Transactions on Engineering and Technology Research
ISSN: 2960-1797, eISSN: 2960-2246 | Volume 5
ACEGE 2025

Assessing the Impact of Adaptive Traffic Signals on Manhattan's Traffic Pattern Using Origin-Destination Analysis and YOLOv8 Real-Time Detection Model

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Abstract. Adaptive Traffic Signal Systems (ATS) have been implemented in Manhattan in an effort to reduce congestion and enhance roadway efficiency, yet their broader impacts on redistributions of traffic have been insufficiently explored. This research estimates the long-term effects of ATS by leveraging the combined application of three supporting methodologies: (1) a comparison of traffic volumes between 2011 and 2018, (2) an Origin–Destination (O-D) examination of trip distributions, and (3) in real-time vehicle detection via the YOLOv8 deep learning algorithm. This research finds a systematic shift and redistribution in traffic volumes between 2011 and 2018. Notably decreased volumes were observed in central north–south corridors like 5th and 6th Avenues, while coastal highways, such as the FDR Drive and West Side Highway, showed considerable increases. O-D analysis put these changes into context by demonstrating that origins have steadily concentrated in outer boroughs while destinations shifted from Lower Manhattan to Midtown West. Finally, YOLOv8-based examination of 2024 traffic data verified that these patterns continue to exist in the mature ATS network.

Keywords: Adaptive Traffic Signals; Traffic Volume Redistribution; Origin–Destination Analysis; YOLOv8; Urban Mobility; Manhattan; Smart Transportation Systems.

1. Introduction

Urban congestion remains one of the most intractable challenges to metropolitan government, and New York City—and especially Manhattan—offers a notable exemplar. Inefficiencies and congestion are exacerbated by traditional fixed-time signal systems, which have no ability to react to changes in demand. Therefore, Adaptive traffic signal systems (ATS) have been developed to adjust signal times in real time and thereby increase intersection capacity and overall network dependability [1, 2]. Preliminary evaluations of the Midtown in Motion (MiM) program in Manhattan, deployed in 2011, confirmed tangible reductions in travel time during the initial 110-block coverage [3]. But such studies focused primarily on short-term performance and threw little light on how ATS could potentially redistribute traffic on a longer scale.

Over the following decade, Manhattan's travel behaviors started to change. Central city avenues like 5th and 6th continued to decrease in vehicle flows, while coastal arterials like the FDR Drive and the West Side Highway took in incremental flows. These changes imply that ATS could function both as a congestion-control instrument and also as a structural agent defining the space-based distribution of traffic within the grid [4].

This paper addresses that question by combining three complementary approaches. First, automated traffic counts from 2011 and 2018, provided by the New York City Department of Transportation [4], are compared to assess long-term redistribution following the expansion of ATS and the integration of the Trans Suite Traffic Control System [5, 6]. By 2018, the city's network had advanced well beyond the initial rollout of ATS, with Trans Suite enabling centralized real-time coordination across more than 12,000 intersections [7, 8]. Second, an Origin–Destination (O-D) analysis, using MTA travel survey data, evaluates the reorientation of trip origins and destinations across boroughs. Third, contemporary traffic camera footage from 2024 is analyzed using YOLOv8, a deep learning detection model, to test whether redistribution observed in earlier datasets persists under the fully developed

ATS regime. Taken together, these methods move beyond delay-centered evaluation to demonstrate ATS as a driver of network-wide reorganization in Manhattan's traffic system.

The rest of this paper is structured such that Section 2 presents a summary of existing literature on adaptive traffic signals, traffic redistribution, and computational detection approaches. Section 3 presents the methodology, which covers the comparison of traffic volumes in 2011–18, O-D analysis, and YOLOv8 deployment. Section 4 reveals the findings, while Section 5 interprets them in relation to learning long-term ATS effects in highly urban areas. Section 6 concludes with important findings and avenues for future research.

2. Literature Review

Adaptive Traffic Signal Systems (ATS) have been thoroughly investigated as an intelligent innovation to reduce urban congestion and maximize network efficiency. However, while earlier research has verified their effectiveness, existing literature also reveals methodological and conceptual flaws that this paper seeks to correct.

One of the earliest assessments of Automated Traffic Signals (ATS) in Manhattan was undertaken by Kington (2012) under the Midtown in Motion (MiM) project, which documented that the installation of ATS across 110 blocks reduced travel times by approximately 10% [3]. This study presented valuable early evidence that ATS minimizes congestion during rush hour. However, its analysis was restricted to short-term reductions in travel times and could not test how traffic flows were redistributing space-wise in the remainder of the network. This paper builds on Kington's results by analyzing traffic volumes between 2011 and 2018 in an effort to describe the long-term and space-wise differentiated effects of ATS.

These findings were extended by Correa and Falcocchio (2022) with the use of real traffic data to compare the performance of Advanced Traffic Signals (ATS) in Midtown [7]. Their case study validated that ATS optimizes performance with real-time intervention and validated the necessity of high-density urban areas. Their analysis, however, considered performance measures only at the intersection scale and could not adjust for systemic changes at a larger scale. Our study uses an Origin–Destination (O-D) analysis to examine how Advanced Traffic Systems (ATS) moderate trip patterns on various corridors and in several boroughs and therefore casts its net wider.

Falcocchio and Prassas (2024) made superior methodological advances by creating performance measures based on GPS-enabled taxis and microwave sensors [8]. Their research pointed to the significance of combining real-time data streams in signal performance evaluation. However, research primarily focused on setting up monitor metrics and not using them to characterize long-term changes in traffic redistribution. This present research expands on their output by adding historical traffic volumes data from the New York City Department of Transportation (NYC DOT) and survey-based origin-destination (O-D) flows to explore systemic patterns of redistribution over several years.

Nasri et al. (2018) demonstrated the use of Propensity Score Matching (PSM) in transportation research and how it could effectively reduce self-selection bias between treated and non-treated traffic zones [10]. In subsequent research, Dai et al. (2022) augmented this framework by presenting a two-dimensional PSM methodology that enables a refined separation of urban transit impacts [11]. Altogether, these works presented sound methodologies for causal inference. However, both studies have a tendency toward methodology over space outcomes with a lessened focus on redistribution patterns. This paper, instead, shifts the focus away from causal inference and toward descriptive spatial analysis—focusing on the redistribution of flows rather than methodology per se.

Khalili and Smyth (2024) showed that the YOLOv8 model could be used to detect traffic, with particular effectiveness in dense and urban settings [9]. Their work involves development that targets the detection of small units and makes YOLOv8 highly appropriate to urban networks of roadways. This research's drawback, however, lies in its methodological direction toward developing the improvement of detection precision rather than using YOLOv8 to perform longitudinal studies on matters related to the redistribution of traffic. This gap the current paper fills by using YOLOv8 both to act as a technical proof-of-concept and to verify past trends in the distribution of traffic in Manhattan with current real-time data.

To sum up, earlier research has shown that Automated Traffic Systems (ATS) can potentially reduce delays and improve traffic flow, while regularly failing to appropriately estimate the long-term redistribution of traffic in space. This research aims to complete this gap by (1) analyzing traffic volumes comparatively between 2011 and 2018, (2) exploring origin-destination (O-D) flows in order to identify redistributions in the destinations and origins of trips, and (3) using YOLOv8 to confirm whether these redistributive patterns persist under the current traffic conditions.

3. Methodology:

3.1. Traffic Volume Comparison on Manhattan Roads (2011 vs. 2018)

Traffic volume changes were explored using the Automated Traffic Volume Counts data drawn from NYC Open Data. Sections of roads in 2011 and 2018 were synchronized to make them comparable in the given years. A 6% correction was applied to distinguish behavioral changes and changes in demographics by considering the population increase in this period. It was calculated the adjusted difference in volumes of traffic this way:

$$\Delta V_{adj} = (V_{2018} - V_{2011}) - (V_{2011} \times 0.06) \tag{1}$$

Where V_{2018} and V_{2011} represent the average vehicle counts on a given segment in 2011 and 2018, respectively. A positive ΔV_{adj} indicates an increase in traffic beyond expected growth, while a negative value indicates a reduction.

The results were presented in ArcGIS with a proportional symbol map. Road segments were highlighted visually according to the amount and direction of change: red, wider lines indicated increases, while blue, thinner lines showed decreases. This cartographic technique transparently portrayed the changes in traffic volumes across Manhattan from 2011 to 2018.

3.2. Origin-Destination Analysis (2018)

To measure the distributions of vehicle journeys in space, an Origin–Destination (O–D) analysis was conducted based on the MTA New York City Travel Survey covering over 130,000 trip records in the five boroughs. In keeping with that, data was only kept to trips on weekdays with vehicle-based modes such as private cars, taxi, and ride-hailing. Each trip's origin and destination were also geographically zoned to a Neighborhood Tabulation Area (NTA) in the software program ArcGIS so that a common base was established to measure trip intensity in areas that have been defined.

The distributions that emerged were illustrated utilizing choropleth maps to discern regions of high and low density. In order to assess clustering, a Hot Spot Analysis was conducted employing the Getis–Ord Gi* statistic, which is articulated as:

$$G^*_i = (\sum_j w_{ij} x_j - \bar{x} \sum_j w_{ij}) / (S\sqrt{(n \sum_j w^2_{ij})} / (n-1)) \tag{2}$$

Where x_j is the attribute value for feature j, w_{ij} is the spatial weight between features i and j, n is the number of features, $\bar{x}$ is the mean of all values, and S is the standard deviation. A statistically significant positive G^*_i identifies a hot spot (high clustering), while a negative value indicates a cold spot (low clustering).

Lastly, the ArcGIS Network Analyst was employed to identify statistically significant hot spots and to calculate shortest-time routes within the framework of the New York City Road network. By such routing analysis, a protocol was established to map out potential high-demand corridors and connect them to existing infrastructure, thereby connecting observed trip demand to roadway usage patterns.

3.3. YOLO v8 Vehicle Detection Model 2024

Incorporating the latest evidence, YOLOv8 model of object detection was used on videos taken at traffic cameras in the year 2024 from purposively selected intersections in Manhattan concurrently with the complete deployment of ATS system. Prior to analysis, the videos were normalized to ensure that they had a stable frame rate and resolution. YOLOv8 model was initialized with a pre-trained weight file (YOLOv8n.pt) and was set to detect several types of vehicles such as cars, trucks, and buses. The architecture processes entire frames in a single pass and thereby supports rapid and precise detection under heavy traffic.

Training was done on a set of labeled vehicle images (Fig. 1), and multiple epochs were employed to fine-tune model performance. At training, the loss function to minimize was:

$$L = L_{box} + L_{cls} + L_{dfl} \tag{3}$$

Where L_{box} represents bounding-box regression loss, L_{cls} denotes classification loss, and L_{dfl} is the distribution focal loss that improves localization accuracy.

After the training process, YOLOv8 processed traffic videos frame by frame and output bounding boxes, class labels, and confidence measures of recognized vehicles. A track algorithm assigned unique identifiers (IDs) to vehicles in successive frames and so avoiding the double counting of object numbers. Final vehicle numbers were summed up based on corresponding categories (cars, trucks, and buses).

Figure 1. Sample Training Images Used for YOLOv8 Model

By combining YOLOv8 detection with the earlier historical comparison and O-D analysis, the methodology created a smooth framework where real-time data in the current year added further strength to long-term patterns. This correlation facilitated a test of whether the redistribution that was recognized in the years between 2011 and 2018 still persisted in 2024, thereby reinforcing the findings with the most recent available proof.

4. Results:

4.1. Traffic Volume Comparison on Manhattan Roads (2011 vs. 2018)

Traffic volume analysis covering the period between 2011 and 2018 exhibits considerable redistributions of motor vehicle flow throughout Manhattan. Coastal highways, like the West Side Highway and the FDR Drive, registered considerable rises in traffic volumes, while broad central thoroughfares—like 5th, 6th, and Park Avenues—registered steady decreases (Figure 2,3). This redistributive pattern illustrates that the introduction of Adaptive Traffic Signals (ATS) has caused motor vehicles to shift away from narrow, clogged streets in Midtown and Lower Manhattan to wider-capacity artery roads that line the periphery of the island.

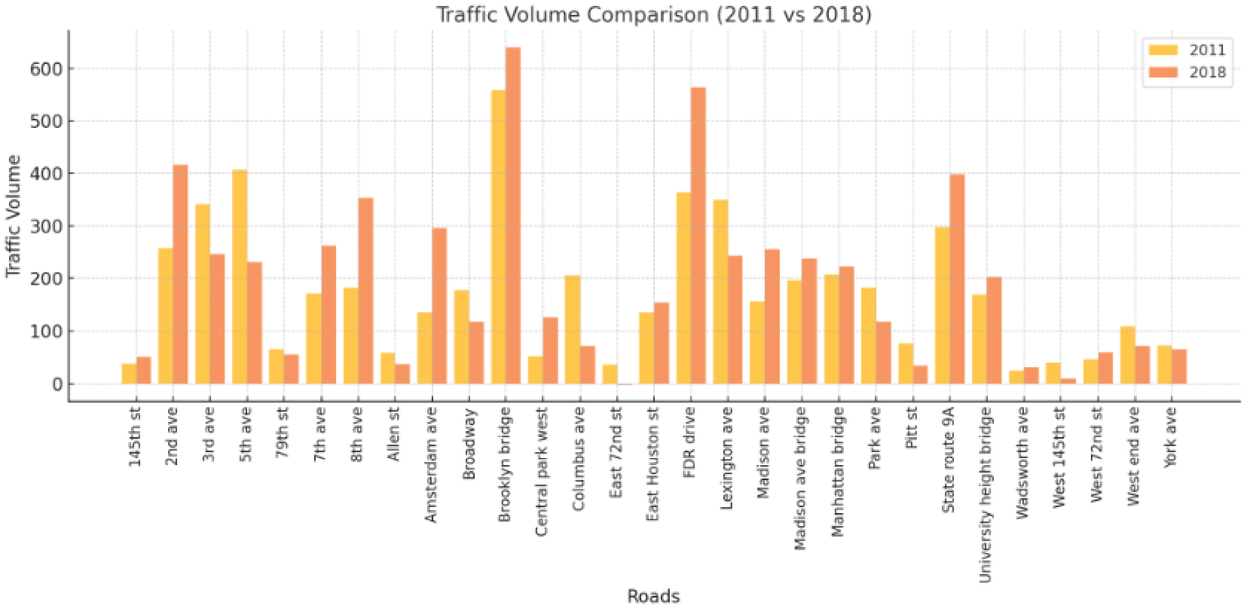


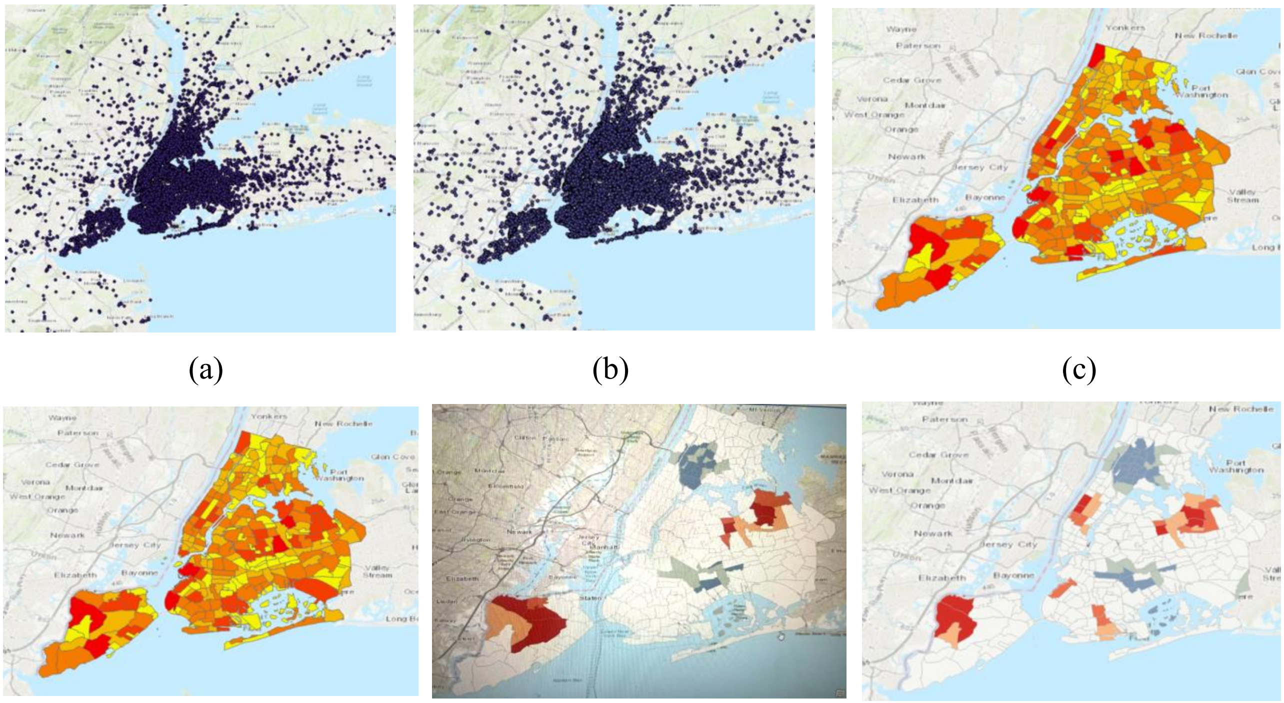
Figure 2. Traffic Volume Comparison Bar Chart on Manhattan Roads (2011 vs. 2018)

Figure 3. Traffic Volume Comparison Map on Manhattan Roads (2011 vs. 2018)

Notably, this trend holds even after correction to account for a 6% population growth over the corresponding interval. Ongoing declining volumes at the city center imply that redistributions described cannot strictly result from increases in demand and instead represent a structural reshaping of travel behavior. These findings lend credibility to the interpretation that ATS decreased local congestion whilst also reshaping overall routing decisions spreading throughout the network in a direction that benefited corridors that could accept increased throughput.

4.2. Origin-Destination Analysis (2018)

Origin-destination analysis reveals a characteristic reallocation of commuter flow within New York City. Origins of places are grouped in the outer boroughs, particularly in Queens and Brooklyn, and destinations of places are grouped in Midtown West more than in Lower Manhattan (Fig. 4). This reallocation indicates that trip demand has been reallocated away from the city's traditional employment center to the west side of Midtown, typical of wider changes in commuter flows, economic processes, or the role of ATS in redistributing accessibility patterns.

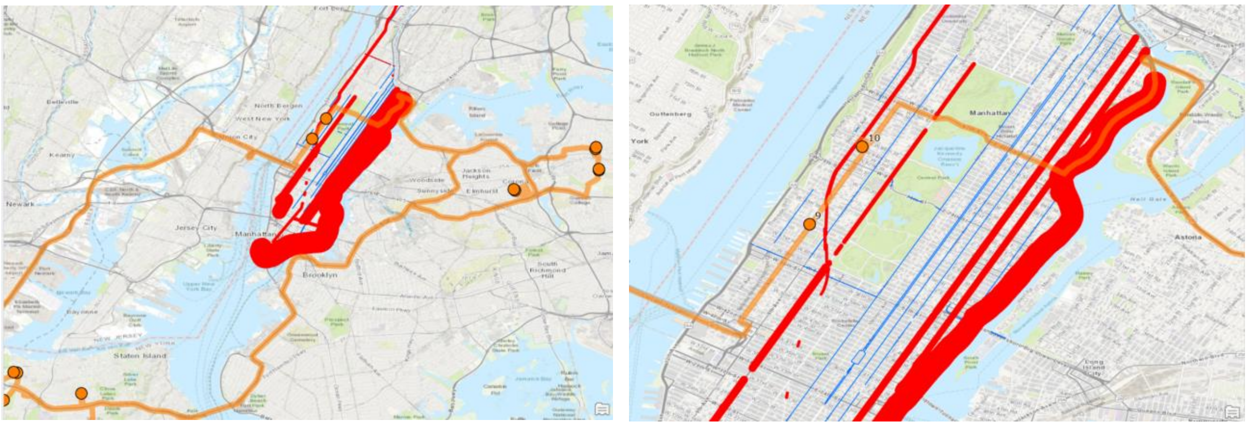


(a) (b) (c)

(d) (e) (f)

Figure 4. Vehicle trip patterns in the New York Metropolitan Area: (a) origin points of trips; (b) destination points of trips; (c) choropleth map of trip origins by Neighborhood Tabulation Area (NTA); (d) choropleth map of trip destinations by NTA; (e) hot spot analysis (Getis–Ord Gi*) of trip origins; and (f) hot spot analysis of trip destinations.

An examination between the shortest-time networks and traffic-volume variations also confirms this interpretation. Many routes that showed an increase between 2011 and 2018—especially the FDR Drive and other coastal highways—correspond to the O–D shortest-time network (Fig. 5). By contrast, main north–south routes, like 5th and 6th Avenues, lie outside these high-demand routes and match observed decreases in level of service (Fig. 5). This coincidence indicates that the flow of trips into Manhattan from outer boroughs has increased reliance on coastal access points while releasing pressure on center avenues.



(a) (b)

Figure 5. Shortest-time path network connecting origin and destination hot spots: (a) citywide view across New York City and surrounding boroughs, and (b) zoomed-in view of Manhattan.

Taken together, the O–D analysis indicates that ATS has facilitated both localized gains in efficiency and wider spatial redistribution. By enhancing smoother flows within high-capacity corridors and easing congestion in central Manhattan, ATS seems to confirm travel patterns that increasingly imply preferring coastal highways to access the city. The results also pose questions about the longer-term consequences of a shift in destinations from Lower Manhattan to Midtown West and possible associations with demographic transition, modal substitution, and changed economic geography.

4.3. YOLOv8 Vehicle Detection Model 2024

YOLOv8 model showed stable increases in performance throughout later training epochs, as shown in Fig. 6. Loss measures related to bounding-box regression, class classification, and distributional focal loss decreased continuously during training and point to increased object localization and vehicle-classification accuracy. At the same time, precision stayed above 0.90, and recall stabilized around 0.95, which indicates a suitable trade-off among false positives and false negatives. In addition, the mean average precision (mAP) increased continuously, and mAP50 and mAP50–95 exceeded 0.80 and 0.50, respectively. Overall, these performance measures confirm that the learned model achieved a level of robustness suitable for real-time observation of traffic under complex urban conditions.

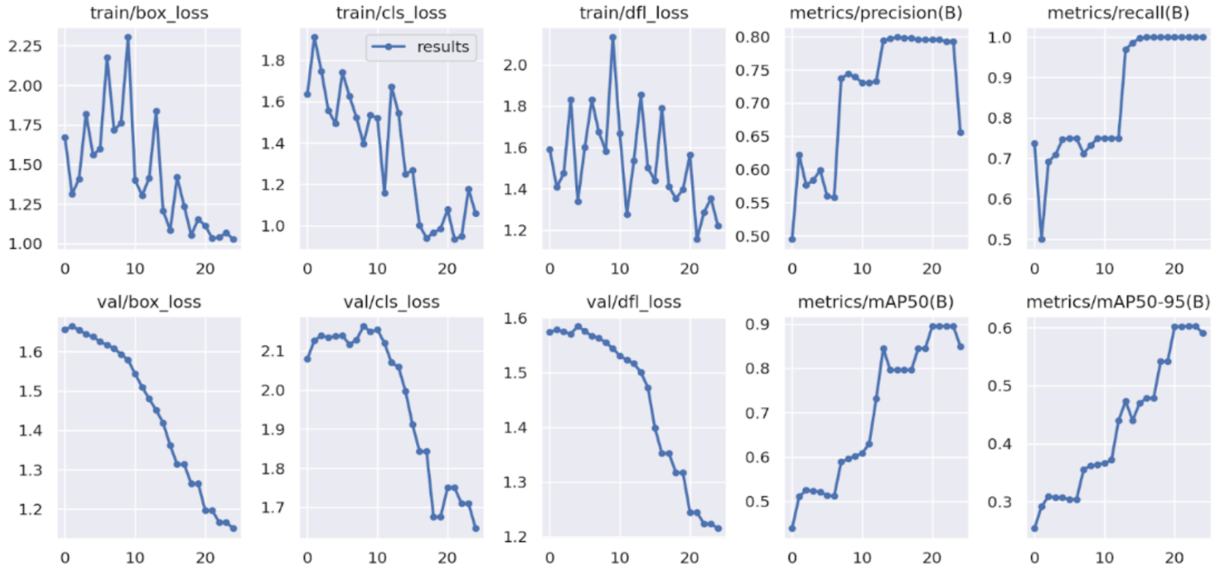


Figure 6. YOLOv8 Training Performance Metrics

YOLOv8 detection outputs showcase its ability in real-time estimation of traffic volumes in Manhattan (Fig. 7). Types of vehicles such as car, truck, and bus were continuously recognized and followed in subsequent frames with each vehicle being assigned a unique identifier in order to prevent duplication in subsequent tallies. This practice ensured that traffic volumes accurately depicted individual vehicles rather than successive detections. Furthermore, the confidence measures supported the credibility of identification, with measures constantly exceeding 0.80 in the case of heavy vehicles like buses, which ensured a predictable level of accuracy in varying classes. All these results confirm that the YOLOv8 model produced traffic volumes of adequate credibility to allow future comparison with historical volume data and Origin–Destination distributions, and hence supplement previous studies with the latest available evidence.

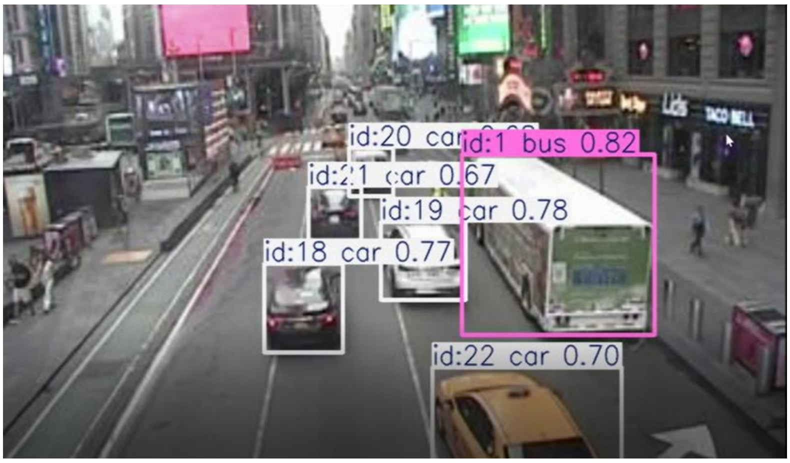


Figure 7. YOLOv8 Resulting Video

Joint analysis of YOLO-detected and historical data both reveals and substantiates a sharp persistence in the pattern of traffic in Manhattan over time. Findings from YOLO detection in 2024 report that volumes of traffic still remain concentrated along a set of primary corridors, namely Amsterdam Avenue, 2nd Avenue, 5th Avenue, and the FDR Drive, which together form a continuous high-intensity grid through Midtown to Uptown. In contrast, Broadway, Columbus Avenue, and Lexington Avenue consistently have lower volumes, in line with their more residential and local functions (Fig. 8).

These distributional patterns have a strong correlation with the historical changes in traffic that have been registered between 2011 and 2018. During this interval, increases in traffic were largely concentrated on the same east-side and central corridors, while west-side corridors continued to lose traffic. This correspondence between the distributions of 2011–2018 and those in 2024 implies that roads that showed growth before the widespread deployment of Adaptive Traffic Signals (ATS) continued to assert their dominance in later years. Such spatial consistency reveals an important attribute of path dependence in the traffic network of Manhattan—high-demand corridors continue to gain and retain high volumes of traffic even a decade after adaptive signal reconstruction (Fig. 8). The results are also supported by the result of statistical analysis carried out in this context. A moderate and statistically important positive correlation was found to exist between the changes in traffic volumes in the period 2011–2018 and the average YOLO volume in 2024 on important thoroughfares (Pearson $r = 0.54$, $p = 0.029$; Spearman $\rho = 0.43$, $p = 0.093$). Thoroughfares that had shown highest increases in the past, like Amsterdam Avenue, FDR Drive, and 5th Avenue, also show highest average YOLO volumes in 2024, while those that had shown previous declines in volumes have the lower end of this distribution. In the regression model, about 30% of the variance in YOLO volumes in 2024 is explained ($R^2 = 0.30$), which implies that while the Advanced Traffic System (ATS) has increased operational effectiveness, it had very little effect on reshaping the underlying spatial hierarchy of traffic (Fig. 9).

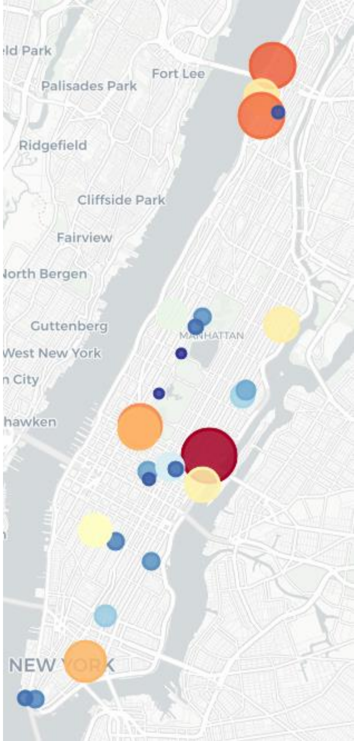


Figure 8. Spatial Distribution of YOLO-Detected Mean Traffic Volume in Manhattan, 2024

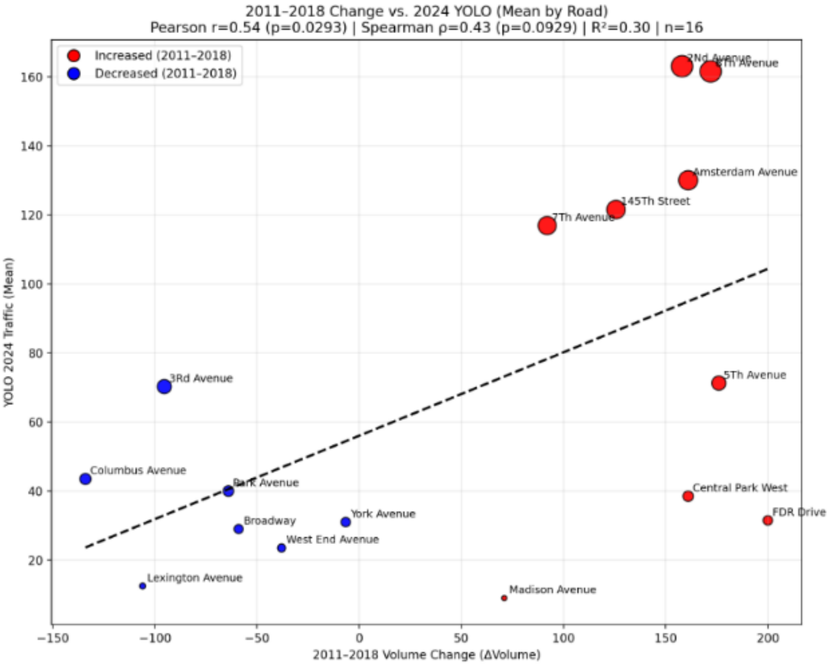


Figure 9. Relationship between Historical Traffic Change (2011–2018) and YOLO-Detected Mean Traffic (2024)

Aggregate results indicate that the traffic flow in Manhattan remained structural in its coherence during an appreciable length of time. While the Adaptive Traffic Signal (ATS) system optimized signal responsiveness and timing and hence localized efficiency gains, its influence was significantly constrained to the micro-level scale. In contrast to redistributing the traffic flows or reshuffling the space-based distribution of road activity, the ATS system functioned to strengthen existing high-traffic corridors. This result complements existing studies [3, 7], which suggest that adaptive control systems optimally supplement optimization in existing demand patterns rather than creating new ones.

5. Discussion:

This research adds to the existing literature on Adaptive Traffic Signal Systems (ATS) by illustrating that its influence extends well past simply short-term congestion relief. An examination of traffic flows between 2011 and 2018 identified that, aside from a reduction in the number of vehicles, the entire Manhattan road network in this timeframe presented a substantial reallocation of traffic flows in addition to it. Particularly, main thoroughfares like 5th and 6th Avenues presented steady declines, while oceanfront roads—namely, the FDR Drive and the West Side Highway—were able to adapt to gains in traffic volumes. In line with previous research that showed increases in efficiency correlate to ATS [3] [7], these results similarly point to the long-term reshaping of the spatio-temporal characteristics of urban flow and names ATS a key structural shaper of urban mobility.

Origin-Destination (O-D) analysis reveals significant indications of how factors underlie changes that have been registered. Trip origins have become more concentrated in the outer boroughs, primarily in such areas as Queens and Brooklyn, and destinations have gradually moved away from Lower Manhattan to Midtown West. From these tendencies, it could reasonably be deduced that the Advanced Traffic System (ATS) does more than respond to existing flows of traffic. Instead, it seems to respond to broader movements by directing cars toward routes with excess capability. In this manner, the ATS serves two functions by acting both as a traffic control and a redistributor of flows of traffic. This interpretation corresponds to earlier scholarly work on the value of real-time data in traffic control [8], while at the same time extending that debate to the urban scale from the level of intersections.

YOLOv8's findings offer up-to-date evidence in research. Redistribution that has endured up to 2024 indicates that the ATS still affects Manhattan's flows of traffic. Khalili and Smyth (2024) [9] commented on technical innovation in small-object detection that was YOLOv8's technical innovation, while our research refers to its applicability in traffic research. This framework enables linkage between computer vision's methodology innovations and questions of policy relating to infrastructure and mobility.

Other assumptions also ought to be validated. Although population growth was taken into consideration, other structural changes like employment center distributions and perceptions towards cycling and transit modes were not considered in the current study. Travel behavior with numerous levels of disparity could have been overlooked with the origin-destination-based examination. Also, the YOLOv8-based analysis was reliant on few cameras. Expanding the coverage in subsequent studies could also validate the results.

The findings indicate that the Advanced Transportation System (ATS) has progressed from a short-term solution to an arrangement that fundamentally alters urban transportation infrastructure. By diverting traffic on high-capacity highways off narrow center city streets, the ATS seemingly increases short-term operational efficiency and system lifespan of the Manhattan transportation system.

6. Conclusion:

To establish the long-term viability of Adaptive Traffic Signals (ATS) in Manhattan, this research employed three related methodologies: examination of historical traffic volumes, an Origin–Destination (O–D) survey, and real-time detection with YOLOv8 technology. It was also discovered that ATS could no longer even provide a temporary solution to lower intersection congestion levels since it has significantly facilitated the redistributions of overall city distribution of traffic in its place.

2011-2018 comparison of volumes revealed a distinct divergence in road usage: inland highways such as 5th and 6th avenues experienced precipitous declines, while ocean-side highways such as the FDR Drive and West Side Highway experienced increases in volumes. O-D analysis provided additional context by reporting that more trips now begin in the outer boroughs and flow to Midtown West, decreasing Lower Manhattan's importance as a destination. Ultimately, such a 2024 YOLOv8-based traffic video analysis also maintained that such redistributive tendencies remained unabated, over a decade after the beginning of the implementation of the Advanced Traffic System (ATS).

Alone, these results imply that ATS performs a function that goes beyond that of sheer congestion control. It also serves structural direction that controls mobility along main artery roads and reduces reliance on internal secondary roads. In this way, ATS achieves efficiency in networks and at the same time furthers the ultimate goal of resilience and sustainability in urban transportation infrastructure.

But limitations still exist. Land cover changes, population growth, and modeshifts to public transportation or bicycles might also affect these trends and were also outside the research purview in this project. All these areas deserve keen examination in future studies. But the example with Manhattan reveals the promise of adaptive signal control to produce benefits that extend well into longer-term efficiency gains; it might have a permanent and transformative influence on urban transportation's spatial dynamics.

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