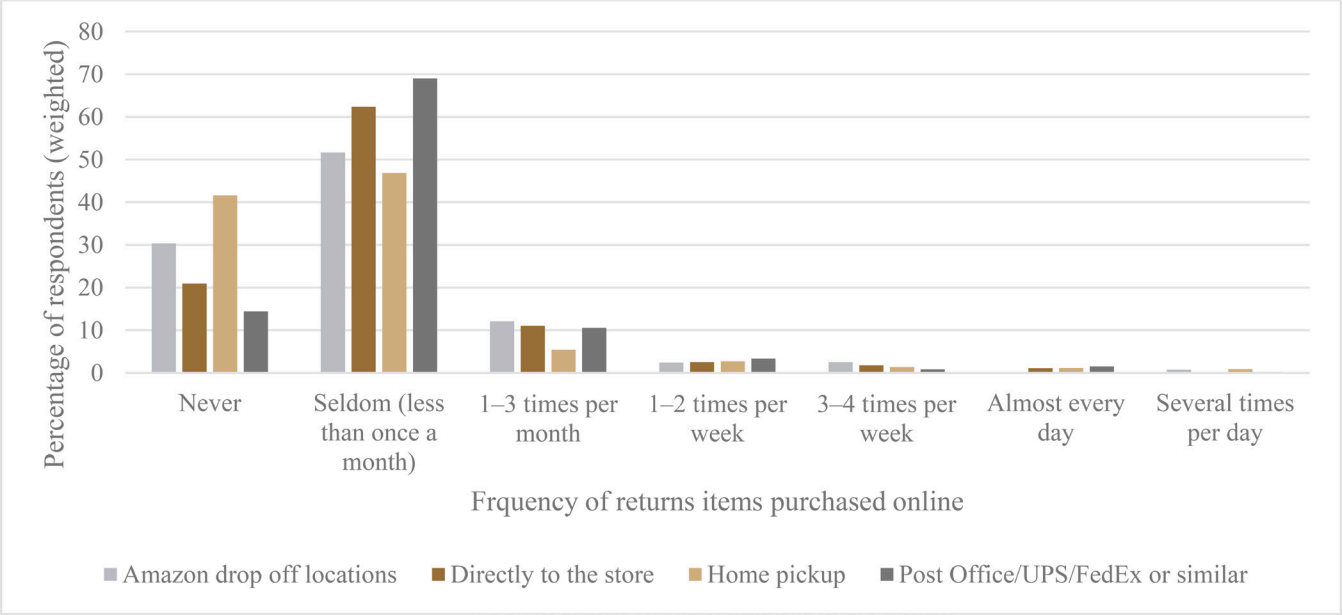


Figure 4.3 Frequency of Returning Products Purchased Online by Return Channel.

reducing delivery costs and improving operational efficiency, respondents appear to place a higher value on the convenience of home delivery. This preference has important implications for transportation systems because home delivery shifts travel activity from consumers to commercial delivery vehicles, potentially altering both passenger and freight travel patterns.

Overall, the findings suggest that e-commerce is affecting shopping-related travel differently across product categories. Goods' purchases appear more likely to substitute for traditional shopping trips, whereas grocery and food purchases continue to involve substantial in-person activity.

4.5.3 Product Return Behavior

Figure 4.3 presents respondents' use of various return channels for products purchased online. The results indicate that returns are relatively infrequent compared with purchase activity, suggesting that most online transactions are completed without generating additional return trips. Among those who do return products, traditional return channels dominate. Returns through shipping carriers and returns to physical stores were considerably more common than home pickup services. This finding highlights the continued importance of brick-and-mortar retail infrastructure within the e-commerce ecosystem. Although purchases may occur online, many consumers continue to rely on physical locations to complete the transaction process through exchanges and returns.

The preference for store-based returns may also help explain why e-commerce has not entirely replaced physical retail. Retail stores increasingly function as fulfillment, pickup, and return locations in addition to serving traditional shopping purposes. Consequently, the relationship between online shopping and travel demand is more complex than a simple substitution of online purchases for shopping trips. From a transportation perspective, returns represent a potentially overlooked component of e-commerce-related travel. While online shopping may reduce some consumer shopping trips, return-related travel and reverse logistics activities may offset a portion of these reductions.

Figure 4.4 further examines the travel behavior associated with product returns by presenting the mode used to complete return trips and the extent to which these trips are combined with other activities. Consistent with the broader shopping travel patterns observed in this study, private automobiles were the predominant mode used for return trips. However, an important finding is that a large share of respondents reported incorporating returns into trips made for other purposes rather than making dedicated return trips. This indicates that return activities are frequently trip chained with routine activities such as commuting, grocery shopping, or other errands.

The prevalence of trip chaining has important implications for evaluating the transportation impacts of e-commerce. Although product returns represent additional travel generated by online shopping, many return trips may not create entirely new vehicle trips because they are integrated into existing travel patterns. Consequently, the net travel impacts of reverse logistics at the household level may be smaller than would be expected if every return required a separate shopping trip. At the same time, these household travel savings are offset by the commercial logistics activities required to transport returned products through shipping and distribution networks. Therefore, understanding both return frequency and the travel behavior associated with returns is important for accurately assessing the overall transportation impacts of e-commerce.

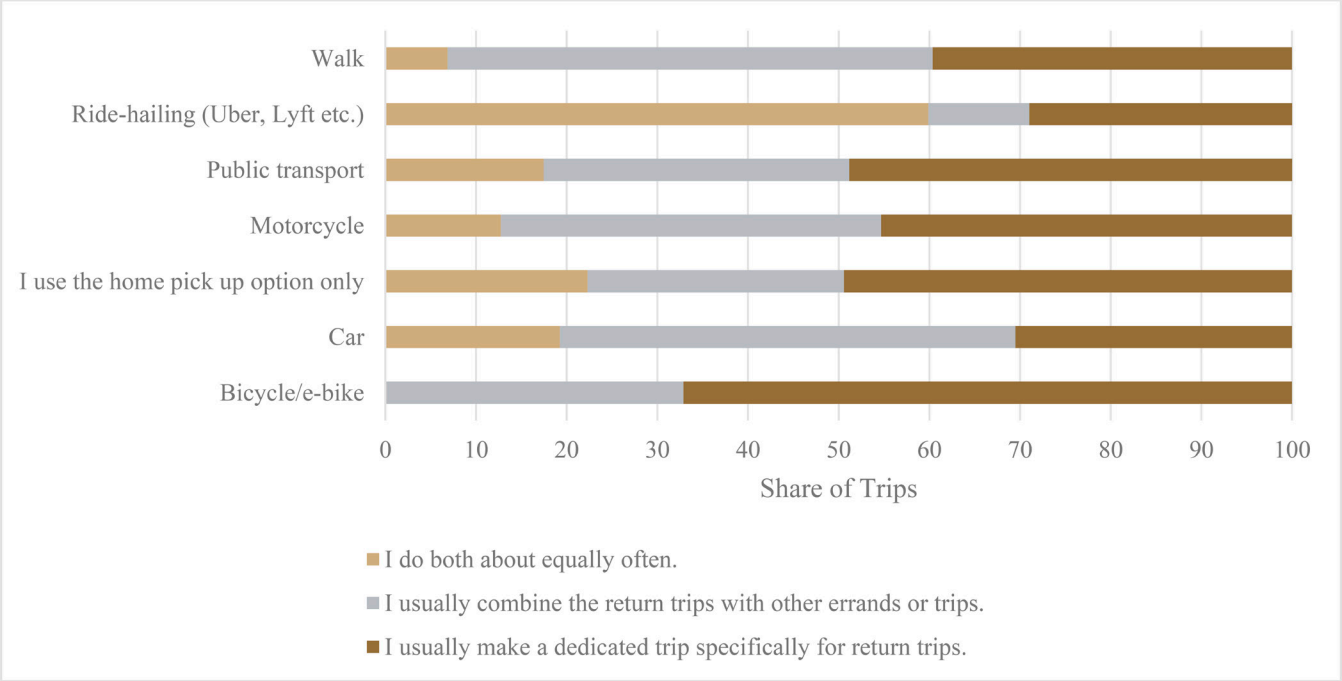


Figure 4.4 Share of Return Trips by Mode and Tendency to Trip Chain.

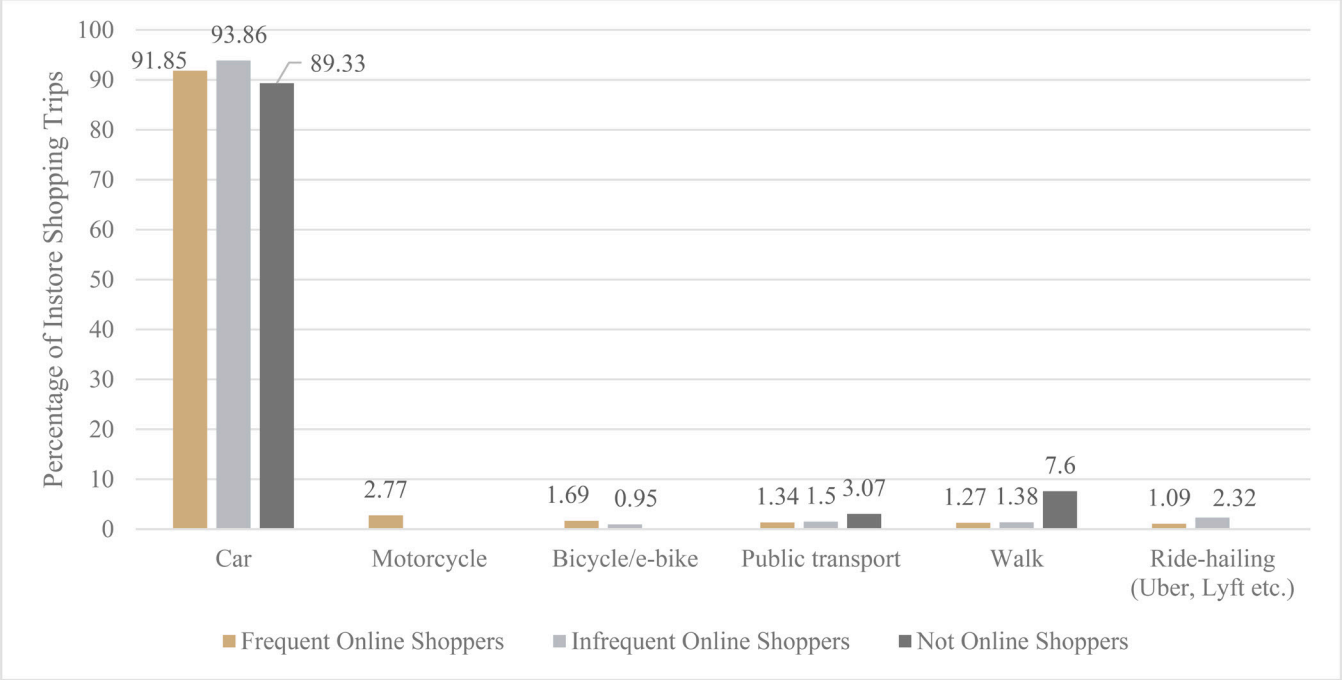


Figure 4.5 Share of Instore Shopping Trips by Shopper Type and Mode.

4.5.4 Shopping Travel Modes

Figure 4.5 and Figure 4.6 present the primary travel modes used for in-store shopping and the relationship between commuting and shopping travel modes across frequent online shoppers, infrequent online shoppers, and respondents who do not shop online. Together, these figures provide insight into whether e-commerce adoption is associated with changes in mode choice for shopping-related travel.

Across all respondent groups, private automobiles overwhelmingly remain the dominant mode for in-store shopping. More than



Figure 4.6 Share of Instore Shopping Trips and Work Trips by Mode and Shopper Type (a) Frequent Online Shoppers, (b) Infrequent Online Shoppers, and (c) Not Online Shoppers.

89% of respondents in each group reported using a personal vehicle for their most recent shopping trip, with only marginal differences observed between frequent online shoppers, infrequent online shoppers, and non-online shoppers. The similarity across these groups suggests that the adoption of online shopping has little influence on the transportation mode chosen for shopping trips.

Instead, the findings indicate that shopping mode choice is largely constrained by the broader transportation environment rather than by shopping channel. Indiana's dispersed land-use patterns, relatively low transit availability outside major urban areas, and high levels of automobile ownership mean that physical shopping trips, when they occur, continue to be predominantly automobile-based regardless of an individual's online shopping habits. Consequently, while e-commerce may reduce the need for some shopping trips, it does not appear to fundamentally alter how consumers travel to stores.

The small differences observed across the three groups are nevertheless informative. Respondents who do not shop online

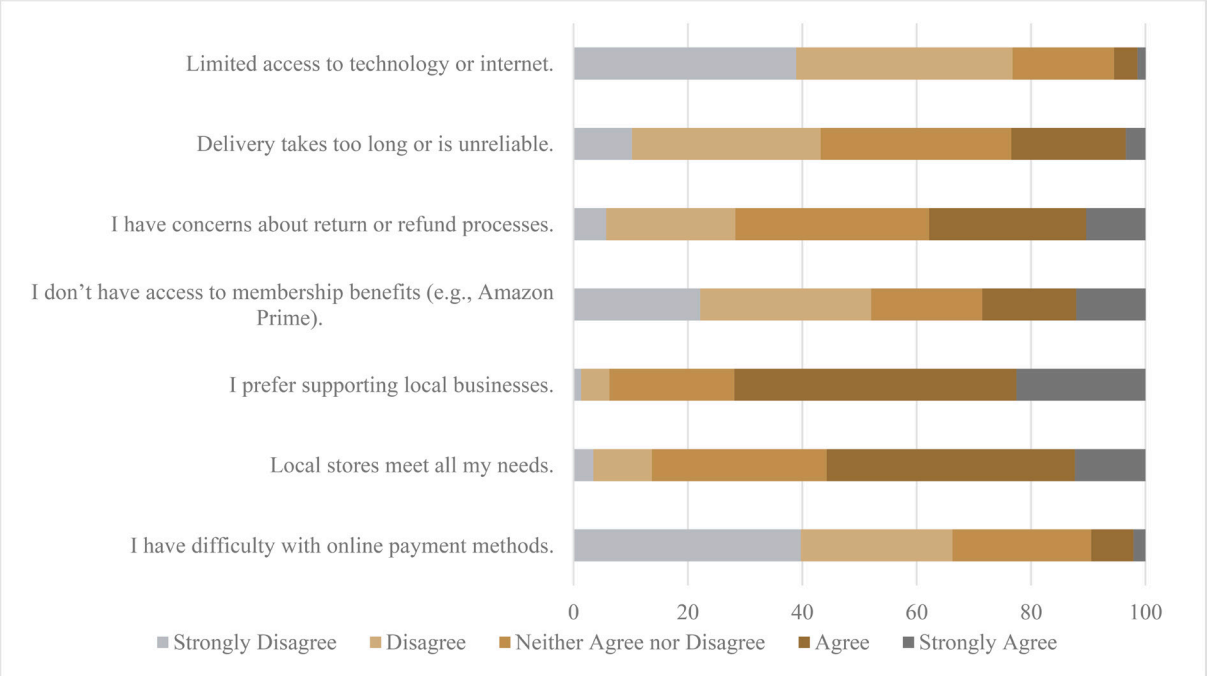


Figure 4.7 Barriers to Shop Online for Infrequent Online Shoppers.

reported slightly higher levels of walking than either frequent or infrequent online shoppers. This may reflect differences in residential location, demographic characteristics, or shopping preferences rather than the direct influence of e-commerce itself. Individuals living in more walkable environments may rely on nearby neighborhood stores and, therefore, perceive fewer benefits from online shopping, whereas residents in automobile-dependent areas may be more likely to adopt e-commerce because online shopping reduces the need to travel longer distances.

While these descriptive results cannot establish causality, they suggest that built environment characteristics may simultaneously influence both online shopping adoption and travel behavior.

The comparison between work and shopping travel modes further demonstrates the stability of individual travel behavior. Respondents who commute by private automobile overwhelmingly also shop by automobile, regardless of their level of e-commerce adoption. This strong correspondence indicates that shopping travel is embedded within broader daily activity patterns rather than representing an independent travel decision. For many households, shopping trips are likely chained with commuting or other mandatory activities, making the private vehicle the natural choice even when online shopping is frequently used for other purchases.

A more interesting pattern emerges among users of alternative commuting modes. Although some respondents commute by walking, bicycling, or public transportation, many of these individuals reported using a car for shopping trips. This suggests that shopping imposes travel requirements that differ from commuting. Retail trips often involve transporting bulky or multiple purchases, visiting stores located in suburban commercial corridors, or combining several errands into a single trip. These characteristics increase the attractiveness of automobile travel even among individuals who regularly use environmentally friendly modes for commuting. Thus, mode substitution appears to occur across trip purposes rather than across shopping channels.

Taken together, these findings indicate that the transportation impacts of e-commerce are unlikely to arise through widespread shifts in travel mode. Instead, the primary behavioral mechanisms appear to involve changes in trip generation, shopping frequency, destination choice, and the redistribution of travel from household passenger vehicles to commercial delivery fleets. This distinction is particularly important for transportation planning. If mode choice remains relatively stable while shopping frequency and freight activity change, the impacts of e-commerce will be reflected less in passenger mode shares and more in vehicle trip patterns, curbside activity, last-mile logistics, and overall network performance. Consequently, incorporating e-commerce into travel demand models requires representing behavioral changes in shopping participation and trip generation rather than assuming substantial changes in mode choice.

4.5.5 Barriers to Online Shopping Among Infrequent Online Shoppers

Figure 4.7 examines perceptions among respondents who shop online infrequently. Interestingly, the results suggest that lack of technological capability is not the primary barrier to online shopping adoption. Most respondents indicated that they believe online shopping would be easy to learn, that they have access to assistance if needed, and that online shopping would likely save time and improve convenience. Instead, the principal barriers appear to relate to trust and reliability of delivery.

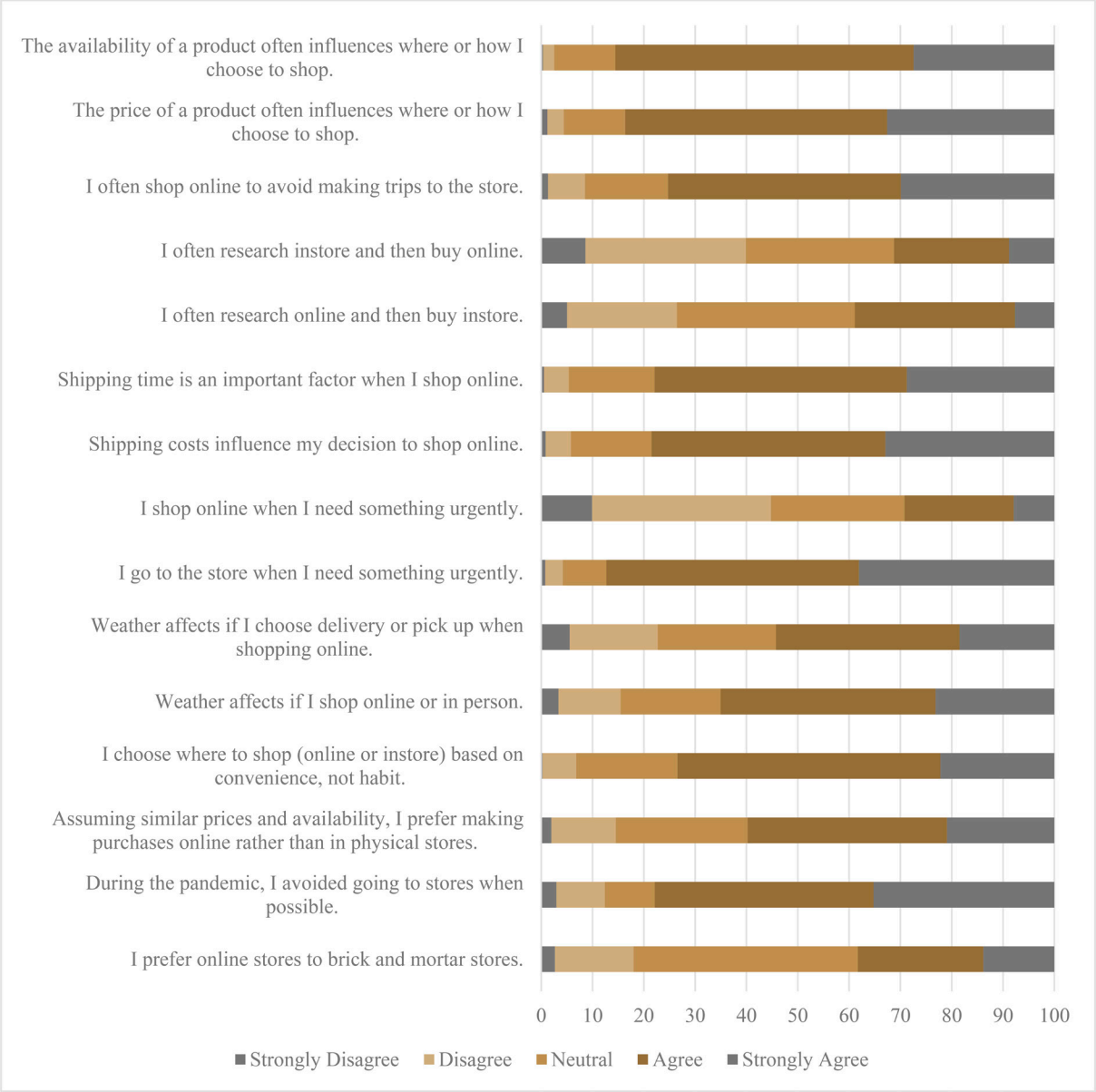


Figure 4.8 Attitudes Towards Shopping Trips: Frequent Online Shoppers.

Concerns regarding package theft and delivery errors were among the most frequently cited issues. These concerns indicate that adoption barriers have shifted from technological access and toward confidence in the delivery process and the broader online shopping experience.

This finding is consistent with broader trends in e-commerce adoption. As internet access and digital literacy have become increasingly widespread, structural barriers have diminished. Remaining resistance appears to stem more from concerns regarding risk, uncertainty, and service quality than from inability to use online platforms. The distinction is important because it suggests that future growth in e-commerce may depend less on improving access to technology and more on enhancing delivery reliability, package security, and consumer trust. Transportation and logistics systems, therefore, play a direct role in shaping the future adoption of online shopping.

4.5.6 Attitudes Toward Shopping Among Frequent Online Shoppers

Figure 4.8 presents the attitudes of frequent online shoppers. Overall, respondents expressed highly favorable perceptions of online shopping, indicating that convenience, ease of use, and perceived usefulness are key drivers of continued adoption. Frequent online shoppers reported high levels of comfort with online purchasing, satisfaction with their experiences, and strong intentions to continue shopping online in the future. These findings suggest that once consumers become accustomed to online

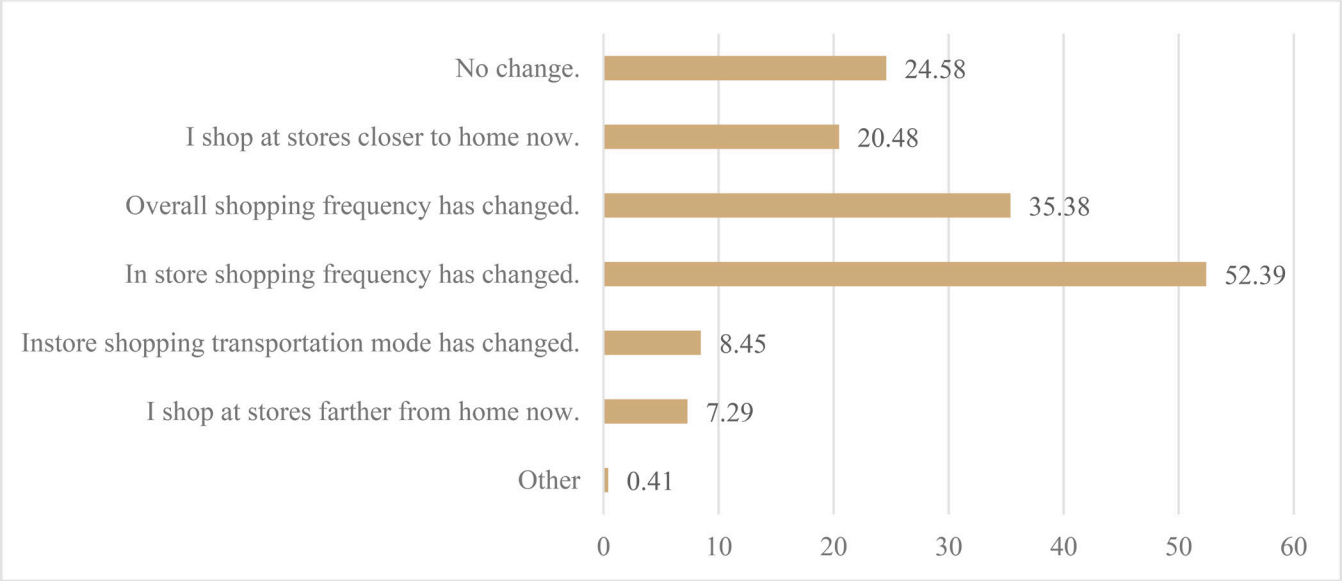


Figure 4.9 Changes to Shopping Behavior After Adopting Online Shopping.

shopping, continued use becomes highly likely. The positive evaluations reported by frequent users indicate that online shopping is not simply a temporary adaptation but has become an established component of consumer behavior.

At the same time, respondents did not appear to view online shopping as a complete replacement for physical retail. A substantial proportion continued to report enjoying visits to physical stores. This pattern suggests that online and in-store shopping often serve different purposes. While online channels may be preferred for convenience-oriented purchases, physical stores continue to provide experiential, recreational, and social benefits that cannot be easily replicated online.

This coexistence of online and in-store shopping has important implications for travel demand. Rather than eliminating shopping trips altogether, e-commerce may alter the frequency, purpose, and destination characteristics of those trips. As a result, transportation impacts are likely to involve changes in travel behavior rather than simple reductions in travel activity.

4.5.7 Changes to Shopping Behavior After Adopting Online Shopping

Figure 4.9 examines self-reported changes in shopping behavior following adoption of online shopping. The most commonly reported change was a modification in the frequency of shopping at physical stores, followed by changes in overall shopping frequency. These findings suggest that the primary effect of e-commerce is not necessarily to eliminate shopping activity but rather to reshape how consumers organize and conduct that activity. Online shopping appears to influence the timing and frequency of purchases more than it affects the basic need to shop. A notable share of respondents also reported shopping at stores closer to home after adopting online shopping. This finding may indicate that e-commerce reduces the need for consumers to travel long distances in search of product variety or availability. Instead, consumers may rely on online channels for specialized purchases while reserving in-person shopping for nearby, convenience-oriented trips.

In contrast, relatively few respondents reported changes in transportation mode. This suggests that although e-commerce may alter shopping frequency and destination choice, its influence on mode choice remains limited. In a predominantly automobile-oriented state such as Indiana, shopping trips that continue to occur are likely to remain automobile based regardless of whether consumers also shop online. Overall, the results indicate that e-commerce influences multiple dimensions of shopping behavior, but the changes are more nuanced than a simple reduction in shopping trips. Shopping destinations, trip frequency, and purchasing patterns appear to be changing alongside continued participation in traditional retail activities.

4.5.8 Changes in Overall Shopping Activity

Figure 4.10 presents respondents' perceptions of changes in their overall shopping activity after adopting online shopping. More respondents reported increases in shopping activity than decreases, suggesting that e-commerce may stimulate additional consumption rather than simply shifting purchases from one channel to another. This finding is particularly important because it challenges the common assumption that online shopping primarily substitutes for in-store shopping. While some consumers may replace physical shopping trips with online purchases, others appear to purchase more frequently once barriers associated with time, travel, and convenience are reduced. The lower transaction costs associated with online shopping may encourage more spontaneous purchases and more frequent engagement in retail activity.

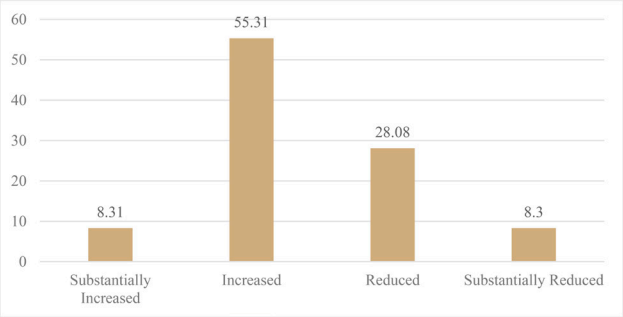


Figure 4.10 Change to Overall Shopping Behavior After Adopting Online Shopping.

At the same time, a substantial minority of respondents reported reductions in shopping activity. For these individuals, online shopping may improve efficiency by enabling better planning, purchase consolidation, and reduced need for exploratory shopping trips. The coexistence of both effects highlights the heterogeneous nature of consumer responses to e-commerce. Taken together, the results suggest that the transportation impacts of online shopping are unlikely to be uniform across the population. Some consumers may reduce shopping travel, while others may maintain or even increase overall purchasing activity. These behavioral differences underscore the importance of modeling e-commerce adoption and shopping behavior at the individual level rather than assuming a single average response across all consumers.

4.6 Summary

This chapter presented the development and implementation of an Indiana-specific e-commerce survey to support the study's objective of understanding how online shopping affects consumer behavior and travel demand. The survey was designed to collect information on online shopping participation, purchasing and return behaviors, attitudes toward e-commerce, and self-reported changes in shopping activity. The sampling approach aimed to obtain a geographically and demographically diverse sample, while the survey included both revealed preference and attitudinal questions.

Results showed that online shopping is a routine activity for many Indiana residents. General merchandise purchases were more common than online grocery or food purchases, and home delivery was preferred across product categories. Returns, however, often continued to involve physical stores or traditional logistics networks, demonstrating the continued connection between online and in-store shopping.

Attitudinal responses indicated that barriers among infrequent online shoppers are less related to technology access and more associated with package theft, delivery reliability, and transaction uncertainty. Frequent online shoppers reported high satisfaction, convenience, and continued intent to use e-commerce.

Overall, the findings show that e-commerce does not simply replace in-store shopping trips. Instead, it reorganizes shopping behavior by changing shopping frequency, destination choice, and the balance between consumer travel and delivery activity. These results provide the empirical foundation for the behavioral models developed in the next chapter and for integration into the agent-based model.

5. MODELING CHANGE IN TRAVEL DEMAND DUE TO E-COMMERCE

5.1 Overview

To assess how future e-commerce adoption may affect travel demand and behavior in Indiana, this chapter examines people's travel preferences for e-commerce and estimates the travel demand changes under alternative adoption scenarios. The survey results introduced in Chapter 4 serve as the main inputs to model such travel behavior changes. Indianapolis was selected as the case study region to align with the surveyed resident population described in Chapter 4 and because of the availability of relevant data.

This chapter first uses NHTS data and consumer shopping records to establish the synthetic trip chains of individuals in years 2017 and 2022. Then, using econometric models informed by the survey data, we characterize heterogeneous shopping preferences through a three-layer decision tree and identify market segments associated with e-commerce adoption. We then developed optimization models for on-demand food delivery and consolidated parcel delivery to estimate the VMT under different e-commerce delivery scenarios. Next, we extend the Integrated Traditional and Transformative Transportation System Use (ITTTS) Model, developed in a previous INDOT-funded project (H. Luo et al., 2022). The extended model is updated from the previous version by incorporating e-commerce-related behaviors, including product returns, in-store pickup of online orders, and additional delivery demand. It can, therefore, evaluate how different future e-commerce adoption scenarios may affect passenger travel, e-commerce deliveries, and overall VMT.

5.2 Literature Review

5.2.1 The Impact of E-Commerce Adoption on Shopping Activities

The rapid expansion of e-commerce has made online shopping an increasingly critical component of household daily activities. Previous studies have examined e-commerce market segmentation and shown that the effects of e-commerce on online and in-store shopping behavior can vary substantially across households and individuals. Cao et al. (2012), for example, used survey data from the Minneapolis–St. Paul region and applied structural equation modeling to examine the relationships among online product search, online purchasing, and traditional store shopping. Their results indicate that online search and online purchasing can reinforce in-store shopping under some conditions. Therefore, instead of replacing in-person trips, online shopping could stimulate more shopping trips, increasing vehicle usage. Dias et al. (2020) estimated a multivariate ordered probit model based on preferences data to

analyze online and in-person participation in grocery, nongrocery and meal-related activities. Their study investigated how shopping frequency varies with household characteristics and examined the extent to which online and in-store shopping function as complements or substitutes. The results indicate that online shopping is more common for utilitarian shopping purposes, whereas in-person shopping remains more prevalent for leisure-oriented shopping activities. Shah et al. (2021) used a latent class model to identify shopper segments based on online shopping behavior and daily travel patterns. They then applied a multinomial logit model to examine how demographic, built environment, and lifestyle characteristics were associated with different shopper types. By integrating travel behavior data from the NHTS with household demographic and socioeconomic data from the American Community Survey (ACS), the study found evidence of both substitution and complementarity between online and in-store shopping. Frequent online shoppers tended to make fewer in-store shopping trips, suggesting a substitution effect, whereas dual-channel shoppers showed higher levels of both online and in-store shopping activity, indicating a complementary relationship. The interaction between delivery demand and store-based shopping also differs by product category and travel mode. Kim and Wang (2021), using New York City mobility survey data, examined retail, grocery, and food deliveries together with in-store shopping trips made by driving and walking. Their results show that the relationship between delivery frequency and store-visit frequency is not uniform: delivery can substitute for some in-person trips while complementing or coexisting with others, depending on delivery type and the mode used for in-store shopping.

The aforementioned studies have reported mixed effects of e-commerce on shopping activities. These shopping demand changes cannot be inferred from online shopping frequency alone. The travel demand shift should be assessed based on different characterizations, such as trip purpose, travel mode, trip distance, and shopping opportunities distributed across a city, to better support transportation planning.

5.2.2 The Impact of E-Commerce on Net VMT

Existing studies have investigated how online shopping services affect VMT after e-commerce is adopted, which translates shopping activity shifts into VMT changes. Suel and Polak (2017) jointly modeled shopping channel, store destination, and travel mode for grocery shopping in London. Their framework treats online shopping as one alternative within a broader choice set that also includes physical stores and travel modes. They found that online shopping was attractive to higher-income early adopters, and that deliveries mainly replaced driving trips, with limited substitution of walking and public transit trips. However, even though their study used trip-level data and mode choice to estimate the VMT effects of e-commerce, it considered only avoided household shopping VMT and omitted the additional delivery-vehicle VMT. Therefore, the net impact on travel demand remained unclear. Stinson et al. (2019) developed an integrated modeling and simulation framework to assess the citywide effects of e-commerce by accounting for both reduced household shopping trips and additional parcel delivery truck movements. Their study shows that e-commerce can reduce passenger shopping VMT, but the net system effect depends on delivery tour efficiency, market penetration, delivery density, and the extent to which online orders actually replace household shopping trips. Furthermore, Jaller et al. (2023) developed a modeling framework to estimate future changes in shopping behavior, last-mile deliveries, and related externalities, emphasizing that future e-commerce impacts depend on household behavior, delivery options, and the evolution of residential delivery demand.

These studies indicate that the net VMT impact of e-commerce is determined by two sides. On the passenger side, online shopping may reduce, induced, or leave unchanged household shopping trips, depending on shopper type, mode, destination, and trip chaining. On the freight side, online orders can generate delivery vehicle tours whose VMT depends on route density, consolidation, service frequency, and delivery time windows. A complete assessment, therefore, requires estimating both changed passenger VMT and added delivery VMT within the same analytical framework.

5.2.3 The Heterogeneity of Food, Grocery, and Goods Delivery

Online deliveries for different product categories are typically fulfilled through distinct delivery modes and transportation networks operated by different e-commerce platforms and logistics providers. In particular, food, grocery, and retail goods delivery differ in service requirements, order characteristics, and routing structures. Prior research on home delivery and shopping trips has shown that delivery impacts vary across product categories and household characteristics such as income and the presence of children, reinforcing the need for category-specific modeling (Spurlock et al., 2020). Moreover, W. Zhang et al. (2019) notes that operational efficiency depends heavily on consolidation, routing, delivery density, and the availability of alternative delivery locations such as parcel lockers or pickup points. These differences justify modeling food, grocery, and retail goods delivery separately when evaluating VMT changes associated with e-commerce.

5.2.4 The Return Activities of Online Shopping

In addition to the initial purchase and delivery process, online shopping can generate additional travel through product returns, exchanges, and pickup-related activities. Prior studies on e-commerce and travel demand have shown that online shopping does not have a single directional effect on travel. It may substitute for in-store shopping trips, complement existing shopping activities, modify trip timing and chaining, or have no systematic effect on travel behavior (Le et al., 2022; Spurlock et al., 2020).

Retail and operations studies have shown that return policies influence both purchase and return decisions, and consumer returns have become a major issue in online retailing and reverse logistics (Janakiraman et al., 2016). From a transportation perspective, returned online purchases create reverse flows from consumers back to retailers, carriers, or consolidation facilities.

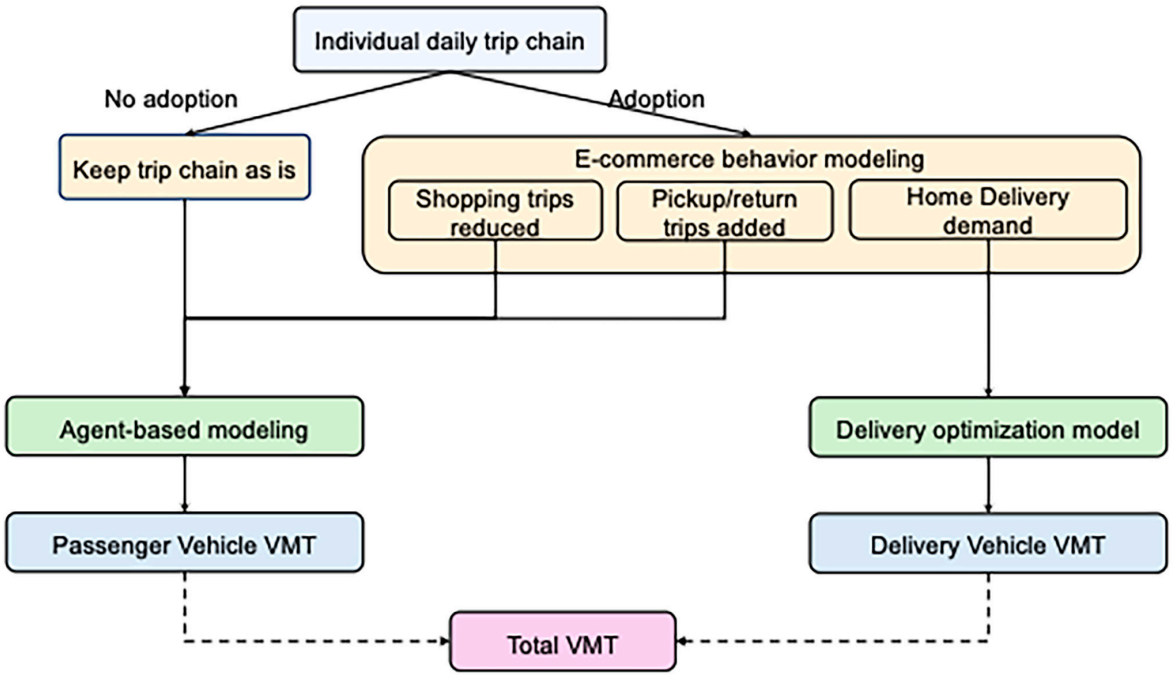


Figure 5.1 E-Commerce Travel Behavior Modeling Framework.

These flows may occur through home pickup, in-store return, post office or carrier drop-off, parcel lockers, or other pickup and drop-off locations.

These findings motivate an integrated modeling approach that combines local stated-preference survey data with travel demand modeling. Survey data can be used to estimate probabilistic e-commerce adoption and behavioral response parameters, while travel demand models can apply these probabilities to individual trip chains.

5.3 Methodology

This section describes the modeling framework used to estimate changes in travel demand associated with e-commerce adoption. The framework combines five components: baseline person-level trip chains, agent-based modeling, probabilistic survey-based e-commerce behavior adjustment, data-driven motif for trip insertion, and delivery optimization models. As a result, this framework allows for evaluating e-commerce based on an integrated passenger-and-delivery perspective. The total VMT with e-commerce considered, therefore, includes both passenger VMT and delivery VMT. The passenger VMT is estimated from modified daily trip chains, while delivery VMT is estimated from optimized delivery routes generated by online orders and return activities.

The overall framework is illustrated in Figure 5.1. The original ITTTS model uses individuals' daily trip chains as inputs to the agent-based model to evaluate passenger-side VMT, without explicitly accounting for the impacts of e-commerce. This study extends the ITTTS framework by adding an e-commerce behavior modeling layer to the existing agent-based travel demand simulation. The added layer captures trip-chain modifications associated with e-commerce adoption. If an individual does not adopt e-commerce, the original trip chain is preserved and evaluated directly using the agent-based modeling. If e-commerce adoption is assigned, the trip chain enters the e-commerce behavior module, where shopping trips may be reduced, pickup or return trips may be inserted, and home-delivery orders may be generated.

5.3.1 Online Shopping Market Segmentation and Probability Assignment

The e-commerce adoption behavior module uses survey data to convert answers related to shopping preferences into individual-level behavioral probabilities. These probabilities serve as the key inputs for determining whether an individual would like to adopt e-commerce, how their shopping frequency changes after adoption, and which online shopping fulfillment channels they are likely to use.

Survey data were used to translate observed e-commerce preferences into individual-level behavioral probabilities for the agent-based model. To align with the hierarchical decision structure of the framework shown in Figure 5.1, a two-stage modeling approach was developed (Figure 5.2). In the first stage, respondents were classified according to their expected change in overall shopping frequency after adopting online shopping, including reduced, unchanged, and increased shopping activity. In the second stage, latent class analysis was applied within the relevant frequency-change groups to identify shopper segments with distinct online shopping, pickup, delivery, and product-category preferences. The resulting behavioral probabilities were then assigned

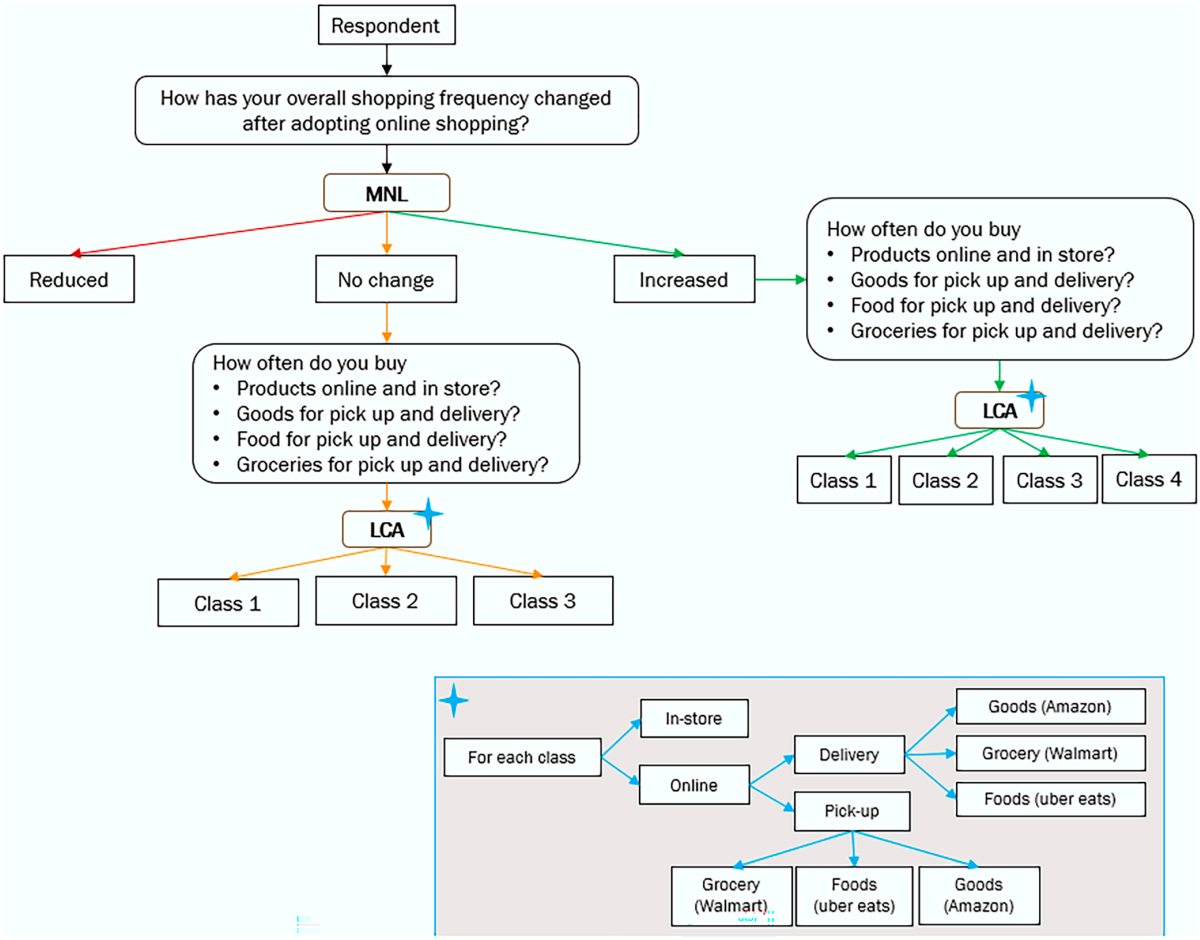


Figure 5.2 Two Stage Modeling Structure Used to Develop Individual Behavioral Probabilities for the Agent-Based Model.

to synthetic persons through demographic matching, allowing the model to represent heterogeneous e-commerce adoption and shopping behavior across individuals. More details of each stage's analysis are provided in Figure 5.2.

In the first stage, the complete weighted survey dataset was used to model whether respondents adopted e-commerce and how their overall shopping frequency changed after adoption. E-commerce adoption was first identified using Question 6, which asks respondents about their online shopping frequency (Appendix C). Respondents who selected "Never" were classified as nonadopters, while all other respondents were classified as e-commerce adopters. For adopters, Question 53 was then used to characterize the direction of shopping-frequency change since adopting online shopping. The original response categories were recoded into three outcomes: Reduced, No Change, and Increased. These outcomes were used as the dependent variable in a weighted multinomial logit model (MNL) estimated in R. MNL is commonly used for unordered discrete outcomes and is grounded in random utility theory, where each respondent is assumed to associate a latent utility with each possible outcome, and the observed outcome is assumed to be the one that provides the highest utility (McFadden, 1974; Train, 2009).

For respondent i and outcome category j, the utility is specified as:

$$U_{ij} = \beta_j X_i + \varepsilon_{ij} \qquad \text{Equation 5.1}$$

where U_{ij} represents the utility associated with outcome j for respondent i; X_i is a vector of observed respondent characteristics; β_j is a vector of category-specific parameters; and ε_{ij} is a random error term. Under the standard multinomial logit specification, the probability that respondent i belongs to category j is expressed as:

$$P_{ij} = \frac{\exp\left(\beta_j X_i\right)}{\sum_k \exp\left(\beta_k X_i\right)} \qquad \text{Equation 5.2}$$

Where P_{ij} is the probability of respondent i being classified into category j, and the summation is taken over all possible outcome categories k. One category is treated as the reference category for model identification. The model parameters are estimated using maximum likelihood estimation. The estimated model produces predicted probabilities for each respondent of belonging to the Reduced, No Change, and Increased categories.

These probabilities are then used to classify respondents into the appropriate branch of the subsequent modeling structure.

All trips made by respondents classified as Reduced were automatically considered to be replaced by e-commerce (Figure 5.1) and so were not classified further. The next stage focuses on modeling online shopping behavior among respondents, whose overall shopping frequency either increased or remained unchanged, to assign probabilities for the changes to behavior. Respondents classified as Increased are assigned to Subset A, while respondents classified as No Change are assigned to Subset B. Similarly, nonadopters are assigned to the no-e-commerce branch of the agent-based simulation. Their trip chains stay the same with no change and are directly input to agent-based modeling.

In the second stage, separate latent class analysis (LCA) models were estimated for Subset A and Subset B using the software LatentGold. LCA is a finite-mixture modeling approach used to identify unobserved, or latent, subgroups within a population based on observed response patterns (Goodman, 1974; McCutcheon, 1987; Vermunt & Magidson, 2004). In this study, LCA is used to identify market segments of shoppers with distinct online shopping behavior patterns within each frequency-change group.

The LCA framework assumes that the population is composed of a finite number of mutually exclusive and exhaustive latent classes. Individuals within the same latent class are expected to have similar behavioral response patterns, while individuals in different classes are expected to differ in their probabilities of engaging in specific shopping behaviors. A key assumption of LCA is local independence, which means that once latent class membership is accounted for, the observed behavioral indicators are assumed to be statistically independent of one another.

The LCA model is estimated based on Equation 5.3:

For respondent i, the probability of observing a particular response pattern Y_i is expressed as:

$$P(Y_i|X_i) = \sum_{c=1}^{C} P(c \mid X_i) \prod_{j=1}^{J} P(Y_{ij|c}) \quad \text{Equation 5.3}$$

where each agent $i = 1,2,\ldots,N$ includes sociodemographic attributes X_i and indicator variables j. If agent i is classified to be in latent class c based on indicator variable j, Y_{ij} is equal to 1, otherwise, 0.

For the latent class analysis, survey respondents who reported adopting e-commerce were first grouped according to their reported change in overall shopping frequency after adopting online shopping. Three mutually exclusive subsets were defined: respondents who reported an increase in shopping frequency (Subset A), respondents who reported no change (Subset B), and respondents who reported a decrease in shopping frequency (Subset C). This stratification allowed the latent class analysis to identify behavioral segments within each shopping-frequency response group, rather than assuming that all e-commerce adopters share the same underlying shopping and fulfillment patterns.

The estimated LCA models produce class-membership probabilities for each respondent and class-specific probabilities for online shopping behavior by mode and channel. These outputs are then used to predict class membership for agents in the agent-based model and to assign behavioral probabilities associated with online shopping mode and channel choice. The latent classes estimated for Subset A represent market segments among shoppers whose overall shopping frequency increased after adopting online shopping. The latent classes estimated for Subset B represent market segments among shoppers whose overall shopping frequency did not change.

The fitted MNL model is used to generate predicted probabilities of shopping-frequency-change outcome for each agent: Reduced, No Change, and Increased. These predicted probabilities represent the likelihood that each individual or agent belongs to each frequency-change category, conditional on the explanatory variables included in the model. The predicted category was then used to determine the appropriate branch of the hierarchical behavioral model. Respondents or agents predicted to belong to the Reduced category were excluded from the next stage of behavioral segmentation, while those predicted to belong to the Increased and No Change categories were passed to the corresponding latent class models.

The latent class analysis models were then used to estimate posterior class-membership probabilities within each subset. For each respondent or agent, the LCA model provides the probability of belonging to each latent shopper segment, based on the observed characteristics and behavioral indicators used in the model. In addition, each latent class is associated with class-specific probabilities for online shopping behavior by mode and channel. These class-membership probabilities and class-specific behavioral probabilities were used to assign agents to shopper segments and to generate online shopping behavior inputs for the agent-based model.

5.3.2 Shopping Trips Identification

Since e-commerce is most likely impacting shopping behaviors, identifying the (non)shopping trips from the original trip chain is critical to simulate varying scenarios that change the shopping behavior. Trip chains without shopping trips may have additional return trips for the items purchased online or pickup trips for orders placed online. In-store shopping trips in the original trip chains are likely adjusted to other types of shopping behaviors due to the impact of e-commerce.

Shopping trips were identified using the trip-purpose variable *Purpose*. The separation of shopping trips from a trip chain is illustrated in Figure 5.3. Following the NHTS codebook, a trip was classified as a shopping trip if its *Purpose* is coded as 40. For each synthetic person in the NHTS trip chains, trips are sorted chronologically by start time to preserve the daily activity-travel sequence. When a shopping trip was detected, its destination coordination was recorded as a shopping location and trip end time was recorded as the shopping time.

Since each traveler's shopping trips may be affected by e-commerce, the identified shopping trips are isolated from each traveler's trip chain to construct a counterfactual trip chain without shopping travel. The merged trip preserved the origin and departure time of the first shopping trip but used the destination and purpose of the next nonshopping trip, thereby representing a direct movement that bypasses the shopping stop. The travel

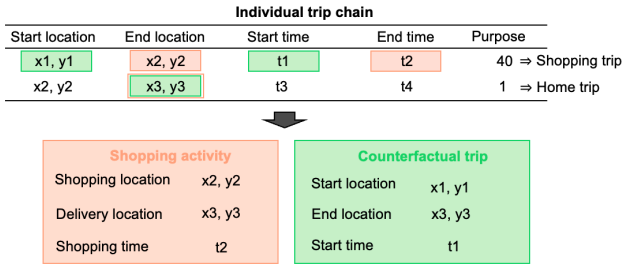


Figure 5.3 Extraction of Shopping Activities and Construction of Counterfactual Trips From Individual Trip Chains.

distance, duration, and arrival time of the merged trip were recalculated later using route planning in the agent-based simulator. For each removed shopping trip, the delivery destination for the purchased item was assigned to the nearest home destination within the same trip chain when a home trip (*Purpose* = 1) was available; otherwise, the final destination of the trip chain was used as a fallback delivery location.

5.3.3 Shopping Trip Adjustment to Account for E-Commerce Adoption

Each identified shopping trip in Section 5.3.2 is processed through a hierarchical decision structure from the survey-based latent class results to account for the potential shopping behavior change due to e-commerce. Customers may adjust their shopping behavior in response to the introduction of e-commerce, with the extent of adjustment varying by individual demographic characteristics. The original average-day trip chains constructed from the NHTS data include only in-store shopping trips. Therefore, the shopping activities within these trip chains may be modified to reflect potential behavioral adjustments associated with e-commerce adoption, including shifts from in-store shopping to online shopping, reductions in in-store shopping frequency, or additional online shopping activity.

To capture these behavioral adjustments and their associated probabilities, we developed a hierarchical probabilistic decision tree, as shown in Figure 5.4, in which every shopping trip is routed through four decision layers: (1) whether the number of shopping trips is reduced, kept unchanged, or increased; (2) whether an in-store shopping trip is substituted by online shopping; (3) whether the online shopping activity is fulfilled through pickup or delivery; and (4) which delivery mode is used. The adjustment probability was derived from the survey results described in Chapter 4. Specifically, individuals in the synthetic population based on the NHTS data were matched with e-commerce survey participants based on demographic characteristics, and the corresponding probabilities were assigned accordingly as described in Section 5.3.1.

The first layer estimates how individuals' overall shopping frequency changes after adopting online shopping. Specifically, the probabilities of reducing, keeping unchanged, and increasing shopping frequency are denoted by $\pi_1(i), \pi_2(i)$ and $\pi_3(i)$, respectively, for latent class i, where $\pi_1(i)+\pi_2(i)+\pi_3(i)=1$. Question 53 was used to calculate the relative probabilities among $\pi_1(i)$, $\pi_2(i)$ and $\pi_3(i)$ for each latent class. "Reducing" indicates that the original shopping trip is removed from the individual's average-day trip chain. "Keeping unchanged" indicates that the original average-day shopping trip is retained, although its shopping mode may change. "Increasing" indicates that one additional online shopping activity is generated in addition to the original shopping trip.

The second layer determines whether an existing in-store shopping trip is replaced by online shopping. For trips classified as "keeping unchanged," as well as the original trips associated with the "increasing" case, each shopping trip in latent class i is assigned as either an in-store trip with probability $p_{in-store}(i)$ or an online shopping activity with probability $p_{online}(i)$, where $p_{in-store}(i)+p_{online}(i)=1$. These probabilities are calculated based on the relative frequency ratio between Q6 and Q45, after mapping weekly shopping frequencies to daily frequencies. We do not generate additional in-store shopping trips, under the assumption that the NHTS data already fully capture individuals' in-store shopping activities.

Each online trip is then split between pickup and delivery fulfillment in the third layer. We estimate this split using Q30

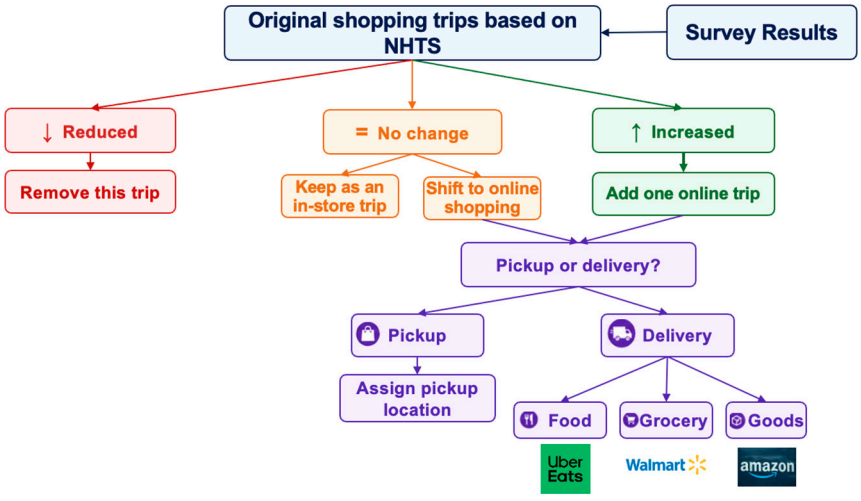


Figure 5.4 The Hierarchical Decision Tree to Adjust Personal Shopping Trips.

(delivery frequency, asked separately for food, grocery, and goods) and Q32 (pickup frequency, asked over the same three product categories), which together provide a complete fulfillment-by-product frequency matrix for each class. The probabilities of using pickup and delivery modes are denoted by $p_{pick}(i)$ and $p_{drop}(i)$, respectively, for each latent class i. Although pickup is considered an online shopping activity, customers still travel to a physical store to collect their orders. Therefore, we assume that a pickup trip follows the same origin-destination pair and start and end times as the corresponding in-store shopping trip in the original trip chain, rather than generating a new travel pattern.

The fourth layer assigns each delivery trip to one of three product categories, which determines the corresponding delivery mode. The probabilities of food, grocery, and goods delivery are denoted by $p_f(i)$, $p_g(i)$, *and* $p_o(i)$, respectively, and are estimated based on Q30. Specifically, food delivery is fulfilled by on-demand delivery services, such as Uber Eats and DoorDash. Grocery delivery is assumed to be fulfilled through store-based delivery, represented by Walmart Supercenter. Goods delivery is assumed to be fulfilled through distributed hub-based delivery offered by Amazon last-mile delivery. Additionally, a grid-based local charged-delivery company is assumed for both grocery and goods delivery to represent versatility in delivery mode.

5.3.4 Intracity Delivery Model for Parcel and Food

Shopping trips identified in Section 5.4.1.4 as being replaced by online delivery are converted into delivery demand according to their assigned delivery modes. Online orders are fulfilled through varying e-commerce delivery modes, depending on order type and delivery urgency, leading to potentially different implications for a city's VMT. Two major delivery modes are consolidated parcel delivery and on-demand food delivery (Greening et al., 2023; X. Zhang et al., 2026). More specifically, consolidated parcel delivery typically serves goods and grocery orders. These orders are collected over time throughout the day before an order cutoff time and then shipped together through scheduled delivery routes (Boysen et al., 2019). In contrast, on-demand food delivery dispatches couriers to restaurants to pickup orders and deliver them shortly when each order is ready, minimizing customer wait time (Yildiz & Savelsbergh, 2019). In this study, we apply two optimization models, one for each delivery mode, to estimate their corresponding VMT.

5.3.4.1 Consolidated Parcel Delivery. Consolidated parcel delivery is modeled as an offline capacitated vehicle routing problem (CVRP). All parcel orders generated within a scenario are accumulated before a cutoff time and jointly routed through a fleet of delivery vehicles (e.g., trucks and vans). Each order is represented by the original in-store shopping location and the home delivery, which is the final delivery stop. As the in-store shopping is substituted by parcel delivery, each route starts from the assigned depot carrying a batch of items, visits each home delivery location once, and returns to the same depot. Each delivery is assumed to have one item. Orders depart from the depot to the home locations directly. The model estimates

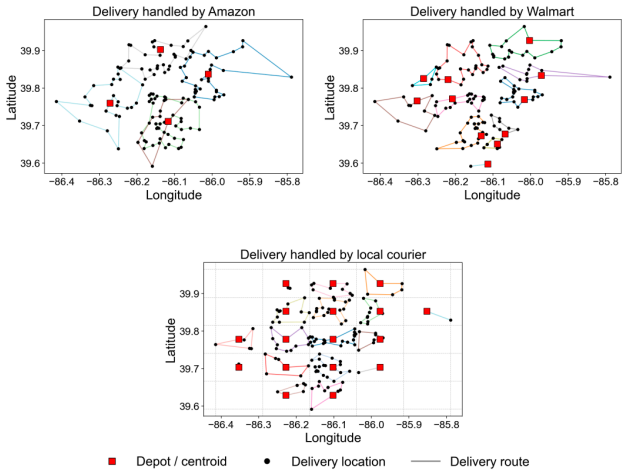


Figure 5.5 Examples of Consolidated Delivery Modes.

delivery VMT by first assigning orders to depots and then solving a route optimization problem for each depot-level delivery batch. In implementation, routes are solved using Gurobi. The objective is to minimize total route distance:

$$\min \sum_{i \in V} \sum_{j \in V, j \neq i} d_{ij} x_{ij} \qquad \text{Equation 5.4}$$

Where V includes the depot and all delivery stops in route. d_{ij} is the distance between two locations i and j and is computed using a flat-earth Euclidean approximation based on the coordinates of locations. Each delivery vehicle is assumed to have a capacity limit of 50 items for each route in this study.

This study considers three base parcel delivery structures as illustrated in Figure 5.5, which together form a complementary delivery market serving the population. First, the store-based strategy represents grocery fulfillment from depots like Walmart Supercenters. Existing Walmart Supercenter locations in the Indianapolis metropolitan area are treated as fixed depots, and this study identifies 14 Supercenters. Each parcel order is assigned to the Supercenter nearest to the home delivery location. If the number of assigned orders exceeds the assumed vehicle capacity, the orders are split into multiple delivery routes.

Second, the distributed-hub strategy represents an Amazon-like last-mile delivery station system. Depot locations are generated synthetically using K-means clustering on the original shopping locations in this study. The number of clusters is determined by the required number of delivery vehicles under the assumed vehicle capacity. The centroid of each cluster is treated as a delivery station, and all orders assigned to that cluster are delivered to their corresponding home locations.

Third, the grid-based local courier strategy represents smaller local delivery operators with neighborhood-scale service areas. The study area is divided into a $N \times N$ grid, with $N = 5$ in this study and each grid is 7 mi × 6 mi. Each grid cell defines one local service area, and the grid-cell centroid is used as the depot. Orders are assigned based on their home delivery locations, so each local courier route serves homes within the same spatial cell.

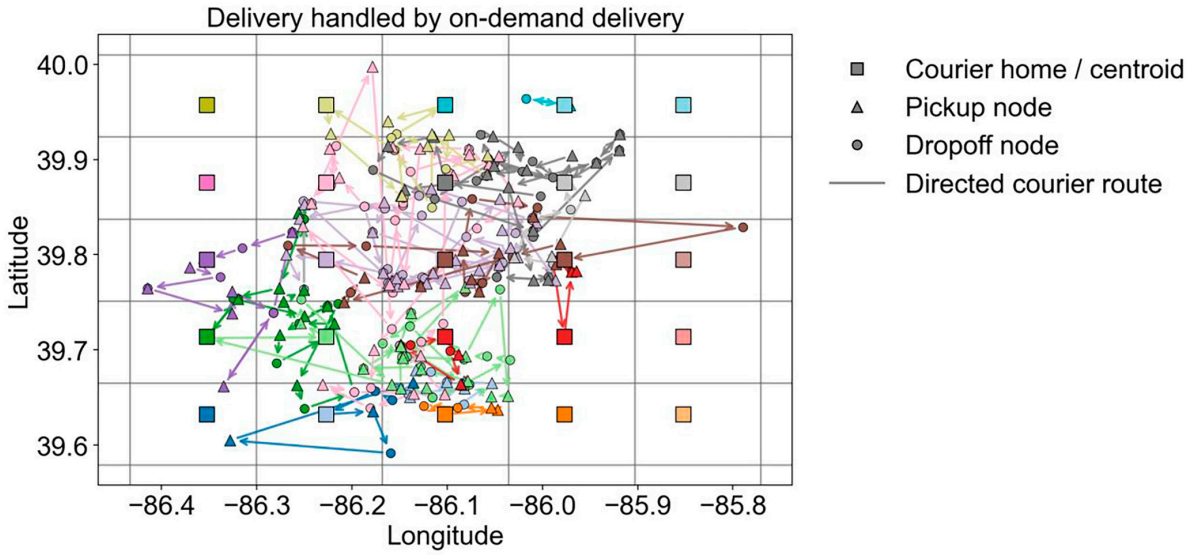


Figure 5.6 An Example of On-Demand Food Delivery Routes.

As the market is typically not dominated by a single company, the competing-provider strategy represents a market in which Amazon-like hubs, Walmart Supercenters, and local couriers simultaneously serve parcel demands. Each identified delivery demand has different probabilities to be served by one of the three delivery modes. Depots for all three systems are first determined independently using the full demand set as described above. Each order is then assigned probabilistically to one of the three providers according to exogenously specified market shares, such as equal shares across Amazon, Walmart, and local couriers. Conditional on the selected provider, the order is assigned to the nearest depot within that provider's predefined depot network. This preserves the spatial structure of each provider while allowing parcel demand to be split across competing delivery systems.

5.3.4.2 On-Demand Food Delivery. On-demand food delivery is modeled as a multicourier pickup and drop-off with time windows (MCPDTW), which is illustrated in Figure 5.6. Unlike consolidated parcel delivery, where orders are pooled and routed after a cutoff time, food delivery orders are released throughout the day and must be picked up shortly after preparation and delivered within a customer-wait-time window.

Each food order o is represented by a pickup location p_o, a drop-off location d_o, and an order placement time r_o. The order placement time is assumed to be the shopping time identified in Section 5.3.2; the original shopping location is used as the pickup location, and the home delivery location is used as the drop-off place. A constant preparation time P is added to the order placement time to define the ready time: $a_o^p = r_o + P$. The pickup time window is $\left[a_o^p, b_o^p\right] = \left[r_o + P, r_o + P + W_p\right]$, where W_p is the allowable pickup window duration. The earliest drop-off time is assumed to be the ready time plus direct travel time from pickup to drop-off: $a_o^d = r_o + P + d_{p_o,d_o}$ and the drop-off time window is $\left[a_o^d, b_o^d\right] = \left[a_o^d, a_o^d + W_d\right]$.

Because the full MCPDTW problem is computationally expensive for daily-scale scenarios using the commercial solver, the model is solved heuristically through local search (Li et al., 2016; Song et al., 2020). Orders are first sorted chronologically by ready time. A greedy insertion heuristic assigns each new order to the feasible courier and pickup–drop-off insertion position that produces the smallest increase in route cost. The initial solution is then improved using local-search neighborhoods, including order relocation, paired relocation, intraroute reinsertion, short route reversal, block moves, swaps, and tail exchanges. Each candidate's move is replayed through the simulator, and only moves satisfying all time-window, precedence, capacity, and return constraints are accepted. The final improved solution provides the estimated on-demand food delivery VMT for the scenario.

5.3.5 Product Return Trip Generation and Motif-Based New Trip Insertion

New trips, including product-return trips and in-store pickup trips, are inserted into existing trip chains based on the corresponding behavior probabilities. For product-return trips, we first identify the candidate drop-off locations within the studied area (Indianapolis). We select UPS, USPS, FedEx, Amazon drop-off hubs, and Walmart Supercenters as candidate return points through Google Maps. These return drop-off locations are illustrated in Figure 5.7. To further determine the location for each individual's return trip from these candidates, we first identify the nearest location in each of the five return-point categories relative to the individual's home location. The actual return point is then randomly selected from these five category-specific nearest candidates.

The probability of generating a return activity is derived from the survey questions related to online purchase returns. Specifically, Q41 is used to identify whether a respondent has

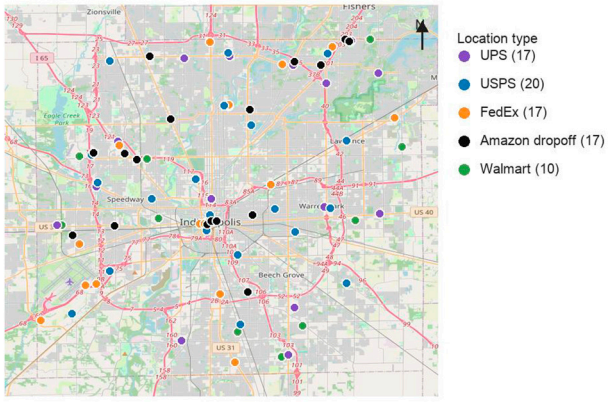


Figure 5.7 Candidate Return Drop-Off Locations for UPS, USPS, FedEx, Amazon, and Walmart Within Marion County.

ever returned an online purchase. For respondents with return experience, Q42_1–Q42_4 are used to characterize the return channel and frequency: Q42_1 corresponds to home pickup, Q42_2 to carrier or post-office drop-off locations such as UPS, USPS, and FedEx, Q42_3 to Amazon drop-off locations, and Q42_4 to store return locations, represented by Walmart in this scenario. The reported frequencies are converted into daily probabilities and assigned to individuals based on their demographic group. If a home-pickup return is generated, meaning that a courier visits the customer's home to collect the returned package, it is treated as a delivery-side pickup demand; if a physical drop-off return is generated, meaning that the traveler returns the package by visiting a physical drop-off location, a return trip is inserted into the individual's daily trip chain using the motif-based insertion procedure, which is explained in the next subsection.

5.3.5.1 New Trip Insertion Based on Motif. The results and insights into motifs from Chapter 3 provide a data-driven basis for the inference of where e-commerce-induced trips can be inserted into existing trip chains, including physical drop-off trips for returning online purchases and pickup trips for collecting online orders at physical stores. Specifically, the shopping-specific motif framework is used to identify where a return- or pickup-related shopping stop could plausibly be added to an observed or synthetic trip chain. The insertion process consists of two steps, as shown in Figure 5.8.

First, for each observed shopping-specific motif from NHTS data, a reduced pattern is derived by removing one shopping stop from the motif. In the baseline scenario, one shopping stop is selected for removal. Additional scenarios are then considered in which multiple shopping stops are inserted into the trip chain to evaluate the sensitivity of the results to different return trip insertion assumptions. This represents a trip chain in which a shopping-related stop is absent and provides a basis for identifying where a product-return or pickup stop could plausibly be inserted. Second, each synthetic trip chain is treated as a reduced motif into which a product-return trip or in-store pickup trip can be inserted. The model then identifies all observed original shopping-specific motifs that could have generated the reduced motif after one shopping stop was removed. Because these original motifs appear with different frequencies in the NHTS data, the empirical share of each original motif conditional on the same reduced motif is calculated. These conditional shares are used as probabilities to reconstruct a trip chain with an inserted product return or pickup trip.

This approach preserves the empirical structure of observed daily travel behavior rather than imposing an arbitrary rule for where return-related shopping stops should occur. Additionally, it allows the reconstruction process to be year-specific, so the 2017 and 2022 NHTS shopping-chain patterns can generate different return-trip insertion probabilities.

5.3.6 E-Commerce Adoption Scenario Simulation and VMT Accounting

E-commerce adoption scenarios are designed using person-level probabilities rather than fixed deterministic assumptions. Survey responses are first matched to synthetic persons based on demographic characteristics, so that each person in the trip-chain population is assigned probabilities for e-commerce adoption, shopping behavior shifts, fulfillment choices, and return-related activities. Each scenario, therefore, represents one probabilistic realization of e-commerce behavior across the synthetic population.

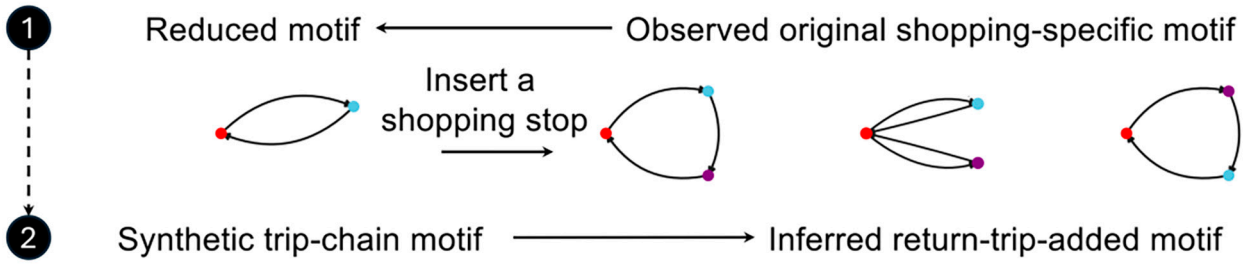


Figure 5.8 The Process of Inferring the Insertion of Return-Trip in a Trip Chain. In 2017, the Three Motifs After Inserting a Shopping Stop Have Relative Probability of 48.1%, 27.8%, and 24.1%; While in 2022, the Three Motifs Have Respective Probabilities of 47.5%, 34.8%, and 17.7%.

TABLE 5.1
E-Commerce Adoption and Sensitivity Scenario Designs.

Scenario	Scenario Design
Before e-commerce	No e-commerce adoption.
2026 baseline e-commerce adoption	Regular e-commerce adoption probabilities based on survey
Higher Food Delivery Adoption	Double the food-delivery adoption frequency
More Food Delivery Couriers	Double both food delivery adoption frequency and number of the couriers, increasing the food delivery order fulfillment
Higher Online Order Pickup in Store	Double the probability of pickup in store for online orders
Higher Product Return Demand	Double daily return-mode probabilities

In addition to the baseline adoption scenario, where e-commerce behavior probabilities are derived from the survey results, we conduct a set of sensitivity analyses to examine how key behavioral change probability would affect VMT outcomes. These scenarios increase food delivery adoption, expand food delivery courier availability, increase the likelihood of online order pickup in store, and raise product-return demand. Table 5.1 summarizes the baseline and sensitivity scenario designs used in the analysis.

For each scenario, the sampling process produces two main outputs: a modified passenger trip chain and a set of e-commerce delivery orders. The modified passenger trip chain is evaluated by the agent-based model to estimate passenger VMT. The delivery orders are then processed by the corresponding delivery optimization models to estimate delivery VMT. Total scenario VMT is calculated as the sum of passenger VMT and delivery VMT. Repeating the scenario simulation produces distributions of passenger VMT (including nonshopping travel, in-store pickup, in-store product return), delivery VMT (including grocery, goods, and food delivery), and total VMT. The inducted VMT is compared with baseline scenario where no e-commerce is introduced in 2017 and 2022 to account for the VMT change due to the e-commerce.

5.4 Results

5.4.1 Market Segmentation of Shoppers

5.4.1.1 Change in Shopping Frequency. The first stage of the online shopping market segmentation model estimated the factors associated with respondents' reported change in overall shopping frequency after adopting online shopping. A weighted MNL model was estimated using Apollo 0.3.5 in R 4.3.2, with the "No Change" category used as the reference outcome. The final log-likelihood was −847.04, improving substantially from the equal-shares log-likelihood of −1255.73. The model produced a rho-squared value of 0.3255 and an adjusted rho-squared value of 0.3135, indicating a reasonable fit for a cross-sectional discrete choice model. Table 5.2 summarizes the estimated MNL coefficients. Since the "No Change" category serves as the reference alternative, positive coefficients indicate a higher likelihood of being classified into the "Increased" or "Decreased" category relative to "No Change," while negative coefficients indicate a lower likelihood.

TABLE 5.2
Weighted Multinomial Logit Model for Change in Shopping Frequency.

	Change in Overall Shopping Frequency	
Variable	**Increased**	**Decreased**
Constant (baseline: No change to shopping frequency)		
Constant	−1.8724***	−0.8431*
	(0.3596)	(0.5015)
Annual Household Income (baseline: less than $75,000)		
Annual Household Income: Greater than $75,000	0.897***	0.8232***
	(0.1844)	(0.2303)
Gender (baseline: female)		
Gender: Male		−0.5032**
		(0.2177)
Race (baseline: all other races)		
Race: African American	−0.7003	
	(0.4285)	
Race: White	−0.9262***	−0.7548***
	(0.2987)	(0.2808)
Age (baseline: over 54 years old)		
Age: 18 to 34 years old	0.6495***	
	(0.2335)	
Age: 35 to 54 years old	0.4744**	
	(0.2163)	
Employment Status (baseline: unemployed)		
Employment Status: Employed	0.416**	
	(0.2102)	
Number of Vehicles per Household (baseline: zero)		
Number of Vehicles per Household: 1		−0.7703
		(0.4918)
Number of Vehicles per Household: 2 or more		−1.0251**
		(0.4926)
Disability Status (baseline: does not have a disability)		
Disability Status: Possess a disability that restricts movement	0.3609	0.5733**
	(0.2077)	(0.2257)
Restricted Log-likelihood = −1255.73		
Log-likelihood = −847.04		
P^2 (rho-squared) = 0.3255		
Adjusted P^2 (adjusted rho-squared) = 0.3135		

The results suggest that household income is one of the strongest predictors of changes in shopping frequency. Respondents with household income of $75,000 or more were significantly more likely to report both increased and decreased shopping frequency relative to no change. This indicates that higher-income respondents were more likely to experience some change in shopping behavior after adopting online shopping, although the direction of that change was not uniform. In other words, e-commerce appears to affect higher-income respondents heterogeneously: for some, it may facilitate additional purchasing activity, while for others, it may improve shopping efficiency and reduce overall shopping frequency.

Gender and vehicle ownership were more strongly associated with decreased shopping frequency. Male respondents



Figure 5.9 LCA Model Selection by Frequency-Change Group.

were significantly less likely to report a decrease in shopping frequency relative to no change. Similarly, respondents in households with two or more vehicles were significantly less likely to report decreased shopping frequency, while the coefficient for one-vehicle households was negative and marginally significant. These findings suggest that households with greater vehicle availability may be less likely to reduce overall shopping activity after adopting online shopping, potentially because access to private vehicles continues to support in-store shopping participation.

Race and age variables also showed meaningful associations. White respondents were significantly less likely to report either increased or decreased shopping frequency relative to no change, indicating a greater tendency toward stable shopping frequency compared with the omitted race category. The coefficient for African American respondents in the Increased outcome was negative but not statistically significant. Respondents in who were 18 to 34 years old were significantly more likely to report increased shopping frequency, while respondents who were 35 to 54 years old were marginally more likely to report increased shopping frequency.

Employment status and disability status provide additional evidence of heterogeneous behavioral responses. Employed respondents were marginally more likely to report increased shopping frequency, which may reflect the convenience value of online shopping for individuals with work-related time constraints. Respondents reporting a disability that restricts movement were significantly more likely to report decreased shopping frequency, while the corresponding coefficient for increased shopping frequency was positive but not statistically significant. This finding may indicate that online shopping enables some respondents with mobility constraints to reduce the frequency of shopping activity, although additional analysis would be needed to distinguish reductions in overall shopping from substitutions between in-store and online channels.

5.4.1.2 Characteristics of Shopper Classes. After estimating the MNL model for change in overall shopping frequency, separate LCA models were estimated for respondents classified into the Increased and No Change groups. Several candidate LCA models were estimated for each group, ranging from two to five clusters. Model selection was based primarily on the Bayesian Information Criterion (BIC), with lower BIC values indicating a preferred balance between model fit and parsimony. Figure 5.9 summarizes the BIC values for the candidate models.

For the No Change group, the four-cluster model produced the lowest BIC value of 7120.68 and was, therefore, selected. The four clusters represent distinct behavioral profiles among respondents whose overall shopping frequency did not change after adopting online shopping. Although these respondents did not report a net change in total shopping frequency, the class profiles (Table 5.3) show meaningful differences in how online and in-store channels are combined.

The covariate results further indicate that class membership varies by sociodemographic characteristics. Age indicators, employment status, gender, race, income, educational attainment, and one-vehicle household status were statistically significant predictors of class membership. The high-engagement omnichannel class had larger shares of employed respondents, male respondents, higher-income respondents, respondents with a bachelor's degree or higher, and one-vehicle households. In contrast, the in-store-oriented class had lower shares

TABLE 5.3
Interpreted Latent Classes for the No Change Group.

Cluster	Share	Suggested Label	Behavioral Interpretation
Cluster 1	41.18%	Routine goods-oriented online shoppers	Respondents in this class report moderate online shopping frequency, with most responses concentrated around monthly to weekly online shopping. In-store shopping remains common. Online fulfillment is mainly associated with goods delivery, while grocery delivery, food delivery, and pickup services are used infrequently.
Cluster 2	29.28%	Moderate multichannel shoppers	This class shows moderate use of both online and in-store shopping. Compared with Cluster 1, respondents in this group show more regular use of delivery and pickup across groceries, food, and goods. This segment appears to represent shoppers who use multiple online fulfillment channels without substantially changing total shopping frequency.
Cluster 3	19.52%	In-store-oriented or minimal e-commerce shoppers	This class is characterized by very low online shopping frequency and near-zero use of delivery and pickup services. In-store shopping remains the dominant shopping channel. This class likely represents respondents who have adopted online shopping only minimally or who have not integrated it into routine purchasing behavior.
Cluster 4	10.03%	High-engagement omnichannel shoppers	This smallest class has the highest online shopping frequency within the No Change group and comparatively higher use of delivery and pickup services. These respondents continue to make in-store shopping trips but also make frequent use of online fulfillment, suggesting that online shopping modifies the composition of shopping activity rather than changing total shopping frequency.

TABLE 5.4
Interpreted Latent Classes for the Increased Group.

Cluster	Share	Suggested Label	Behavioral Interpretation
Cluster 1	40.66%	Balanced omnichannel growth shoppers	Respondents in this class report relatively frequent online shopping and continued in-store shopping. They also show moderate use of delivery and pickup across product categories. This class represents shoppers for whom online shopping appears to add activity across multiple fulfillment channels rather than replacing one dominant mode.
Cluster 2	40.21%	Goods-oriented online growth shoppers	This class reports moderate online and in-store shopping frequency, but delivery and pickup activity is concentrated more heavily around goods. Grocery and food delivery are comparatively less common, and pickup use is limited. This suggests that increased shopping frequency for this group may be driven primarily by general merchandise purchases.
Cluster 3	19.14%	High-frequency delivery-intensive shoppers	This class shows the highest online shopping frequency and comparatively high delivery activity, particularly for groceries and food. In-store shopping also remains active, indicating that online shopping may complement rather than replace physical shopping. This class represents the most intensive e-commerce users among respondents whose overall shopping frequency increased.

of employed and higher-income respondents. These findings suggest that even among respondents whose total shopping frequency remained unchanged, the form of shopping participation differs across demographic groups.

For the Increased group, as shown in Table 5.4, the three-cluster model produced the lowest BIC value of 2867.90 and was selected. The three clusters represent distinct types of shoppers whose overall shopping frequency increased after adopting online shopping.

The Increased-group results suggest that growth in shopping frequency is not uniform. For some respondents, additional shopping activity is distributed across online, in-store, delivery, and pickup channels. For others, the increase appears more concentrated in goods-related online purchases. A smaller but important segment exhibits high-frequency online shopping and intensive delivery use, which has the greatest potential to affect delivery demand and last-mile VMT.

The covariate model for the Increased group shows that age, income, one-vehicle household status, and driving status are statistically significant predictors of class membership, while gender is marginally significant. The high-frequency delivery-intensive class has the largest share of higher-income respondents and male respondents and also has a relatively high share of one-vehicle households. These patterns suggest that high-intensity e-commerce adoption is associated with both socioeconomic characteristics and household mobility resources.

Across both LCA models, the classes are distinguished more strongly by online fulfillment behavior than by in-store shopping frequency alone. In both the Increased and No Change groups, pickup and delivery indicators contribute substantially to class differentiation, while in-store shopping frequency varies less sharply across classes.

5.4.2 Travel Demand Impact of E-Commerce Under Different Scenarios

Figure 5.10 compares projected full-population daily VMT before e-commerce and under 2026 baseline e-commerce adoption. The results were generated based on a simulation scale of 100,000 people. Each result was then scaled by a factor of 9.94851 to represent Marion County's projected 2026 population of 994,851. For scenarios informed by the 2017 NHTS data, projected total daily VMT increased from 18.10 million miles before e-commerce to 19.84 million miles under baseline adoption. This represented an increase of 1.74 million miles, or 9.6%. A similar pattern is observed for the scenarios informed by the 2022 NHTS data. The projected total daily VMT increased from 12.64 million miles before e-commerce to 13.72 million miles under baseline adoption. This represented an increase of 1.08 million miles, or 8.5%.

The VMT decomposition shows that e-commerce does not simply replace passenger shopping trips with delivery travel. Adoption also generates passenger VMT through online order pickup, additional in-store shopping, and product-return trips. These passenger-side changes occur alongside delivery VMT from food, grocery, goods, local courier, and return-pickup services.

Figure 5.11 further presents the breakdown of total daily VMT under different e-commerce sensitivity scenarios. For scenarios informed by the 2017 NHTS data, projected total daily VMT was 18.10 million miles before e-commerce and 19.84 million miles under baseline adoption (+9.6%). Higher Food Delivery Adoption produced 19.37 million miles with ten couriers (+7.0%) and 19.88 million miles with 1,000 couriers (+9.8%). The resulting VMT difference between different number of couriers therefore reflects the importance of greater courier capacity to fulfill potential food delivery demands. Higher Online Order Pickup in Store produced the largest increase, reaching 21.06 million miles (+16.4%). Higher Product Return Demand increased projected total daily VMT to 20.47 million miles (+13.1%).

For scenarios informed by the 2022 NHTS data, projected total daily VMT was 12.64 million miles before e-commerce and 13.72 million miles under baseline adoption (+8.5%). Higher Food Delivery Adoption produced 13.37 million miles with ten couriers (+5.8%) and 13.59 million miles with 1,000 couriers (+7.5%). Higher Online Order Pickup in Store again produced the largest increase, reaching 14.35 million miles (+13.5%). Higher Product Return Demand produced a similar total of 14.34 million miles (+13.5%). All percentages are measured relative to the corresponding before-e-commerce scenario.

Overall, the results show that e-commerce increases system-level VMT using both 2017 and 2022 NHTS data as travel

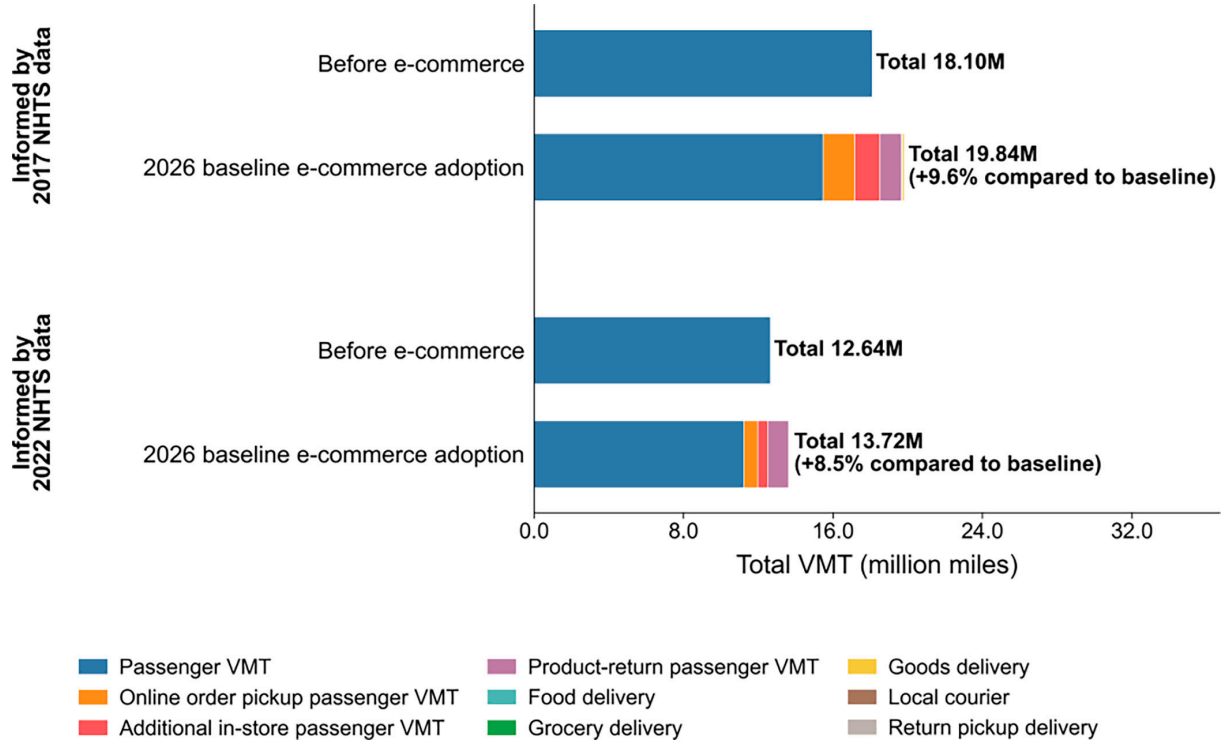


Figure 5.10 Projected Total Daily VMT Before E-Commerce and Under 2026 Baseline E-Commerce Adoption for Marion County's Projected 2026 Population of 994,851. The Bars Decompose Passenger and Delivery VMT Using Travel-Demand Patterns Informed by the 2017 and 2022 NHTS Data. Values Are Deterministic Proportional Projections From One Simulation at the Scale of 100,000 People; No Uncertainty Intervals Are Shown.

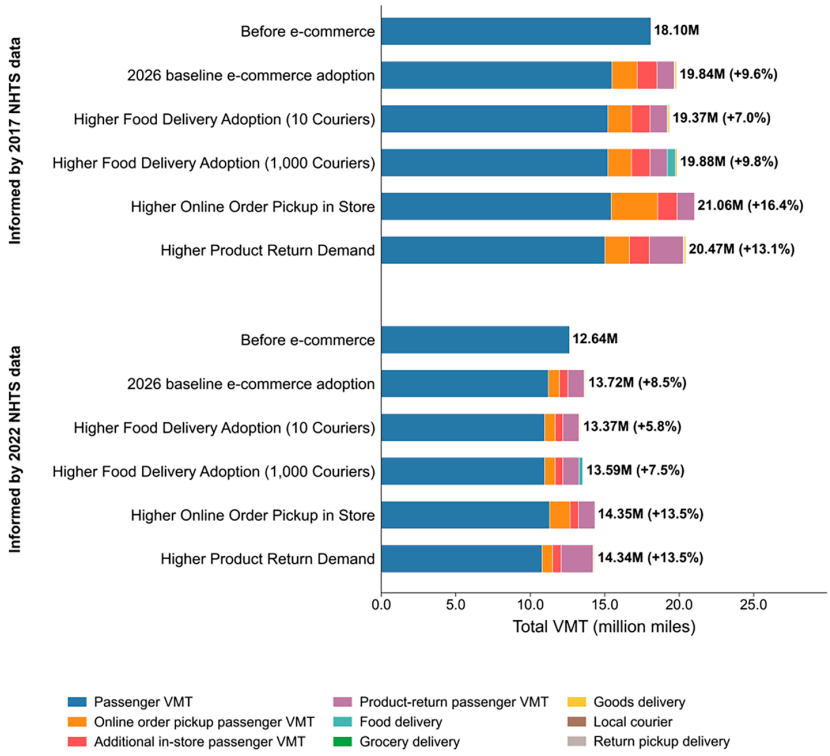


Figure 5.11 Projected Total Daily VMT Under Six Scenario Settings for Marion County's Projected 2026 Population of 994,851. The Figure Compares Before E-Commerce, 2026 Baseline Adoption, Higher Food Delivery Adoption With 10 Couriers, a Paired 1,000-Courier Food-Routing Sensitivity, Higher Online Order Pickup in Store, and Higher Product Return Demand. Results Use Travel-Demand Patterns Informed by the 2017 and 2022 NHTS Data and Are Proportional Projections of Results From Simulations at the Scale of 100,000 People.

pattern inputs. The increase is driven by both passenger travel adjustments and delivery VMT. Delivery vehicles contribute a relatively small but non-negligible amount of additional VMT, while the larger impact comes from how e-commerce changes individual daily trip chains. This finding highlights the importance of modeling e-commerce as an integrated passenger-and-delivery behavior system instead of treating online shopping only as a freight demand generator.

5.5 Summary

This chapter developed an integrated framework to evaluate how e-commerce adoption may affect travel demand in Indiana, using Indianapolis as the case study area. The analysis combined Indiana-specific e-commerce survey data, NHTS-based synthetic trip chains, agent-based travel demand modeling, data-driven motif analysis, and delivery optimization models. This integrated structure allows e-commerce to be represented not only as a source of delivery demand, but also as a behavioral change that can modify passenger trip chains through reduced shopping trips, online delivery, in-store pickup, and product-return activities.

The projected full-population results show that 2026 e-commerce adoption increases total VMT in an average day under both the 2017 and 2022 NHTS-informed settings. The 100,000-people scenario results were proportionally scaled to Marion County's projected 2026 population of 994,851. Across the baseline adoption and sensitivity analysis scenarios, total VMT in an average day increases by approximately 5.8% to 16.4% relative to the corresponding before-e-commerce scenario, depending on the NHTS data source and scenario assumptions. Although passenger VMT from non-shopping trip chains decreases slightly, this reduction is more than offset by passenger travel associated with online order pickup in store, additional in-store shopping, and product-return trips, together with delivery-related VMT. Overall, e-commerce does not simply replace passenger shopping trips with delivery travel. Instead, it reshapes passenger activity patterns while adding delivery demand, resulting in a net increase in system-level VMT.

The delivery results also show meaningful differences across delivery categories. Food delivery has the highest VMT per order regardless of which year's data is used as inputs, while local courier delivery has the lowest average VMT per order. Grocery and goods delivery fall between these two categories, with their VMT depending on depot structure, delivery density, and order assignment. These findings indicate that e-commerce delivery impacts should not be represented using a single average delivery rate; food, grocery, goods, and local courier delivery operate through different logistics structures and generate different VMT outcomes.

6. CONCLUSION

This study addressed two related needs for INDOT: improving the local basis for trip generation estimates used in Traffic Impact Studies and developing a modeling framework to evaluate how e-commerce may affect passenger travel, delivery activity, and total daily VMT. Together, the two tasks show that both development-related traffic and e-commerce-related travel demand are sensitive to local context, land-use characteristics, behavioral heterogeneity, and emerging logistics patterns. Therefore, Indiana-specific data and locally calibrated procedures are important complements to national reference tools.

6.1 Development of Indiana-Specific Trip Generation Procedures

6.1.1 Synthesis of Key Findings

The first part of this study developed Indiana-specific trip generation procedures for selected industrial and service land uses frequently encountered in INDOT Traffic Impact Studies. The analysis focused on land uses identified as priorities by INDOT, including high-cube warehouse facilities, fast-food restaurants with drive-through windows, gasoline/service stations with convenience markets, and truck stops. Field traffic counts were collected at representative Indiana sites during generator and adjacent-street peak periods, and site-level independent variables such as gross floor area, parking supply, seating, and fueling capacity were compiled to support model development.

The results indicate that national ITE trip generation estimates do not always align with observed traffic volumes at Indiana sites. For industrial warehouse land uses, the ITE estimates generally overestimated observed traffic volumes, although the magnitude of the difference varied by site and peak period. For fast-food restaurants, the standard LU 934 category tended to underestimate trips at higher-volume locations, while the newer LU 929 category produced higher estimates but did not consistently improve agreement with field observations. For gasoline/service stations and truck stops, the results also showed that national rates may not fully capture local operating conditions or the influence of site-specific characteristics.

The Indiana-specific regression models demonstrated that locally collected data can improve understanding of trip generation behavior. However, the results also showed that model reliability depends heavily on the number of sites available, the range of site characteristics represented in the dataset, and the strength of the relationship between trip activity and the selected independent variables. In some cases, small sample sizes and operational variability limited the ability to develop statistically robust models. These limitations are consistent with common challenges in local trip generation studies and indicate that the models should be used as supplemental guidance rather than as complete replacements for established ITE procedures.

Overall, the findings suggest that uncalibrated national trip generation rates may lead to either overestimation or underestimation of traffic impacts in Indiana. Overestimation may result in unnecessarily conservative mitigation requirements, higher development costs, or inefficient allocation of infrastructure resources. Underestimation may result in insufficient access improvements, underestimated roadway capacity needs, and potential operational or safety concerns. Locally calibrated procedures can help INDOT and local agencies evaluate whether submitted TIS estimates are reasonable for Indiana conditions.

6.1.2 Implementation

The Indiana-specific trip generation results developed in this study can be used by INDOT as supplemental guidance during TIS review. Rather than replacing the ITE Trip Generation Manual, the locally observed rates, directional splits, and regression equations can serve as a reasonableness check when reviewing proposed developments similar to the sites included in this study. When ITE-based estimates differ substantially from Indiana-specific observations, reviewers may request additional justification, sensitivity testing, or supporting data from applicants.

In the longer term, INDOT could maintain a statewide trip generation database populated with future permit applications, TIS submissions, and postdevelopment traffic counts. This would allow the Indiana-specific models to be periodically updated, improve confidence in local trip generation procedures, and support more consistent decision making across districts.

Future data collection should prioritize land uses with high traffic impacts, limited local observations, or rapidly changing operating characteristics. Additional observations across a wider range of site sizes, geographic contexts, and access conditions would strengthen future calibration efforts. Continued coordination between INDOT, local agencies, consultants, and developers would also improve the availability of permit records, site plans, and traffic count data needed for long-term model refinement.

6.2 Models for E-Commerce Demand: Implications for INDOT's Travel

6.2.1 Synthesis of Key Findings

The second part of the study developed a modeling framework to evaluate how e-commerce adoption may affect travel demand and the associated VMT in Indiana. The framework combines Indiana-specific survey data, NHTS-based trip chains, market segmentation models, motif-based trip insertion, agent-based travel demand modeling, and delivery optimization models. This integrated approach explicitly considers the multi-channel impact of e-commerce on travel demand: e-commerce may reduce some in-store shopping trips, generate additional pickup or return trips, and create new delivery vehicle travel.

The Indiana-specific survey provides the behavioral foundation for representing heterogeneous e-commerce adoption and shopping responses in the travel demand model. Using the survey data, this study employed a multinomial logit model and latent class analysis to translate observed shopping preferences into probabilistic travel behavior inputs.

The scenario analysis highlights that e-commerce affects travel demand through multiple interacting channels. Across 100 simulation repetitions, total daily VMT per person increased in scenarios informed by both NHTS 2017 and 2022 data, rising by 5.8% to 16.4% relative to the no-e-commerce baseline. Most of this increase was associated with passenger trip–chain changes, including pickup, return, and modified shopping activities, while delivery vehicles contributed a smaller but still measurable share. The delivery results further show that VMT impacts differ by fulfillment type: food delivery, grocery delivery, goods delivery, and local courier services produce different VMT-per-order patterns because they operate through different routing and depot structures. This supports modeling e-commerce as a set of behavior and logistics pathways rather than as a single average delivery effect.

6.2.2 Implementation

The e-commerce modeling framework provides a scenario-based tool for evaluating emerging travel demand patterns in Indiana. Encouraging e-commerce adoption alone does not necessarily reduce VMT, because online shopping may also generate pickup trips, return trips, and additional delivery activity. Results from this work provide some insights for planners, business sectors, and governments. First, INDOT and local planning agencies can use the modeling framework to evaluate how different e-commerce adoption scenarios may affect passenger travel and delivery VMT. The results show that most of the VMT increase comes from passenger-side trip-chain adjustments rather than delivery vehicles alone. While e-commerce adoption can replace some in-store shopping trips, it may also create rebound effects by generating additional home-pickup, return, and in-store pickup trips, which can increase total daily VMT. This suggests that future travel demand models should explicitly account for pickup trips, return trips, and modified shopping chains instead of assuming that online shopping simply replaces in-store shopping.

Second, public agencies and the private sector can encourage e-commerce systems that reduce redundant passenger travel and improve delivery consolidation. For example, shared delivery services, coordinated delivery windows, parcel lockers, and centralized pickup or return locations may help reduce fragmented delivery activity and unnecessary individual vehicle trips.

Last, the model can support future updates to long-term transportation plans and travel demand forecasting tools. INDOT could maintain and periodically update e-commerce behavior inputs using new survey data, NHTS releases, delivery activity data, and local observations of pickup and return behavior. As more data become available, the framework can be recalibrated and extended to other Indiana regions. This would allow INDOT and Metropolitan Planning Organizations to better anticipate how evolving shopping behavior may affect VMT, infrastructure needs, land use patterns, and investment planning.

In conclusion, this study demonstrates the value of combining Indiana-specific data with established national resources and advanced modeling methods. The trip generation component provides a stronger local basis for evaluating development-related traffic impacts, while the e-commerce component provides a flexible framework for assessing emerging changes in shopping behavior and delivery demand. Together, these tools can help INDOT improve traffic impact review, enhance statewide travel demand forecasting, and make more informed transportation investment decisions in a changing mobility environment.

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APPENDICES

Appendix A. Recorded Vehicle Counts and Comparison With ITE Predictions

Appendix B. Indiana Specific Trip Generation Curves

Appendix C. Indiana Specific E-Commerce Survey Instrument

Appendix A. Recorded Vehicle Counts and Comparison With ITE Predictions

A.1 Land Use Code: 154

Land Use Description: High-Cube Transload and Short-Term Storage Warehouse

A.1.1 Site 1: 1801 Innovation Blvd, Clayton, IN 46118

A.1.1.1 Recorded Traffic Counts

		Driveway 1						Driveway 2						ALL DRIVEWAYS	
		Enter		Exit		Total		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	8	1	2	0	10	1	2	1	2	2	4	3	14	4
7:15	7:30	16	0	2	0	18	0	1	1	2	1	3	2	21	2
7:30	7:45	10	0	1	0	11	0	5	5	0	0	5	5	16	5
7:45	8:00	14	0	0	0	14	0	4	3	1	1	5	4	19	4
8:00	8:15	11	0	0	0	11	0	3	1	1	1	4	2	15	2
8:15	8:30	11	0	1	0	12	0	1	1	2	2	3	3	15	3
8:30	8:45	10	0	4	0	14	0	1	1	2	1	3	2	17	2
8:45	9:00	8	0	0	0	8	0	3	2	4	3	7	5	15	5
9:00	9:15	2	0	1	0	3	0	3	3	4	2	7	5	10	5
9:15	9:30	3	0	3	1	6	1	2	2	2	2	4	4	10	5
9:30	9:45	1	0	2	1	3	1	0	0	3	2	3	2	6	3
9:45	10:00	1	0	1	0	2	0	3	2	2	1	5	3	7	3
15:00	15:15	8	0	66	0	74	0	2	2	4	4	6	6	80	6
15:15	15:30	3	0	18	0	21	0	3	3	2	2	5	5	26	5
15:30	15:45	1	0	6	0	7	0	3	3	3	3	6	6	13	6
15:45	16:00	8	0	14	0	22	0	2	2	3	3	5	5	27	5
16:00	16:15	10	0	49	0	59	0	3	2	3	2	6	4	65	4
16:15	16:30	14	0	10	0	24	0	3	3	1	1	4	4	28	4
16:30	16:45	4	0	9	0	13	0	3	3	2	2	5	5	18	5
16:45	17:00	1	0	9	0	10	0	2	1	1	1	3	2	13	2
17:00	17:15	3	0	10	0	13	0	1	1	5	4	6	5	19	5
17:15	17:30	2	0	4	0	6	0	4	4	2	2	6	6	12	6
17:30	17:45	0	0	3	0	3	0	1	1	3	3	4	4	7	4
17:45	18:00	0	0	6	0	6	0	0	0	2	2	2	2	8	2

A.1.1.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	9:00–10:00	15	18	33	45.45	54.55	9:00, 9:15	10
Generator PM	15:00–16:00	30	116	146	20.55	79.45	15:00	80
Street AM	7:15–8:15	64	7	71	90.14	9.86	7:15	21
Street PM	16:00–17:00	40	84	124	32.26	67.74	16:00	65

A.1.1.3 ITE Predictions Corresponding to LU 154 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	1422000	170	78	22	2010–2016 (16 studies)	Equation Given by ITE
Generator PM	1422000	200	34	66	2010–2016 (17 studies)	Equation Given by ITE
Street AM	1422000	100	77	23	2010–2016 (64 studies)	Average Rate Line
Street PM	1422000	128	28	72	2010–2016 (64 studies)	Average Rate Line

A.1.2 Site 2: 2100 Innovation Blvd, Mooresville, IN 46158

A.1.2.1 Recorded Traffic Counts

		Driveway 1						Driveway 2					
		Enter		Exit		Total		Enter		Exit		Total	
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks
7:00	7:15	5	0	0	0	5	0	1	1	0	0	1	1
7:15	7:30	0	0	1	0	1	0	1	1	1	1	2	2
7:30	7:45	0	0	0	0	0	0	1	1	0	0	1	1
7:45	8:00	1	0	1	0	2	0	1	1	1	1	2	2
8:00	8:15	2	0	0	0	2	0	1	1	0	0	1	1
8:15	8:30	0	0	0	0	0	0	0	0	1	1	1	1
8:30	8:45	1	0	0	0	1	0	2	2	3	3	5	5
8:45	9:00	1	0	0	0	1	0	1	1	0	0	1	1
9:00	9:15	0	0	0	0	0	0	2	2	3	3	5	5
9:15	9:30	1	0	0	0	1	0	5	5	4	4	9	9
9:30	9:45	1	0	2	0	3	0	1	1	0	0	1	1
9:45	10:00	2	0	0	0	2	0	0	0	1	1	1	1
15:00	15:15	1	0	34	0	35	0	0	0	0	0	0	0
15:15	15:30	1	0	12	0	13	0	0	0	0	0	0	0
15:30	15:45	0	0	9	0	9	0	1	1	0	0	1	1
15:45	16:00	1	0	1	0	2	0	2	2	2	2	4	4
16:00	16:15	0	0	11	0	11	0	0	0	0	0	0	0
16:15	16:30	0	0	3	0	3	0	1	1	0	0	1	1
16:30	16:45	0	0	3	0	3	0	1	1	1	1	2	2
16:45	17:00	0	0	4	0	4	0	0	0	2	1	2	1
17:00	17:15	1	0	1	0	2	0	0	0	0	0	0	0
17:15	17:30	0	0	0	0	0	0	0	1	0	0	0	1
17:30	17:45	1	0	4	0	5	0	0	0	1	1	1	1
17:45	18:00	1	0	4	0	5	0	0	0	0	0	0	0

		Driveway 3						ALL DRIVEWAYS	
		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	3	0	2	0	5	0	10	0
7:15	7:30	1	1	1	1	2	2	3	2
7:30	7:45	0	0	0	0	0	0	0	0
7:45	8:00	3	1	0	0	3	1	5	1
8:00	8:15	0	0	3	3	3	3	5	3
8:15	8:30	0	0	1	1	1	1	1	1
8:30	8:45	0	0	0	0	0	0	1	0
8:45	9:00	1	0	0	0	1	0	2	0
9:00	9:15	0	0	0	0	0	0	0	0
9:15	9:30	0	0	1	1	1	1	2	1
9:30	9:45	0	0	0	0	0	0	3	0
9:45	10:00	4	1	0	0	4	1	6	1
15:00	15:15	2	0	29	0	31	0	66	0
15:15	15:30	1	1	6	0	7	1	20	1
15:30	15:45	0	0	7	1	7	1	16	1
15:45	16:00	0	0	1	1	1	1	3	1
16:00	16:15	2	1	3	0	5	1	16	1
16:15	16:30	0	0	3	1	3	1	6	1
16:30	16:45	0	0	1	0	1	0	4	0
16:45	17:00	0	0	1	0	1	0	5	0
17:00	17:15	1	1	2	0	3	1	5	1
17:15	17:30	0	0	1	1	1	1	1	1
17:30	17:45	0	0	0	0	0	0	5	0
17:45	18:00	0	0	0	0	0	0	5	0

A.1.2.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	9:00–10:00	16	11	27	59.26	40.74	15:00.0	11
Generator PM	15:00–16:00	9	101	110	8.18	91.82	15:00	66
Street AM	7:00–8:00	17	7	24	70.83	29.17	7:00	11
Street PM	16:00–17:00	4	32	36	11.11	88.89	16:00	16

A.1.2.3 ITE Predictions Corresponding to LU 154 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	729000	73	78	22	2010–2016 (16 studies)	Equation Given by ITE
Generator PM	729000	118	34	66	2010–2016 (17 studies)	Equation Given by ITE
Street AM	729000	51	77	23	2010–2016 (64 studies)	Average Rate Line
Street PM	729000	66	28	72	2010–2016 (64 studies)	Average Rate Line

A.1.3 Site 3: 5220 Whitestown Pkwy, Whitestown, IN 46075

A.1.3.1 Recorded Traffic Counts

		Driveway 1						Driveway 2						ALL DRIVEWAYS	
		Enter		Exit		Total		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	1	0	1	1	2	1	1	0	2	1	3	1	5	2
7:15	7:30	0	0	1	1	1	1	0	0	0	0	0	0	1	1
7:30	7:45	1	0	0	0	1	0	2	0	0	0	2	0	3	0
7:45	8:00	1	1	1	0	2	1	4	1	2	1	6	2	8	3
8:00	8:15	1	0	1	0	2	0	2	0	4	0	6	0	8	0
8:15	8:30	1	1	3	1	4	2	2	0	0	0	2	0	6	2
8:30	8:45	1	0	2	1	3	1	2	1	2	0	4	1	7	2
8:45	9:00	0	0	1	1	1	1	1	0	4	1	5	1	6	2
9:00	9:15	0	0	0	0	0	0	1	0	1	0	2	0	2	0
9:15	9:30	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9:30	9:45	3	1	3	1	6	2	1	0	1	0	2	0	8	2
9:45	10:00	0	0	0	0	0	0	1	0	3	0	4	0	4	0
15:00	15:15	4	4	1	0	5	4	0	0	3	1	3	1	8	5
15:15	15:30	5	4	5	1	10	5	3	2	4	0	7	2	17	7
15:30	15:45	1	0	1	0	2	0	0	0	3	0	3	0	5	0
15:45	16:00	0	0	4	1	4	1	1	1	2	1	3	2	7	3
16:00	16:15	1	1	2	0	3	1	3	2	4	1	7	3	10	4
16:15	16:30	2	1	0	0	2	1	0	0	2	1	2	1	4	2
16:30	16:45	1	1	0	0	1	1	1	1	0	0	1	1	2	2
16:45	17:00	0	0	3	0	3	0	2	1	4	0	6	1	9	1
17:00	17:15	2	0	0	0	2	0	1	1	4	0	5	1	7	1
17:15	17:30	0	0	2	1	2	1	0	0	1	1	1	1	3	2
17:30	17:45	1	1	1	0	2	1	1	0	0	0	1	0	3	1
17:45	18:00	2	0	1	1	3	1	1	0	2	0	3	0	6	1

A.1.3.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	9:00–10:00	6	8	14	42.86	57.14	15:00.0	8
Generator PM	15:00–16:00	14	23	37	37.84	62.16	15:15	17
Street AM	7:45–8:45	14	15	29	48.28	51.72	7:45, 8:00	8
Street PM	16:00–17:00	10	15	25	40.00	60.00	16:00	10

A.1.3.3 ITE Predictions Corresponding to LU 154 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	319503	16	78	22	2010–2016 (16 studies)	Equation Given by ITE
Generator PM	319503	62	34	66	2010–2016 (17 studies)	Equation Given by ITE
Street AM	319503	22	77	23	2010–2016 (64 studies)	Average Rate Line
Street PM	319503	29	28	72	2010–2016 (64 studies)	Average Rate Line

A.1.4 Site 4: 3150 Couden Drive, Lebanon, IN 46052

A.1.4.1 Recorded Traffic Counts

		Driveway 1						Driveway 2					
		Enter		Exit		Total		Enter		Exit		Total	
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks
7:00	7:15	5	0	0	0	5	0	1	1	0	0	1	1
7:15	7:30	0	0	1	0	1	0	1	1	1	1	2	2
7:30	7:45	0	0	0	0	0	0	1	1	0	0	1	1
7:45	8:00	1	0	1	0	2	0	1	1	1	1	2	2
8:00	8:15	2	0	0	0	2	0	1	1	0	0	1	1
8:15	8:30	0	0	0	0	0	0	0	0	1	1	1	1
8:30	8:45	1	0	0	0	1	0	2	2	3	3	5	5
8:45	9:00	1	0	0	0	1	0	1	1	0	0	1	1
9:00	9:15	0	0	0	0	0	0	2	2	3	3	5	5
9:15	9:30	1	0	0	0	1	0	5	5	4	4	9	9
9:30	9:45	1	0	2	0	3	0	1	1	0	0	1	1
9:45	10:00	2	0	0	0	2	0	0	0	1	1	1	1
15:00	15:15	1	0	34	0	35	0	0	0	0	0	0	0
15:15	15:30	1	0	12	0	13	0	0	0	0	0	0	0
15:30	15:45	0	0	9	0	9	0	1	1	0	0	1	1
15:45	16:00	1	0	1	0	2	0	2	2	2	2	4	4
16:00	16:15	0	0	11	0	11	0	0	0	0	0	0	0
16:15	16:30	0	0	3	0	3	0	1	1	0	0	1	1
16:30	16:45	0	0	3	0	3	0	1	1	1	1	2	2
16:45	17:00	0	0	4	0	4	0	0	0	2	1	2	1
17:00	17:15	1	0	1	0	2	0	0	0	0	0	0	0
17:15	17:30	0	0	0	0	0	0	0	1	0	0	0	1
17:30	17:45	1	0	4	0	5	0	0	0	1	1	1	1
17:45	18:00	1	0	4	0	5	0	0	0	0	0	0	0

		Driveway 3						ALL DRIVEWAYS	
		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	3	0	2	0	5	0	10	0
7:15	7:30	1	1	1	1	2	2	3	2
7:30	7:45	0	0	0	0	0	0	0	0
7:45	8:00	3	1	0	0	3	1	5	1
8:00	8:15	0	0	3	3	3	3	5	3
8:15	8:30	0	0	1	1	1	1	1	1
8:30	8:45	0	0	0	0	0	0	1	0
8:45	9:00	1	0	0	0	1	0	2	0
9:00	9:15	0	0	0	0	0	0	0	0
9:15	9:30	0	0	1	1	1	1	2	1
9:30	9:45	0	0	0	0	0	0	3	0
9:45	10:00	4	1	0	0	4	1	6	1
15:00	15:15	2	0	29	0	31	0	66	0
15:15	15:30	1	1	6	0	7	1	20	1
15:30	15:45	0	0	7	1	7	1	16	1
15:45	16:00	0	0	1	1	1	1	3	1
16:00	16:15	2	1	3	0	5	1	16	1
16:15	16:30	0	0	3	1	3	1	6	1
16:30	16:45	0	0	1	0	1	0	4	0
16:45	17:00	0	0	1	0	1	0	5	0
17:00	17:15	1	1	2	0	3	1	5	1
17:15	17:30	0	0	1	1	1	1	1	1
17:30	17:45	0	0	0	0	0	0	5	0
17:45	18:00	0	0	0	0	0	0	5	0

A.1.4.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	9:00–10:00	16	11	27	59.26	40.74	15:00.0	11
Generator PM	15:00–16:00	9	101	110	8.18	91.82	15:00	66
Street AM	7:00–8:00	17	7	24	70.83	29.17	7:00	11
Street PM	16:00–17:00	4	32	36	11.11	88.89	16:00	16

A.1.4.3 ITE Predictions Corresponding to LU 154 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	729000	73	78	22	2010–2016 (16 studies)	Equation Given by ITE
Generator PM	729000	118	34	66	2010–2016 (17 studies)	Equation Given by ITE
Street AM	729000	51	77	23	2010–2016 (64 studies)	Average Rate Line
Street PM	729000	66	28	72	2010–2016 (64 studies)	Average Rate Line

A.2 Land Use Code: 155

Land Use Description: High-Cube Parcel Hub Warehouse

A.2.1 Site 1: 2633 Westpoint Blvd, Mooresville

A.2.1.1 Recorded Traffic Counts

		Driveway 2*						Driveway 3						ALL DRIVEWAYS	
		Enter		Exit		Total		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	1	1	0	0	1	1	2	0	2	0	4	0	4	0
7:15	7:30	1	1	1	1	2	2	13	0	0	0	13	0	13	0
7:30	7:45	1	1	0	0	1	1	45	1	2	0	47	1	47	1
7:45	8:00	1	0	0	0	1	0	32	0	6	0	38	0	38	0
8:00	8:15	2	2	3	3	5	5	7	0	1	0	8	0	8	0
8:15	8:30	0	0	1	1	1	1	1	0	1	1	2	1	2	1
8:30	8:45	0	0	0	0	0	0	1	0	1	0	2	0	2	0
8:45	9:00	0	0	0	0	0	0	2	0	0	0	2	0	2	0
9:00	9:15	2	1	3	1	5	2	2	0	0	0	2	0	2	0
9:15	9:30	0	0	0	0	0	0	1	0	1	0	2	0	2	0
9:30	9:45	2	1	1	1	3	2	2	0	2	0	4	0	4	0
9:45	10:00	1	1	1	1	2	2	0	0	0	0	0	0	0	0
15:00	15:15	5	0	1	0	6	0	3	3	1	1	4	4	4	4
15:15	15:30	7	0	3	0	10	0	7	2	1	1	8	3	8	3
15:30	15:45	5	0	5	0	10	0	0	0	3	3	3	3	3	3
15:45	16:00	5	0	0	0	5	0	1	1	0	0	1	1	1	1
16:00	16:15	1	0	3	0	4	0	1	1	2	2	3	3	3	3
16:15	16:30	4	0	6	0	10	0	1	1	0	0	1	1	1	1
16:30	16:45	2	0	9	0	11	0	1	1	1	0	2	1	2	1
16:45	17:00	1	0	1	0	2	0	0	0	1	1	1	1	1	1
17:00	17:15	0	0	10	0	10	0	0	0	0	0	0	0	0	0
17:15	17:30	4	0	27	0	31	0	0	0	0	0	0	0	0	0
17:30	17:45	3	0	41	0	44	0	1	1	0	0	1	1	1	1
17:45	18:00	2	0	11	0	13	0	0	0	0	0	0	0	0	0
18:00	18:15	1	0	3	0	4	0	0	0	1	1	1	1	1	1
		* Driveway 1 closed													

A.2.1.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	7:15–8:15	97	9	106	91.51	8.49	7:30	47
Generator PM	15:00–16:00	11	5	16	68.75	31.25	15:15	8
Street AM	7:15–8:15	97	9	106	91.51	8.49	7:30	47
Street PM	15:00–16:00	11	5	16	68.75	31.25	15:15	8

A.2.1.3 ITE Predictions Corresponding to LU 155 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Year	Equation Source
Generator AM	729000	95	52	48	2009–2021 (2 studies)	Average Rate Line
Generator PM	729000	146	50	50	2009–2021 (2 studies)	Average Rate Line
Street AM	729000	88	75	25	All	Average Rate Line
Street PM	729000	103	41	59	All	Average Rate Line

A.2.2 Site 2: 2723 Westpoint Blvd, Mooresville, IN 46158

A.2.2.1 Recorded Traffic Counts

		Driveway 1						ALL DRIVEWAYS	
		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	9	0	3	0	12	0	12	0
7:15	7:30	10	0	4	0	14	0	14	0
7:30	7:45	6	0	1	1	7	1	7	1
7:45	8:00	20	0	2	0	22	0	22	0
8:00	8:15	10	0	7	0	17	0	17	0
8:15	8:30	5	0	3	0	8	0	8	0
8:30	8:45	1	0	0	0	1	0	1	0
8:45	9:00	4	0	4	1	8	1	8	1
9:00	9:15	3	1	1	0	4	1	4	1
9:15	9:30	2	0	1	1	3	1	3	1
9:30	9:45	3	0	4	0	7	0	7	0
9:45	10:00	3	1	1	0	4	1	4	1
15:00	15:15	7	4	4	3	11	7	11	7
15:15	15:30	7	3	5	3	12	6	12	6
15:30	15:45	11	7	19	4	30	11	30	11
15:45	16:00	8	0	8	1	16	1	16	1
16:00	16:15	9	2	9	1	18	3	18	3
16:15	16:30	2	1	12	4	14	5	14	5
16:30	16:45	7	0	55	1	62	1	62	1
16:45	17:00	6	2	10	1	16	3	16	3
17:00	17:15	3	0	45	2	48	2	48	2
17:15	17:30	6	0	20	3	26	3	26	3
17:30	17:45	24	0	23	2	47	2	47	2
17:45	18:00	20	1	9	0	29	1	29	1
18:00	18:15	1	0	8	0	9	0	9	0

A.2.2.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM		7:15–8:15	46	14	60.00	76.67	7:45	22
Generator PM		16:30–17:30	22	130	152.00	14.47	16:30	62
Street AM		7:15–8:15	46	14	60.00	76.67	7:45	22
Street PM		16:30–17:30	22	130	152.00	14.47	16:30	62

A.2.2.3 ITE Predictions Corresponding to LU 155 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Year	Equation Source
Generator AM	22	132	52	48	2009–2021 (2 studies)	Average Rate Line
Generator PM	62	203	50	50	2009–2021 (2 studies)	Average Rate Line
Street AM	22	122	75	25	All	Average Rate Line
Street PM	62	143	41	59	All	Average Rate Line

A.3 Land Use Code: 934

Land Use Description: Fast-Food Restaurant with Drive-Through Window

A.3.1 Site 1: 1225 N Baldwin Ave, Marion, IN 46952

A.3.1.1 Recorded Traffic Counts

		Driveways 1+2*						Driveway 3						ALL DRIVEWAYS	
		Enter		Exit		Total		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	12	0	12	1	24	1	0	0	1	0	1	0	25	1
7:15	7:30	17	0	15	0	32	0	0	0	2	0	2	0	34	0
7:30	7:45	19	0	13	0	32	0	5	0	6	0	11	0	43	0
7:45	8:00	25	0	16	0	41	0	0	0	6	0	6	0	47	0
8:00	8:15	26	0	20	0	46	0	1	0	2	0	3	0	49	0
8:15	8:30	26	0	24	0	50	0	3	0	7	0	10	0	60	0
8:30	8:45	24	0	15	0	39	0	5	0	4	0	9	0	48	0
8:45	9:00	17	0	23	0	40	0	3	0	5	0	8	0	48	0
11:45	12:00	22	0	15	0	37	0	2	0	7	0	9	0	46	0
12:00	12:15	27	0	19	0	46	0	4	0	4	0	8	0	54	0
12:15	12:30	23	0	23	0	46	0	2	0	6	0	8	0	54	0
12:30	12:45	18	0	18	0	36	0	4	0	6	0	10	0	46	0
12:45	13:00	20	0	18	0	38	0	3	0	10	0	13	0	51	0
16:00	16:15	13	0	8	0	21	0	0	0	7	0	7	0	28	0
16:15	16:30	11	0	9	0	20	0	3	0	2	0	5	0	25	0
16:30	16:45	21	0	13	0	34	0	1	0	4	0	5	0	39	0
16:45	17:00	13	0	17	0	30	0	6	0	5	0	11	0	41	0
17:00	17:15	17	0	17	0	34	0	2	0	8	0	10	0	44	0
17:15	17:30	12	0	11	0	23	0	2	0	1	0	3	0	26	0
17:30	17:45	16	0	11	0	27	0	1	0	4	0	5	0	32	0
17:45	18:00	10	0	14	0	24	0	0	0	2	0	2	0	26	0

A.3.1.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	11:45–12: 45	102	98	200			12:00, 12:15	54
Generator PM	12:00–13:00	101	104	205			12:00, 12:15	54
Street AM	8:00–9:00	105	100	205	51.22	48.78	8:15	60
Street PM	16:30–17:30	74	76	150	49.33	50.67	17:00	44

A.3.1.3 ITE Predictions Corresponding to LU 934 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	4400	201	52	48	2010–2024 (64 studies)	Provided by ITE
Generator PM	4400	236	50	50	2010–2024 (70 studies)	Provided by ITE
Street AM	4400	153	51	49	2010–2024 (31 studies)	Average Rate Line
Street PM	4400	142	51	49	2010–2024 (73 studies)	Average Rate Line

Peak Period	Seating - In	Seating - Out	Seating Total	Independent Variable = Seating Capacity				
				Total	In (%)	Out (%)	Years	Equation Source
Generator AM	70	0	70	70	51	49	1995–2023 (3 studies)	Average Rate Line
Generator PM	70	0	70	123	50	50	1995–2023 (5 studies)	Equation Given by ITE
Street AM	70	0	70	83	52	48	1993–2023 (9 studies)	Average Rate Line
Street PM	70	0	70	68	53	47	1993–2023 (14 studies)	Average Rate Line

A.3.1.4 ITE Predictions Corresponding to LU 929 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	4400	218	50	50	All	Average Rate Line
Generator PM	4400	309	50	50	All	Average Rate Line
Street AM	4400	114	52	48	All	Average Rate Line
Street PM	4400	257	50	50	All	Average Rate Line

A.3.2 Site 2: 2203 N State St, Greenfield, IN 46140

A.3.2.1 Recorded Traffic Counts

		Driveway 1						Driveway 2					
		Enter		Exit		Total		Enter		Exit		Total	
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks
7:00	7:15	4	0	4	0	8	0	4	0	4	0	8	0
7:15	7:30	5	0	2	0	7	0	6	0	6	0	12	0
7:30	7:45	3	0	0	0	3	0	4	0	3	0	7	0
7:45	8:00	10	0	0	0	10	0	5	0	10	0	15	0
8:00	8:15	10	0	0	0	10	0	2	0	16	0	18	0
8:15	8:30	10	0	0	0	10	0	4	0	8	1	12	1
8:30	8:45	4	0	0	0	4	0	3	0	9	0	12	0
8:45	9:00	8	0	0	0	8	0	5	0	12	0	17	0
11:45	12:00	16	0	0	0	16	0	13	0	20	0	33	0
12:00	12:15	22	0	3	0	25	0	13	0	41	0	54	0
12:15	12:30	23	0	2	0	25	0	12	2	30	0	42	2
12:30	12:45	16	0	0	0	16	0	9	1	36	1	45	2
12:45	13:00	18	0	2	0	20	0	11	0	33	0	44	0
16:00	16:15	10	0	1	0	11	0	4	0	18	0	22	0
16:15	16:30	10	0	0	0	10	0	14	0	18	0	32	0
16:30	16:45	9	0	0	0	9	0	9	0	12	0	21	0
16:45	17:00	19	0	2	0	21	0	5	0	19	0	24	0
17:00	17:15	13	0	1	0	14	0	9	0	22	0	31	0
17:15	17:30	14	0	0	0	14	0	15	0	19	0	34	0
17:30	17:45	12	0	0	0	12	0	9	0	17	0	26	0
17:45	18:00	14	0	2	0	16	0	7	0	22	0	29	0

		Driveway 3						ALL DRIVEWAYS	
		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	3	0	3	0	6	0	22	0
7:15	7:30	6	0	4	0	10	0	29	0
7:30	7:45	2	0	3	0	5	0	15	0
7:45	8:00	3	0	4	0	7	0	32	0
8:00	8:15	10	0	7	0	17	0	45	0
8:15	8:30	7	1	6	0	13	1	35	2
8:30	8:45	6	0	2	0	8	0	24	0
8:45	9:00	5	0	6	0	11	0	36	0
11:45	12:00	14	0	16	0	30	0	79	0
12:00	12:15	13	0	10	0	23	0	102	0
12:15	12:30	21	0	12	2	33	2	100	4
12:30	12:45	16	1	8	1	24	2	85	4
12:45	13:00	15	0	8	0	23	0	87	0
16:00	16:15	11	0	8	0	19	0	52	0
16:15	16:30	13	0	6	0	19	0	61	0
16:30	16:45	10	0	7	0	17	0	47	0
16:45	17:00	8	0	10	0	18	0	63	0
17:00	17:15	14	0	6	0	20	0	65	0
17:15	17:30	7	0	13	0	20	0	68	0
17:30	17:45	6	0	12	0	18	0	56	0
17:45	18:00	10	0	6	0	16	0	61	0

A.3.2.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	11:45–12:45	188	178	366	51.37	48.63	00:00.0	102
Generator PM	12:00–13:00	189	185	374	50.53	49.47	12:00	102
Street AM	8:00–9:00	74	66	140	52.86	47.14	8:00	45
Street PM	16:45–17:45	131	121	252	51.98	48.02	17:15	68

A.3.2.3 ITE Predictions Corresponding to LU 934 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	4978	227	52	48	2010–2024 (64 studies)	Provided by ITE
Generator PM	4978	267	50	50	2010–2024 (70 studies)	Provided by ITE
Street AM	4978	173	51	49	2010–2024 (31 studies)	Average Rate Line (auto generate)
Street PM	4978	161	51	49	2010–2024 (73 studies)	Average Rate Line (auto generate)

Peak Period	Seating - In	Seating - Out	Seating Total	Independent Variable = Seating Capacity				
				Total	In (%)	Out (%)	Years	Equation Source
Generator AM	95	28	123	145	51	49	1995–2023 (3 studies)	Average Rate Line
Generator PM	95	28	123	172	50	50	1995–2023 (5 studies)	Equation Given by ITE
Street AM	95	28	123	145	52	48	1993–2023 (9 studies)	Average Rate Line
Street PM	95	28	123	119	53	47	1993–2023 (14 studies)	Average Rate Line

A.3.2.4 ITE Predictions Corresponding to LU 929 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	4978	246	50	50	All	Average Rate Line
Generator PM	4978	350	50	50	All	Average Rate Line
Street AM	4978	129	52	48	All	Average Rate Line
Street PM	4978	290	50	50	All	Average Rate Line

A.3.3 Site 3: 763 E Tournament Trl, Westfield, IN 46074

A.3.3.1 Recorded Traffic Counts

		Driveway 1						Driveway 2						ALL DRIVEWAYS	
		Enter		Exit		Total		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	10	0	9	0	19	0	10	0	8	0	18	0	37	0
7:15	7:30	13	0	7	0	20	0	10	0	8	0	18	0	38	0
7:30	7:45	13	0	19	0	32	0	8	0	8	0	16	0	48	0
7:45	8:00	17	1	14	1	31	2	14	1	6	0	20	1	51	3
8:00	8:15	14	0	17	0	31	0	9	0	20	0	29	0	60	0
8:15	8:30	28	0	18	1	46	1	15	0	12	0	27	0	73	1
8:30	8:45	26	0	20	0	46	0	12	0	19	0	31	0	77	0
8:45	9:00	15	0	12	0	27	0	4	0	7	0	11	0	38	0
11:45	12:00	36	2	23	0	59	2	24	1	42	3	66	4	125	6
12:00	12:15	48	0	31	0	79	0	27	0	23	0	50	0	129	0
12:15	12:30	41	0	33	0	74	0	29	0	27	0	56	0	130	0
12:30	12:45	41	0	40	0	81	0	33	0	21	0	54	0	135	0
12:45	13:00	22	0	35	0	57	0	35	0	31	0	66	0	123	0
16:00	16:15	19	0	11	0	30	0	7	0	8	0	15	0	45	0
16:15	16:30	27	0	21	0	48	0	8	0	14	0	22	0	70	0
16:30	16:45	16	0	18	0	34	0	7	0	13	0	20	0	54	0
16:45	17:00	17	0	13	0	30	0	10	0	13	0	23	0	53	0
17:00	17:15	19	0	14	0	33	0	9	0	16	0	25	0	58	0
17:15	17:30	26	0	18	0	44	0	17	0	13	0	30	0	74	0
17:30	17:45	22	0	19	0	41	0	14	0	19	0	33	0	74	0
17:45	18:00	16	0	29	0	45	0	10	0	10	0	20	0	65	0

A.3.3.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	11:45–12:45	279	240	519	53.76	46.24	30:00.0	135
Generator PM	12:00–13:00	276	241	517	53.38	46.62	12:30	135
Street AM	7:45–8:45	135	126	261	51.72	48.28	8:30	77
Street PM	17:00–18:00	133	138	271	49.08	50.92	17:15, 17:30	74

A.3.3.3 ITE Predictions Corresponding to LU 934 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	5850	267	52	48	2010–2024 (64 studies)	Provided by ITE
Generator PM	5850	314	50	50	2010–2024 (70 studies)	Provided by ITE
Street AM	5850	203	51	49	2010–2024 (31 studies)	Average Rate Line (auto generate)
Street PM	5850	189	51	49	2010–2024 (73 studies)	Average Rate Line (auto generate)

Peak Period	Seating - In	Seating - Out	Seating Total	Independent Variable = Seating Capacity				
				Total	In (%)	Out (%)	Years	Equation Source
Generator AM	100	32	132	132	51	49	1995–2023 (3 studies)	Average Rate Line
Generator PM	100	32	132	179	50	50	1995–2023 (5 studies)	Equation Given by ITE
Street AM	100	32	132	156	52	48	1993–2023 (9 studies)	Average Rate Line
Street PM	100	32	132	123	53	47	1993–2023 (14 studies)	Average Rate Line

A.3.3.4 ITE Predictions Corresponding to LU 929 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	5850	290	50	50	All	Average Rate Line
Generator PM	5850	411	50	50	All	Average Rate Line
Street AM	5850	152	52	48	All	Average Rate Line
Street PM	5850	342	50	50	All	Average Rate Line

A.4 Land Use Code: 945

Land Use Description: Gasoline/Service Station with Convenience Market

A.4.1 Site 1: 1229 N Baldwin Ave, Marion, IN 46952

A.4.1.1 Recorded Traffic Counts

		Driveway 1						Driveway 2						ALL DRIVEWAYS	
		Enter		Exit		Total		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	4	1	8	1	12	2	5	1	1	1	6	2	18	4
7:15	7:30	6	0	2	0	8	0	7	0	6	1	13	1	21	1
7:30	7:45	8	0	6	0	14	0	9	2	5	0	14	2	28	2
7:45	8:00	9	2	3	1	12	3	8	1	6	0	14	1	26	4
8:00	8:15	4	0	5	1	9	1	6	0	9	3	15	3	24	4
8:15	8:30	12	1	3	0	15	1	6	1	4	2	10	3	25	4
8:30	8:45	5	0	12	1	17	1	6	0	4	0	10	0	27	1
8:45	9:00	7	3	3	0	10	3	3	0	5	1	8	1	18	4
15:45	16:00	2	1	5	1	7	2	4	1	8	2	12	3	19	5
16:00	16:15	10	0	6	1	16	1	4	0	5	0	9	0	25	1
16:15	16:30	4	1	5	0	9	1	6	0	6	0	12	0	21	1
16:30	16:45	7	1	5	0	12	1	6	0	4	2	10	2	22	3
16:45	17:00	9	0	6	0	15	0	7	0	11	0	18	0	33	0
17:00	17:15	9	1	5	0	14	1	2	0	4	0	6	0	20	1
17:15	17:30	7	0	5	0	12	0	4	0	7	1	11	1	23	1
17:30	17:45	6	0	3	1	9	1	7	1	7	0	14	1	23	2
17:45	18:00	7	1	5	0	12	1	2	0	9	2	11	2	23	3

A.4.1.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	7:30–8:30	62	41	103	60.19	39.81	7:30	28
Generator PM	15:45–16:45	20	23	43	49.43	50.57	16:15	12
Street AM	7:30–8:30	62	41	103	60.19	39.81	7:30	28
Street PM	16:00–17:00	53	48	101	52.48	47.52	16:45	35

A.4.1.3 ITE Predictions Corresponding to LU 945 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	4230	273	51	49	All (54 studies)	Average Rate Line (auto generate)
Generator PM	4230	273	50	50	All (62 studies)	Average Rate Line (auto generate)
Street AM	4230	275	51	49	All (59 studies)	Average Rate Line (auto generate)
Street PM	4230	258	50	50	All (66 studies)	Average Rate Line (auto generate)

Peak Period	Fueling Stations	Independent Variable = Number of Fueling Stations				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	24	538	51	49	2010–2022 (57 studies)	Average Rate Line
Generator PM	24	540	50	50	2010–2022 (61 studies)	Average Rate Line
Street AM	24	523	52	48	2010–2022 (56 studies)	Average Rate Line
Street PM	24	508	50	50	2010–2022 (60 studies)	Average Rate Line

A.4.2 Site 2: 11437 US Hwy 52 S, Clarks Hill, IN 47930

A.4.2.1 Recorded Traffic Counts

		Driveway 1						Driveway 2						ALL DRIVEWAYS	
		Enter		Exit		Total		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	6	0	3	0	9	0	7	1	10	0	17	1	26	1
7:15	7:30	10	0	5	1	15	1	6	1	11	1	17	2	32	3
7:30	7:45	9	0	11	2	20	2	12	2	9	0	21	2	41	4
7:45	8:00	7	1	10	1	17	2	16	0	14	2	30	2	47	4
8:00	8:15	6	1	13	0	19	1	22	0	16	1	38	1	57	2
8:15	8:30	5	0	4	0	9	0	13	0	12	0	25	0	34	0
8:30	8:45	2	1	4	1	6	2	6	0	11	0	17	0	23	2
8:45	9:00	4	2	2	0	6	2	8	0	6	2	14	2	20	4
15:45	16:00	10	1	12	0	22	1	19	0	22	2	41	2	63	3
16:00	16:15	10	2	6	0	16	2	12	0	11	1	23	1	39	3
16:15	16:30	10	1	9	0	19	1	16	0	15	2	31	2	50	3
16:30	16:45	8	2	9	0	17	2	12	0	17	1	29	1	46	3
16:45	17:00	13	1	4	0	17	1	8	0	12	1	20	1	37	2
17:00	17:15	14	0	10	1	24	1	16	1	16	0	32	1	56	2
17:15	17:30	5	2	12	0	17	2	10	0	10	0	20	0	37	2
17:30	17:45	3	0	3	0	6	0	10	0	9	2	19	2	25	2
17:45	18:00	10	0	8	1	18	1	20	0	11	0	31	0	49	1

A.4.2.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	7:30–8:30	71	71	142	50.00	50.00	8:00	57
Generator PM	15:45–16:45	76	68	144	52.78	47.22	15:45	63
Street AM	7:15–8:15	76	74	150	50.67	49.33	8:00	57
Street PM	16:00–17:00	70	73	143	48.95	51.05	17:00	56

A.4.2.3 ITE Predictions Corresponding to LU 945 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	2952	191	51	49	All (54 studies)	Average Rate Line (auto generate)
Generator PM	2952	190	50	50	All (62 studies)	Average Rate Line (auto generate)
Street AM	2952	192	51	49	All (59 studies)	Average Rate Line (auto generate)
Street PM	2952	180	50	50	All (66 studies)	Average Rate Line (auto generate)

Peak Period	Fueling Stations	Independent Variable = Number of Fueling Stations				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	14	209	50	50	2010–2022 (57 studies)	Average Rate Line
Generator PM	14	239	50	50	2010–2022 (61 studies)	Average Rate Line
Street AM	14	194	50	50	2010–2022 (56 studies)	Average Rate Line
Street PM	14	221	50	50	2010–2022 (60 studies)	Average Rate Line

A.4.3 Site 3: 1374 Flaxmill Rd, Huntington, IN 46750

A.4.3.1 Recorded Traffic Counts

		Driveway 1						ALL DRIVEWAYS	
		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	8	0	13	1	21	1	19	0
7:15	7:30	22	1	15	0	37	1	20	0
7:30	7:45	27	0	26	1	53	1	32	0
7:45	8:00	19	3	17	2	36	5	31	2
8:00	8:15	8	3	16	3	24	6	31	0
8:15	8:30	17	0	12	0	29	0	46	1
8:30	8:45	15	1	17	0	32	1	46	0
8:45	9:00	12	1	11	1	23	2	27	0
15:45	16:00	10	1	12	0	22	1	57	0
16:00	16:15	18	0	22	0	40	0	30	0
16:15	16:30	21	0	16	0	37	0	48	0
16:30	16:45	22	2	17	1	39	3	34	0
16:45	17:00	9	0	18	1	27	1	30	0
17:00	17:15	12	0	11	0	23	0	33	0
17:15	17:30	8	0	10	0	18	0	44	0
17:30	17:45	10	1	4	0	14	1	41	0
17:45	18:00	4	0	11	1	15	1	45	0

A.4.3.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	7:30–8:30	90	89	179	50.28	49.72	7:30	53
Generator PM	15:45–16:45	97	101	198	48.99	51.01	16:00	40
Street AM	7:30–8:30	90	89	179	50.28	49.72	7:30	53
Street PM	16:15–17:15	97	92	189	51.32	48.68	16:00	40

A.4.3.3 ITE Predictions Corresponding to LU 945 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	4230	273	51	49	All (54 studies)	Average Rate Line (auto generate)
Generator PM	4230	273	50	50	All (62 studies)	Average Rate Line (auto generate)
Street AM	4230	275	51	49	All (59 studies)	Average Rate Line (auto generate)
Street PM	4230	258	50	50	All (66 studies)	Average Rate Line (auto generate)

Peak Period	Fueling Stations	Independent Variable = Number of Fueling Stations				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	14	269	51	49	2010–2022 (57 studies)	Average Rate Line
Generator PM	14	270	50	50	2010–2022 (61 studies)	Average Rate Line
Street AM	14	263	52	48	2010–2022 (56 studies)	Average Rate Line
Street PM	14	354	50	50	2010–2022 (60 studies)	Average Rate Line

A.5 Land Use Code: 950

Land Use Description: Truck Stop

A.5.1 Site 1: 2400 E 200 N, Lafayette, IN 47905

A.5.1.1 Recorded Traffic Counts

		Driveway 1						Driveway 2					
		Enter		Exit		Total		Enter		Exit		Total	
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks
7:00	7:15	27	1	25	1	52	2	7	6	0	0	7	6
7:15	7:30	15	1	17	1	32	2	7	5	1	1	8	6
7:30	7:45	24	2	23	0	47	2	8	6	1	1	9	7
7:45	8:00	21	0	22	2	43	2	4	2	2	0	6	2
8:00	8:15	34	0	24	1	58	1	9	6	0	0	9	6
8:15	8:30	12	2	20	0	32	2	11	9	2	1	13	10
8:30	8:45	15	0	16	2	31	2	8	6	1	1	9	7
8:45	9:00	16	1	18	1	34	2	15	14	0	0	15	14
11:45	12:00	19	0	15	0	34	0	9	5	1	0	10	5
12:00	12:15	26	0	22	0	48	0	13	9	2	1	15	10
12:15	12:30	23	0	22	0	45	0	14	10	1	0	15	10
12:30	12:45	19	1	26	0	45	1	6	1	0	0	6	1
12:45	13:00	31	0	27	0	58	0	10	7	2	1	12	8
13:00	13:15	18	0	20	1	38	1	17	16	1	1	18	17
16:00	16:15	31	0	25	0	56	0	12	12	1	1	13	13
16:15	16:30	16	0	27	1	43	1	13	10	1	0	14	10
16:30	16:45	13	0	14	0	27	0	13	12	1	1	14	13
16:45	17:00	17	0	15	0	32	0	11	11	0	0	11	11
17:00	17:15	25	0	22	0	47	0	11	10	1	1	12	11
17:15	17:30	23	0	19	0	42	0	11	11	0	0	11	11
17:30	17:45	12	0	15	0	27	0	6	5	1	1	7	6
17:45	18:00	19	0	21	0	40	0	9	8	2	1	11	9

		Driveway 3						ALL DRIVEWAYS	
		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	1	1	10	9	11	10	70	18
7:15	7:30	3	3	10	8	13	11	51	19
7:30	7:45	1	0	12	9	13	9	11	18
7:45	8:00	2	2	3	3	5	5	60	9
8:00	8:15	0	0	13	7	13	7	80	14
8:15	8:30	4	3	12	7	16	10	58	22
8:30	8:45	1	0	15	12	16	12	45	21
8:45	9:00	3	2	17	16	20	18	60	34
11:45	12:00	1	1	15	13	16	14	55	19
12:00	12:15	5	5	11	8	16	13	74	23
12:15	12:30	3	1	13	10	16	11	73	21
12:30	12:45	1	0	15	10	16	10	64	12
12:45	13:00	4	4	8	5	12	9	75	17
13:00	13:15	1	1	11	11	12	12	69	30
16:00	16:15	3	3	22	20	25	23	85	36
16:15	16:30	2	2	12	10	14	12	73	23
16:30	16:45	3	2	18	14	21	16	61	29
16:45	17:00	2	1	11	9	13	10	59	21
17:00	17:15	4	3	18	16	22	19	75	30
17:15	17:30	4	4	15	14	19	18	69	29
17:30	17:45	4	3	11	10	15	13	50	19
17:45	18:00	5	4	12	12	17	16	63	25

A.5.1.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	11:45–12:45	139	143	282	49.29	50.71	12:00	79
Generator PM	12:15–13:15	147	146	293	50.17	49.83	12:45	82
Street AM	8:00–9:00	128	138	266	48.12	51.88	8:00	80
Street PM	16:00–17:00	136	147	283	48.06	51.94	16:00	94

A.5.1.3 ITE Predictions Corresponding to LU 950 in the 11th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	3400	14	50	50	All (4 studies)	Calculated using data points
Generator PM	3400	120	51	49	All (5 studies)	Calculated using data points
Street AM	3400	19	50	50	All	Equation Given by ITE
Street PM	3400	351	53	47	All (8 studies)	Calculated using data points

A.5.1.4 ITE Predictions Corresponding to LU 955 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	3400	No data				
Generator PM	3400	No data				
Street AM	3400	157	51	49	2017–2022 (9 studies)	Equation Given by ITE
Street PM	3400	148	49	51	2017–2022 (9 studies)	Equation Given by ITE

Peak Period	Fueling Stations	Independent Variable = Number of Fueling Stations				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	36	No data				
Generator PM	36	No data				
Street AM	36	344	51	49	2017–2022 (9 studies)	Equation Given by ITE
Street PM	36	414	49	51	2017–2022 (9 studies)	Equation Given by ITE

A.5.2 Site 2: 1875 S Campbell Xing, Tipton, IN 46072

A.5.2.1 Recorded Traffic Counts

		Driveway 1						Driveway 1						ALL DRIVEWAYS	
		Enter		Exit		Total		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	5	5	13	13	18	18	30	4	31	6	61	10	79	28
7:15	7:30	16	14	17	14	33	28	35	5	36	3	71	8	104	36
7:30	7:45	9	9	14	13	23	22	29	1	29	3	58	4	81	26
7:45	8:00	10	9	16	15	26	24	31	4	33	2	64	6	90	30
8:00	8:15	11	10	19	19	30	29	33	1	26	4	59	5	89	34
8:15	8:30	6	5	8	8	14	13	26	0	36	6	62	6	76	19
8:30	8:45	24	24	10	10	34	34	27	2	20	1	47	3	81	37
8:45	9:00	14	13	17	17	31	30	36	3	29	7	65	10	96	40
11:45	12:00	14	14	7	7	21	21	36	3	27	4	63	7	84	28
12:00	12:15	4	4	16	14	20	18	34	1	31	2	65	3	85	21
12:15	12:30	11	9	11	9	22	18	38	2	50	4	88	6	110	24
12:30	12:45	9	9	11	11	20	20	36	1	31	1	67	2	87	22
12:45	13:00	18	18	12	12	30	30	33	2	38	3	71	5	101	35
13:00	13:15	11	10	15	13	26	23	29	0	29	2	58	2	84	25
16:00	16:15	15	15	14	13	29	28	26	0	24	0	50	0	79	28
16:15	16:30	8	8	7	7	15	15	31	6	34	4	65	10	80	25
16:30	16:45	11	10	11	11	22	21	37	1	36	1	73	2	95	23
16:45	17:00	14	13	13	12	27	25	32	0	37	1	69	1	96	26
17:00	17:15	10	9	9	8	19	17	38	0	33	0	71	0	90	17
17:15	17:30	8	7	8	6	16	13	33	1	38	0	71	1	87	14
17:30	17:45	11	9	11	9	22	18	29	1	34	0	63	1	85	19
17:45	18:00	6	6	7	7	13	13	21	1	25	0	46	1	59	14

A.5.2.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	11:45–12:45	182	184	366	49.73	50.27	15:00.0	110
Generator PM	12:15–13:15	185	197	382	48.43	51.57	12:15	110
Street AM	7:15–8:15	174	190	364	47.80	52.20	7:15	104
Street PM	16:30–17:30	183	185	368	49.73	50.27	16:45	96

A.5.2.3 ITE Predictions Corresponding to LU 950 in the 11th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	2800	14	50	50	All (4 studies)	Calculated using data points
Generator PM	2800	99	51	49	All (5 studies)	Calculated using data points
Street AM	2800	-3.794	50	50	All	Provided by ITE
Street PM	2800	352	53	47	All (8 studies)	Calculated using data points

A.5.2.4 ITE Predictions Corresponding to LU 955 in the 12th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	2800	No data				
Generator PM	2800	No data				
Street AM	2800	149	51	49	2017–2022 (9 studies)	Provided by ITE
Street PM	2800	136	49	51	2017–2022 (9 studies)	Provided by ITE

Peak Period	Fueling Stations	Independent Variable = Number of Fueling Stations				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	34	No data				
Generator PM	34	No data				
Street AM	34	328	51	49	2017–2022 (9 studies)	Provided by ITE
Street PM	34	392	49	51	2017–2022 (9 studies)	Provided by ITE

A.5.3 Site 3: 7612 Pendleton Pike, Indianapolis, IN 46226

A.5.3.1 Recorded Traffic Counts

		Driveway 1						Driveway 2						Driveway 3					
		Enter		Exit		Total		Enter		Exit		Total		Enter		Exit		Total	
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks
7:00	7:15	4	0	0	0	4	0	9	0	5	0	14	0	11	0	9	0	20	0
7:15	7:30	6	0	0	0	6	0	16	0	8	0	24	0	10	0	12	0	22	0
7:30	7:45	5	0	0	0	5	0	24	0	9	0	33	0	4	0	12	0	16	0
7:45	8:00	2	0	1	0	3	0	15	0	6	0	21	0	12	0	14	0	26	0
8:00	8:15	1	0	1	0	2	0	9	0	6	0	15	0	13	0	14	0	27	0
8:15	8:30	7	2	0	0	7	2	19	0	11	0	30	0	11	0	10	0	21	0
8:30	8:45	5	2	0	0	5	2	8	0	10	0	18	0	12	0	13	0	25	0
8:45	9:00	1	1	0	0	1	1	9	0	7	0	16	0	12	0	11	0	23	0
11:45	12:00	1	0	1	0	2	0	8	2	6	0	14	2	4	0	1	0	5	0
12:00	12:15	1	0	1	0	2	0	11	2	5	2	16	4	8	0	11	1	19	1
12:15	12:30	1	1	3	0	4	1	10	0	5	0	15	0	3	0	6	1	9	1
12:30	12:45	3	3	0	0	3	3	7	0	2	0	9	0	4	1	5	0	9	1
12:45	13:00	1	0	0	0	1	0	5	0	4	0	9	0	1	0	2	0	3	0
13:00	13:15	1	0	0	0	1	0	14	0	2	0	16	0	0	0	2	0	2	0
16:00	16:15	0	0	1	0	1	0	6	0	2	0	8	0	6	0	5	0	11	0
16:15	16:30	0	0	0	0	0	0	8	0	7	0	15	0	10	0	7	0	17	0
16:30	16:45	0	1	0	1	0	2	5	0	4	0	9	0	7	0	5	0	12	0
16:45	17:00	0	0	0	0	0	0	4	0	3	0	7	0	6	0	5	0	11	0
17:00	17:15	0	2	3	0	3	2	6	0	5	0	11	0	4	0	4	0	8	0
17:15	17:30	0	0	0	0	0	0	9	0	2	0	11	0	10	0	10	0	20	0
17:30	17:45	0	0	0	0	0	0	7	0	5	0	12	0	5	0	8	0	13	0
17:45	18:00	0	0	0	0	0	0	4	0	6	0	10	0	12	0	2	0	14	0

		Driveway 4						Driveway 5					
		Enter		Exit		Total		Enter		Exit		Total	
From	To	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks	All	Trucks
7:00	7:15	8	0	17	0	25	0	3	1	1	0	4	1
7:15	7:30	11	0	17	0	28	0	5	1	6	0	11	1
7:30	7:45	5	0	15	0	20	0	1	1	9	1	10	2
7:45	8:00	14	0	14	0	28	0	2	1	5	0	7	1
8:00	8:15	15	0	15	0	30	0	1	0	2	1	3	1
8:15	8:30	16	0	21	0	37	0	3	1	2	1	5	2
8:30	8:45	21	0	18	0	39	0	4	0	2	0	6	0
8:45	9:00	16	0	25	0	41	0	4	0	1	1	5	1
11:45	12:00	7	1	11	0	18	1	5	1	1	1	6	2
12:00	12:15	15	0	16	0	31	0	1	0	0	0	1	0
12:15	12:30	8	0	12	0	20	0	3	1	1	1	4	2
12:30	12:45	8	1	7	0	15	1	2	0	0	0	2	0
12:45	13:00	10	1	14	2	24	3	3	2	3	2	6	4
13:00	13:15	5	0	15	0	20	0	1	1	2	1	3	2
16:00	16:15	8	1	9	0	17	1	1	1	0	0	1	1
16:15	16:30	4	0	11	0	15	0	1	1	0	0	1	1
16:30	16:45	11	1	11	1	22	2	4	2	2	1	6	3
16:45	17:00	10	1	16	0	26	1	0	0	1	1	1	1
17:00	17:15	11	0	12	1	23	1	2	0	0	0	2	0
17:15	17:30	7	1	8	0	15	1	0	0	0	0	0	0
17:30	17:45	12	0	7	0	19	0	0	0	2	1	2	1
17:45	18:00	8	0	15	1	23	1	3	0	1	0	4	0

		Driveway 6						ALL DRIVEWAYS	
		Enter		Exit		Total			
From	To	All	Trucks	All	Trucks	All	Trucks	ALL	TRUCKS
7:00	7:15	2	0	3	0	5	0	68	0
7:15	7:30	3	1	4	2	7	3	87	3
7:30	7:45	1	0	1	0	2	0	76	0
7:45	8:00	0	0	4	0	4	0	82	0
8:00	8:15	2	1	2	1	4	2	78	2
8:15	8:30	0	0	4	0	4	0	99	2
8:30	8:45	1	1	5	1	6	2	93	4
8:45	9:00	0	0			0	0	81	1
11:45	12:00	0	0	6	3	6	3	45	6
12:00	12:15	1	1	2	1	3	2	71	7
12:15	12:30	1	1	2	2	3	3	51	5
12:30	12:45	1	1	4	2	5	3	41	8
12:45	13:00	3	2	2	0	5	2	42	5
13:00	13:15	0	0	1	1	1	1	40	1
16:00	16:15	0	0	0	1	0	1	37	2
16:15	16:30	0	0	0	2	0	2	47	2
16:30	16:45	0	0	1	0	1	0	44	4
16:45	17:00	0	0	1	1	1	1	45	2
17:00	17:15	2	0	1	2	3	2	48	5
17:15	17:30	1	0	0	1	1	1	47	2
17:30	17:45	0	0	0	0	0	0	44	0
17:45	18:00	0	1	0	0	0	1	47	2

A.5.3.2 Peak Hour Counts

Peak Period	Time	In (Count)	Out (Count)	Total	In (%)	Out (%)	Peak 15-min Period	Count for Peak 15
Generator AM	11:45–12:45	113	108	221	51.13	48.87	00:00.0	72
Generator PM	12:15–13:15	95	94	189	50.26	49.74	12:15	55
Street AM	7:45–8:45	193	180	373	51.74	48.26	8:15	104
Street PM	16:15–17:15, 17:00–18:00	95, 103	99, 91	194	48.97, 53.09	51.03, 46.91	17:45	51

A.5.3.3 ITE Predictions Corresponding to LU 950 in the 11th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	6000	14	50	50	All (4 studies)	Calculated using data points
Generator PM	6000	208	51	49	All (5 studies)	Calculated using data points
Street AM	6000	114	50	50	All	Provided by ITE
Street PM	6000	345	53	47	All (8 studies)	Calculated using data points

A.5.3.4 ITE Predictions Corresponding to LU 950 in the 11th Edition of the ITE Trip Generation Manual

Peak Period	GFA (in square feet)	Independent Variable = GFA				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	6000	No data				
Generator PM	6000	No data				
Street AM	6000	192	51	49	2017–2022 (9 studies)	Provided by ITE
Street PM	6000	202	49	51	2017–2022 (9 studies)	Provided by ITE

Peak Period	Fueling Stations	Independent Variable = Number of Fueling Stations				
		Total	In (%)	Out (%)	Years	Equation Source
Generator AM	24	No data				
Generator PM	24	No data				
Street AM	24	247	51	49	2017–2022 (9 studies)	Provided by ITE
Street PM	24	282	49	51	2017–2022 (9 studies)	Provided by ITE

Appendix B. Indiana Specific Trip Generation Curves

154 - High-Cube Transload and Short-Term Storage Warehouse

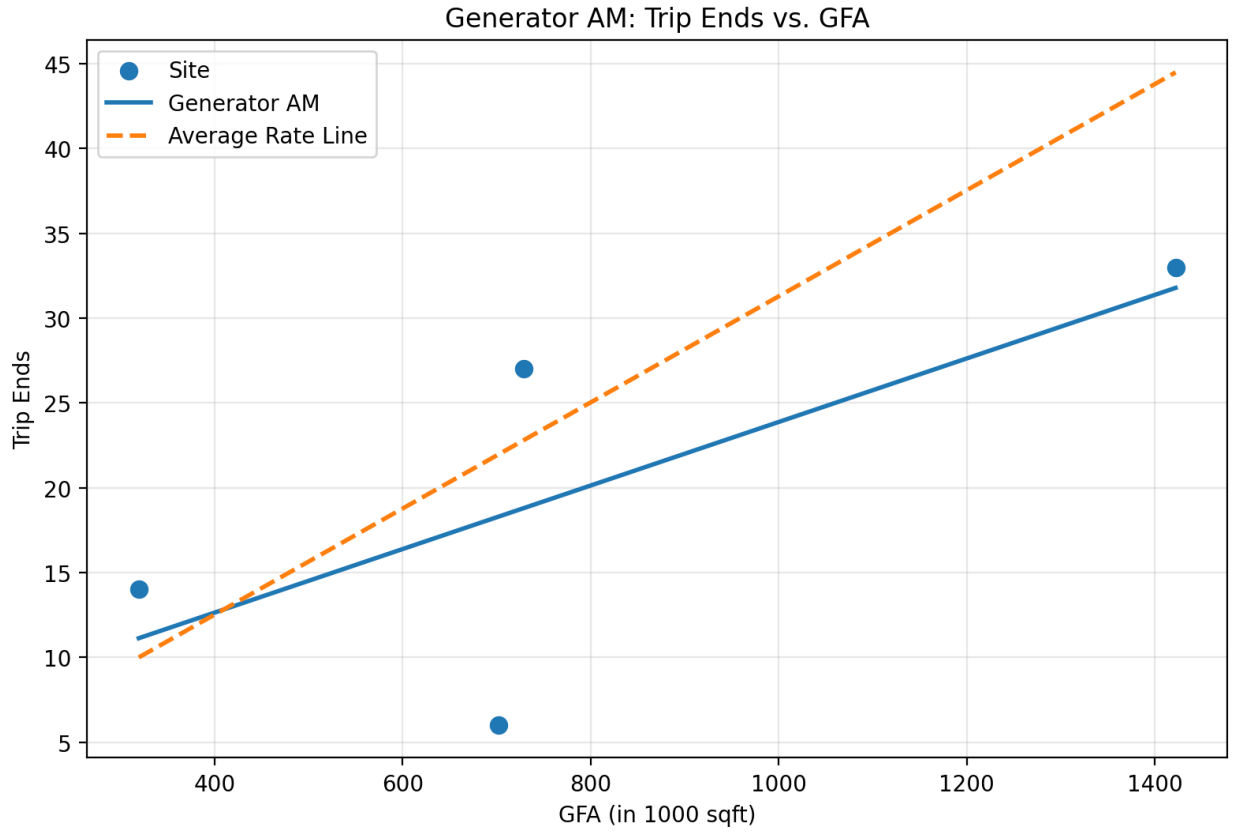
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 9 and 10 a.m.
Number of Studies: 4
1000 Sq. Ft. GFA: 0.79
Directional Distribution: 45% entering, 55% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
54.78	8.55–28.15	0.01

Data Plot and Equation

Equation	R^2
T = 0.0187(X) + 5.1416	0.4931



154 - High-Cube Transload and Short-Term Storage Warehouse

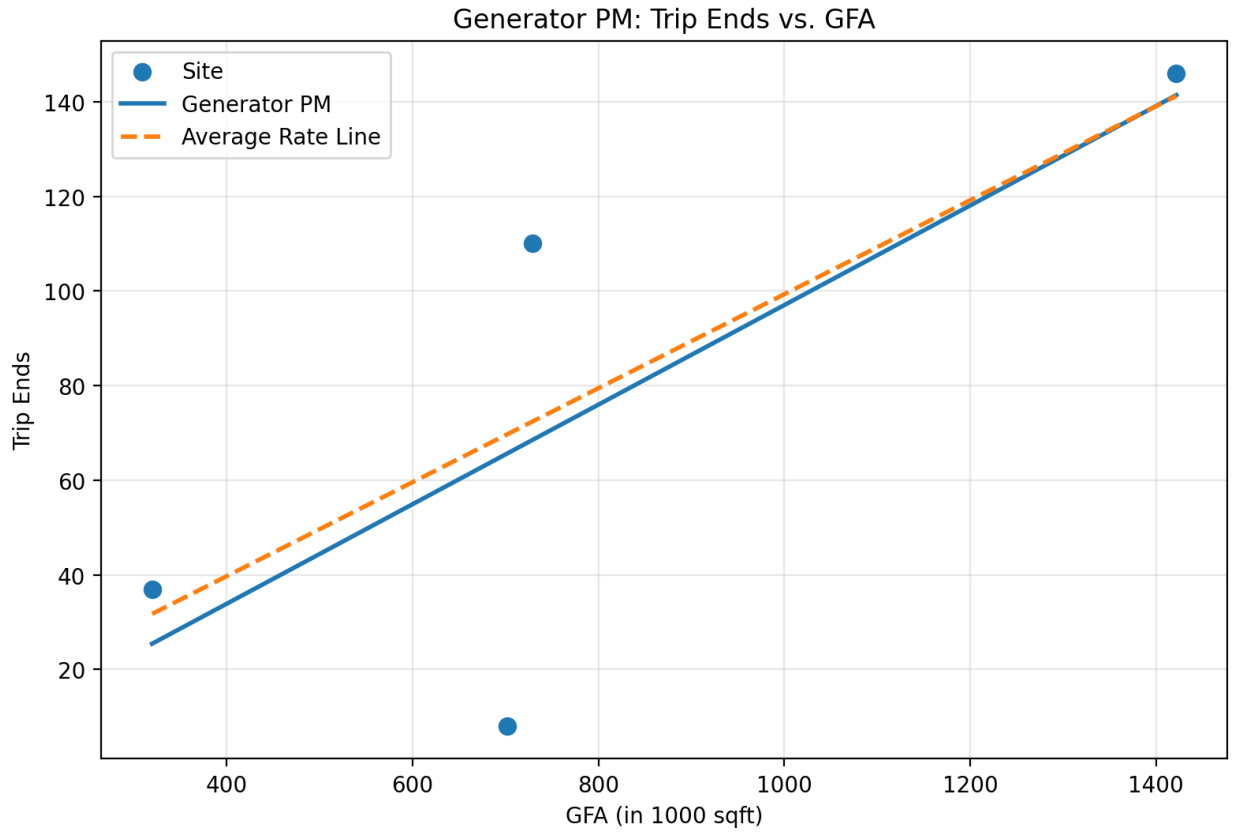
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 3 and 4 p.m.
Number of Studies: 4
1000 Sq. Ft. GFA: 0.79
Directional Distribution: 26% entering, 74% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
99.31	11.40–150.89	0.03

Data Plot and Equation

Equation	R^2
T = 0.1052(X) − 8.1862	0.5736



154 - High-Cube Transload and Short-Term Storage Warehouse

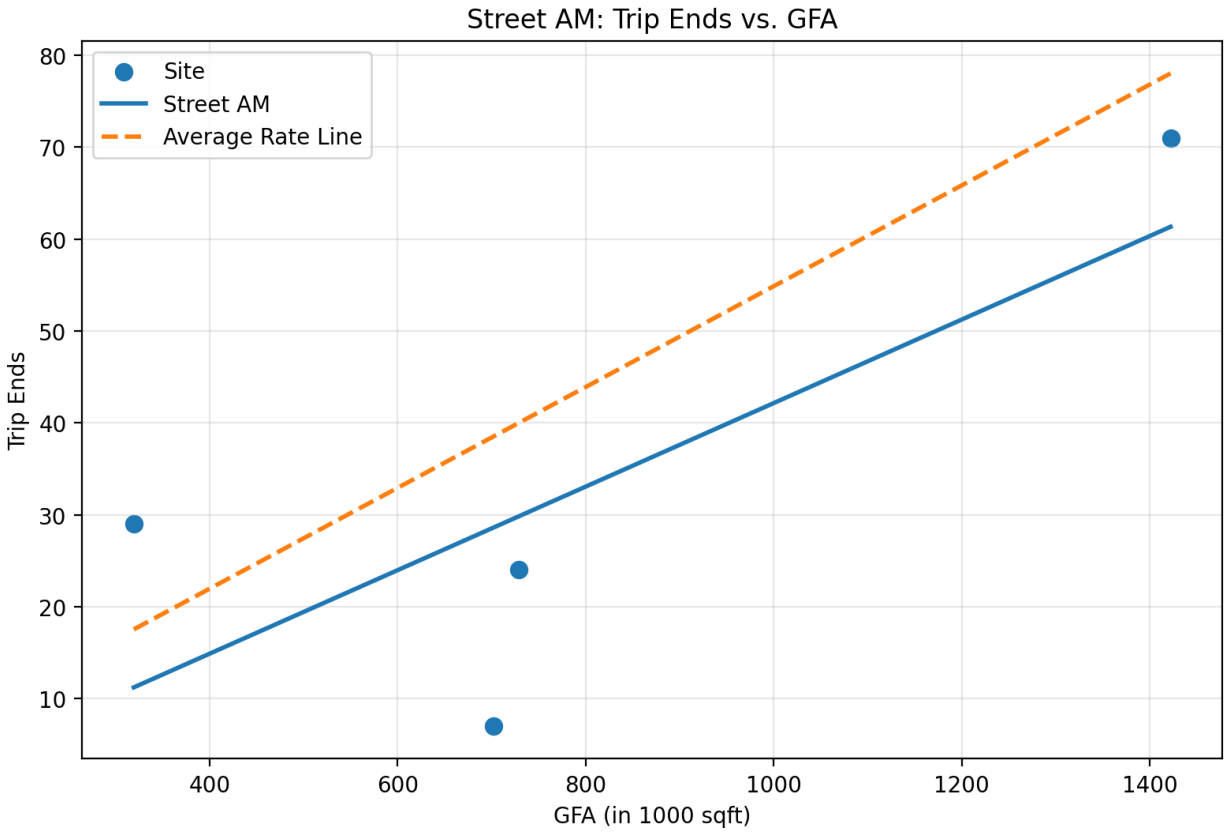
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 4
1000 Sq. Ft. GFA: 0.79
Directional Distribution: 70% entering, 30% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
54.87	9.97–90.77	0.02

Data Plot and Equation

Equation	R^2
T = 0.0455(X) − 3.3024	0.5893



154 - High-Cube Transload and Short-Term Storage Warehouse

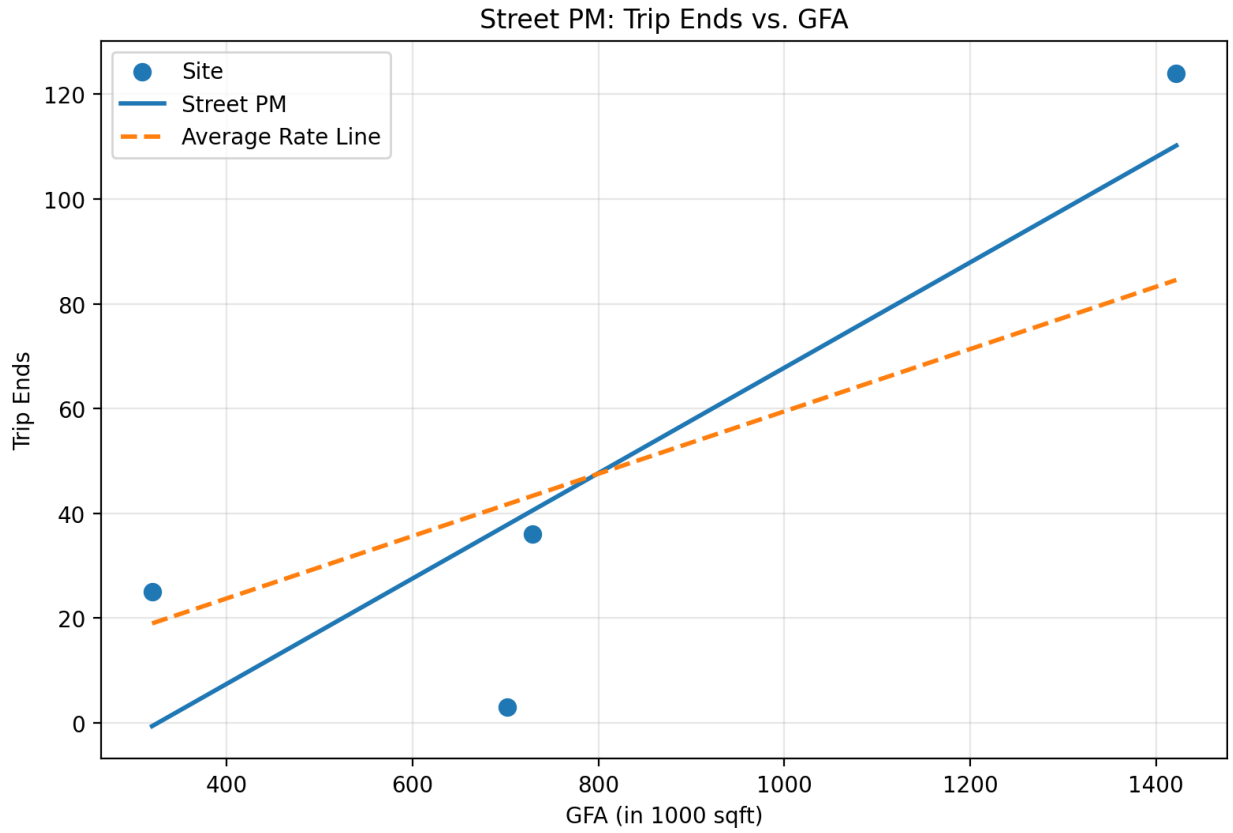
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 4
1000 Sq. Ft. GFA: 0.79
Directional Distribution: 29% entering, 71% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
59.47	4.27–87.20	0.02

Data Plot and Equation

Equation	R^2
T = 0.1005(X) − 32.7343	0.7544



154 - High-Cube Transload and Short-Term Storage Warehouse

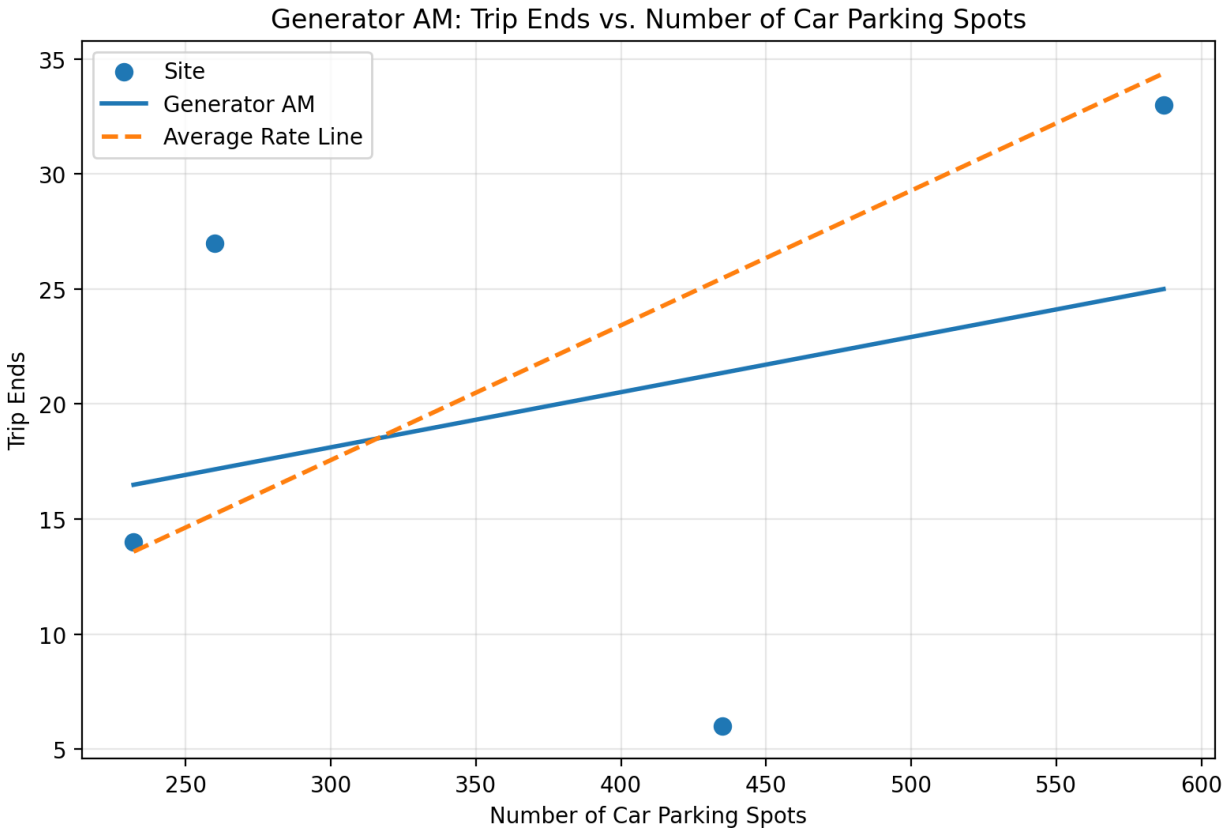
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 9 and 10 a.m.
Number of Studies: 4
Number of Car Parking Spots: 378.5
Directional Distribution: 45% entering, 55% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.06	0.01–0.10	0.02

Data Plot and Equation

Equation	R^2
T = 0.0240(X) + 10.9301	0.1049



154 - High-Cube Transload and Short-Term Storage Warehouse

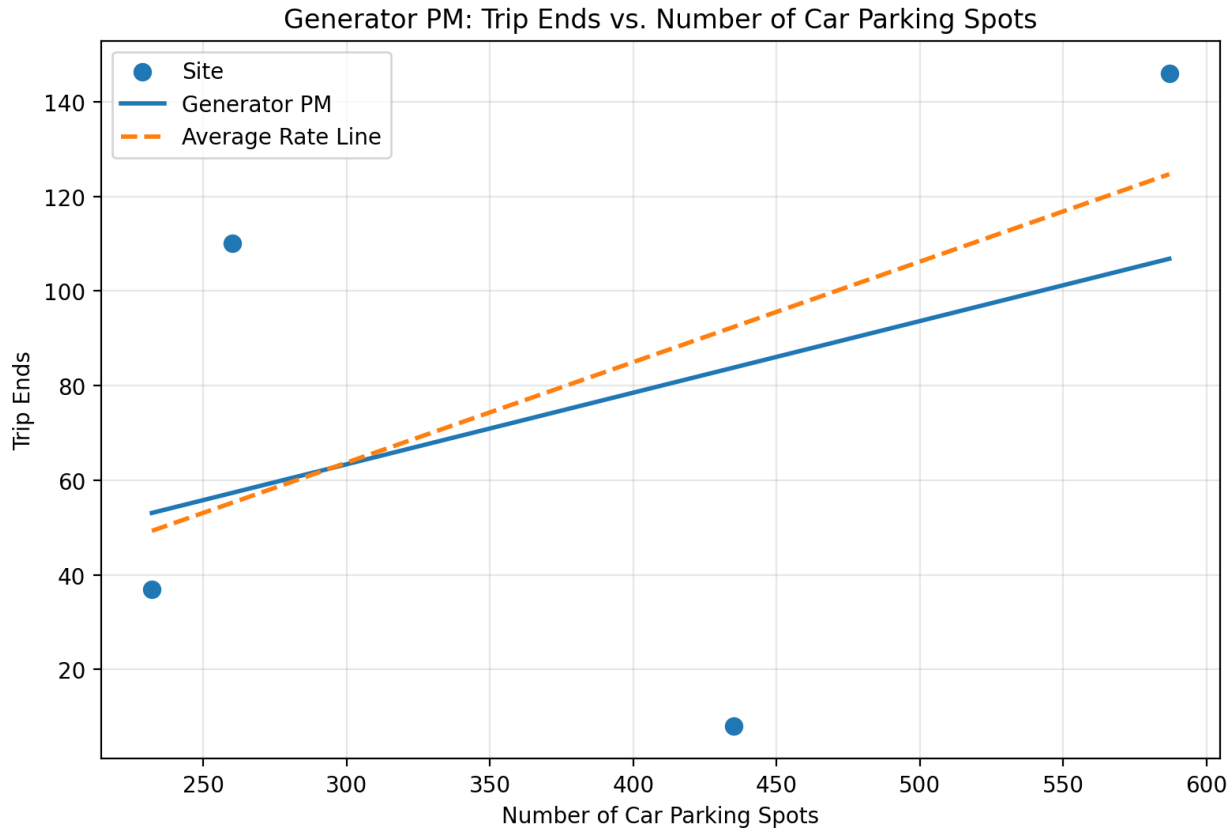
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 3 and 4 p.m.
Number of Studies: 4
Number of Car Parking Spots: 0.79
Directional Distribution: 26% entering, 74% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.21	0.02–0.42	0.1

Data Plot and Equation

Equation	R^2
T = 0.1514(X) + 17.9584	0.1543



154 - High-Cube Transload and Short-Term Storage Warehouse

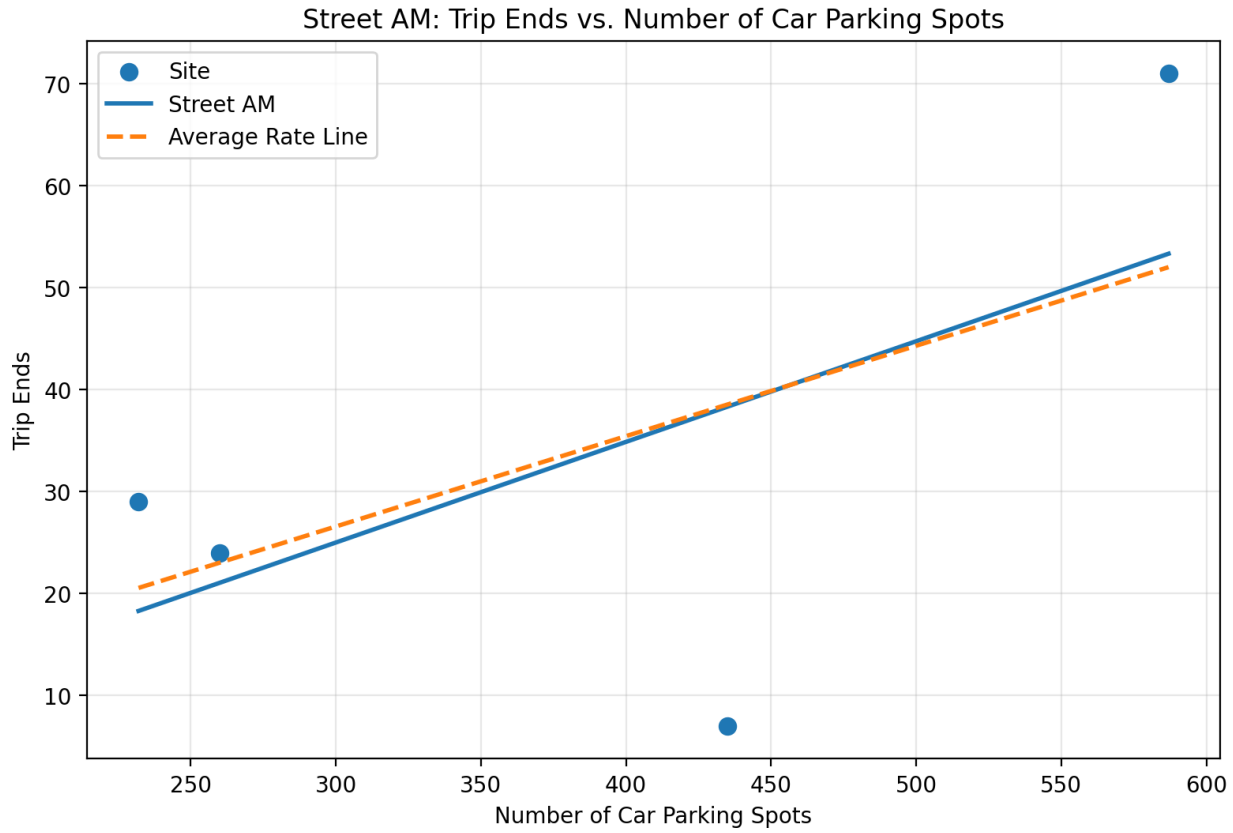
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 4
Number of Car Parking Spots: 0.79
Directional Distribution: 70% entering, 30% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.09	0.02–0.13	0.03

Data Plot and Equation

Equation	R^2
T = .0987(X) − 4.5915	0.3608



154 - High-Cube Transload and Short-Term Storage Warehouse

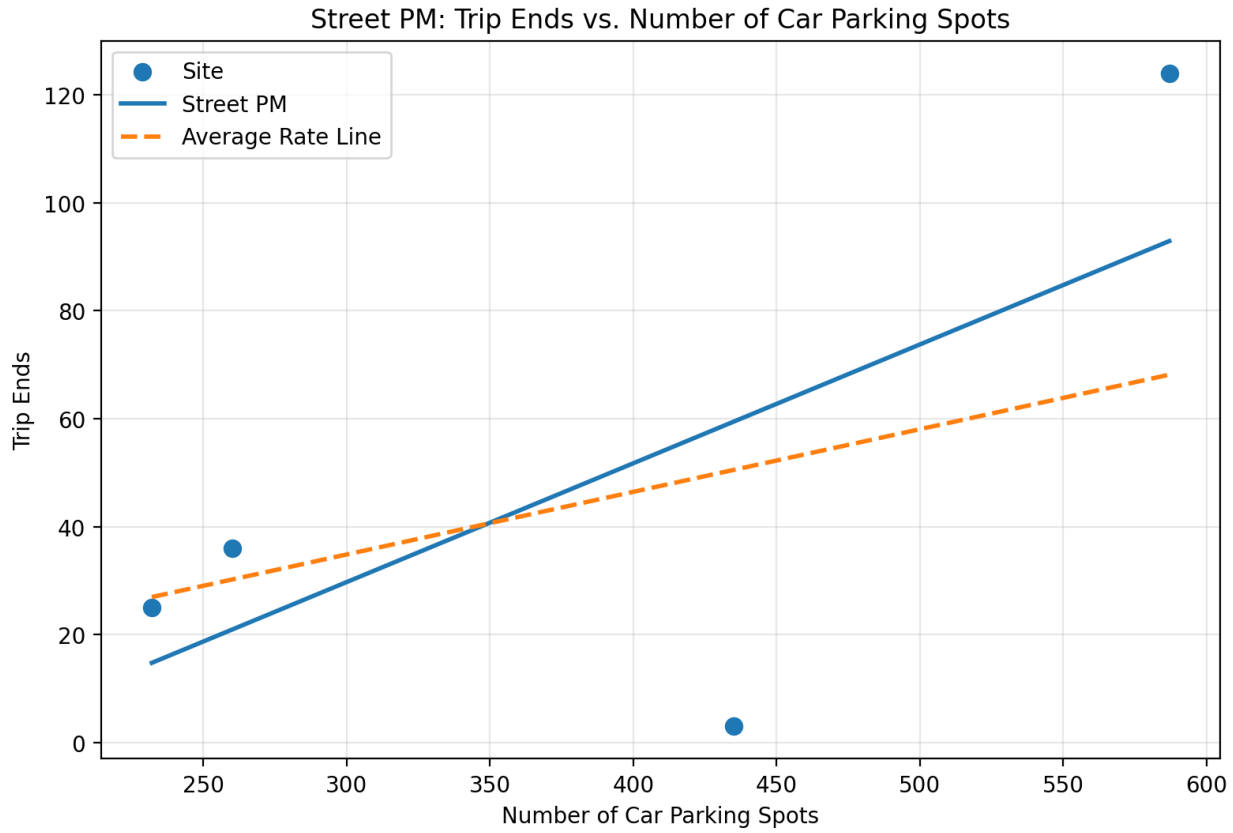
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 4
Number of Car Parking Spots: 0.79
Directional Distribution: 29% entering, 71% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.12	0.01–0.04	0.05

Data Plot and Equation

Equation	R^2
T = 0.2202(X) − 36.3521	0.4705



154 - High-Cube Transload and Short-Term Storage Warehouse

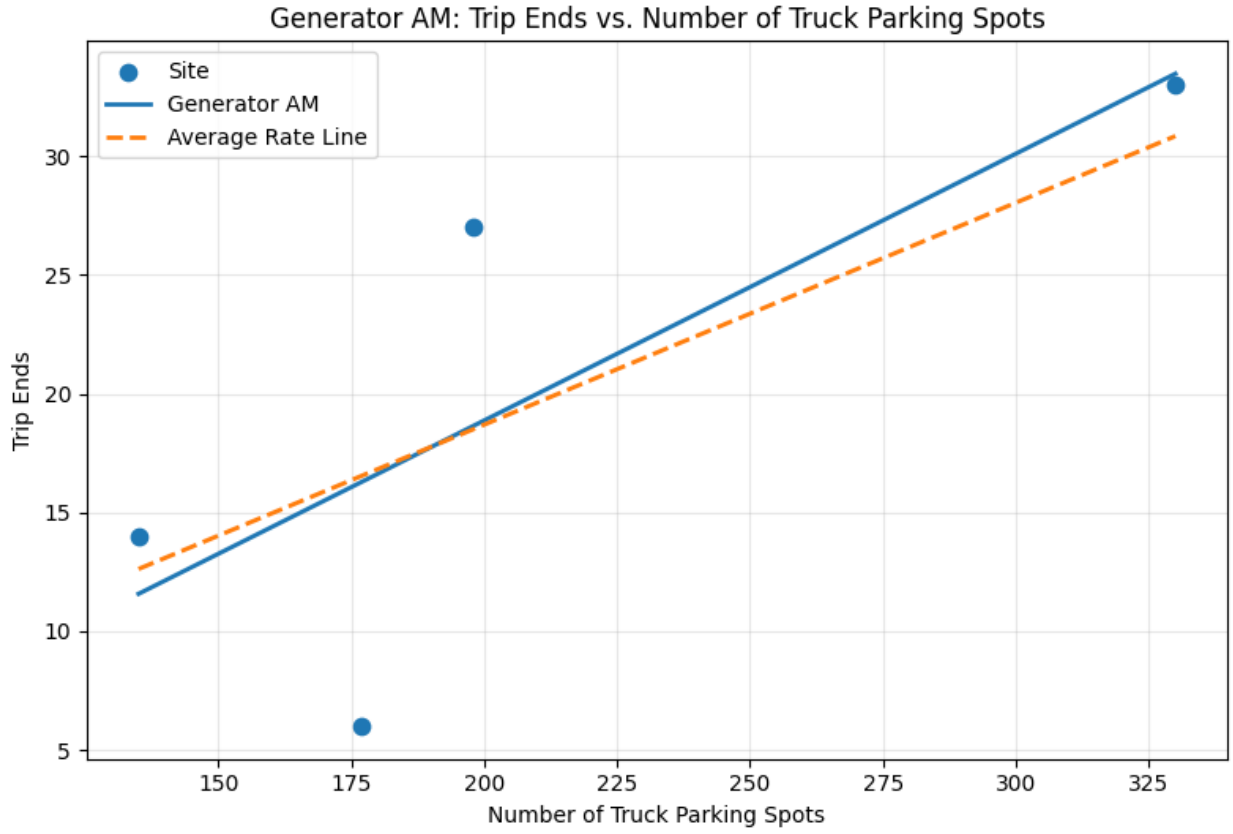
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 9 and 10 a.m.
Number of Studies: 4
Number of Truck Parking Spots: 0.79
Directional Distribution: 45% entering, 55% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.09	0.03–0.14	0.02

Data Plot and Equation

Equation	R^2
T = 0.1123(X) − 3.5902	0.5961



154 - High-Cube Transload and Short-Term Storage Warehouse

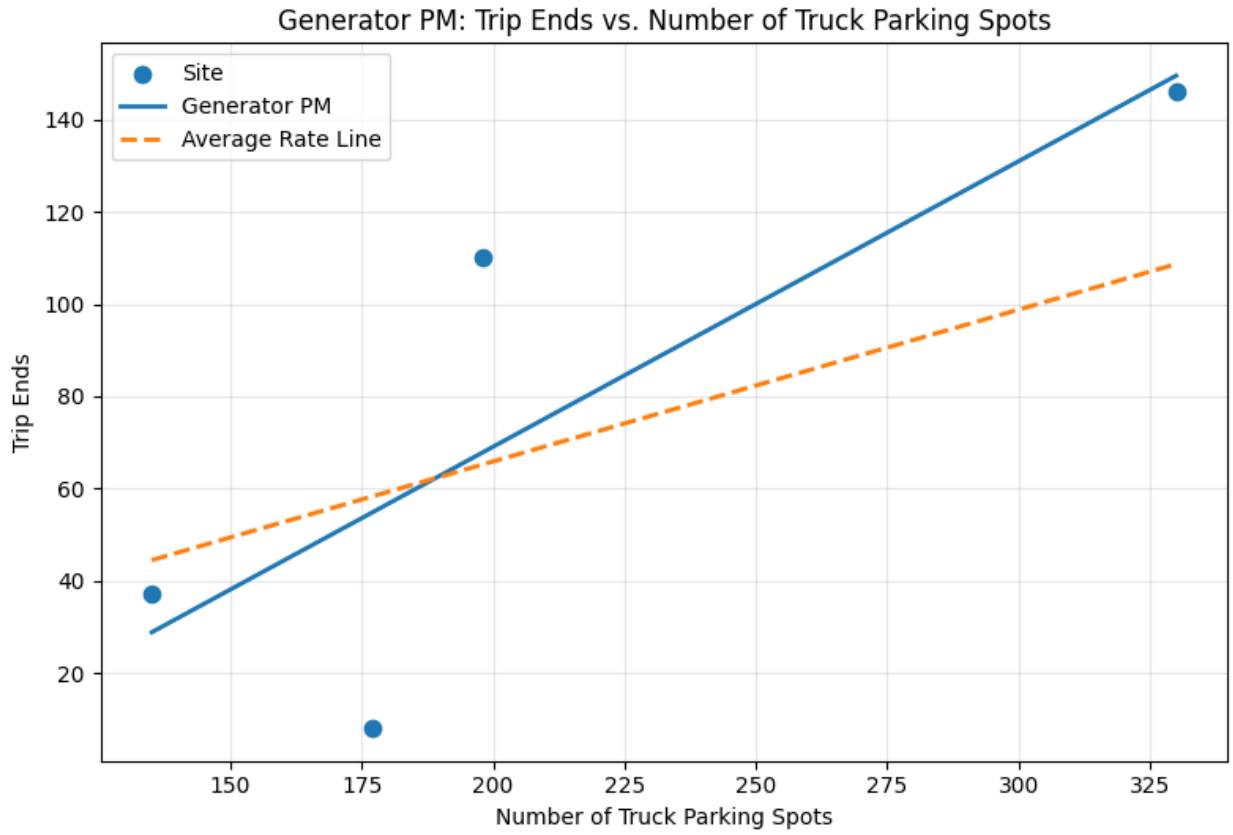
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 3 and 4 p.m.
Number of Studies: 4
Number of Truck Parking Spots: 0.79
Directional Distribution: 26% entering, 74% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.33	0.05–0.56	0.13

Data Plot and Equation

Equation	R^2
T = 0.6191(X) − 54.7627	0.6679



154 - High-Cube Transload and Short-Term Storage Warehouse

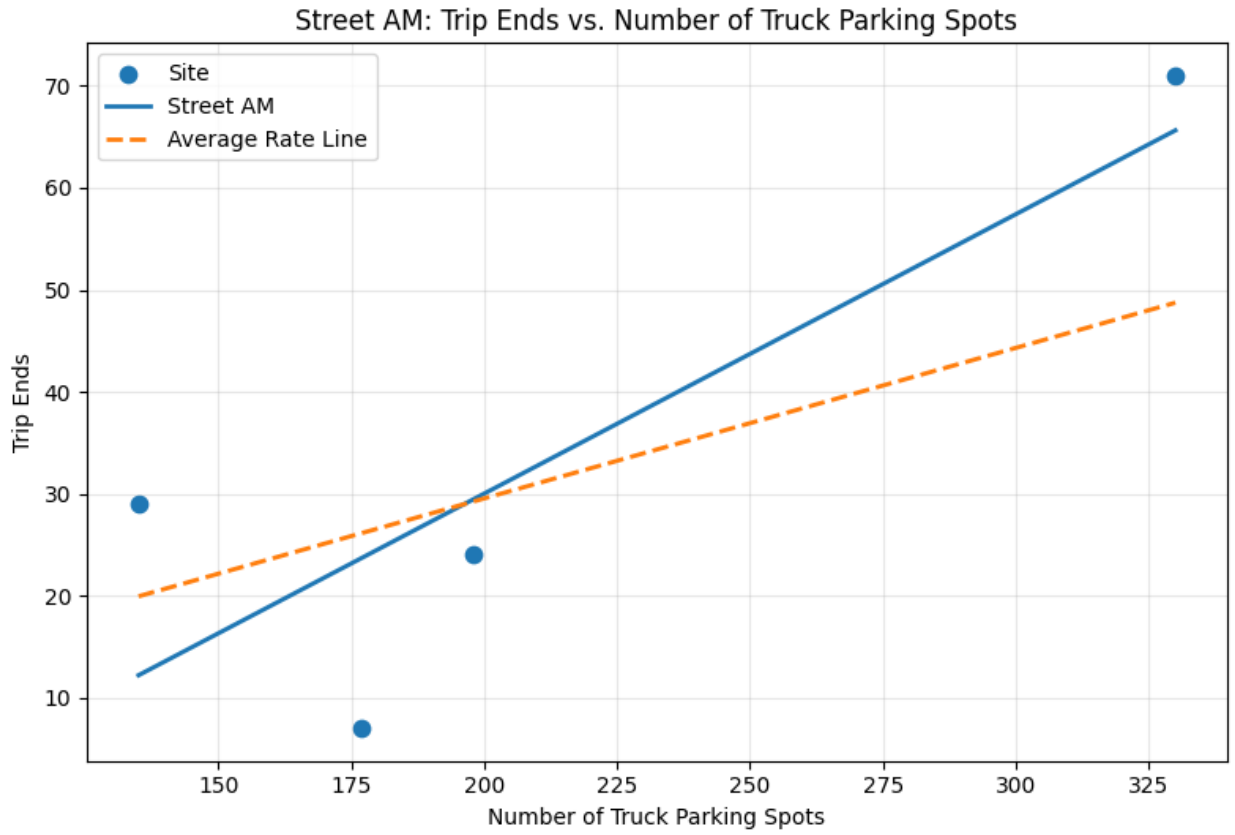
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 4
Number of Truck Parking Spots: 0.79
Directional Distribution: 70% entering, 30% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.15	0.04–0.22	0.05

Data Plot and Equation

Equation	R^2
T = 0.2741(X) − 24.8029	0.7203



154 - High-Cube Transload and Short-Term Storage Warehouse

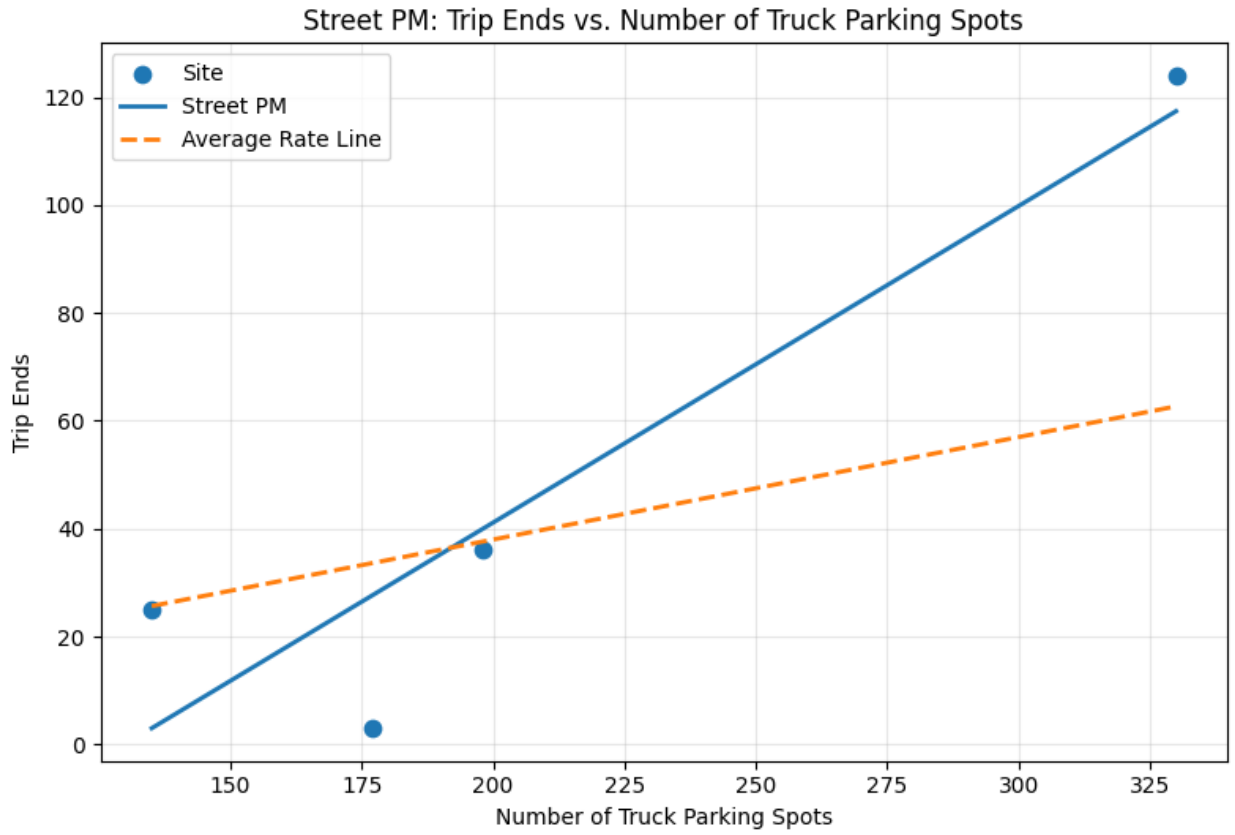
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 4
Number of Truck Parking Spots: 0.79
Directional Distribution: 29% entering, 71% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.19	0.02–0.38	0.08

Data Plot and Equation

Equation	R^2
T = 0.5868(X) − 76.2261	0.8642



154 - High-Cube Transload and Short-Term Storage Warehouse

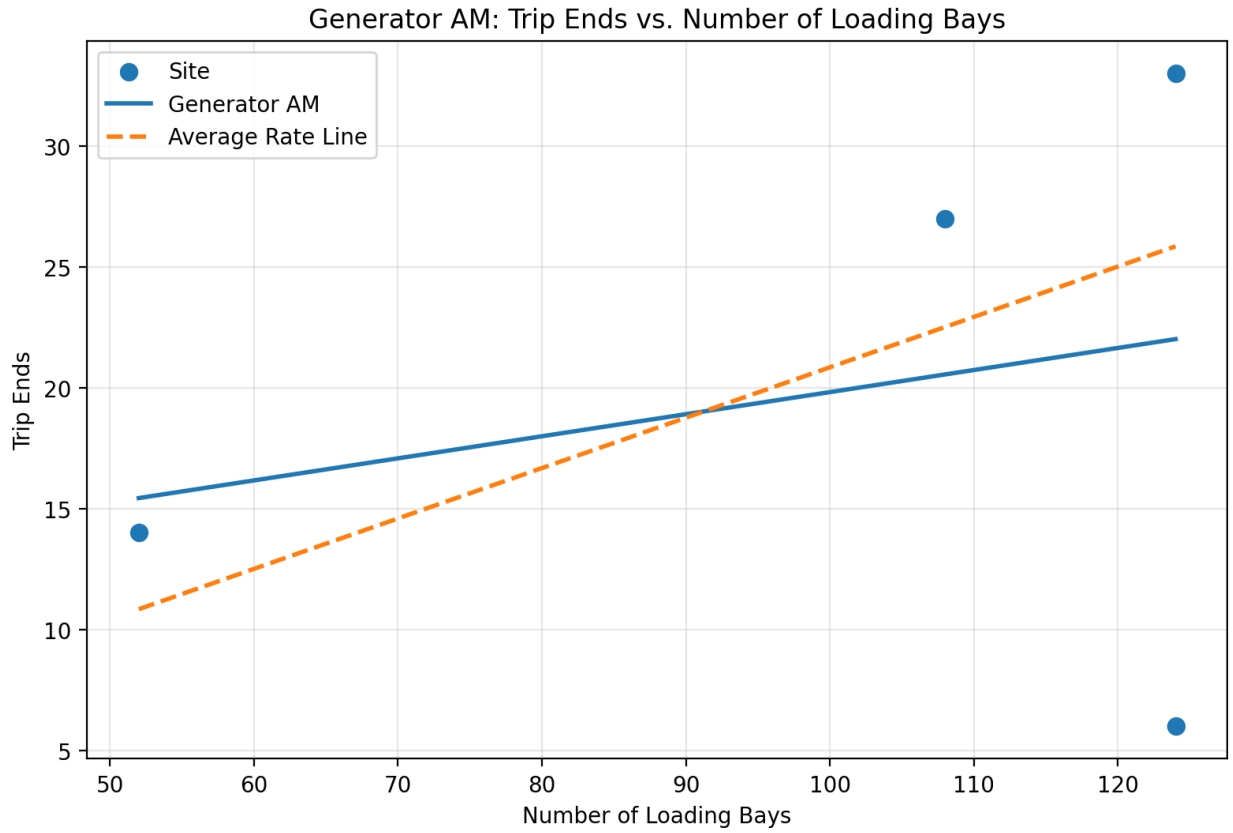
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 9 and 10 a.m.
Number of Studies: 4
Number of Truck Loading Bays: 0.79
Directional Distribution: 45% entering, 55% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.21	0.05–0.27	0.06

Data Plot and Equation

Equation	R^2
T = 0.0913(X) + 10.6849	0.0649



154 - High-Cube Transload and Short-Term Storage Warehouse

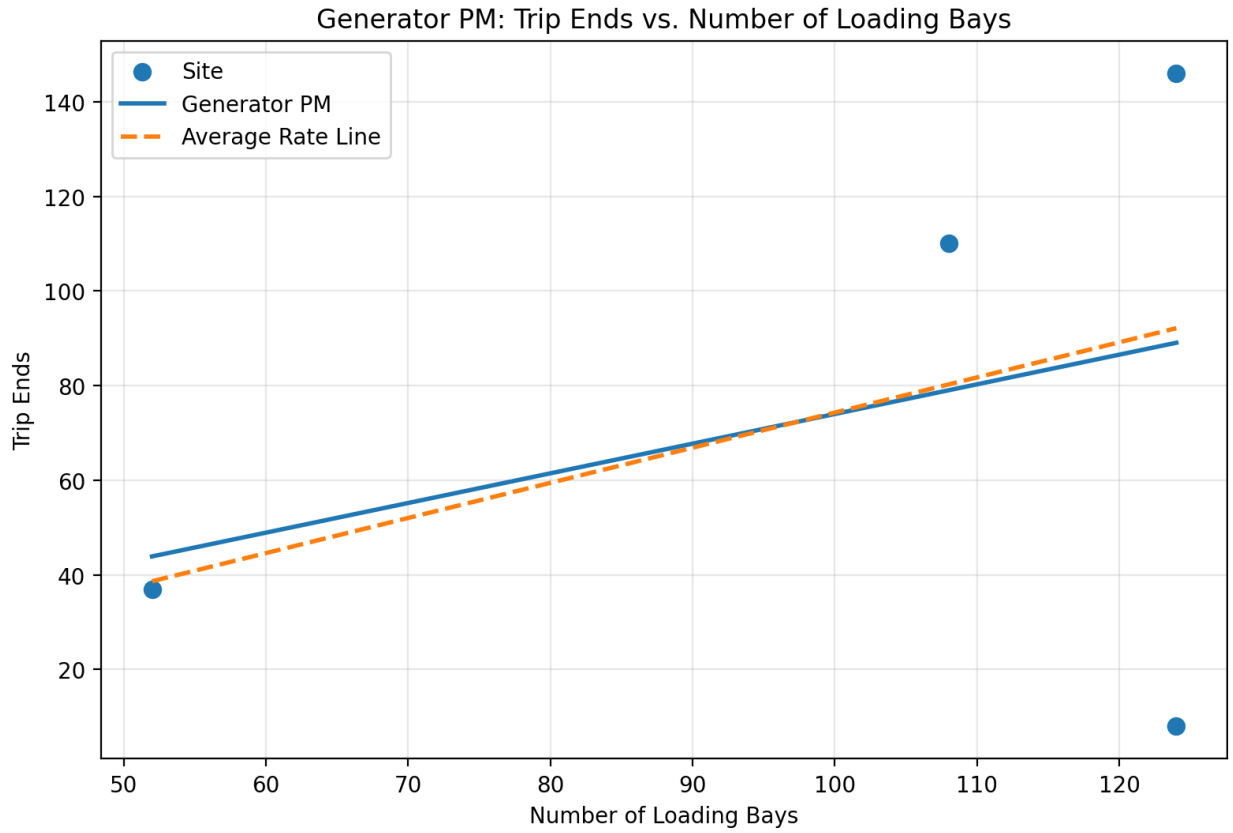
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 3 and 4 p.m.
Number of Studies: 4
Number of Truck Loading Bays: 0.79
Directional Distribution: 26% entering, 74% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.75	0.06–1.18	0.28

Data Plot and Equation

Equation	R^2
T = 0.6273(X) + 11.2671	0.1130



154 - High-Cube Transload and Short-Term Storage Warehouse

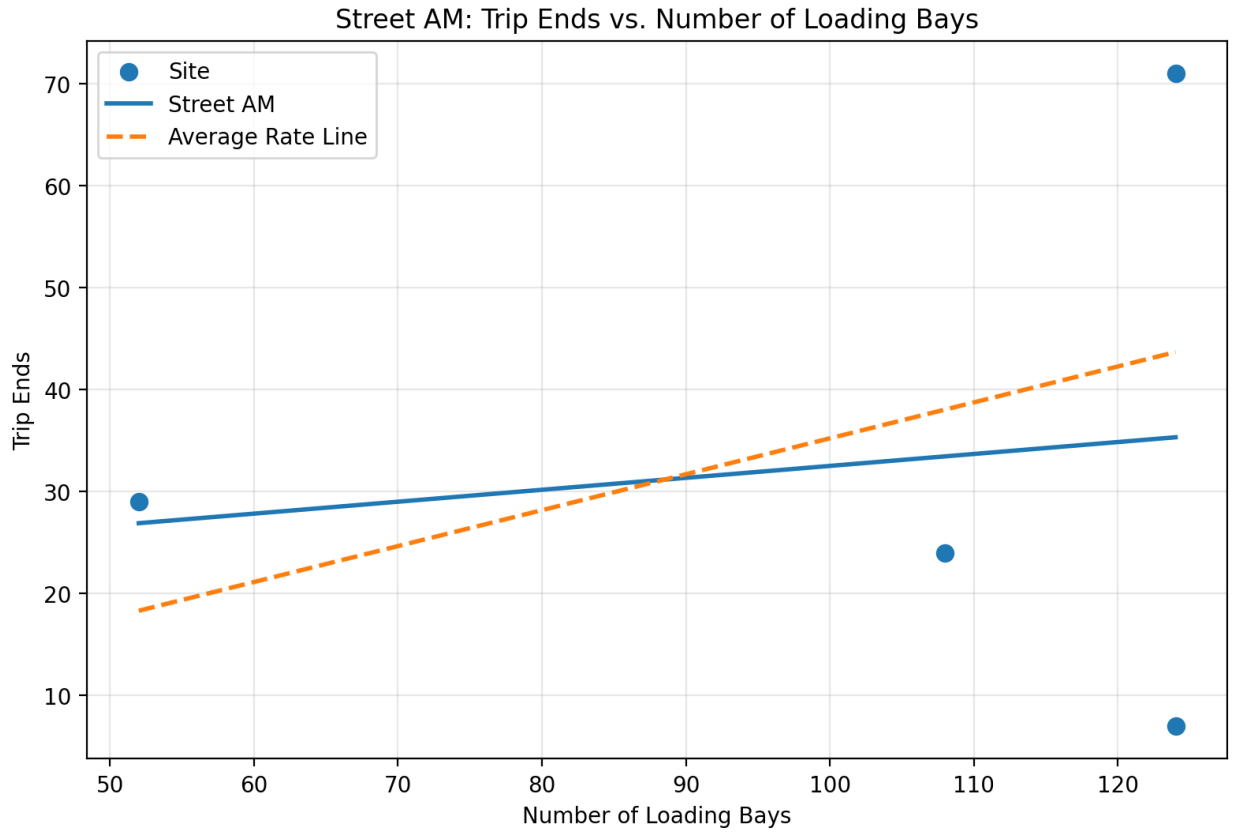
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 4
Number of Truck Loading Bays: 0.79
Directional Distribution: 70% entering, 30% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.35	0.06–0.57	0.15

Data Plot and Equation

Equation	R^2
T = 0.1170(X) + 20.8151	0.0216



154 - High-Cube Transload and Short-Term Storage Warehouse

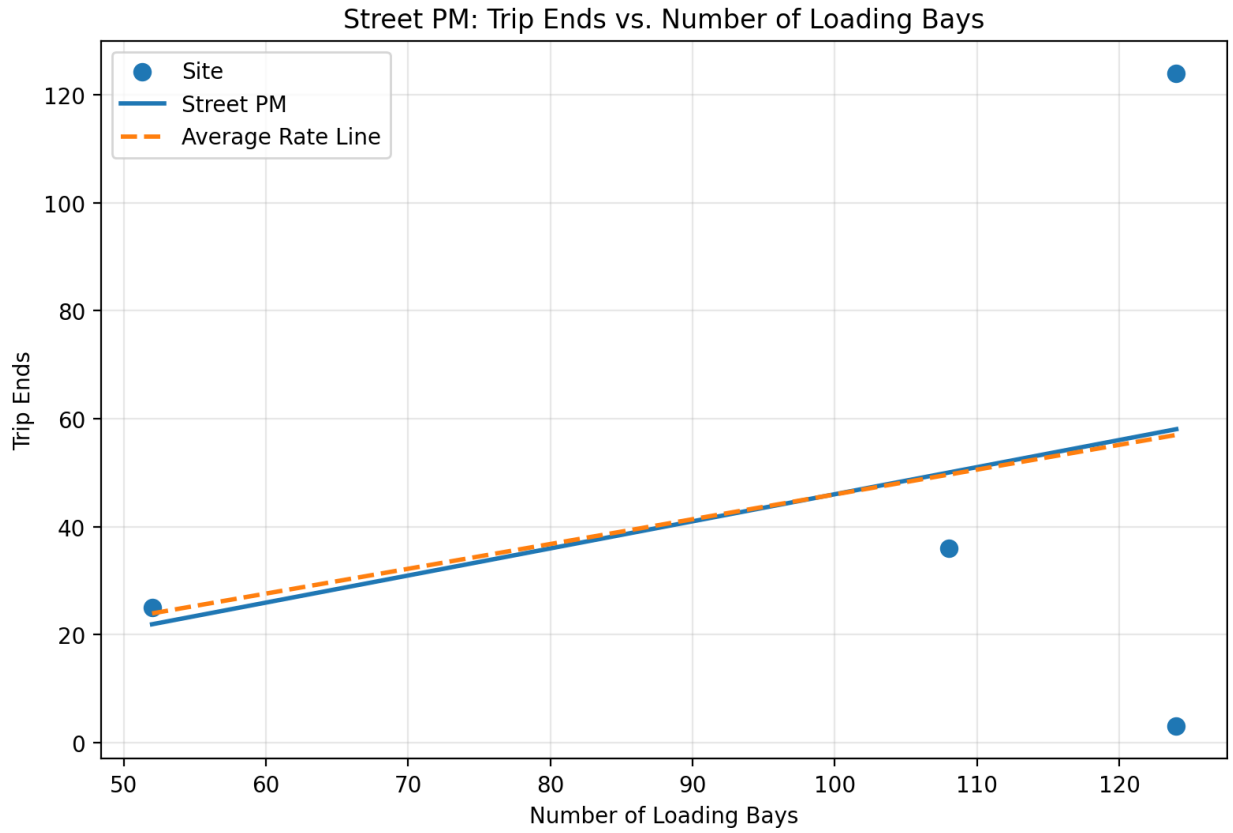
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 4
Number of Truck Loading Bays: 0.79
Directional Distribution: 29% entering, 71% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.46	0.02–1	0.24

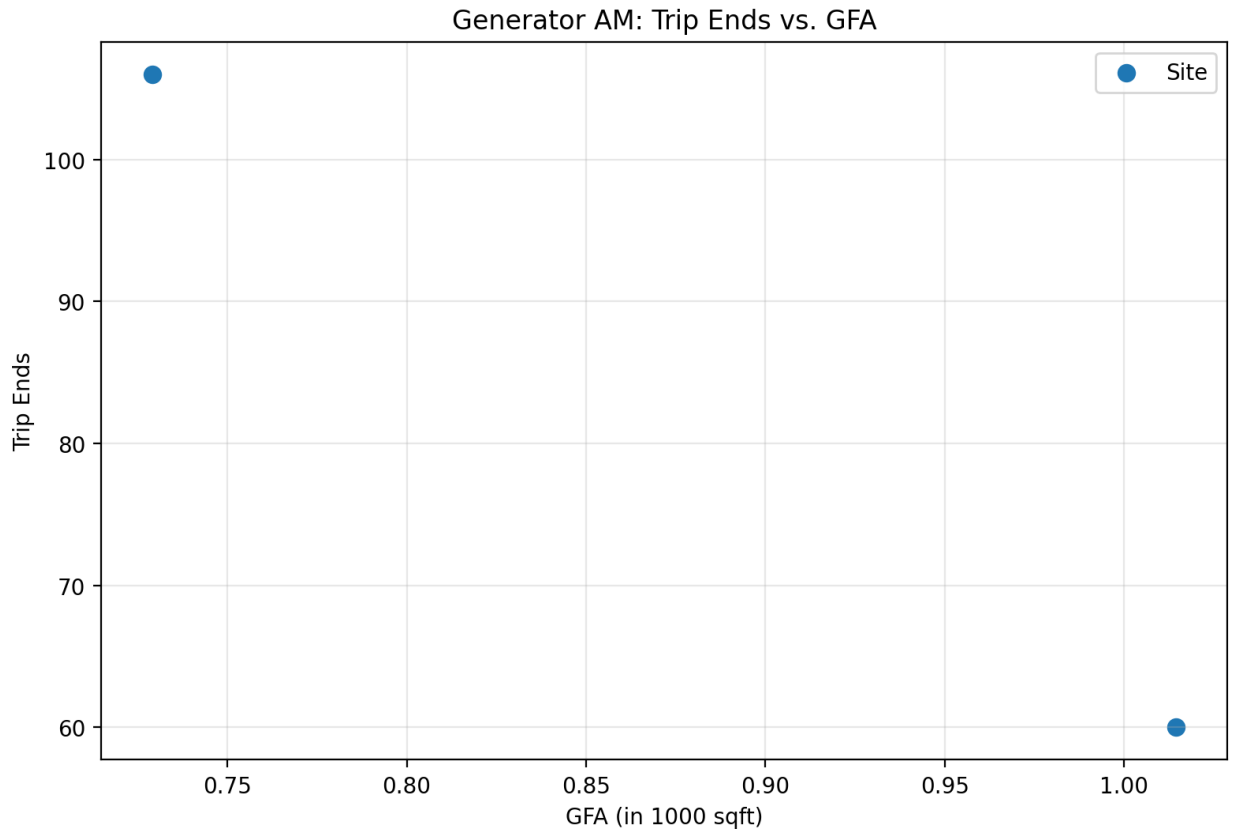
Data Plot and Equation

Equation	R^2
T = 0.5023(X) − 4.2329	0.1044



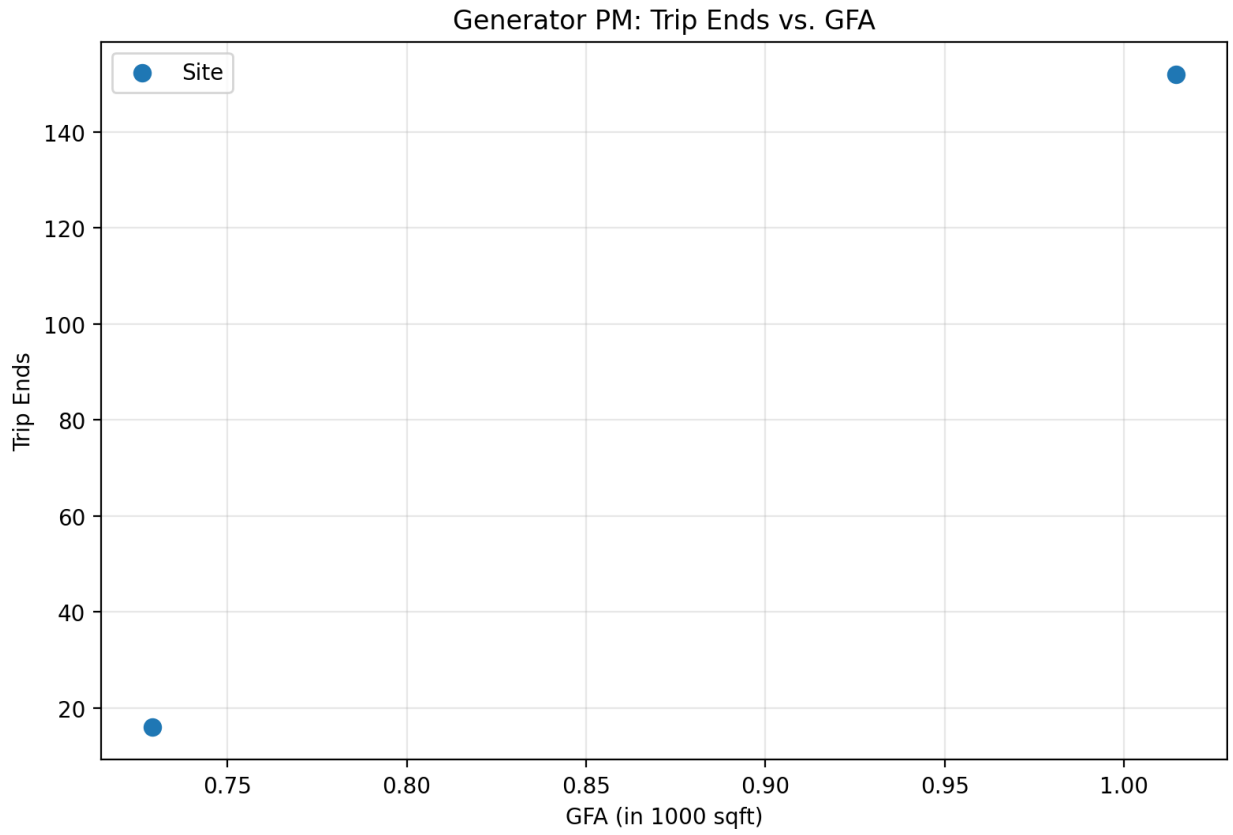
155 - High-Cube Parcel Hub Warehouse

Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 8:15 and 9:15 a.m.
Number of Studies: 2
1000 Sq. Ft. GFA: 0.87
Directional Distribution: 84% entering, 16% exiting



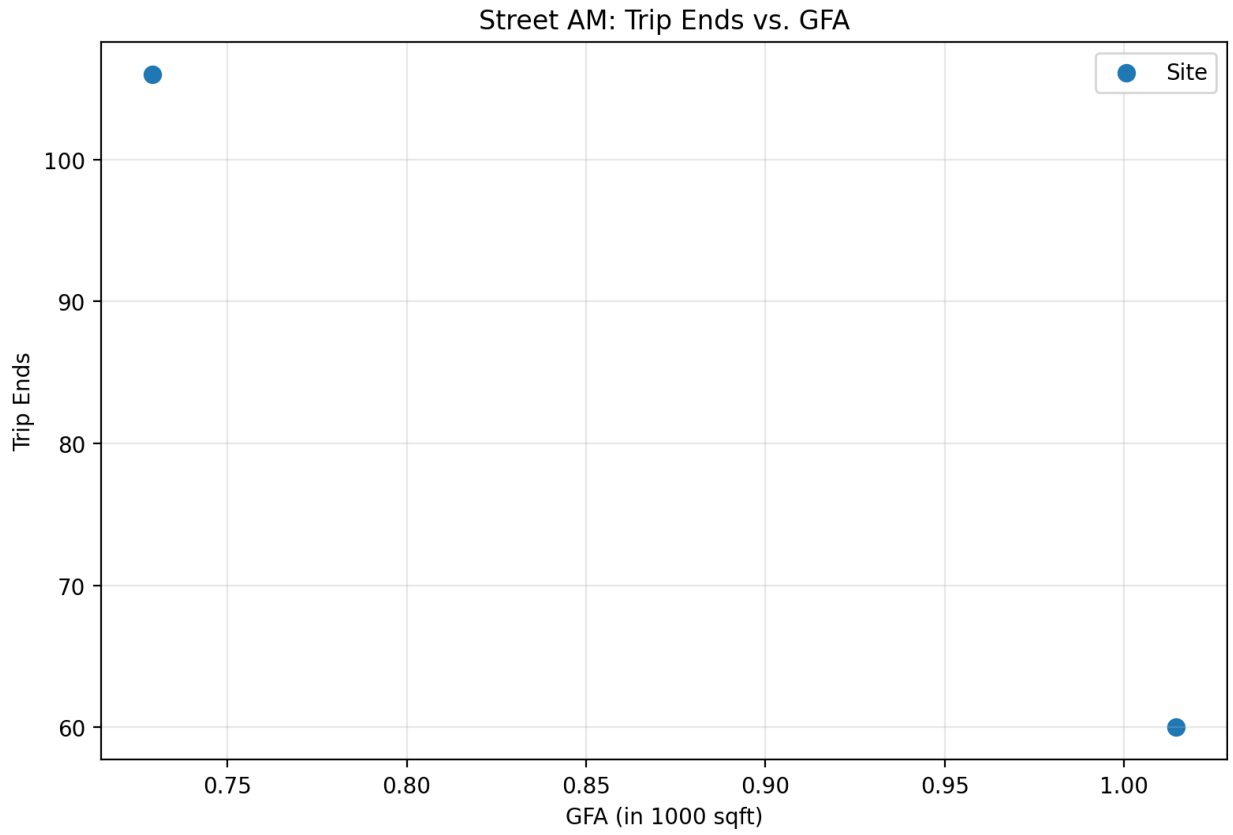
155 - High-Cube Parcel Hub Warehouse

Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 5:15 and 6:15 p.m.
Number of Studies: 2
1000 Sq. Ft. GFA: 0.87
Directional Distribution: 42% entering, 58% exiting



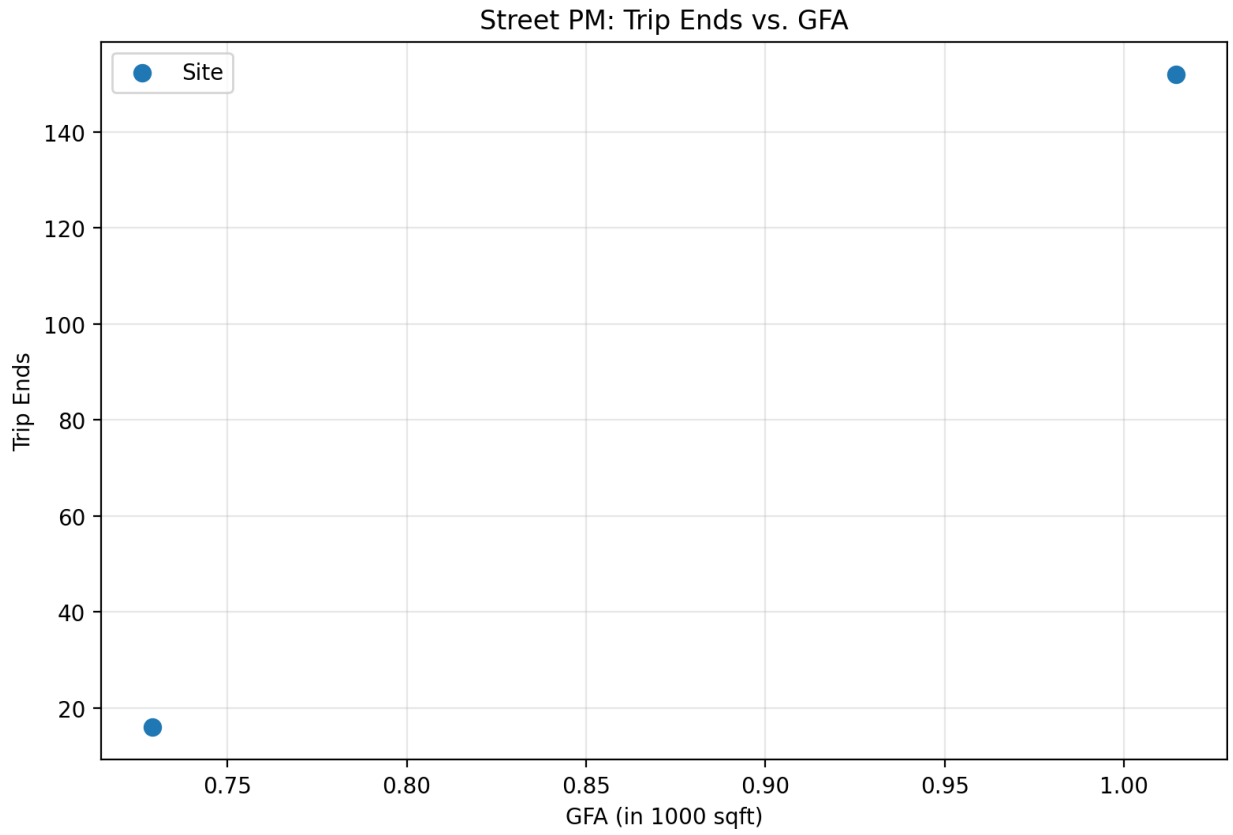
155 - High-Cube Parcel Hub Warehouse

Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 2
1000 Sq. Ft. GFA: 0.87
Directional Distribution: 84% entering, 16% exiting



155 - High-Cube Parcel Hub Warehouse

Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 2
1000 Sq. Ft. GFA: 0.87
Directional Distribution: 42% entering, 58% exiting



934 - Fast-Food Restaurant with Drive-Through Window

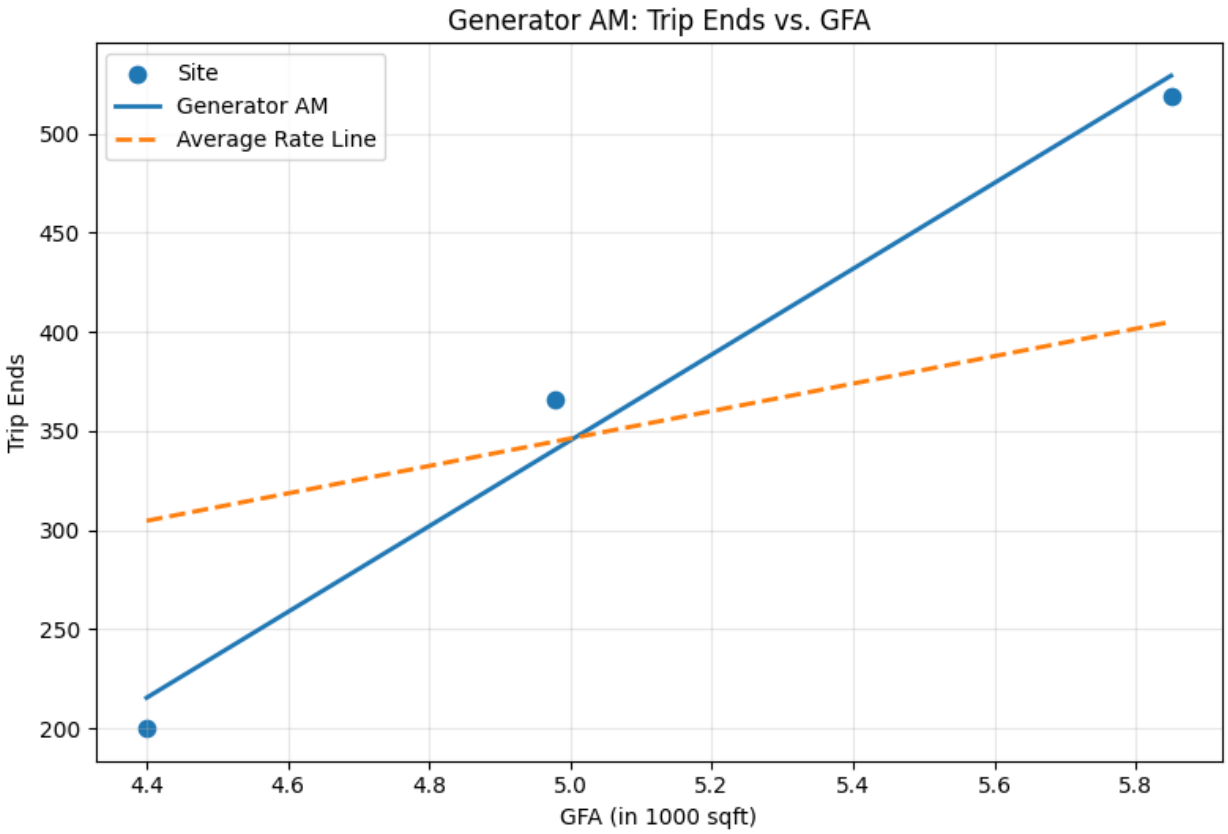
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 11:45 a.m. and 12:45 p.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 5.076
Directional Distribution: 45% entering, 55% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
69.23	45.46–88.72	15.52

Data Plot and Equation

Equation	R^2
T = 216.4282(X) − 736.9228	0.9805



934 - Fast-Food Restaurant with Drive-Through Window

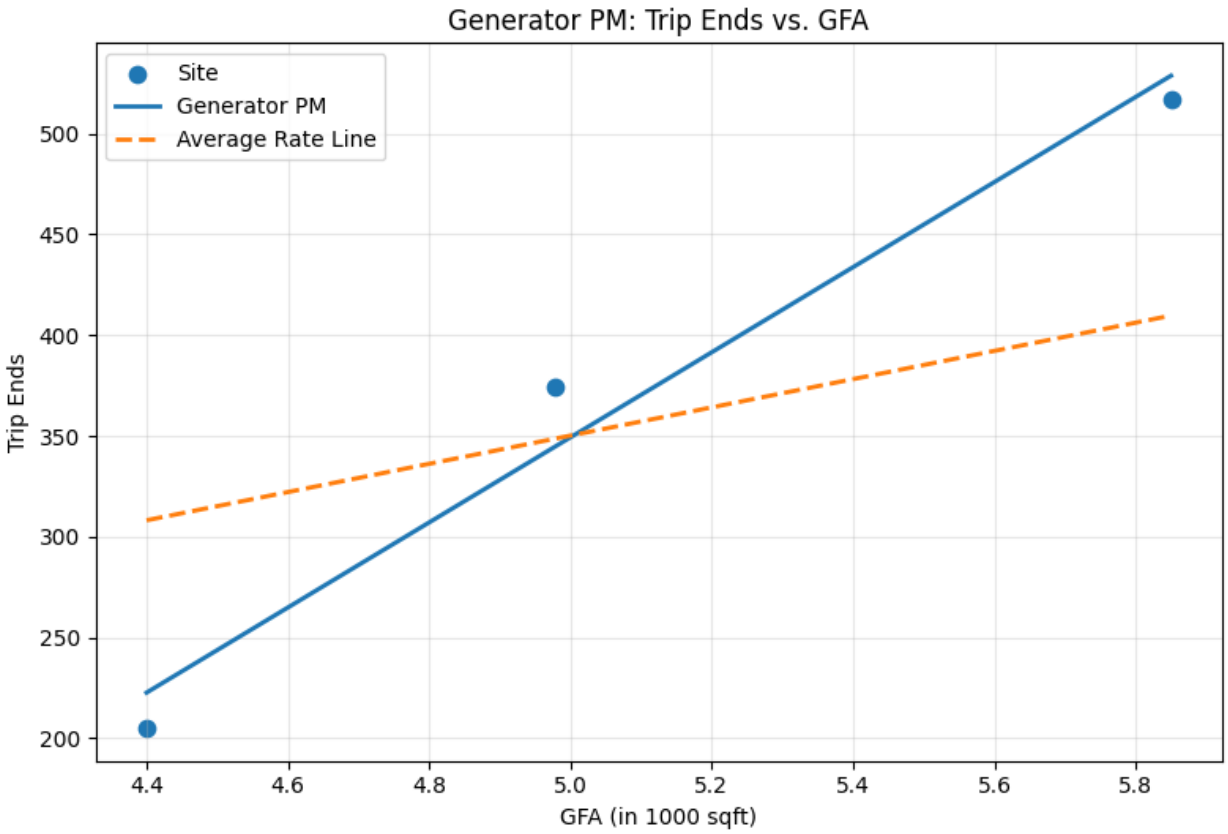
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 12 and 1 p.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 5.076
Directional Distribution: 51% entering, 49% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
70.03	46.59–88.38	15.1

Data Plot and Equation

Equation	R^2
T = 211.0681(X) − 706.0484	0.9731



934 - Fast-Food Restaurant with Drive-Through Window

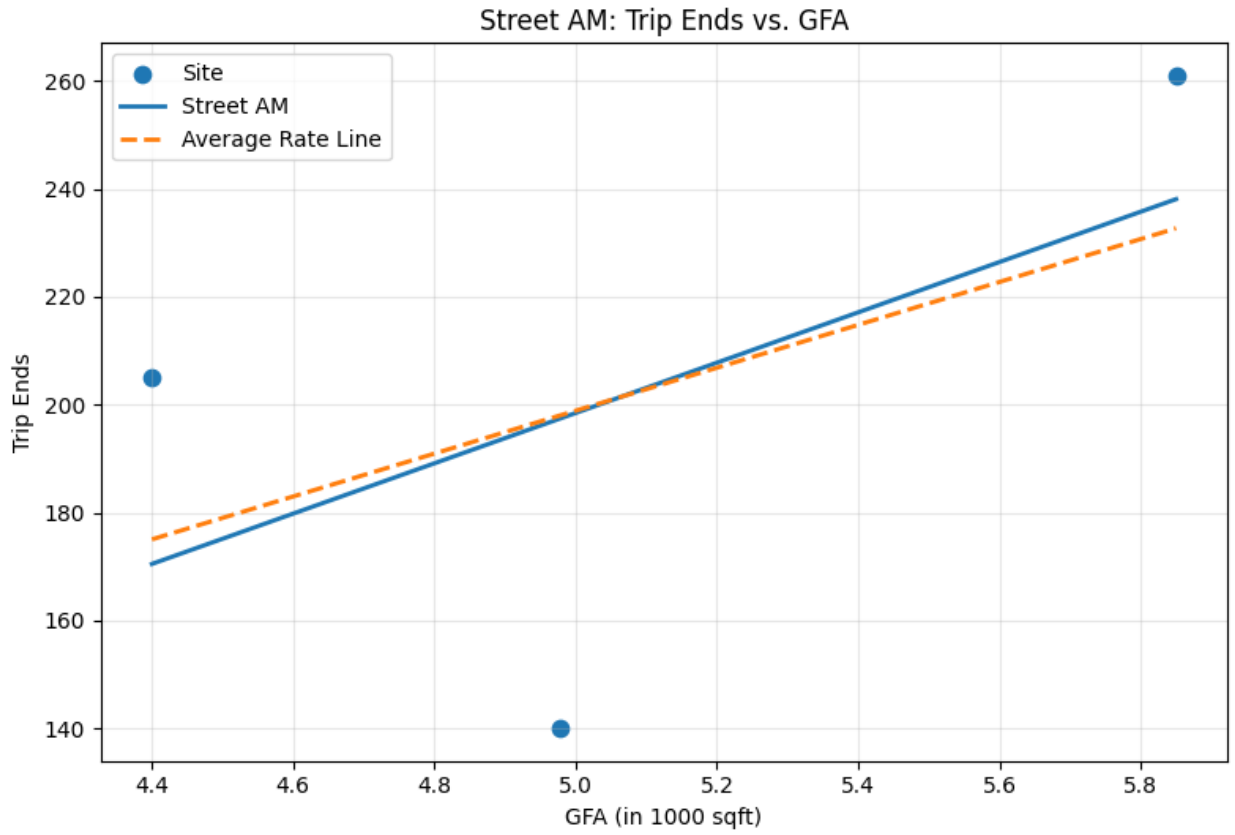
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 5.076
Directional Distribution: 52% entering, 48% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
39.78	28.12–46.59	7.17

Data Plot and Equation

Equation	R^2
y = 46.6511x − 34.8009	0.3162



934 - Fast-Food Restaurant with Drive-Through Window

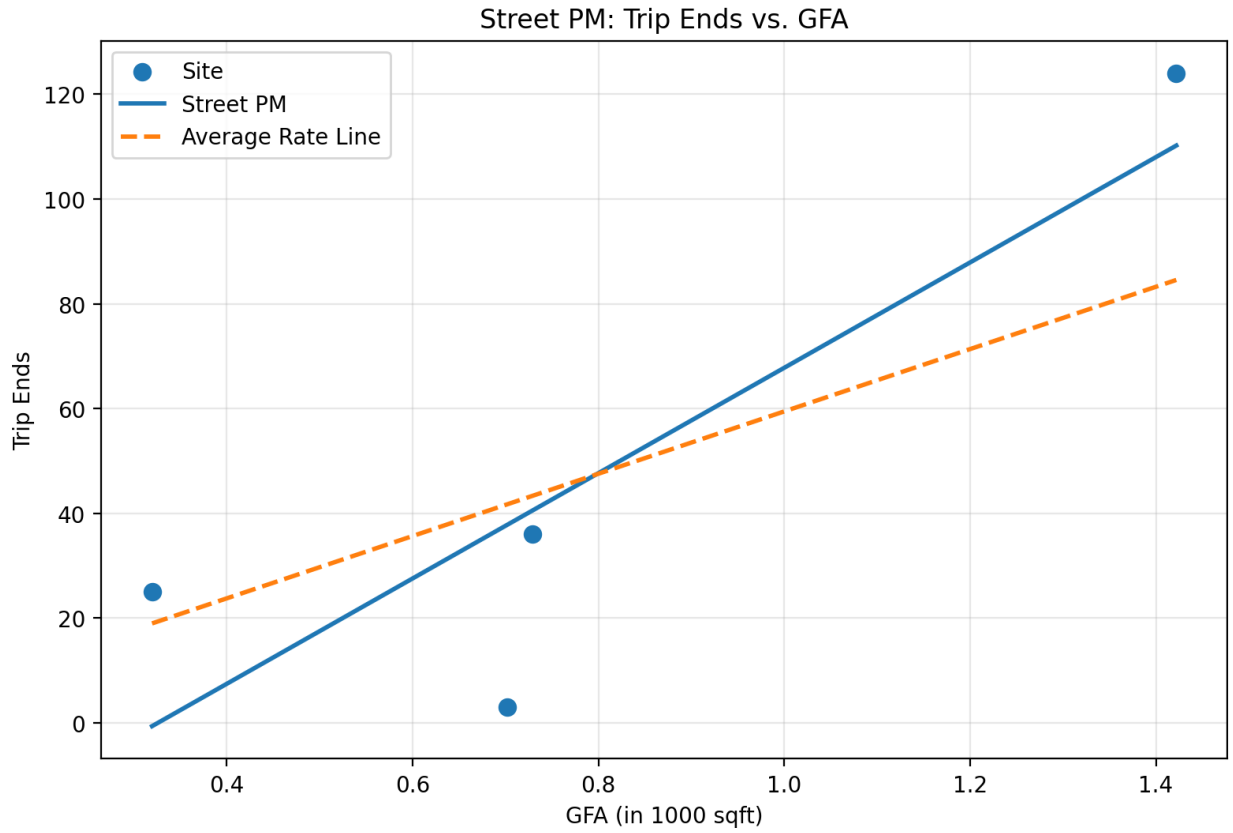
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 5.076
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
43.68	34.09–50.62	6.07

Data Plot and Equation

Equation	R^2
T = 78.5038(X) − 174.1517	0.7755



934 - Fast-Food Restaurant with Drive-Through Window

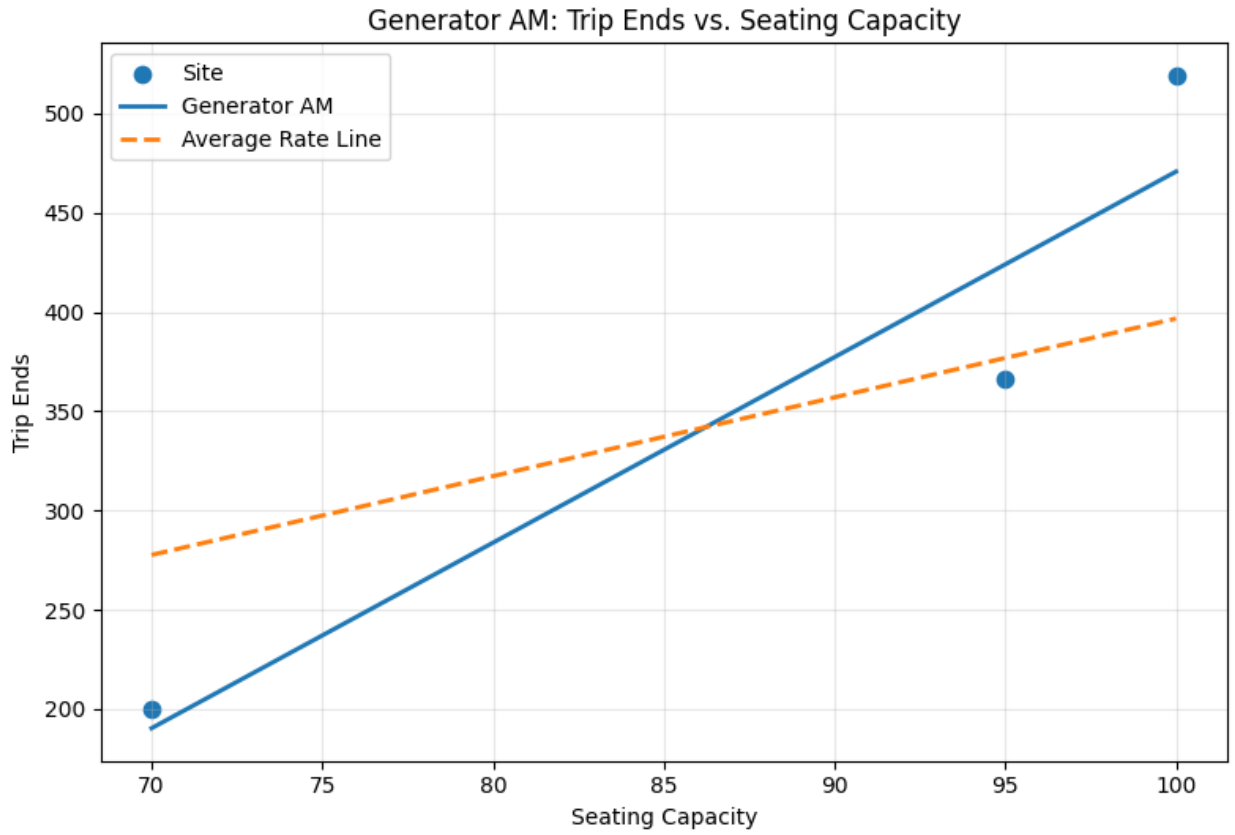
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 11:45 a.m. and 12:45 p.m.
Number of Studies: 3
Average Indoor Seating Capacity: 88.33
Directional Distribution: 45% entering, 55% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
3.97	2.86–5.19	0.83

Data Plot and Equation

Equation	R^2
T = 9.3452(X) − 463.8226	0.8863



934 - Fast-Food Restaurant with Drive-Through Window

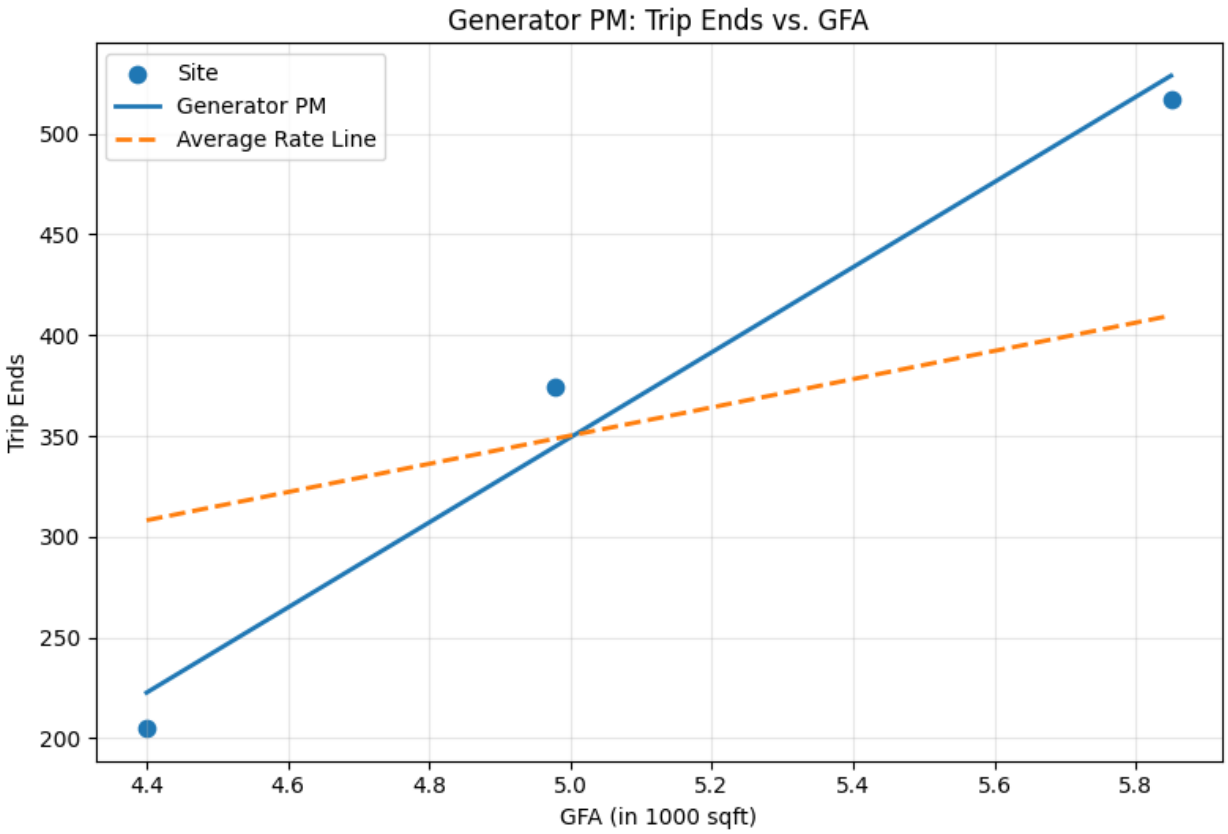
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 12 and 1 p.m.
Number of Studies: 3
Average Indoor Seating Capacity: 88.33
Directional Distribution: 51% entering, 49% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
4.11	2.93–5.17	0.79

Data Plot and Equation

Equation	R^2
T = 9.2258(X) − 449.6129	0.9014



934 - Fast-Food Restaurant with Drive-Through Window

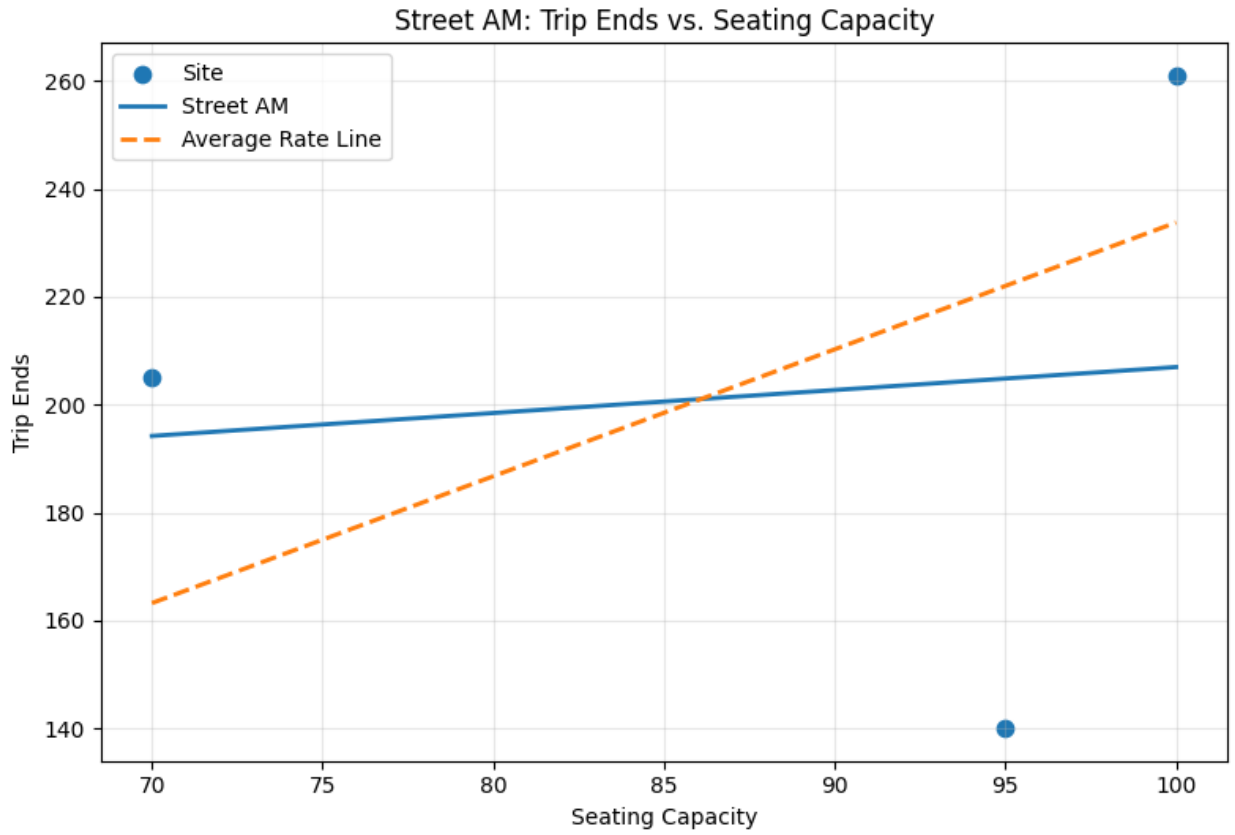
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 3
Average Indoor Seating Capacity: 88.33
Directional Distribution: 52% entering, 48% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
2.33	1.47–2.93	0.54

Data Plot and Equation

Equation	R^2
T = 0.4258(X) + 164.3871	0.0128



934 - Fast-Food Restaurant with Drive-Through Window

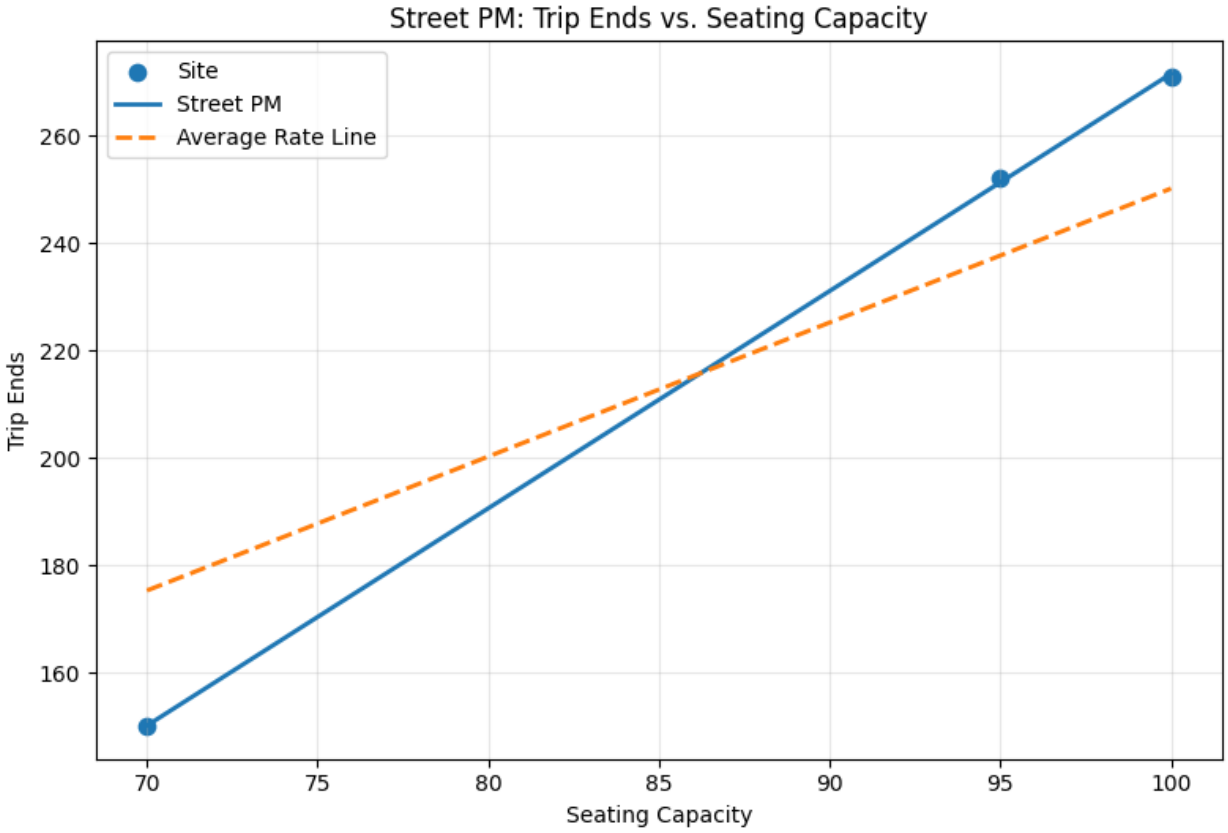
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 3
Average Indoor Seating Capacity: 88.33
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
43.68	34.09–50.62	0.22

Data Plot and Equation

Equation	R^2
T = 4.0484(X) − 133.2742	0.9999



945 - Convenience Store/Gas Stations

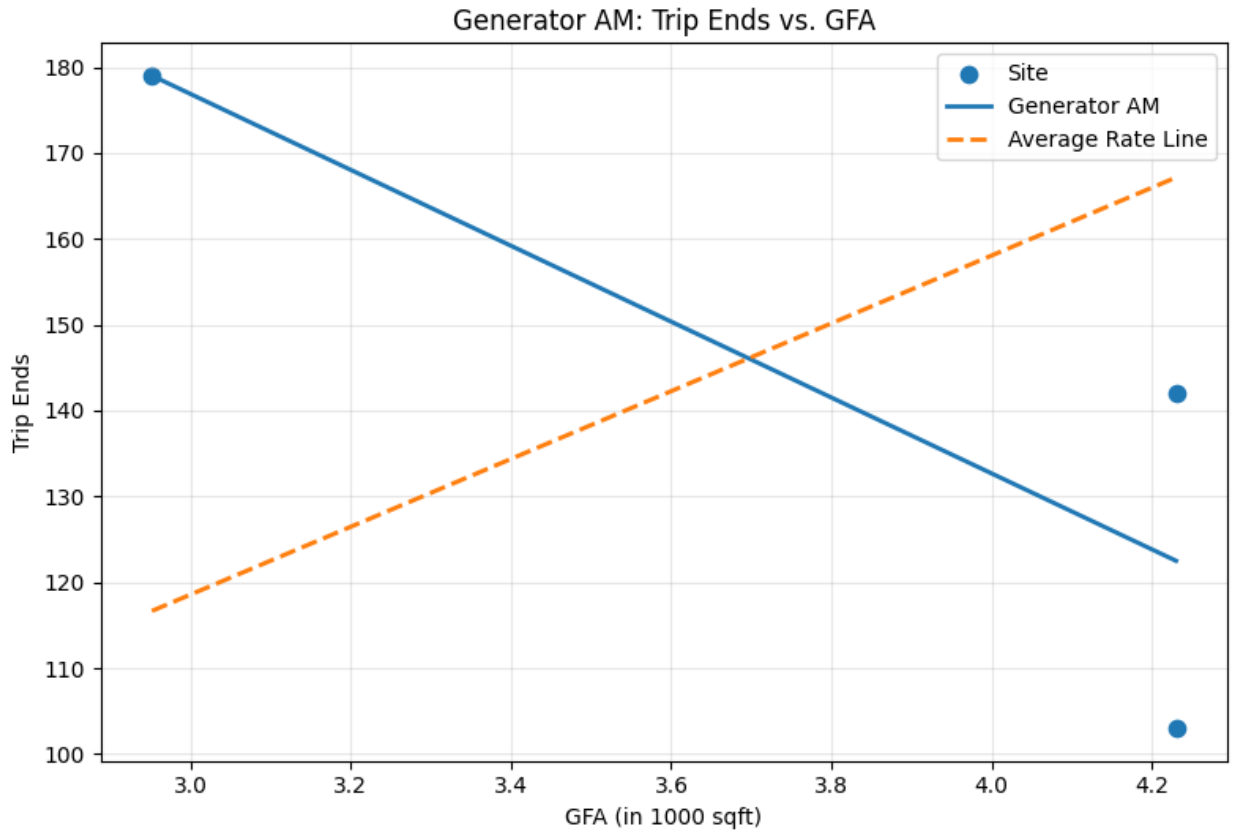
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 7:30 and 8:30 a.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 3.80
Directional Distribution: 53% entering, 47% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
39.52	24.35–60.64	13.34

Data Plot and Equation

Equation	R^2
T = -44.2097(X) + 309.5070	0.7367



945 - Convenience Store/Gas Stations

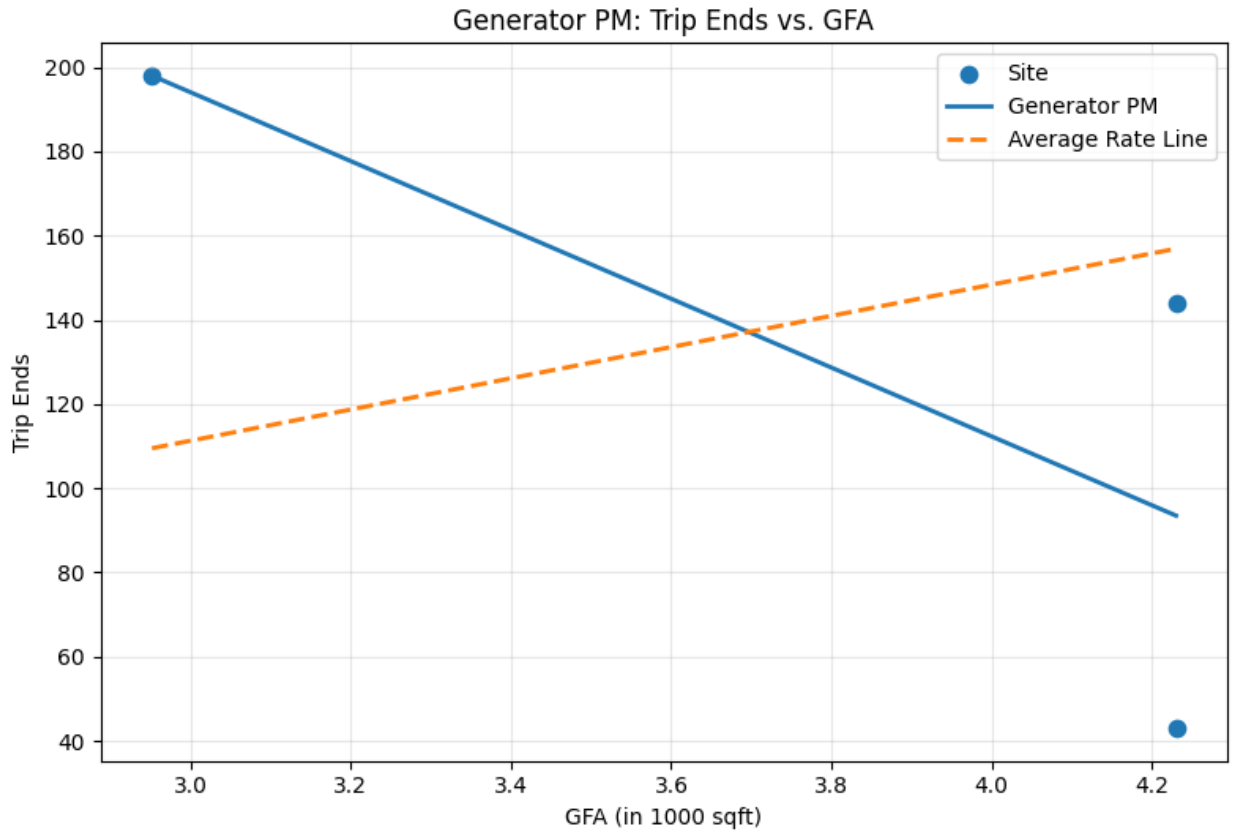
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 3:45 and 4:45 p.m.
Number of Studies: 3
Average Indoor Seating Capacity: 88.33
Directional Distribution: 49% entering, 51% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
37.09	10.17–67.07	20.21

Data Plot and Equation

Equation	R^2
T = -81.7684(X) + 439.3803	0.5880



945 - Convenience Store/Gas Stations

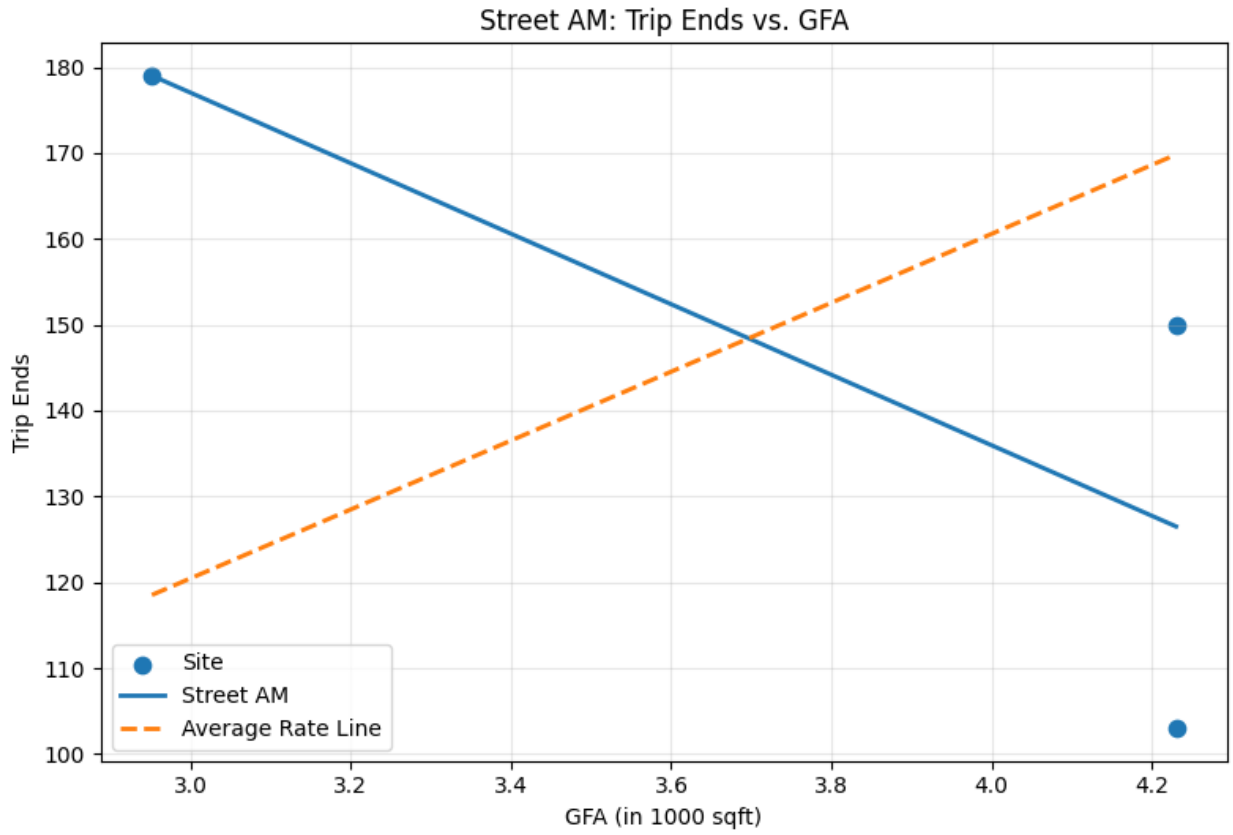
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 3.80
Directional Distribution: 54% entering, 46% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
40.15	24.35–60.64	13.15

Data Plot and Equation

Equation	R^2
T = -41.0798(X) + 300.2676	0.6246



945 - Convenience Store/Gas Stations

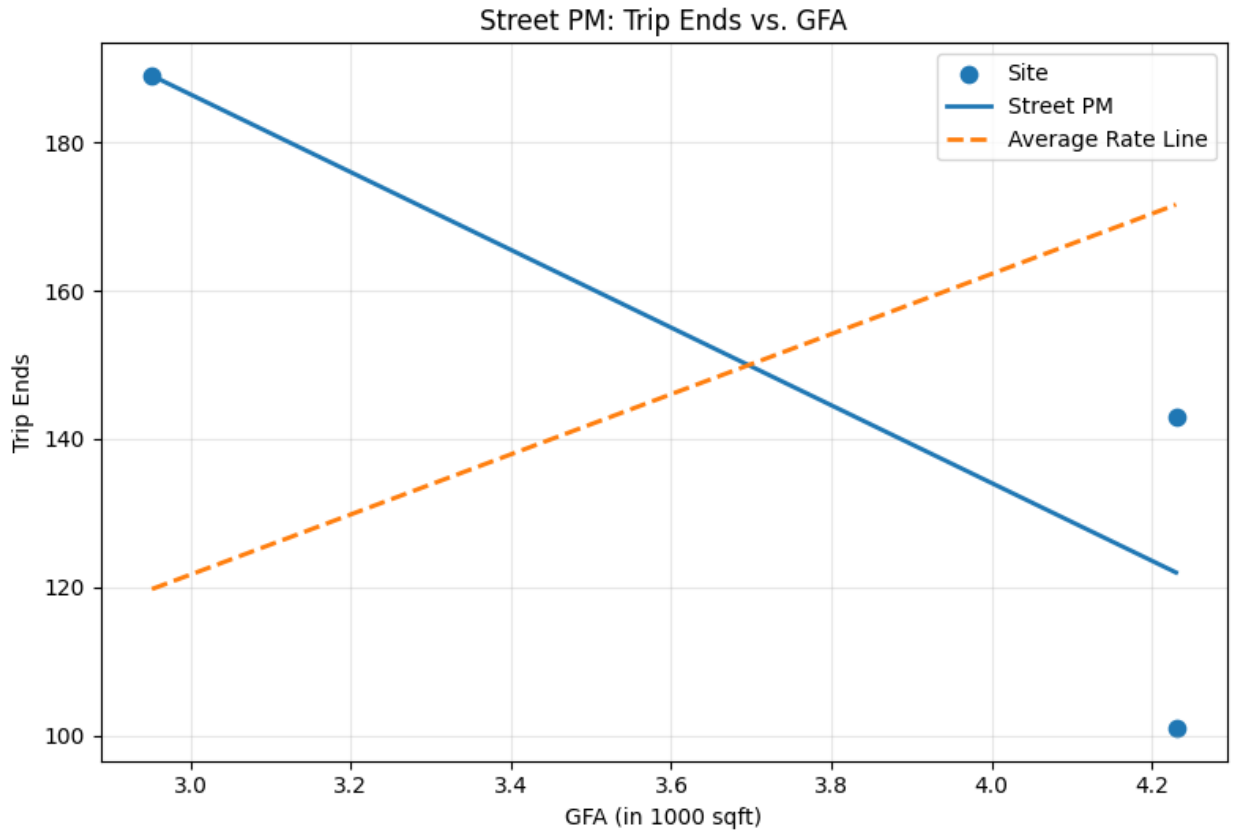
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 3.80
Directional Distribution: 51% entering, 49% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
40.57	23.88–64.02	14.79

Data Plot and Equation

Equation	R^2
T = -52.4257(X) + 343.7606	0.7724



945 - Convenience Store/Gas Stations

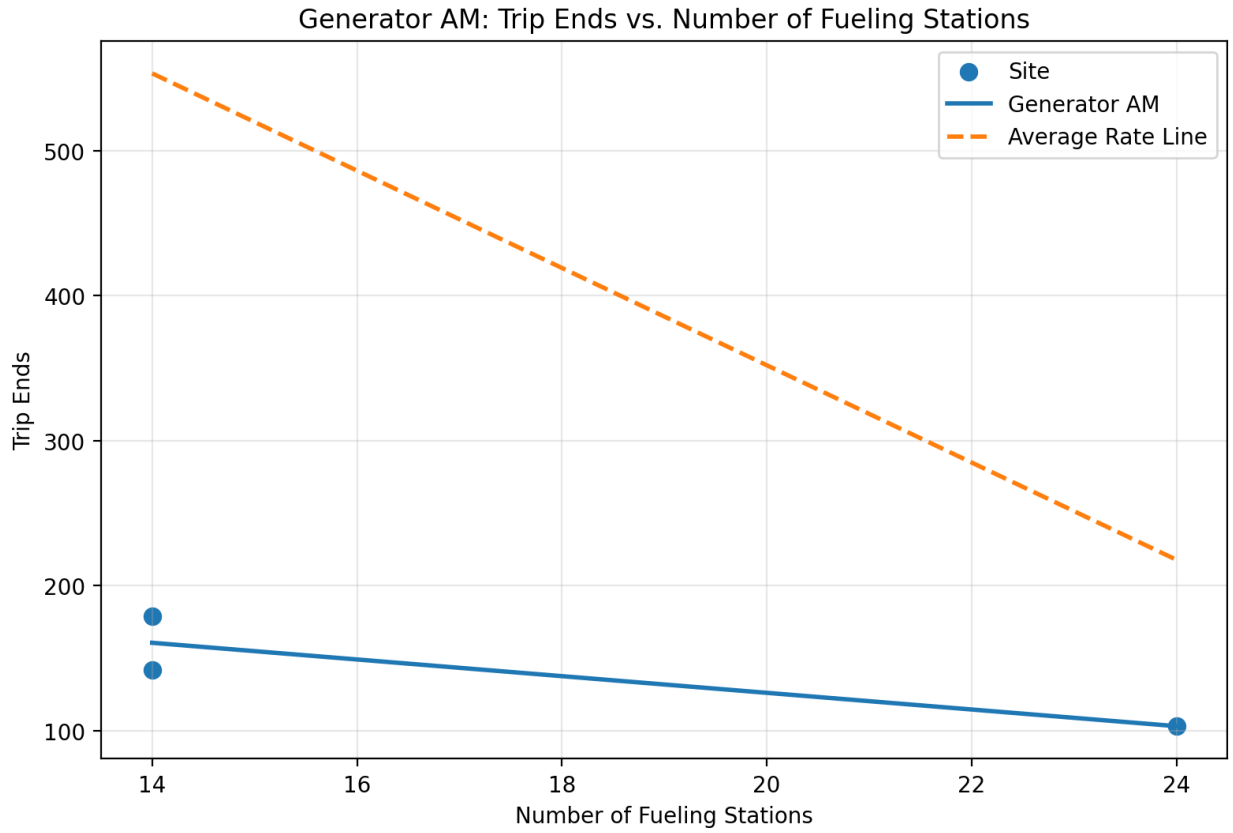
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 7:30 and 8:30 a.m.
Number of Studies: 3
Average Number of Fueling Stations: 3.80
Directional Distribution: 53% entering, 47% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
9.07	4.29–12.79	3.07

Data Plot and Equation

Equation	R^2
T = -5.7500(X) + 241.0000	0.7630



945 - Convenience Store/Gas Stations

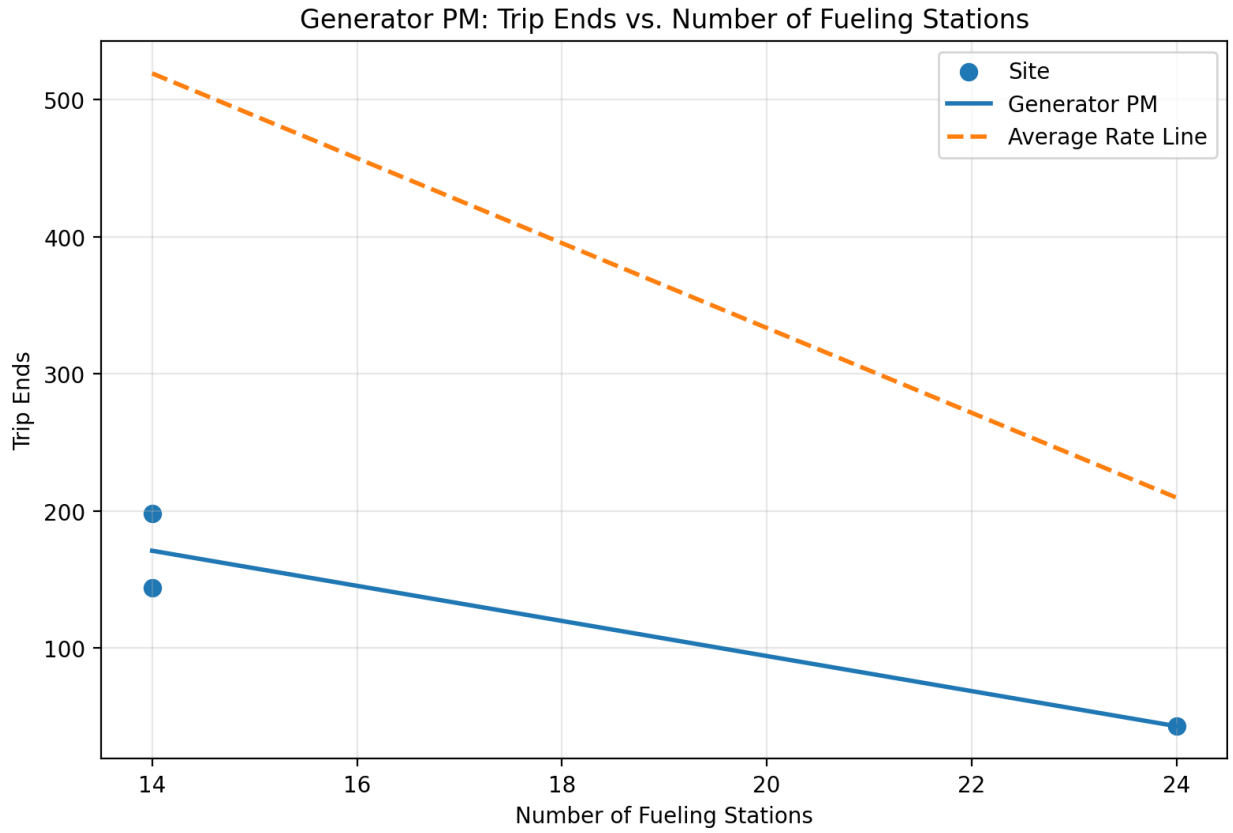
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 3:45 and 4:45 p.m.
Number of Studies: 3
Average Number of Fueling Stations: 3.80
Directional Distribution: 49% entering, 51% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
8.74	1.79–14.14	4.47

Data Plot and Equation

Equation	R^2
T = -12.8000(X) + 350.2000	0.8822



945 - Convenience Store/Gas Stations

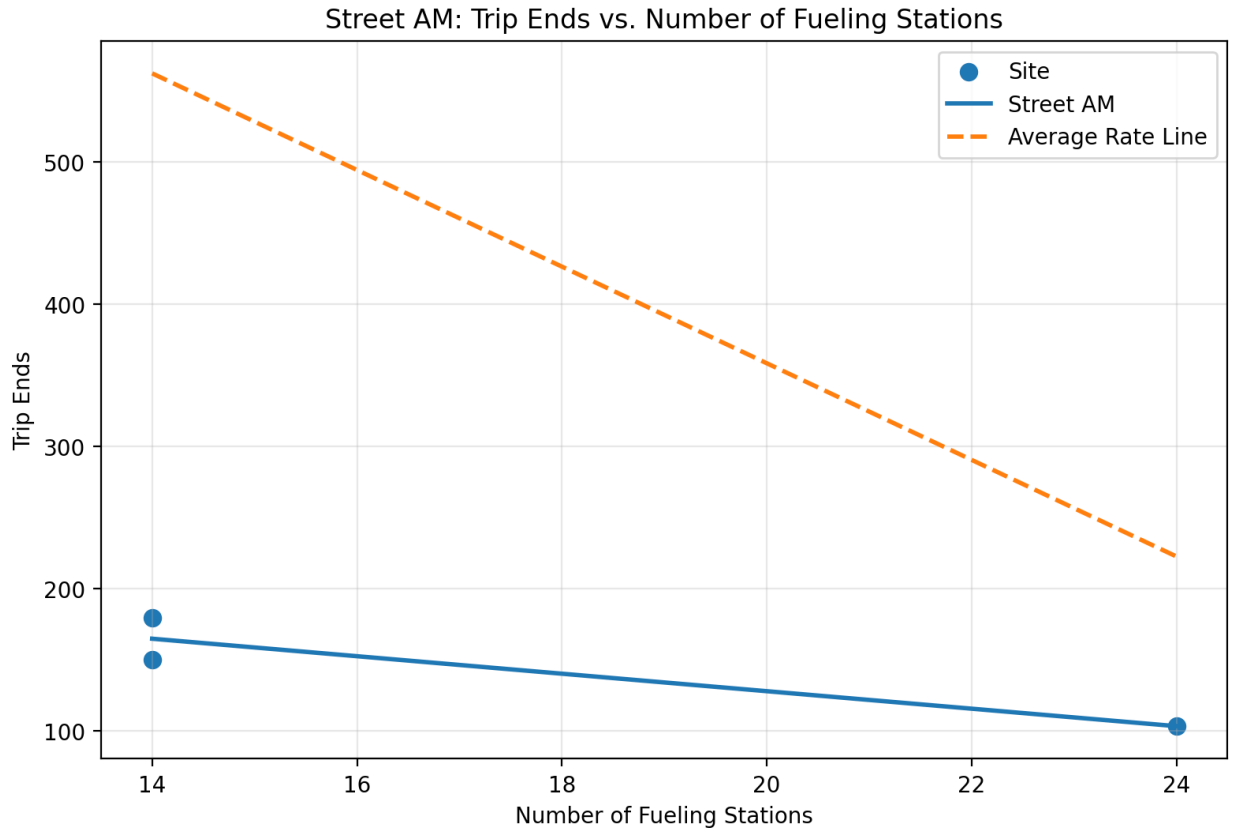
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 3
Average Number of Fueling Stations: 3.80
Directional Distribution: 54% entering, 46% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
9.26	4.29–12.79	3.13

Data Plot and Equation

Equation	R^2
T = -6.1500(X) + 250.6000	0.8571



945 - Convenience Store/Gas Stations

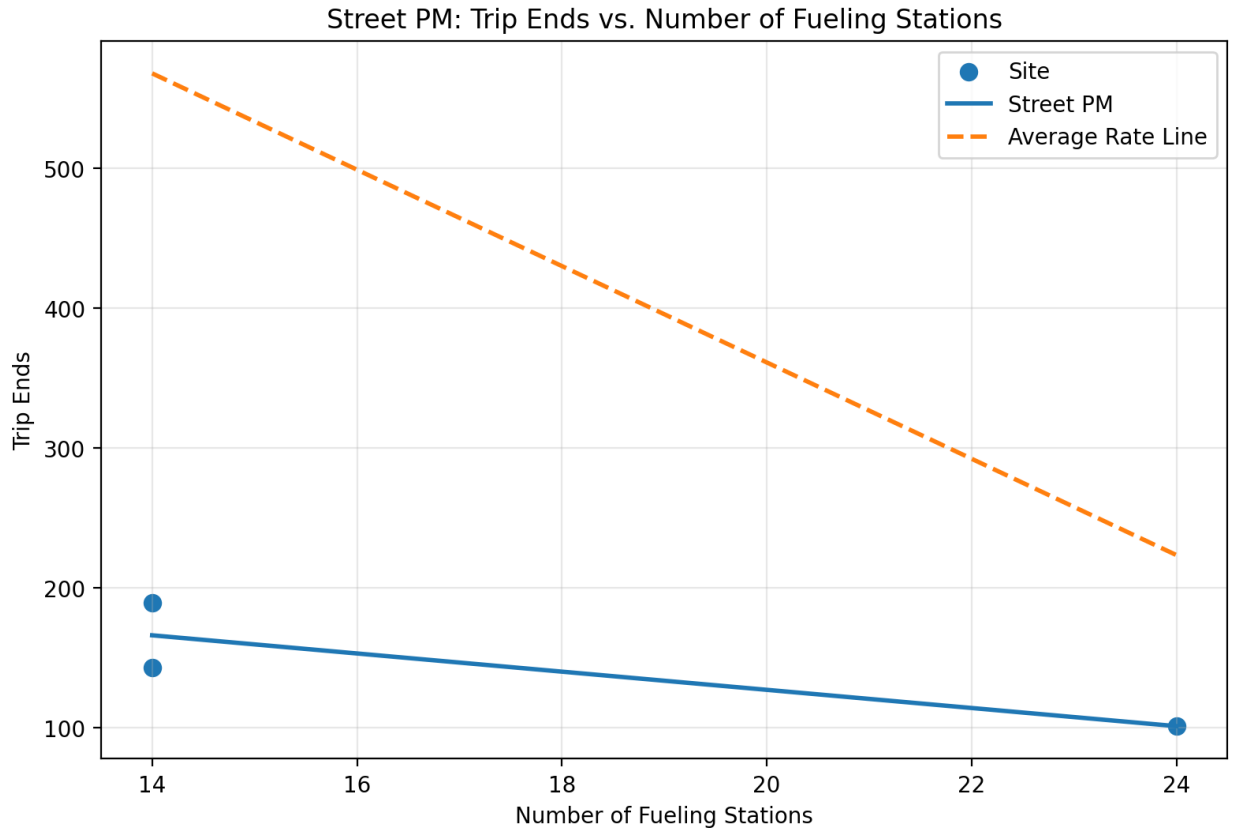
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 3
Average Number of Fueling Stations: 3.80
Directional Distribution: 51% entering, 49% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
9.31	4.21–13.5	3.33

Data Plot and Equation

Equation	R^2
T = -6.5000(X) + 257.0000	0.7269



950 - Truck Stops

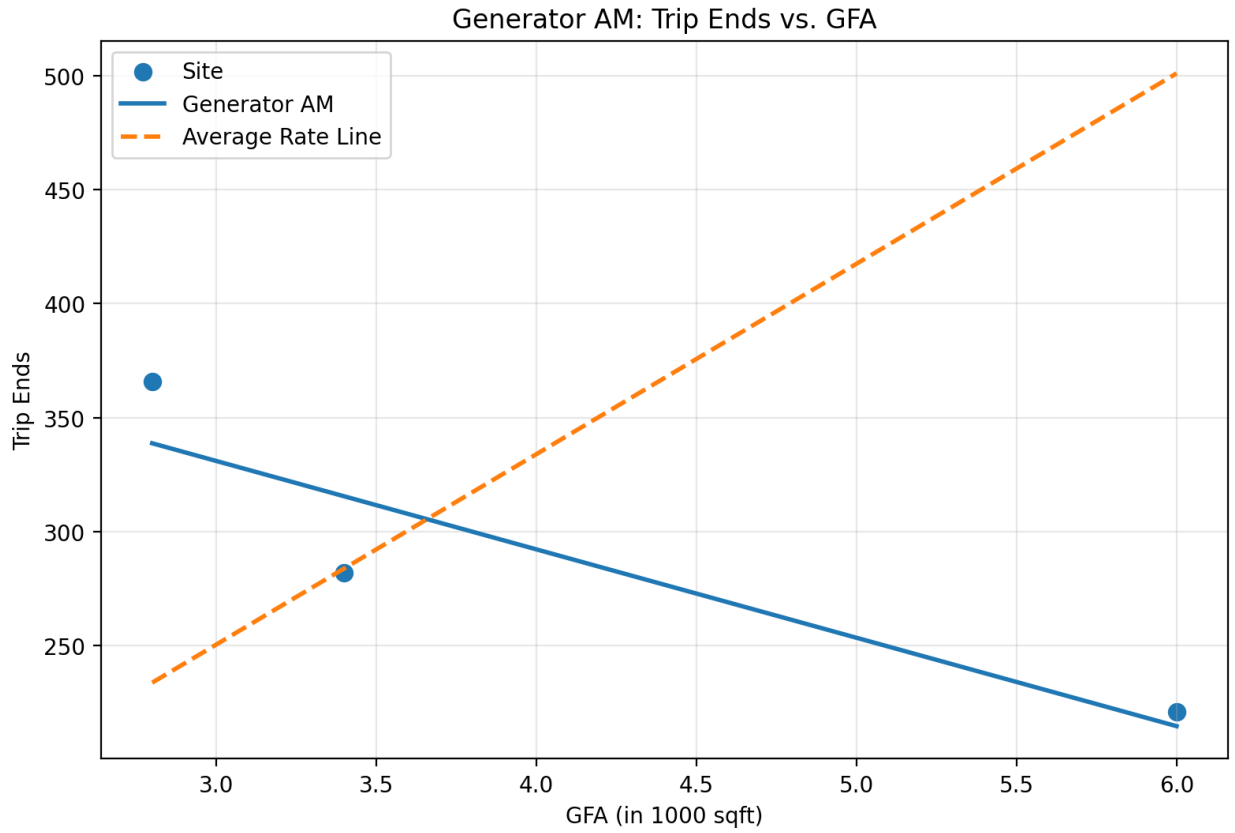
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 11:45 a.m. and 12:45 p.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 4.07
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
83.50	36.83–130.71	33.19

Data Plot and Equation

Equation	R^2
T = -38.7673(X) + 447.3203	0.8204



950 - Truck Stops

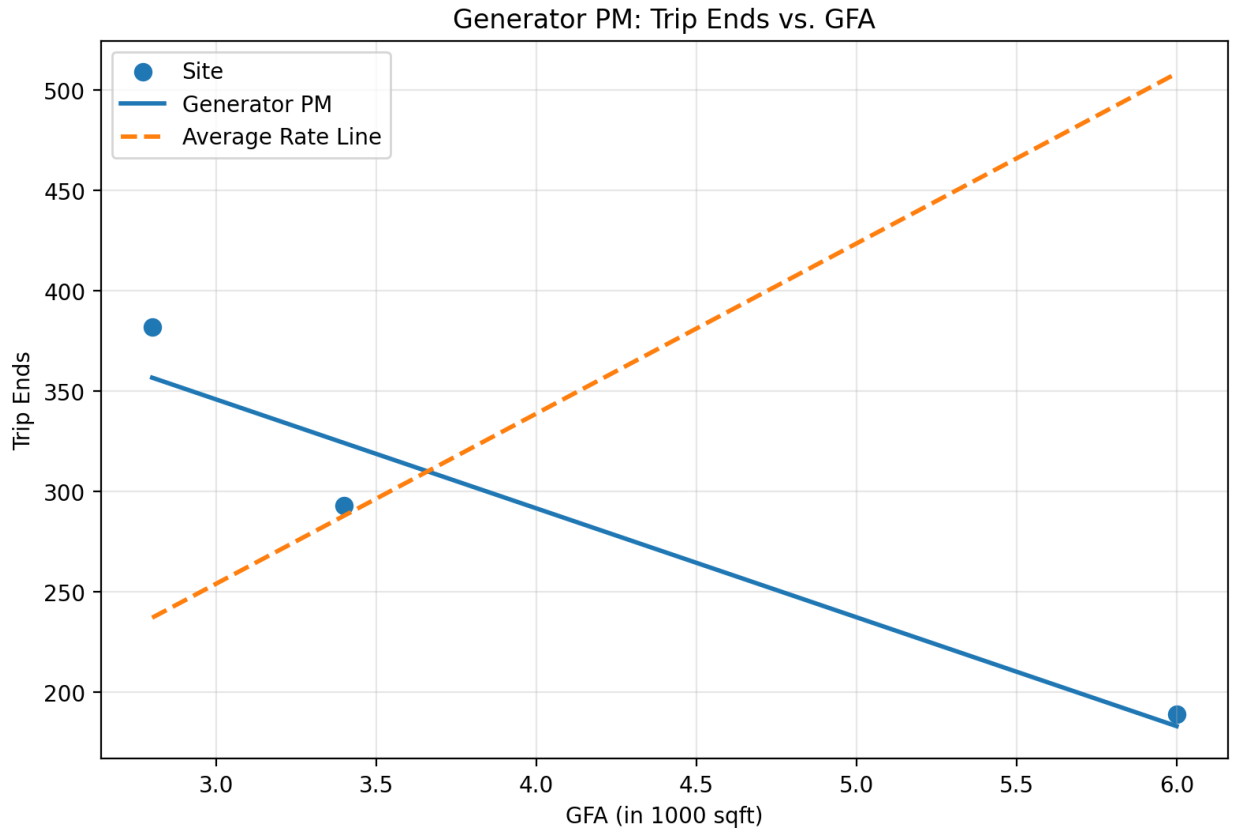
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 12:15 and 1:15 p.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 4.07
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
84.70	31.50–136.43	37.11

Data Plot and Equation

Equation	R^2
T = -54.2281(X) + 508.5276	0.9118



950 - Truck Stops

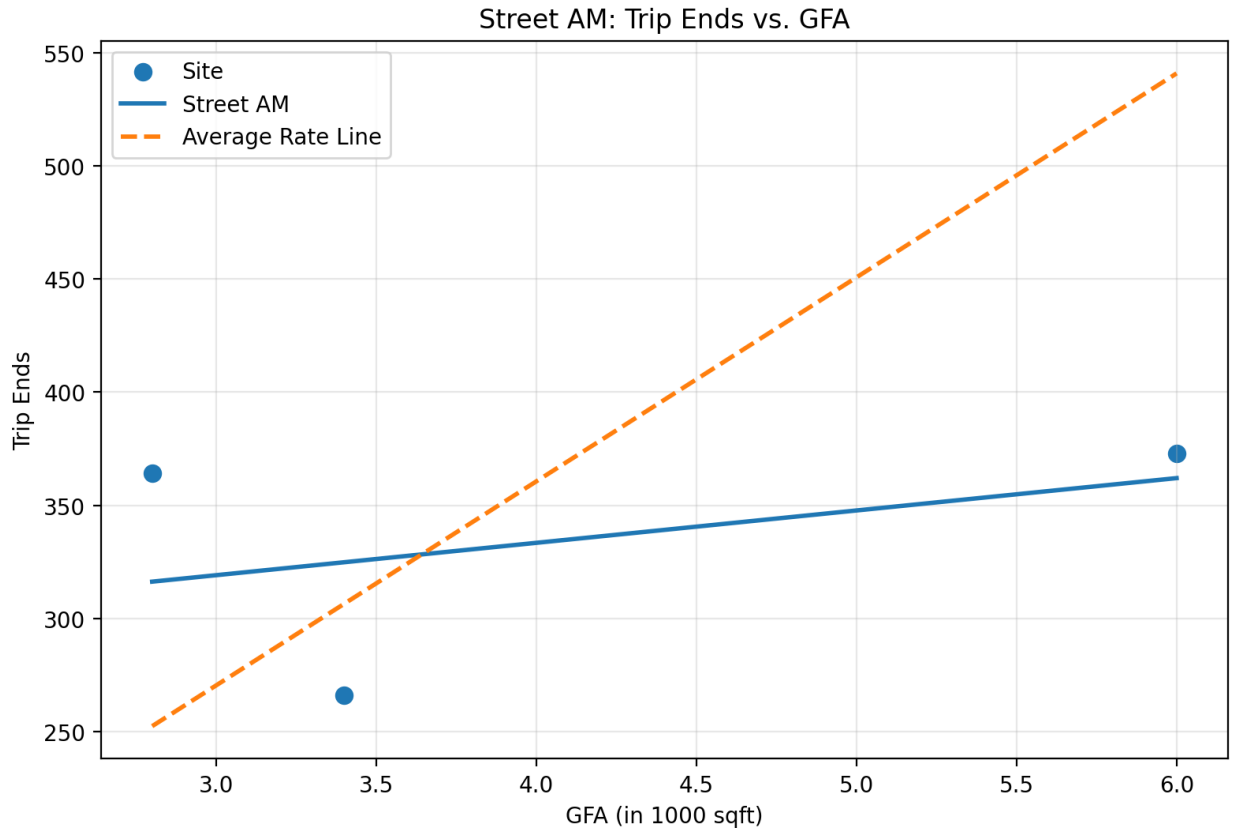
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 4.07
Directional Distribution: 49% entering, 51% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
90.13	62.17–130.00	25.07

Data Plot and Equation

Equation	R^2
T = 14.2972(X) + 276.1912	0.1679



950 - Truck Stops

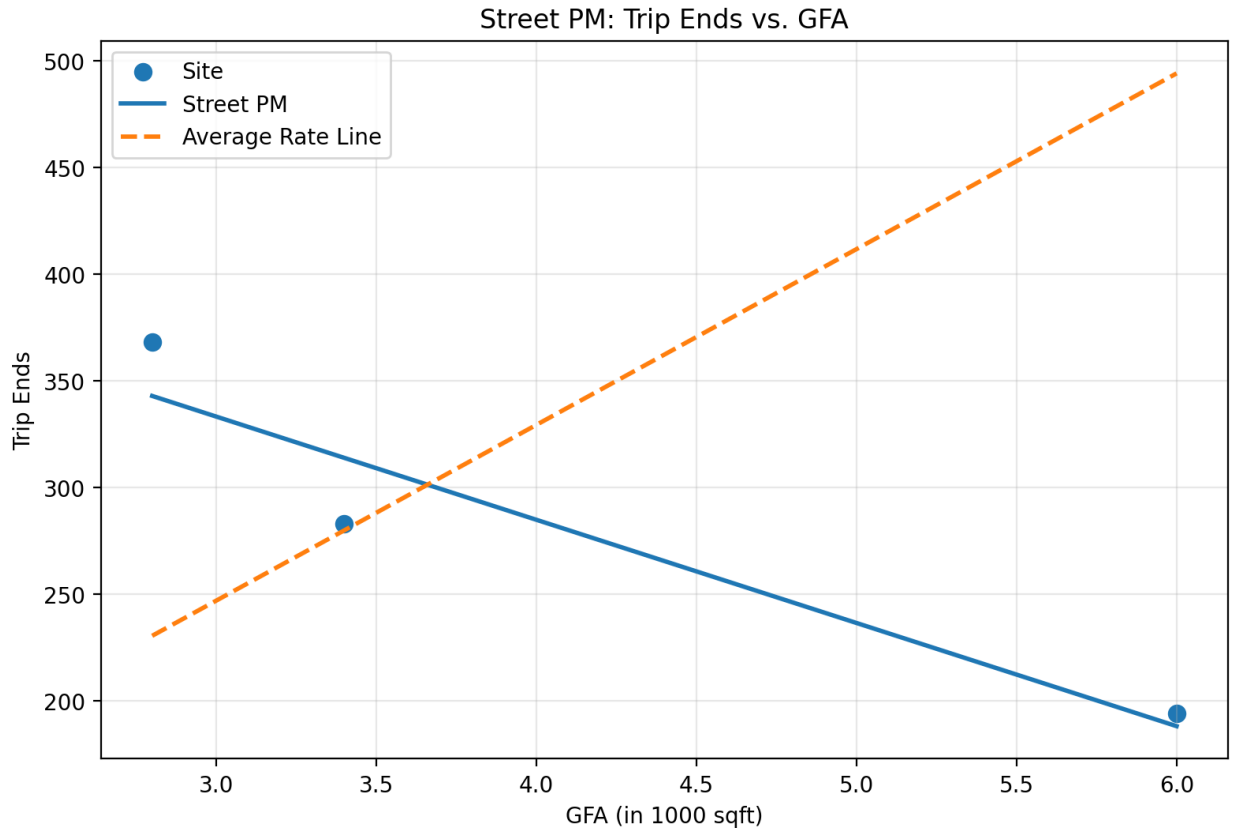
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 3
1000 Sq. Ft. GFA: 4.07
Directional Distribution: 49% entering, 51% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
82.33	32.33–131.43	35.04

Data Plot and Equation

Equation	R^2
T = -48.3410(X) + 478.2535	0.8931



950 - Truck Stops

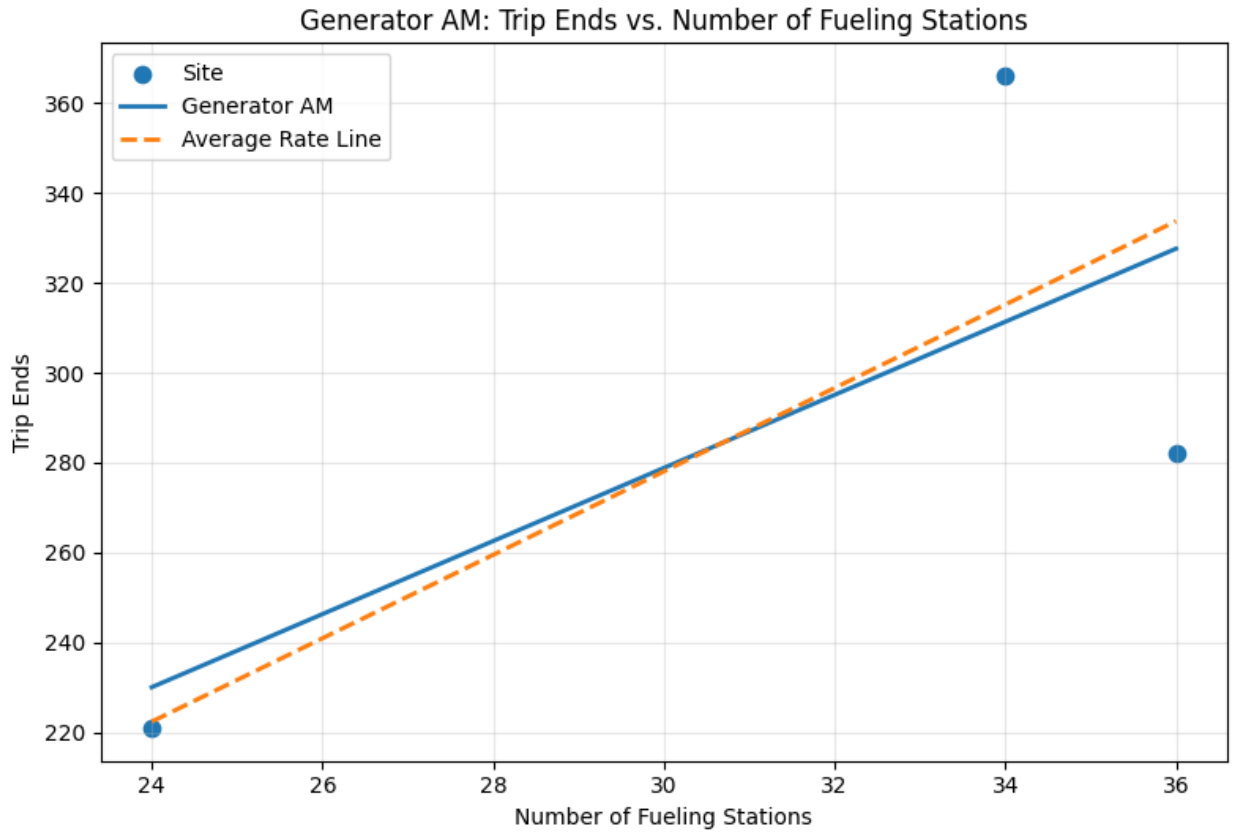
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 11:45 a.m. and 12:45 p.m.
Number of Studies: 3
Average Number of Fueling Stations: 31.33
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
9.27	7.83–10.76	1.04

Data Plot and Equation

Equation	R^2
T = 8.1210(X) + 35.2097	0.5143



945 - Truck Stops

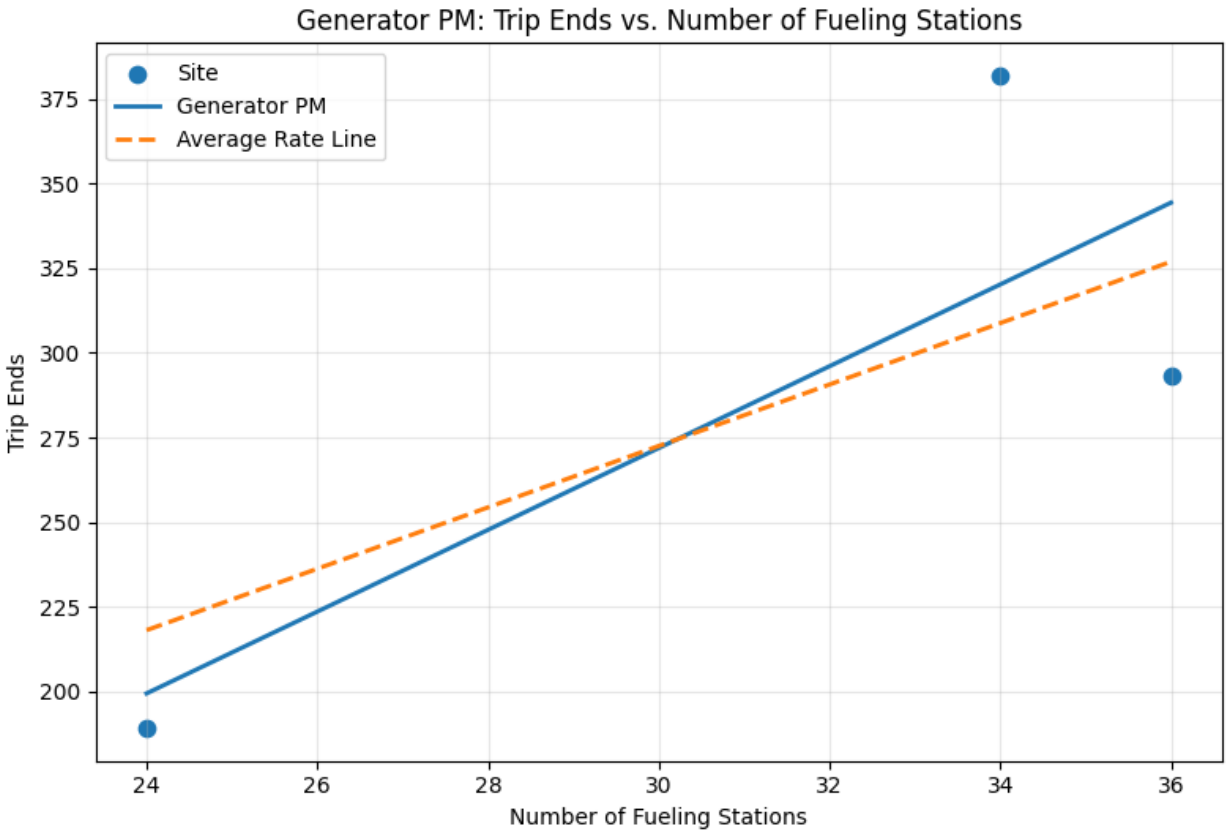
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 12:15 and 1:15 p.m.
Number of Studies: 3
Average Number of Fueling Stations: 31.33
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
9.08	7.88–11.24	1.32

Data Plot and Equation

Equation	R^2
T = 12.0968(X) − 91.0323	0.6482



950 - Truck Stops

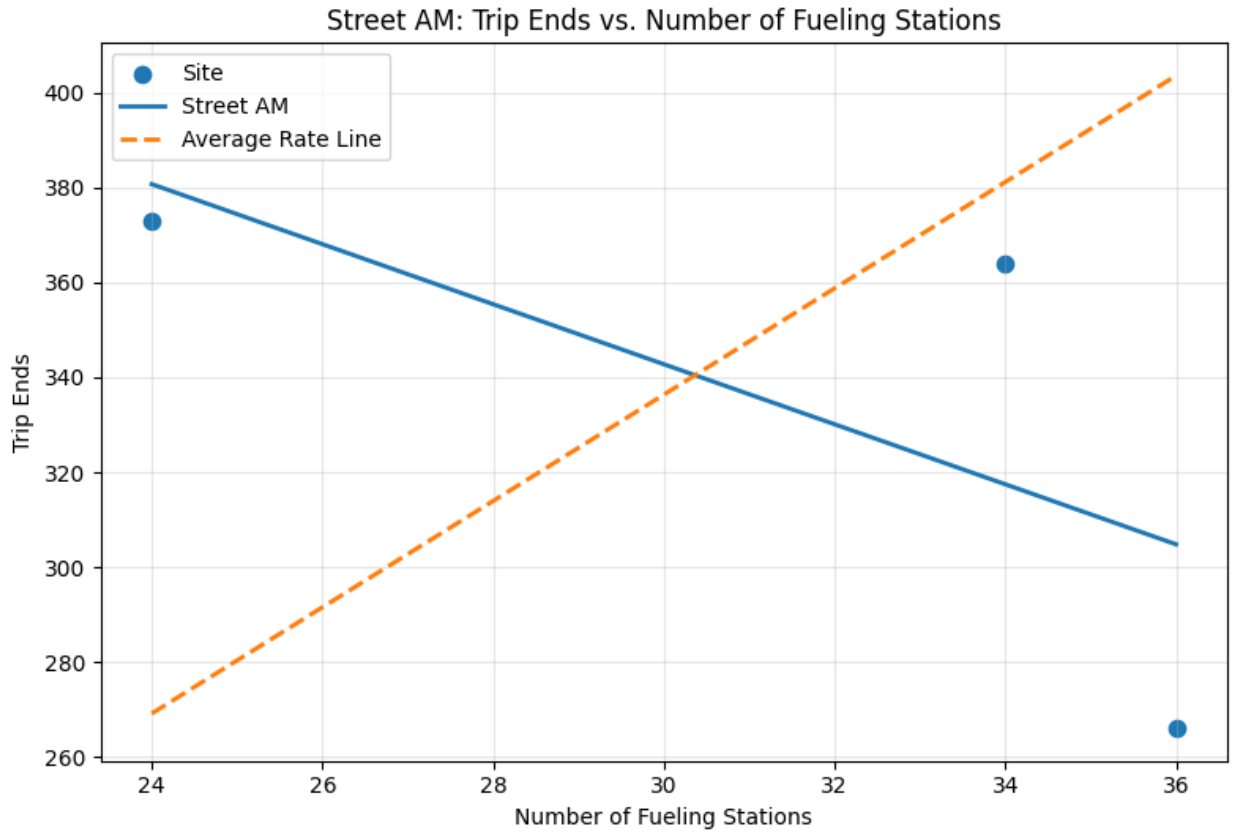
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 3
Average Number of Fueling Stations: 31.33
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
11.21	7.39–15.54	2.9

Data Plot and Equation

Equation	R^2
T = -6.3306(X) + 532.6935	0.4703



950 - Truck Stops

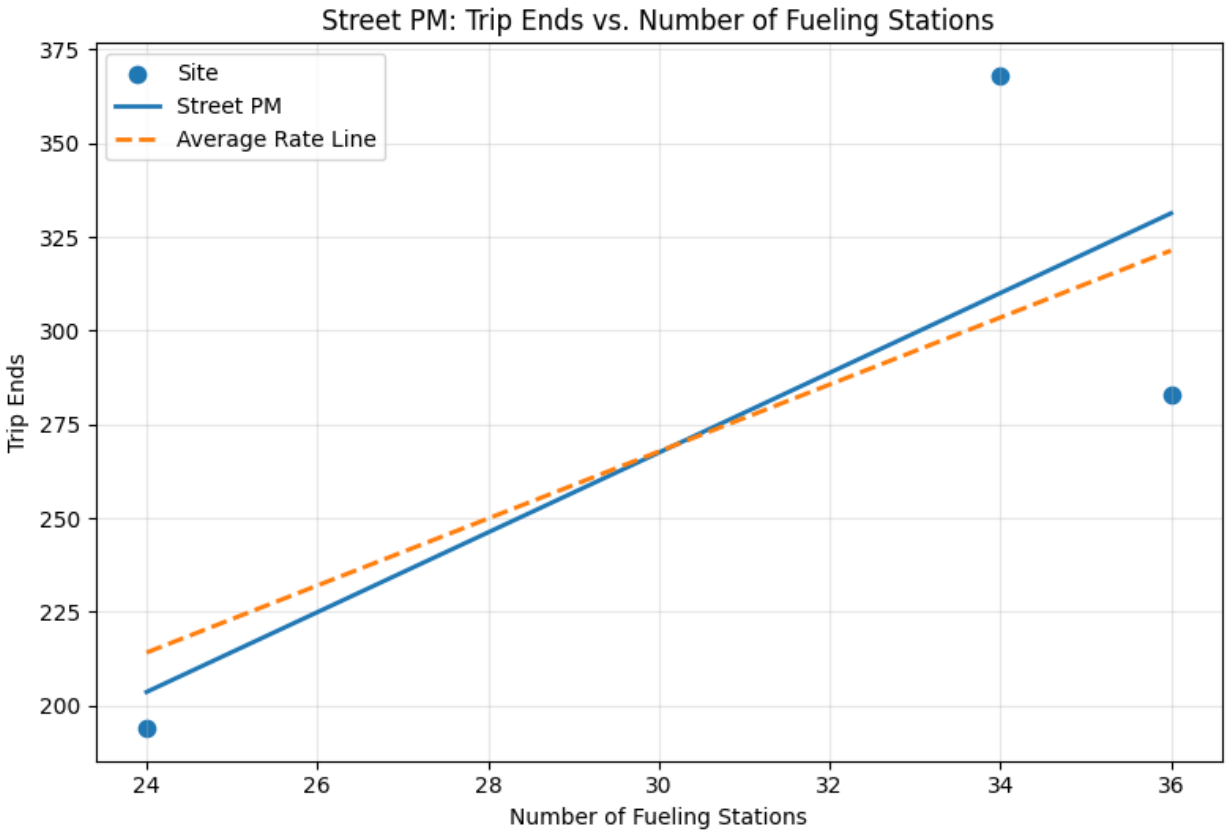
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 3
Average Number of Fueling Stations: 31.33
Directional Distribution: 49% entering, 51% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
8.93	7.86–10.82	1.17

Data Plot and Equation

Equation	R^2
T = 10.6371(X) − 51.6290	0.6178



950 - Truck Stops

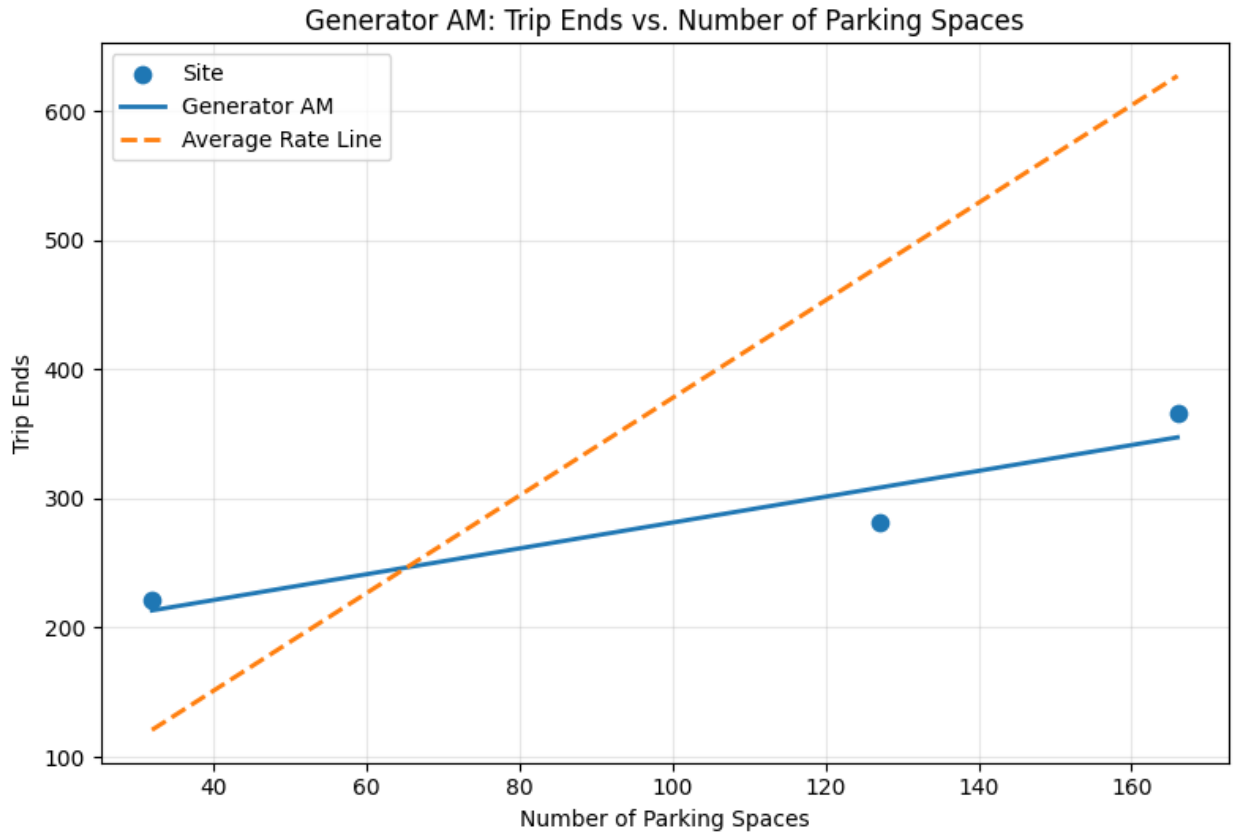
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 11:45 a.m. and 12:45 p.m.
Number of Studies: 3
Average Number of Parking Spaces: 108.33
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.71	0.24–1.24	1.92

Data Plot and Equation

Equation	R^2
T = 1.0000(X) + 181.3371	0.8962



945 - Truck Stops

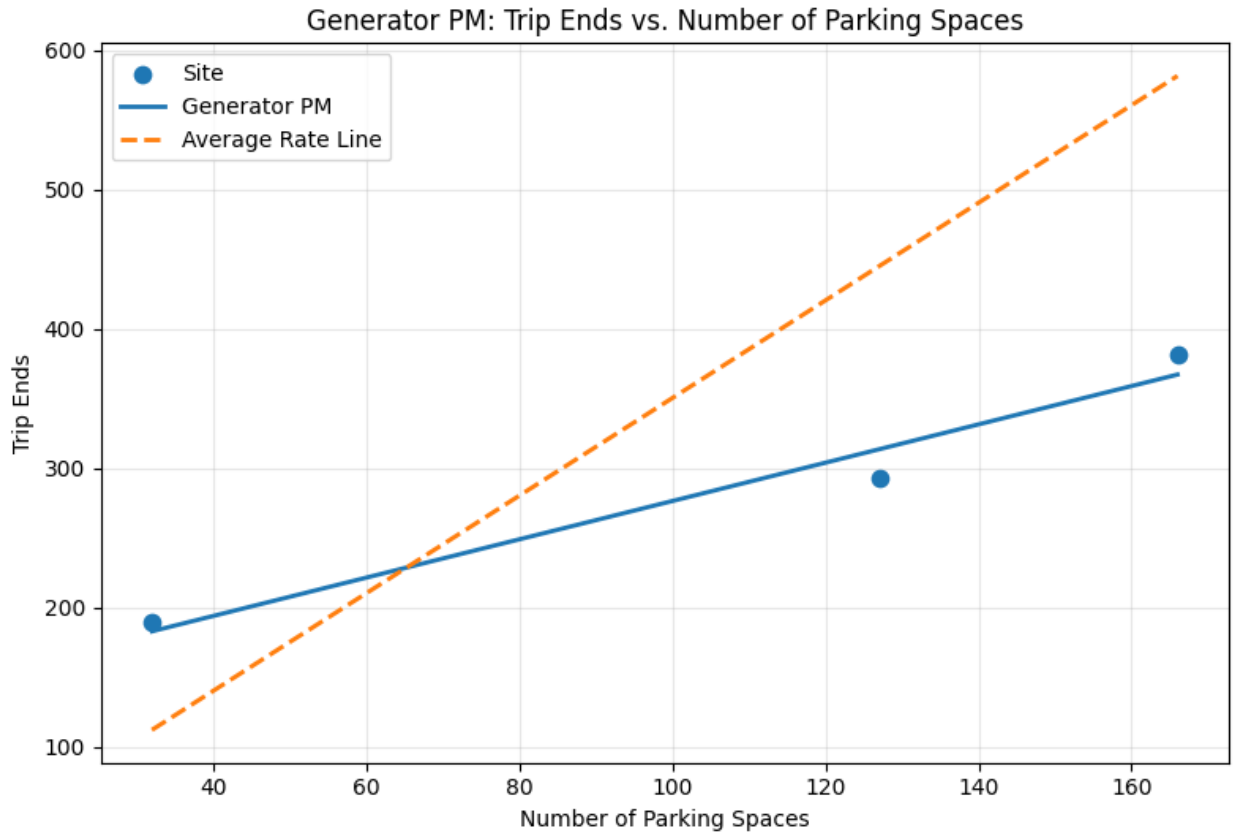
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Generator,
Between 12:15 and 1:15 p.m.
Number of Studies: 3
Average Number of Parking Spaces: 108.33
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.68	0.22–1.16	1.47

Data Plot and Equation

Equation	R^2
T = 1.3758(X) + 138.9552	0.9636



950 - Truck Stops

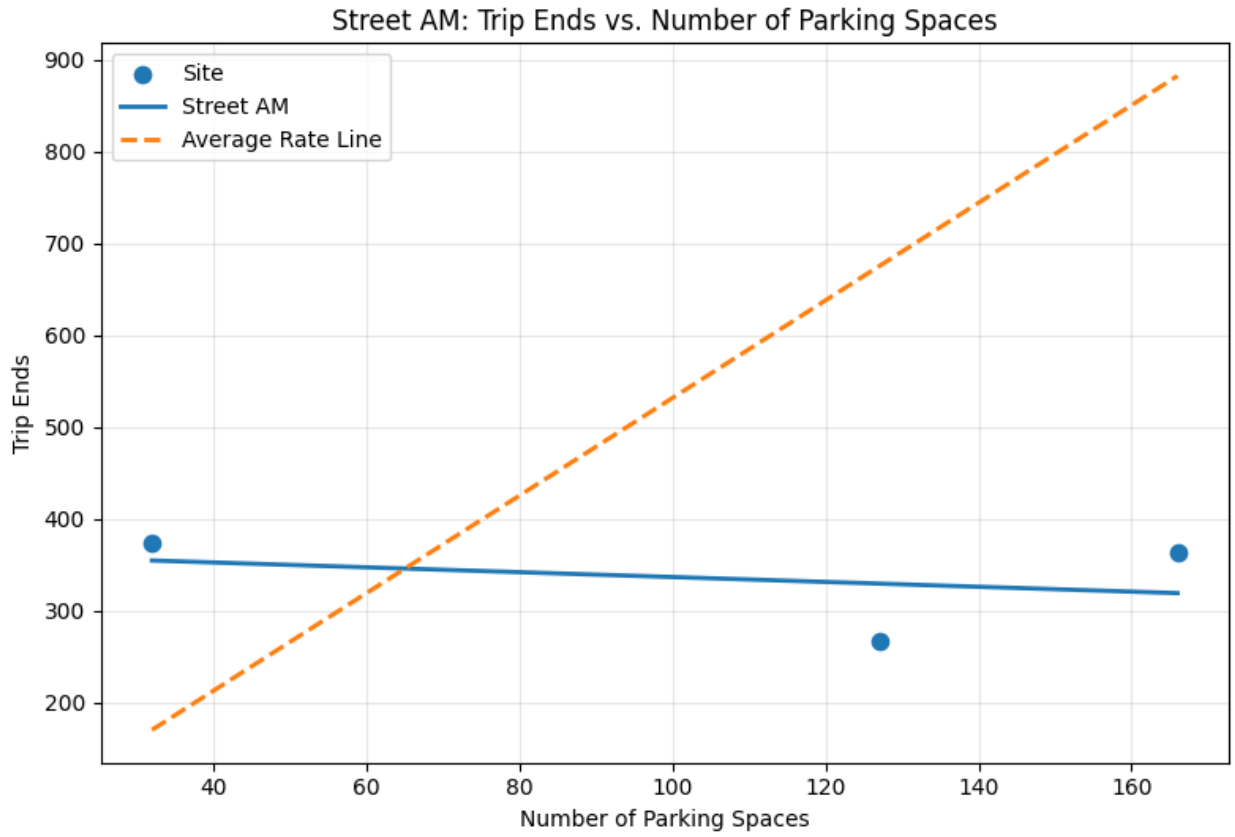
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 7 and 9 a.m.
Number of Studies: 3
Average Number of Parking Spaces: 108.33
Directional Distribution: 50% entering, 50% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.74	0.22–1.16	3.88

Data Plot and Equation

Equation	R^2
T = -0.2649(X) + 363.0263	0.0946



950 - Truck Stops

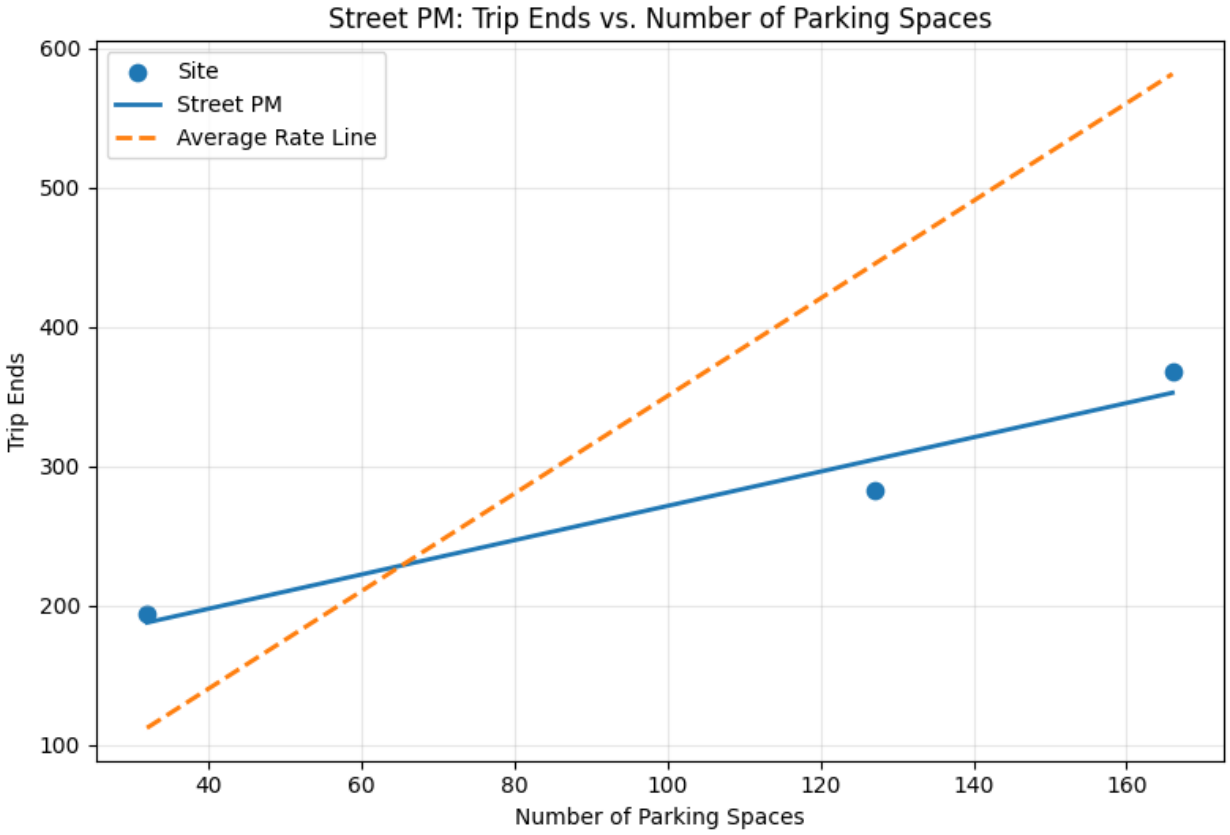
Vehicle Trip Ends vs: **1000 Sq. Ft. GFA**
On a: **Weekday,**
Peak Hour of Adjacent Street,
Between 4 and 6 p.m.
Number of Studies: 3
Average Number of Parking Spaces: 108.33
Directional Distribution: 49% entering, 51% exiting

Vehicle Trip Generation per 1000 Sq. Ft. GFA

Average Rate	Range of Rates	Standard Deviation
0.72	0.24–1.27	1.57

Data Plot and Equation

Equation	R^2
T = 1.2310(X) + 148.3082	0.9509



Appendix C. Indiana Specific E-Commerce Survey Instrument

Respondents	Q#	Question / Instruction	Response Options	Display Logic/Notes
All	Q1	Research Participant Information Sheet	Informational text	Includes purpose, risks, benefits, confidentiality, contacts
All	Q2	I agree to participate...	Checked consent box	Required to continue
All	Q3	How old are you?	• 17 or younger • 18-24 • 25-34 • 35-44 • 45-54 • 55-64 • 65+	Terminate if 17 or younger
All	Q4	Are you a resident of Indiana?	• Yes • No	Terminate if No
All	Q6	How often do you buy products online, including groceries, prepared meals, and other physical goods?	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	Determines branch: • Respondents who choose *Never* follow the *Non-Shopper* branch • Respondents who choose *Seldom* follow the Infrequent Shopper branch • All others follow the *Frequent Shopper* branch
Non-shopper	Q7	How familiar are you with online shopping?	• I've never heard of it. • I've heard of it, but don't know much. • I have a basic understanding. • I know about online shopping, but I have not used it before.	

Non-shopper	Q8	Have you ever used an online shopping website or app?	• Yes, but did not go through with the purchase. • No, I have not used an online shopping service before.	If Q7 != Never heard
Non-shopper	Q9	Why didn't you complete your online purchase?	• I had trouble understanding how to place the order. • The payment process was confusing or didn't work. • The product I wanted wasn't available. • I was worried about the safety when paying online. • I wasn't sure if the product would be of good quality. • I didn't know how returns or refunds work. • The website or app was hard to use. • I changed my mind. • I decided to shop at a store instead. • Other (text response)	If Q8=Yes
Non-shopper	Q10	Do you ask someone else to place orders on your behalf?	• Yes • No	
Non-shopper	Q11	Why did you ask someone else...?	• I'm not comfortable using technology. • They have access to an account or membership I don't. • We share items or orders regularly. • Other (text response)	If Q10=Yes

Non-shopper	Q12	How often does someone else place orders on your behalf?	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	If Q10=Yes
Infrequent Shopper	Q13	Do you ask someone else to place orders on your behalf?	• Yes • No	
Infrequent Shopper	Q14	Why did you ask someone else...?	• I'm not comfortable using technology. • They have access to an account or membership I don't. • We share items or orders regularly. • Other (text response)	If Q13 = Yes
Infrequent Shopper	Q15	How often does someone else place orders on your behalf?	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	If Q13 = Yes
Non-shopper	Q16	How often do you shop in stores?	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	

Non-shopper	Q17	Select the number seventeen from the list.	• 56 • 92 • 17 • 47	Wrong answer terminates survey
Non-shopper	Q18	What is the primary mode of transport you use to make in-store shopping trips:	• Car • Motorcycle • Bicycle/e-bike • Public transport • Walk • Ride-hailing (Uber, Lyft etc.)	Q16 != Never
Non-shopper	Q19	How do you usually plan your shopping trips? (Please select the option that best describes your typical behavior.)	• I usually make a dedicated trip specifically for shopping. • I usually combine shopping trips with other errands or trips. • I do both about equally often.	Q16 != Never
Non-shopper	Q20 (1)	I believe using online shopping apps or websites would help me shop more efficiently.	• Strongly Disagree • Disagree • Neither Agree nor Disagree • Agree • Strongly Agree	
Non-shopper	Q20 (2)	Shopping online would make my life easier and more convenient.		
Non-shopper	Q20 (3)	I think shopping online might be a good way to buy the things I need.		
Non-shopper	Q20 (4)	I believe online shopping would save time compared to going to a store.		
Non-shopper	Q20 (5)	People important to me would approve of me shopping online.		
Non-shopper	Q20 (6)	My friends and family think I should use online shopping services.		
Non-shopper	Q20 (7)	To show you are paying attention, please select "Strongly Disagree" here.		

Non-shopper	Q20 (8)	I have the support that I need to learn to shop online.		
Non-shopper	Q20 (9)	People around me expect that I will shop online.		
Non-shopper	Q20 (10)	I think learning to shop online would be easy for me.		
Non-shopper	Q20 (11)	I believe online stores would be easy to navigate.		
Non-shopper	Q20 (12)	I expect that completing purchases online would require little effort.		
Non-shopper	Q20 (13)	If I needed to shop online, I would consider trying it.		
Non-shopper	Q20 (14)	I am open to using online shopping services in the future.		
Non-shopper	Q20 (15)	I might recommend online shopping to others if I had a good experience.		
Non-shopper	Q20 (16)	I am concerned about package theft when it comes to online delivery.		
Non-shopper	Q20 (17)	I am concerned about my purchases being delivered to the wrong house.		
Frequent Shopper	Q24	How many years have you been shopping online?	• 2-years or less • 2–5 years • 5–10 years • More than 10 years	
Frequent Shopper	Q25	Who do you place orders for? [select all that apply]	• Yourself • Others in the same household (e.g., partner, children, parents, roommates) • Others not in the same household (e.g., relatives, friends, neighbors, gifts to other people) • Shared use (e.g., cleaning supplies, toilet paper, furniture—items used by	

			multiple people in the household)	
Frequent Shopper	Q26	What was the reason for ordering on behalf of someone else? [select all that apply]	• It was a gift. • They were not comfortable using technology. • You have access to an account or membership they do not. • We share items or orders regularly. • They do not have internet access. • Other (text input)	If Q25 includes others
Frequent Shopper	Q27	Mark all the ways you have received your online purchases in the past 6 months	• Delivered to my home address • Delivered to my work/school address • Delivered to someone else's home (safety concerns, gifts, ordering on behalf of someone else) • Pick up at the store of purchase • Pick up at a manned pickup point, like UPS Access Point • Pick up at an automated locker, like Amazon Locker • Other, please specify (text input)	

Frequent Shopper	Q28	What kind of products do you order online? [select all that apply]	• Groceries (fresh food, pantry items, or household products for same day/earliest pick-up; meal kits such as HelloFresh or Blue Apron) • Food (prepared food, e.g., restaurant delivery, ready-to-eat meal services such as Factor or Freshly) • Goods (e.g., clothing, electronics, household supplies)	
Frequent Shopper	Q29	How do you usually receive your online purchase? Groceries (fresh food, pantry items, or household products for same day/earliest pick-up; meal kits such as HelloFresh or Blue Apron) Food (prepared food, e.g., restaurant delivery, ready-to-eat meal services such as Factor or Freshly) Goods (e.g., clothing, electronics, household supplies)	• Delivered to my home address • Delivered to my work/school address • Delivered to someone else's home (safety concerns, gifts, ordering on behalf of someone else) • Pick up at the store of purchase • Pick up at a manned pickup point, like UPS Access Point • Pick up at an automated locker, like Amazon Locker	Only asked about products selected in Q28
Frequent Shopper	Q30	How often do you purchase online and have it delivered? Groceries (fresh food, pantry items, or household products for same day/earliest pick-up; meal kits such as HelloFresh or Blue Apron) Food (prepared food, e.g., restaurant delivery, ready-to-eat meal services such as Factor or Freshly) Goods (e.g., clothing, electronics, household supplies)	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	Only asked about products selected in Q28 and if any delivery modes are chosen in Q27
Frequent Shopper	Q31	Select the number seventeen from the list.	• 27 • 92 • 17 • 47	Wrong answer terminates survey

Frequent Shopper	Q32	How often do you purchase online and pick it up? Groceries (fresh food, pantry items, or household products for same day/earliest pick-up; meal kits such as HelloFresh or Blue Apron) Food (prepared food, e.g., restaurant delivery, ready-to-eat meal services such as Factor or Freshly) Goods (e.g., clothing, electronics, household supplies)	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	Only asked about products selected in Q28 and if any pickup modes are chosen in Q27
Frequent Shopper	Q33	When picking up online orders, do you use different modes of transportation depending on the type of product (e.g., groceries, prepared food, or other goods)? For example, you might walk to pick up prepared food, but drive to pick up groceries or other goods.	• Yes • No	If any pickup modes are chosen in Q28
Frequent Shopper	Q34	What is the primary mode of transport you use for pick-up orders: Groceries (fresh food, pantry items, or household products for same day/earliest pick-up; meal kits such as HelloFresh or Blue Apron) Food (prepared food, e.g., restaurant delivery, ready-to-eat meal services such as Factor or Freshly) Goods (e.g., clothing, electronics, household supplies)	• Car • Motorcycle • Bicycle/e-bike • Public transport • Walk • Ride-hailing (Uber, Lyft etc.)	Only asked about products selected in Q28 and if Q33 = Yes
Frequent Shopper	Q35	What is the primary mode of transport you use for pick-up orders:	• Car • Motorcycle • Bicycle/e-bike • Public transport • Walk • Ride-hailing (Uber, Lyft etc.)	If Q33=No
Frequent Shopper	Q36	How do you usually plan your pick-up trips? (Please select the option that best describes your typical behavior.)	• I usually make a dedicated trip specifically for pickup. • I usually combine the pickup with other errands or trips. • I do both about equally often.	If any pickup modes are chosen in Q28

Frequent Shopper	Q37	How frequently do you pay for faster delivery?	• Always • Often (more than 60% of the time) • Sometimes (about 50% of the time) • Occasionally (less than 40% of the time) • Never	
Frequent Shopper	Q38	Several companies offer incentives to customers who opt for alternative delivery options, such as delayed shipping, consolidated packaging, or fewer shipments. Here are some notable examples: Amazon: No-Rush Shipping: Customers selecting No-Rush Shipping at checkout may receive immediate discounts on their current order or rewards applied to their account for future purchases. Walmart – occasionally offers slower shipping options in exchange for digital rewards or greener delivery. Target: Target has implemented no-rush shipping options, providing customers with store credit to select slower delivery times. Would you be willing to wait longer for an alternative delivery option in exchange for perks like store credit or discounts?	• Yes – in all cases • Yes – but only for non-urgent orders • No	
Frequent Shopper	Q39	Have you ever used package lockers for delivery?	• Yes • No	
Frequent Shopper	Q40	Do you have any concerns about the safe delivery of your packages? [select all that apply]	• No concerns • Package theft (e.g., porch piracy) • Delivery to the wrong address • Damage during transit • Lost or misplaced packages • Other (please specify) (text input)	
Frequent Shopper	Q41	Have you ever returned a product purchased online?	• Yes, at least once • No, never.	

Frequent Shopper	Q42	How often do you return via each method: Home pickup Post Office/UPS/FedEx or similar Amazon drop off locations Directly to the store	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	If Q41 = Yes
Frequent Shopper	Q43	What is the primary mode of transport you use to return orders:	• Car • Motorcycle • Bicycle/e-bike • Public transport • Walk • Ride-hailing (Uber, Lyft etc.)	If Q41 = Yes
Frequent Shopper	Q44	How do you usually plan your return trips? (Please select the option that best describes your typical behavior.)	• I usually make a dedicated trip specifically for return trips. • I usually combine the return trips with other errands or trips. • I do both about equally often	If Q41 = Yes
Infrequent Shopper	Q157	How often do you make purchases at stores now?	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	
Infrequent Shopper	Q158	Select the number seventeen from the list.	• 56 • 92 • 17 • 47	

Infrequent Shopper	Q159	What is the primary mode of transport you use to make in-store shopping trips:	• Car • Motorcycle • Bicycle/e-bike • Public transport • Walk • Ride-hailing (Uber, Lyft etc.)	
Infrequent Shopper	Q160	How do you usually plan your shopping trips? (Please select the option that best describes your typical behavior.)	• I usually make a dedicated trip specifically for shopping. • I usually combine shopping trips with other errands or trips. • I do both about equally often.	
Frequent Shopper	Q45	How often do you make purchases at stores now?	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	
Frequent Shopper	Q46	Pick the word that does not belong with the others.	• Red • Blue • Elephant • Green	
Frequent Shopper	Q47	What is the primary mode of transport you use to make in-store shopping trips:	• Car • Motorcycle • Bicycle/e-bike • Public transport • Walk • Ride-hailing (Uber, Lyft etc.)	
Frequent Shopper	Q48	How do you usually plan your shopping trips? (Please select the option that best describes your typical behavior.)	• I usually make a dedicated trip specifically for shopping.	

			• I usually combine shopping trips with other errands or trips. • I do both about equally often.	
Infrequent Shopper and Frequent Shopper	Q50	Which of the following have changed for you after adopting online shopping? [select all that apply]	• Overall shopping frequency has changed. • In store shopping frequency has changed. • Instore shopping transportation mode has changed. • I shop at stores closer to home now. • I shop at stores farther from home now. • No change. • Other (text input)	
Infrequent Shopper and Frequent Shopper	Q51	Since you began shopping online, how have the following changed? Overall in-store shopping Grocery shopping in stores Shopping for goods in stores Takeout from restaurants	• Substantially Reduced • Reduced • No Change • Increased • Substantially Increased	If Q50 = In store shopping frequency has changed.
Infrequent Shopper and Frequent Shopper	Q52	How often did you make purchases in stores before adopting online shopping? Overall in-store shopping Grocery shopping in stores Shopping for goods in stores Takeout from restaurants	• Never • Seldom (less than once a month) • 1–3 times per month • 1–2 times per week • 3–4 times per week • Almost every day • Several times per day	If Q50 = In store shopping frequency has changed.
Infrequent Shopper and Frequent Shopper	Q53	Since you began shopping online, how has your overall shopping frequency (online and in-store combined) changed?	• Substantially Reduced • Reduced • No Change • Increased • Substantially Increased	If Q50 = Overall shopping frequency has changed.

Infrequent Shopper and Frequent Shopper	Q54	What is the primary mode of transport you used to make in-store shopping trips before adopting online shopping?	• Car • Motorcycle • Bicycle/e-bike • Public transport • Walk • Ride-hailing (Uber, Lyft etc.)	If Q50 = Instore shopping transportation mode has changed.
Infrequent Shopper	Q21 (1)	I have difficulty with online payment methods.	• Strongly Disagree • Disagree • Neither Agree nor Disagree • Agree • Strongly Agree	
Infrequent Shopper	Q21 (2)	Local stores meet all my needs.		
Infrequent Shopper	Q21 (3)	I prefer supporting local businesses.		
Infrequent Shopper	Q21 (4)	I don't have access to membership benefits		
Infrequent Shopper	Q21 (4)	I have concerns about return or refund processes.		
Infrequent Shopper	Q21 (5)	Delivery takes too long or is unreliable.		
Infrequent Shopper	Q21 (6)	Limited access to technology or internet.		
Infrequent Shopper	Q22	Please share any other reasons you may have for using online shopping portals less frequently.	Text input	
Infrequent Shopper	Q22 (1)	When I've used it, online shopping helped me shop more efficiently.	• Strongly Disagree • Disagree • Neither Agree nor Disagree • Agree • Strongly Agree	
Infrequent Shopper	Q22 (2)	Online shopping made it easier to get what I needed.		
Infrequent Shopper	Q22 (3)	I've found that shopping online saves time compared to going to a store.		
Infrequent Shopper	Q22 (4)	It's been easy for me to learn how to shop online.		
Infrequent Shopper	Q22 (5)	I've found online stores fairly easy to navigate.		
Infrequent Shopper	Q22 (6)	To show you are paying attention, please select "Strongly Disagree" here.		
Infrequent Shopper	Q22 (7)	I've been able to complete purchases online without much difficulty.		

Infrequent Shopper	Q22 (8)	I might use online shopping more often in the future.		
Infrequent Shopper	Q22 (9)	I'm considering using online shopping services instead of going in-store.		
Infrequent Shopper	Q22 (10)	I would recommend online shopping to others based on my experience.		
Frequent Shopper	Q55 (1)	Using online shopping services has been as easy as I expected.		
Frequent Shopper	Q55 (2)	Online stores are as simple and intuitive to navigate as I anticipated.		
Frequent Shopper	Q55 (3)	Completing purchases online requires as little effort as I thought it would.		
Frequent Shopper	Q55 (4)	Checking the availability of items online is as straightforward as I expected.		
Frequent Shopper	Q56 (1)	Online shopping makes my purchasing more convenient.		
Frequent Shopper	Q56 (2)	Online shopping improves my efficiency in shopping.		
Frequent Shopper	Q56 (3)	Online shopping enhances the quality of my shopping experience.		
Frequent Shopper	Q56 (4)	Online stores enable me to access useful product information to make my decisions.		
Frequent Shopper	Q56 (5)	To show you are paying attention, please select "Strongly Disagree" here.		
Frequent Shopper	Q56 (6)	I am satisfied with using e-commerce services.		
Frequent Shopper	Q56 (7)	Online shopping has been a pleasant experience.		
Frequent Shopper	Q56 (8)	I feel comfortable shopping online.		
Frequent Shopper	Q56 (9)	I like shopping online.		
Frequent Shopper	Q56 (10)	I like going to the store.		
Frequent Shopper	Q56 (11)	I intend to continue using online shopping services in the future.		

Frequent Shopper	Q56 (12)	I prefer online stores to brick and mortar stores.		
Frequent Shopper	Q56 (13)	I will recommend online shopping to others.		
Frequent Shopper	Q57 (1)	During the pandemic, I avoided going to stores when possible.		
Frequent Shopper	Q57 (2)	Shipping costs influence my decision to shop online.		
Frequent Shopper	Q57 (3)	Shipping time is an important factor when I shop online.		
Frequent Shopper	Q57 (4)	I often research online and then buy in-store.		
Frequent Shopper	Q57 (5)	I often research instore and then buy online.		
Frequent Shopper	Q57 (6)	I often shop online to avoid making trips to the store.		
Frequent Shopper	Q57 (7)	The price of a product often influences where or how I choose to shop.		
Frequent Shopper	Q57 (8)	The availability of a product often influences where or how I choose to shop.		
Frequent Shopper	Q57 (9)	To show you are paying attention, please select "Strongly Agree" here.		
Frequent Shopper	Q57 (10)	Assuming similar prices and availability, I prefer making purchases online rather than in physical stores.		
Frequent Shopper	Q57 (11)	I choose where to shop (online or in-store) based on convenience, not habit.		
Frequent Shopper	Q57 (12)	Weather affects if I shop online or in person.		
Frequent Shopper	Q57 (13)	Weather affects if I choose delivery or pick up when shopping online.		
Frequent Shopper	Q57 (14)	I go to the store when I need something urgently.		
Frequent Shopper	Q57 (15)	I shop online when I need something urgently.		

Infrequent Shopper and Frequent Shopper	Q58	How do you usually pay for online purchases?	• Credit Card • Debit Card • Cash • Klarna/Afterpay or other Buy Now Pay Later options • Paypal/Venmo or other online payment options	
All	Q59	Do you have internet access at home?	• Yes • No	
All	Q60	How many years have you been using the Internet for?	• Less than 2 years • 2 to 5 years • 5 to 10 years • 10 to 15 years • 15 to 20 years • 20+ years	
All	Q61	On average, how much time do you spend online each day for personal use (excluding work or school-related activities)? Please include activities like: Browsing or shopping on websites or apps, watching videos or streaming content, using social media, messaging, emailing, or reading news.	• Less than 1 hour per week • Less than 1 hour per day • 1–2 hours per day • 3–4 hours per day • 5 or more hours per day	
All	Q62	Did you work for pay or profit last week?	• Yes • No	
All	Q63	If you did not work last week, were you:	• Temporarily absent from a job/business • Looking for work/unemployed • A homemaker • Going to school • Retired • Doing something else	If Q62=No

All	Q64	How many hours did you work for pay or profit last week?	• 1–9 hours • 10–19 hours • 20–29 hours • 30–39 hours • 40 hours • More than 40 hours	If Q62=Yes
All	Q65	Which of the following best describes where you work?	• Only one work location outside of home • Work location regularly varies (different offices/jobsites) • Only work at home (telework, self-employed) • Drive/travel for work (driver, sales)	If Q62=Yes
All	Q66	How often do you work only at home for an entire workday instead of traveling to a usual workplace?	• Never • Rarely • One or two days a week • Three or four days a week • Five or more days a week	If Q66!=Only work at home
All	Q67	How do you get to work usually?	• Car • Motorcycle • Bicycle/e-bike • Public transport • Walk • Ride-hailing (Uber, Lyft etc.)	If Q62=Yes
All	Q68	How do you describe yourself?	• Male • Female • Prefer to self-describe	

All	Q69	Choose one or more races that you consider yourself to be [select all that apply]	• White or Caucasian • Black or African American • American Indian/Native American or Alaska Native • Asian • Native Hawaiian or Other Pacific Islander • Other (text input) • Prefer not to say	
All	Q70	Are you of Spanish, Hispanic, or Latino origin?	• Yes • No	
All	Q71	What best describes your current housing situation?	• Single family • Apartment • Assisted living • Other (text input)	
All	Q135	Are you a renter?	• Yes • No • Not applicable	
All	Q72	Select the third option.	• 1 - Owned by you • 2 - Occupied by you without payment of rent • 3 - Owned by someone else in the household • 4 - Rented by you or someone in the household	Wrong answer terminates survey
All	Q73	How many people currently live in your household (including yourself) that are 18 years or older?	0 to 10+	
All	Q74	How many people currently live in your household (including yourself) that are 5 to 17 years old?	0 to 10+	
All	Q75	How many people currently live in your household (including yourself) that are under the age of 5?	0 to 10+	

All	Q76	Which best describes the building where you live?	• One-family house detached from any other house • One-family house attached to one or more houses (e.g., condo or townhouse) • Building with 2 or more apartments • Mobile home • Boat, Recreational Vehicle (RV)/Motorhome, van, etc.	
All	Q77	What is the highest level of education you have completed?	• Some high school or less • High school diploma or GED • Some college, but no degree • Associates or technical degree • Bachelor's degree • Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS etc.) • Prefer not to say	
All	Q78	What was your total household income before taxes during the past 12 months?	• Less than $15,000 • $15,000-$24,999 • $25,000-$49,999 • $50,000-$74,999 • $75,000-$99,999 • $100,000-$149,999 • $150,000 or more • Prefer not to say	
All	Q79	What is your current marital status?	• Married • Living with a partner • Widowed • Divorced/Seperated • Never been married	

All	Q80	How many vehicles are in your household?	• 0 • 1 • 2 • 3 • 4+	
All	Q81	Do you have a condition or disability?	• No, I do not. • Yes, I have had this condition for 6 months or less. • Yes, I have had this condition for more than 6 months. • Yes, I have had this condition for my entire life.	
All	Q82	Do you use any of the following? Please select all that apply:	• Walking cane or stick • Walker or crutches • Device to aid the blind or visually impaired, such as a white cane, guide dog, etc. • Motorized scooter or wheelchair • Manual scooter or wheelchair • Something else (please specify) (text input) • None of the above	If Q81 != No
All	Q83	If you have a condition or disability, has it caused you to: (Please select all that apply)	• Reduce your day-to-day travel • Ask others for rides • Limit driving to daytime • Give up driving altogether • Use the bus or subway less frequently • Use an agency's special transportation services (e.g., dial-a-ride) • Use ride-hailing services (Uber, Lyft etc.)	If Q81 != No

			• Not been affected	
All	Q84	Do you drive?	• Yes • No	If Q83!=not given up driving
All	Q85	What is your home zip code?	Open text	
All	Q86	What is the ZIP code of your main activity outside the home (like work, study, medical)?	Open text	
All	Q87	Do you have any other comments to add about your shopping habits or the survey? (optional)	Open text	Optional

About the Joint Transportation Research Program (JTRP)

On March 11, 1937, the Indiana Legislature passed an act which authorized the Indiana State Highway Commission to cooperate with and assist Purdue University in developing the best methods of improving and maintaining the highways of the state and the respective counties thereof. That collaborative effort was called the Joint Highway Research Project (JHRP). In 1997 the collaborative venture was renamed as the Joint Transportation Research Program (JTRP) to reflect the state and national efforts to integrate the management and operation of various transportation modes.

The first studies of JHRP were concerned with Test Road No. 1—evaluation of the weathering characteristics of stabilized materials. After World War II, the JHRP program grew substantially and was regularly producing technical reports. Over 1,600 technical reports are now available, published as part of the JHRP and subsequently JTRP collaborative venture between Purdue University and what is now the Indiana Department of Transportation.

Free online access to all reports is provided through a unique collaboration between JTRP and Purdue Libraries. These are available at docs.lib.purdue.edu/jtrp/.

Further information about JTRP and its current research program is available at engineering.purdue.edu/JTRP.

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