Investigating the Impact of Pedestrian Hybrid Beacons on the Effectiveness of Adaptive Traffic Control Systems

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Abstract: Many transportation agencies have been deploying adaptive traffic control systems (ATCSs) to enhance the efficiency of signalized intersections and arterial networks. However, the benefits of ATCSs vary across roadways due to factors such as traffic volume, network configurations, and the influence of other intelligent transportation systems (ITS). Pedestrian hybrid beacons (PHBs) are ITS utilized as pedestrian control devices, usually deployed between signalized intersections. PHBs can affect the effectiveness of ATCSs and, hence, need to be considered during ATCS deployments and performance evaluations. This study used a corridor in Tucson, Arizona, to evaluate the impact of PHB activations on the travel time along a corridor with an ATCS. Controller event-based data were used to show the effects of the number of PHB activations on ATCS operations. Other factors were also examined, such as traffic volume, number of pushbutton activations at signalized intersections, time of day, and day of the week. The results indicated that travel time increased with PHB activations, especially during morning peaks. Two activations within five minutes showed a 126% (90 s) travel time increase for upstream segments, and three activations saw a 38.5% (27 s) travel time increase for segments with PHB installed. A regression analysis showed a 3.3% and 6.7% travel time increase for each PHB activation every 15 min in upstream segments and segments with PHB installed, respectively. This study's findings highlight the importance of considering the PHB impact for practitioners selecting ATCS deployment sites for optimal performance. **DOI: 10.1061/JTEPBS.TEENG-8661.** © *2025 American Society of Civil Engineers.*

Author keywords: Adaptive traffic control systems (ATCSs); Pedestrian hybrid beacons (PHBs); Travel time; Controller event-based data.

Introduction

Adaptive traffic control systems (ATCSs) dynamically adjust signal timing parameters, such as splits, offsets, cycle lengths, and phase sequences, in near real-time, based on detection data and operational settings (Urbanik et al. 2015). These most widely deployed ATCSs, such as Split Cycle Offset Optimization Technique (SCOOT), Sydney Coordinated Adaptive Traffic System (SCATS), Adaptive Control Software (ACS) Lite, Kadence, and In|Sync, have proven to improve traffic conditions (Ban et al. 2014; Fontaine et al. 2015; Mitrovic et al. 2023). Despite ATCSs' success, their effectiveness can be affected by factors, such as detection layouts, traffic conditions, network types, urban settings, and system monitoring (Dutta and McAvoy 2010; Fontaine et al. 2015; Stevanovic et al. 2019; Tian et al. 2011). For example, ATCSs demonstrated more significant benefits in networks experiencing moderate traffic than those with high traffic (Stevanovic et al. 2019) and in roadways in suburban areas than urban areas (Stevanovic et al. 2019).

Intelligent Transportation Systems (ITS) deployed in the same corridor with ATCSs can also affect their operational performance. Understanding the effects is crucial for determining suitable locations for ATCS installations, as the presence of special traffic signal operations can pose challenges for certain ATCSs (Dobrota et al. 2020). One such ITS is Pedestrian Hybrid Beacons (PHBs), formerly known as High-Intensity Activated CrossWalK (HAWK) signals, used to warn and control traffic at unsignalized locations to assist pedestrians in crossing streets or highways at marked crosswalks (FHWA 2023). PHBs operate by bringing vehicles to a complete stop at locations where they are deployed. PHB operations are opposite to the ATCS mode of operations, which aims to promote traffic progression and reduce travel time. There are approximately 43 states in the US that have installed PHBs, with the most installations in Arizona (DeLorenzo et al. 2019).

The widely documented benefits of PHBs on pedestrian safety (Fitzpatrick and Park 2010; Fitzpatrick et al. 2021; Pulugurtha et al. 2018; Zhang et al. 2024) could suggest more future deployments. Therefore, it is essential to understand the extent of the influence of PHB activations on corridors with ATCSs for agencies to assess the future potential of ATCS deployments along corridors with PHBs and evaluate the impacts of their future deployments along corridors with ATCSs. Currently, few studies examined the influence of PHBs. Although one study indicated that the mobility impacts of PHBs, such as delay and maximum queue length, may extend to downstream and upstream intersections (Teketi and Pulugurtha 2020), no ATCSs were in operation in this study.

One potential reason for the lack of studies could be the unavailability of PHB activation information, which can be acquired

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by connecting PHBs with traffic controllers. However, the traffic controller event-based data (hereafter, "event-based data") at PHBs is rare because not all agencies archive the data due to limitations in their databases, concerns about cost-effectiveness, or the perception that collecting such data may not align with their operational goals (Zhang et al. 2024).

The objective of this study is to evaluate the mobility impact of PHB operations on ATCSs. This study uses precise PHB activation information from the controller event-base data to show the effects of PHB activations on travel time along segments with an ATCS. The impact of the number of activations on segment types, including upstream and downstream of the PHBs and segments with the PHB, is evaluated. This study also explores how other factors, including traffic volume, number of pedestrian calls at signalized intersections, and temporal effects, influence ATCS operations along the corridors with PHBs. The study results are significant in helping transportation agencies decide whether to account for the impact of PHBs when determining appropriate locations for ATCSs to enhance overall performance. The findings from this study also make agencies aware of the implications of future PHB deployments along corridors with ATCSs.

Literature Review

Although ATCSs have been implemented worldwide and have demonstrated a notable ability to enhance traffic conditions, their operational effectiveness can be impacted by various factors. Ban et al. (2014) and Fontaine et al. (2015) revealed that ATCSs exhibited limited performance in oversaturated traffic conditions. Similarly, Stevanovic et al. (2019) collected findings from 85 evaluations of ATCSs, revealing that ATCSs yielded higher mobility benefits on networks with moderate traffic (AADT between 35,000 and 55,000) than on those with high traffic (AADT over 55,000). Additionally, several studies indicated that ATCSs showed more significant traffic mobility improvements when previous signal timings were fixed or outdated; however, the impact was less significant in well-designed corridors (Dutta and McAvoy 2010; Fontaine et al. 2015; Stevanovic et al. 2019; Tian et al. 2011).

Stevanovic et al. (2019) reported that most efficiency-based measures, such as travel time, delay, number of stops, and queue length, showed improvement in two intersecting corridors and mixed networks with ATCSs, whereas side-street delay worsened by 6.3% in a single corridor with ATCS deployment. Additionally, suburban and urban environments saw enhancements in all efficiency-related measures with ATCS deployment, except for a 6.2% increase in side-street delay in urban settings (Stevanovic et al. 2019). Moreover, ATCSs demanded daily attention compared to that of traditional time-of-day plans, given their dynamic nature in achieving the expected mobility improvements (Dutta and McAvoy 2010; Stevanovic et al. 2019).

However, to our knowledge, none of the evaluation studies assessed the mobility impact of PHBs at locations at which they are deployed and their adjacent adaptive-controlled signalized intersections. PHBs were first implemented in Arizona, with expansion to more than 43 states in the United States (DeLorenzo et al. 2019). Although most studies focused on motorist compliance and the safety effectiveness of PHBs (Arhin and Noel 2010; Fitzpatrick et al. 2021; Godavarthy and Russell 2016), a few studies delved into the mobility impact of PHBs. Schroeder et al. (2008) observed that PHB signals were more effective in reducing delay than standard pedestrian-actuated signals. Godavarthy and Russell (2016) also found that delays for drivers at PHBs were reduced by more than 90% compared to those at signalized crossings. Li and Zhang (2011) found that PHBs effectively reduced pedestrian delays under high traffic demand. However, PHBs caused excessive delays for pedestrians at stop-controlled intersections with typically low traffic volumes compared to those with traditional crosswalks (Li and Zhang 2011). Teketi and Pulugurtha (2020) evaluated the effect of PHBs on operational performance measures at the mid-block crosswalk location and the adjacent signalized intersection. However, the assessment was conducted through simulations rather than utilizing empirical data sets.

There is a lack of comprehensive investigations into the mobility effects, particularly concerning travel time, associated with PHBs and their influence on nearby signalized intersections operating with ATCSs. Specifically, the effects of the number of PHB activations, traffic volume, number of pedestrian calls for adjacent signalized intersections, and temporal factors were not examined. This study addresses these limitations, and its findings aim to assist transportation agencies in making informed decisions on whether to incorporate the impact of PHBs in their considerations when selecting optimal locations for ATCSs.

Study Corridor

This study was based on a corridor with five signalized intersections, with an ATCS in operation along Ajo Way, from Mission Road to Twelfth Avenue in Tucson, Arizona, as shown in Fig. 1. Six road segments were considered, that is, the segment with PHB installed and the associated upstream and downstream segments, represented by the blue box in Fig. 1. The primary objective of the ATCS along the corridor is to enhance mainline progression by minimizing travel time and optimizing throughputs. The secondary aim is to achieve traffic equilibrium by reducing delays for side streets and pedestrians. Cycle lengths, offsets, splits, and other parameters are not predetermined for the controller; instead, it operates with the ATCS by detecting vehicles and making phase omits and calls based on real-time data. Although adjustments can be made to cycle lengths, splits, and offsets, phase sequences remain fixed and cannot be altered. Additionally, there is no coordination

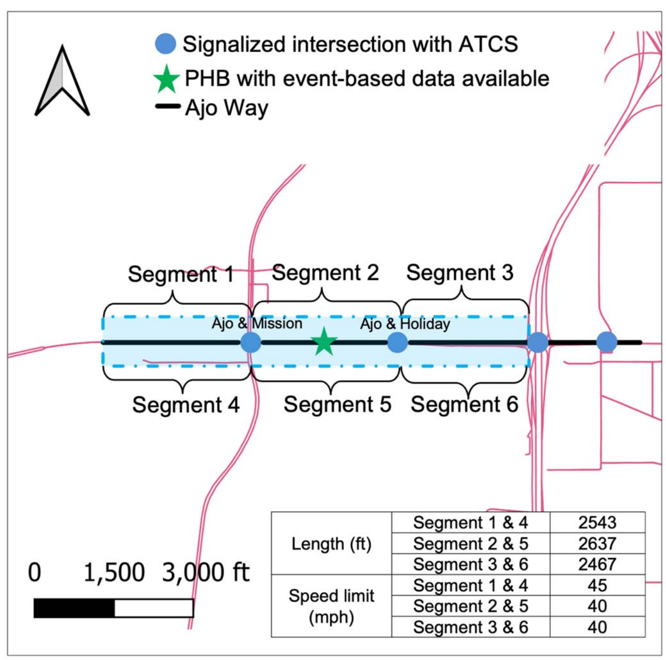

Fig. 1. Study locations.

between PHBs and traffic signals. In this study corridor, at pedestrian actuation, the PHB displays a flashing yellow signal followed by a steady yellow signal for a total of approximately 8 s to alert drivers. Then, both steady red signals are activated for an approximate 7-s pedestrian walk interval. This is followed by alternating flashing red signals during an approximate 18-s pedestrian clearance interval.

Data Description

Three data sets were used to evaluate the mobility impact of PHBs along the corridor with the ATCS: INRIX travel time data, controller event-based data, and traffic volume data. The data were collected during weekdays for six months between April and October 2022. INRIX data were provided by the Arizona Department of Transportation. Event-based data were sourced from the Tucson Department of Traffic Mobility (TDTM), and traffic volume data were also provided by TDTM and aggregated at 15-min intervals.

INRIX Data

INRIX data represent compiled information from millions of GPS-enabled vehicles, mobile devices, conventional road sensors, historical traffic flow data from transportation agencies, and various other sources (INRIX 2023). These varied data sources are fused to provide real-time estimations of travel time and incident information (Kondyli et al. 2016).

The speed and travel time data from INRIX are collected per minute per INRIX segment within Arizona. In the year 2018, access was granted to the rich repository of INRIX travel time data specific to Tucson, Arizona. Within the framework of the study, this detailed travel time data were collected from six road segments: the segments with the installed PHB and the upstream and downstream segments, as depicted in Fig. 1.

Event-Based Data

High-resolution event-based data represent an enriched data set with precise timestamps of various events. Sample data are provided in Fig. 2. When a pedestrian activates the pushbutton at a PHB location, the traffic controller logs the events, such as "Pedestrian Call Registered," "Walk," and "Flashing Don't Walk," for each phase until the PHB signal is no longer activated (Zhang et al. 2024). Similarly, critical events, such as "Phase Begin Green," "Phase Begin Yellow Clearance," and "Phase Begin Red Clearance," are logged by traffic controllers at signalized intersections.

Event-based data have been collected and archived at more than 60 PHB locations in Tucson, Arizona, since 2018, including the specific PHB location examined in this study. Additionally, event-based data are available for most signalized intersections in Tucson, Arizona. Using precise PHB activation information, descriptive and statistical analyses were conducted in this study to evaluate the impact of PHB activations on travel time in road segments with PHB deployed and in upstream and downstream segments.

Data Summary

Table 1 summarizes the statistics of the variables evaluated in this study. Summary statistics for downstream segments were excluded from Table 1 and the following regression analysis due to a lack of volume data. The response variable used in this study is the average travel time per road segment. Explanatory variables include number of PHB activations, the major road's approach volume, maximum approach volume for minor directions, time of day (AM and PM peaks, midday, and night), day of the week [Mondays, Fridays, and typical weekdays (Tuesdays to Thursdays)], and the number of pushbutton activations at signalized intersections.

This study considered pedestrian pushbutton activations at the nearest downstream intersection and the second nearest intersection (hereafter, "nearby" and "distant" intersections). There are two primary types of pedestrian pushbutton activations at each intersection, each with different effects on the target segment. The first type is for pedestrians crossing the major road, which is the study corridor used. The second type is for pedestrians crossing a minor road, which at these intersections refers to a cross-street intersecting with the study corridor. Therefore, four variables associated with pedestrian pushbutton activations were included in the analysis: the number that cross a major road at the nearby intersection, the number that cross a minor road at the nearby intersection, the number that cross a major road at the distant intersection, and the number that cross the minor road at the distant intersection.

Methodology

Regression analyses were used to examine the effects of PHB activations on travel time along segments with PHB installed and those upstream of the PHB within an ATCS-controlled corridor. Previous studies showed that traditional regression models, such as

TimeStamp	DeviceID	EventID	Parameter
2022-04-04 07:26:16	307	2	4
2022-04-04 07:26:16	307	22	2
2022-04-04 07:26:16	307	45	4
2022-04-04 07:26:19	307	7	2
2022-04-04 07:26:19	307	8	2
2022-04-04 07:26:19	307	23	2
2022-04-04 07:26:19	307	4	2
2022-04-04 07:26:19	307	3	2
2022-04-04 07:26:19	307	43	2
2022-04-04 07:26:23	307	10	2

(a)

TimeStamp	DeviceID	EventID	Parameter
2022-04-04 00:00:05	479	3	4
2022-04-04 00:00:05	479	3	8
2022-04-04 00:00:05	479	7	4
2022-04-04 00:00:07	479	7	8
2022-04-04 00:00:07	479	8	4
2022-04-04 00:00:07	479	8	8
2022-04-04 00:00:07	479	2	2
2022-04-04 00:00:07	479	2	6
2022-04-04 00:00:07	479	62	6
2022-04-04 00:00:07	479	43	2

(b)

Fig. 2. Sample event-based data: (a) event-based data for PHB; and (b) event-based data for signalized intersection.

Table 1. Summary statistics of analysis variables

Variables	Upstream segments Min	Max	Mean	Std. dev.	Count (proportion)	Segments with PHB installed Min	Max	Mean	Std. dev.	Count (proportion)
Average travel time	28	1,110	152	65	—	40	883	174	65	—
Number of PHB activations	0	8	0.37	0.85	—	0	8	0.37	0.85	—
Approach volume for major directions	10	691	199	123	—	10	602	202	123	—
Maximum approach volume for minor directions	0	479	87	89	—	0	479	88	89	—
Number of pushbutton activations										
Cross major road at the nearby intersection	0	11	0.70	1.02	0	0	11	0.70	1.01	—
Cross minor road at the nearby intersection	0	16	1.17	1.24	0	0	16	1.17	1.24	—
Cross major road at the distant intersection	0	11	0.70	1.01	0	0	11	0.70	1.02	—
Cross minor road at the distant intersection	0	16	1.16	1.24	0	0	16	1.16	1.24	—
Time of day										
AM peak	—	—	—	—	1,953 (8.4%)	—	—	—	—	1,942 (8.3%)
Midday	—	—	—	—	6,839 (29.3%)	—	—	—	—	6,841 (29.3%)
PM peak	—	—	—	—	1,950 (8.3%)	—	—	—	—	1,957 (8.4%)
Night	—	—	—	—	12,617 (54%)	—	—	—	—	12,616 (54%)
Day of the week										
Mondays	—	—	—	—	4,445 (19%)	—	—	—	—	4,437 (19%)
Typical weekdays (Tuesdays to Thursdays)	—	—	—	—	14,170 (60.7%)	—	—	—	—	14,185 (60.7%)
Fridays	—	—	—	—	4,744 (20.3%)	—	—	—	—	4,734 (20.3%)

Note: Data was aggregated at 15-min intervals.

normal, lognormal, gamma, Weibull, and finite mixture, were explored for travel time modeling and analysis (Al-Deek and Emam 2007; Guo et al. 2010; Kim and Mahmassani 2014; Pu 2011). Travel time in this study was observed to follow a right-skewed normal distribution. Hence, four regression models—lognormal, Weibull, normal-normal finite mixture, and lognormal-lognormal finite mixture—were explored, and the best-fit model was utilized for the following analyses. Other factors, including traffic volume, pedestrian pushbutton activations at nearby and distant downstream signalized intersections, and temporal effects, were also included in the regression analysis. The following sections describe the lognormal, Weibull, normal-normal finite mixture, and lognormal-lognormal finite mixture regression models.

Lognormal Regression Model

The traditional liner regression model was defined as follows as Eq. (1):

$$y = \beta_0 + \beta_1 x_1 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon \tag{1}$$

where β_0 = intercept; β_1 to β_n = coefficients for the response variables (x_1 to x_n), such as the number of PHB activations; and ε = error term assumed to follow a normal distribution with the mean equal to 0 and variance of σ^2. Assuming the response variable y, that is, 15-min average travel time per road segment in this study, follows a lognormal distribution (Pu 2011), that is, the probability density function of y can be written as (Ajiferuke and Famoye 2015)

$$f(y|x) = \frac{1}{y\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{\ln(y) - \mu(x)}{\sigma}\right)^2\right] \tag{2}$$

$$\mu(x) = \beta_0 + \beta_1 x_1 + \beta_1 x_1 + \cdots + \beta_n x_n \tag{3}$$

The expectation $E(y|x)$ and the variance $V(y|x)$ were described as

$$E(y|x) = \exp\left(\mu(x) + \frac{\sigma^2}{2}\right) \tag{4}$$

$$V(y|x) = [\exp(\sigma^2 - 1)] \times [\exp(2\mu(x) + \sigma^2)] \tag{5}$$

Weibull Regression Model

The Weibull distribution is commonly used in reliability engineering and survival analysis, for which it serves to model the time until failure or the lifetime of a component or system (Cavalcante et al. 2023; Zhang 2016). Some studies also employed the Weibull distribution to model the travel time distribution (Al-Deek and Emam 2007). The distribution of the average travel time, y, as a function of covariates were written as

$$\ln(y) = \beta_0 + \beta_1 x_1 + \beta_1 x_1 + \cdots + \beta_n x_n + \alpha\varphi \tag{6}$$

$$\varphi \sim \text{Gamma}(0, \alpha) \tag{7}$$

where φ is assumed to follow the Gamma distribution, $\text{Gamma}(0, \alpha)$; and α = shape parameter.

The effects of covariates are multiplicative on the hazard scale in the proportional hazard model. The hazard function $h(y|x)$ of the Weibull regression model in proportional hazard form is

$$h(y|x) = \gamma y^{\gamma-1} \exp(-(\beta_0 + \beta_1 x_1 + \beta_1 x_1 + \cdots + \beta_n x_n)) \tag{8}$$

where if the shape parameter $1 < \gamma < 2.6$, the Weibull distribution is positively skewed; if $2.6 < \gamma < 3.7$, the distribution could approximate the normal distribution; if $\gamma > 3.7$, the Weibull distribution is negatively skewed (Al-Deek and Emam 2007).

Finite Mixture Regression

The travel time is likely to exhibit sophisticated distributions due to the impact of various traffic conditions and different seasons. Finite mixture models have proven to be useful extensions of traditional statistical models for effectively capturing this heterogeneity in travel time data during modeling and analysis (Kim and Mahmassani 2014). The overall probability distribution $f(y|x)$ is then obtained by mixing those component distributions as follows (Guo et al. 2010):

$$f(y|x) = \sum_{k=1}^{K} \omega_k f_k(y|x) \tag{9}$$

where k = predefined number of components in this study; $f_k(y|x)$ = conditional probability density function of y given component k, that is, the kth mixture component $f_k(y|x)$ represents the distribution of travel time corresponding to a specific traffic condition, such as congested state; and ω_k = positive mixture coefficient, representing the probability of each component.

This study tested two types of two-component mixture distributions on the travel time data: normal-normal and lognormal-lognormal, and the probability density function of each is shown in Eqs. (10) and (11), respectively

$$f(y|x) = \omega_1 \frac{1}{\sigma_1\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{y-\mu_1(x)}{\sigma_1}\right)^2\right] + (1-\omega_1)\frac{1}{\sigma_2\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{y-\mu_2(x)}{\sigma_2}\right)^2\right] \tag{10}$$

$$f(y|x) = \omega_1 \frac{1}{y\sigma_1\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{\ln(y)-\mu_1(x)}{\sigma_1}\right)^2\right] + (1-\omega_1)\frac{1}{\sigma_2\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{\ln(y)-\mu_2(x)}{\sigma_2}\right)^2\right] \tag{11}$$

where σ_1 and σ_2 = shape parameters of each distribution.

Model Assessment

Akaike information criterion (AIC) and McFadden pseudo R^2 were used to compare the models and select the best model fit, as shown in Eqs. (12) and (13)

$$AIC = -2 \times LL_\theta + 2 \times P \tag{12}$$

$$McFadden\ pseudo\ R^2 = 1 - \frac{LL_\theta}{LL_0} \tag{13}$$

where LL_θ = log-likelihood at convergence; and LL_0 = log-likelihood of the constant-only model.

The mean absolute deviance (MAD) and mean square prediction error (MSPE) were also calculated to compare the prediction performance of all fitted models on the validation data set. The data were divided into training (80%) and testing (20%) data sets. The training set was utilized for model development, while the testing set was employed to assess the prediction performance of the fitted models. The equations used to calculate MSPE and MAD are

$$\mathrm{MSPE} = \frac{1}{N \times \bar{y}} \sum (y_i - \hat{y}_i)^2 \tag{14}$$

$$\mathrm{MAD} = \frac{1}{N \times \bar{y}} \sum |y_i - \hat{y}_i| \tag{15}$$

where N = sample size of the validation data set; $\bar{y}$ = observed average travel time; and y_i and $\hat{y}_i$ = observed and predicted average travel time for the ith row in the data set.

Results and Discussion

Descriptive Analysis

Event-based and INRIX travel time data used in this section for each road segment were aggregated into five-minute intervals to ensure a sufficient number of PHB activations within each interval, following the approach taken in previous studies (Haule et al. 2021; Hojati et al. 2016). A matched case-control design was used in the descriptive analysis, considering travel time could be influenced by several factors concurrently (Wali et al. 2018; Yu and Abdel-Aty 2013). An interval was labeled "case" if at least one PHB activation occurred within the five-minute interval. An interval was labeled "control" if no PHB activations occurred within the five-minute interval. Given that more controls than cases are expected, four "control" instances were paired with each corresponding "case" based on the following criteria: identical time intervals (e.g., the "case" and four "control" instances happened from 8:00 a.m. to 8:05 a.m.), matching days of the week, and alignment with the same season. This matching process aimed to mitigate potential influences from external factors, such as volume and temporal effects.

Fig. 3 illustrates the number of 5-min intervals according to the amount of PHB activations across four analysis periods: AM peak, midday, PM peak, and night. These analysis periods were determined based on regular peak periods in Tucson, Arizona. Based on the observation, the maximum number of PHB activations within any 5-min interval was four. Cases with three PHB activations during the PM peak and Night periods, as well as intervals with more than four activations, were excluded from this section due to limited sample size (less than 15).

Impact of PHB Activations on Travel Time for Upstream Segments

Fig. 4 compares the average travel time with and without PHB activations for upstream segments. The top and bottom rows of

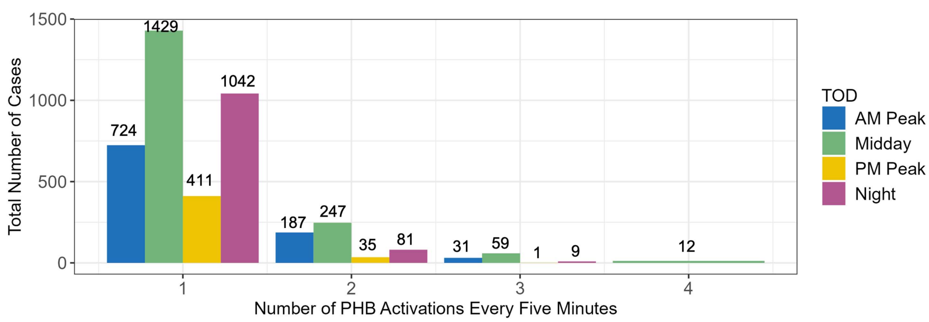

Fig. 3. Total number of aggregated time intervals.

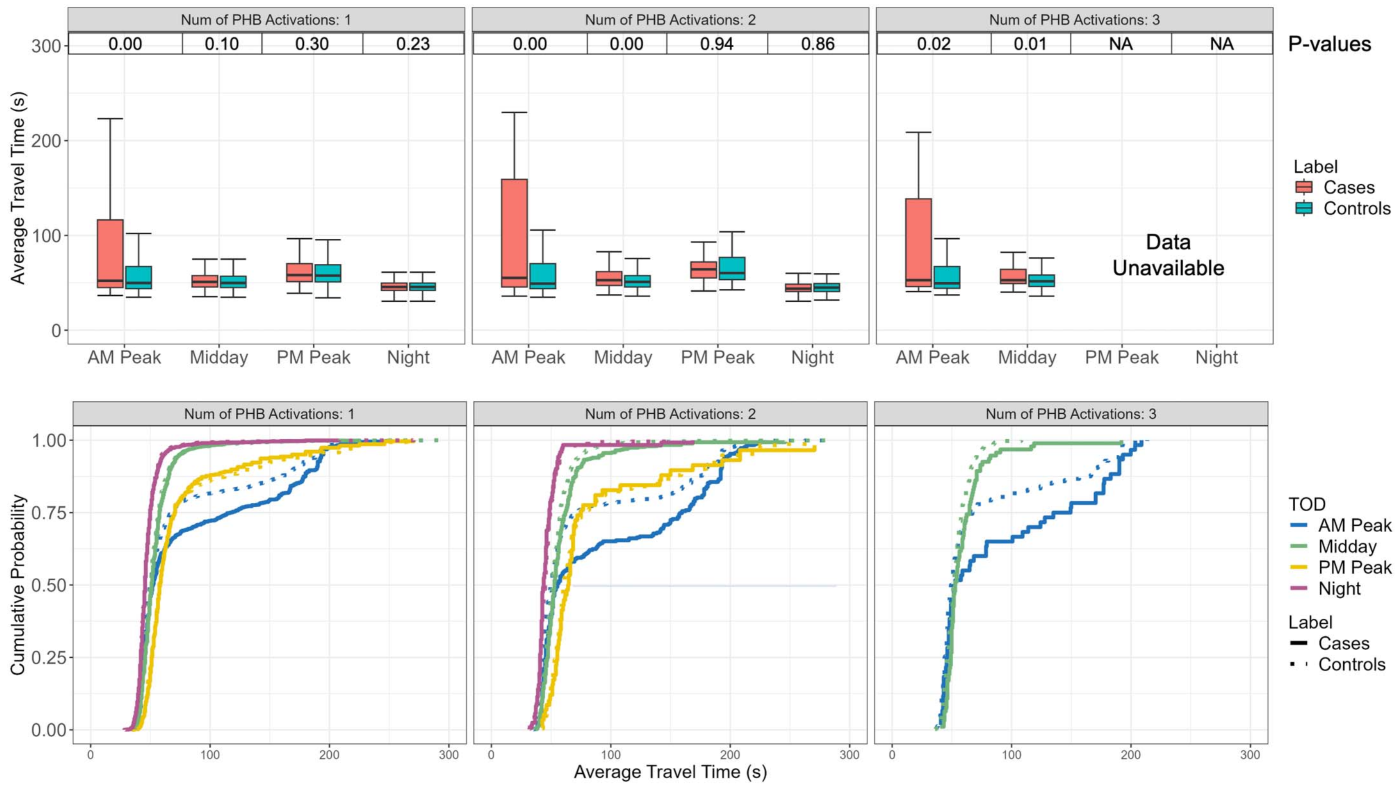

Fig. 4. Boxplots and cumulative distribution function plots for average travel time on upstream segments.

each graphic show boxplots and cumulative distribution function plots, respectively, depicting travel time for both "case" and "control" groups, categorized by the number of PHB activations across various evaluation periods. Additionally, p-values from Welch t-tests for comparison groups were included in the boxplots.

During AM peaks, travel time with PHB activations was statistically significantly longer than those without PHB activations, irrespective of the frequency of PHB activations within five-minute intervals. Notably, the most significant impact on travel time was observed with two PHB activations within five-minute intervals, resulting in a 126% (90 s) travel time increase compared to the 75th percentile. One potential explanation could be that when PHBs are activated, vehicles are required to come to a complete stop. This can create a shockwave that propagates backward to upstream vehicles (Gao et al. 2019).

In Midday periods, travel time with PHB activations demonstrated statistical significance compared to those without PHB activations (when PHB was activated two or three times) based on t-test results. However, the values of travel time did not display a significant difference regardless of the frequency of PHB activations within five-minute intervals. During PM peaks and Night periods, no significant difference was observed between travel time with and without PHB activations.

Impact of PHB Activations on Travel Time for Segments with PHB Installed

Fig. 5 compares the average travel time with and without PHB activations for the road segments with one PHB installed. During AM peaks and Midday periods, travel time with PHB activations was statistically significantly longer than those without PHB activations regardless of the frequency of PHB activations within five-minute intervals. The most significant impact was observed with three PHB activations within five-minute intervals during AM peaks and Midday periods, resulting in a 38.5% (27 s) and 39.5% (25 s) increase, respectively, from the medians. The potential reason could be that vehicles resume from a stopping or reduced speed position after pedestrians have crossed, leading to a delay in recovering to their original speed. No significant difference was observed between "case" and "control" groups in PM peaks and Night periods.

Impact of PHB Activations on Travel Time for Downstream Segments

Fig. 6 shows the average travel time with and without PHB activations for downstream segments. The travel time with PHB activations was significantly longer than that without PHB activations during AM peaks and Midday periods. The increase in travel time for downstream segments was comparatively lower than what was observed along segments with PHB and upstream segments. This could potentially be because downstream vehicles have already regained their original speed. Additionally, upstream segments tended to experience slightly higher congestion than downstream segments. Moreover, no significant difference was observed when PHBs were activated during PM peaks and Night periods.

Factors Affecting Travel Time

Factor Selection and Model Assessment

The effects of the number of PHB activations on travel time and the influence of other factors, such as volume and temporal effects, were evaluated using a regression analysis. Due to the resolution limitation of the volume data, all data were aggregated into 15-min intervals in this section. Initially, predictors such as the number of PHB activations, approach volume of major directions, maximum approach volume of two minor directions, total green time for

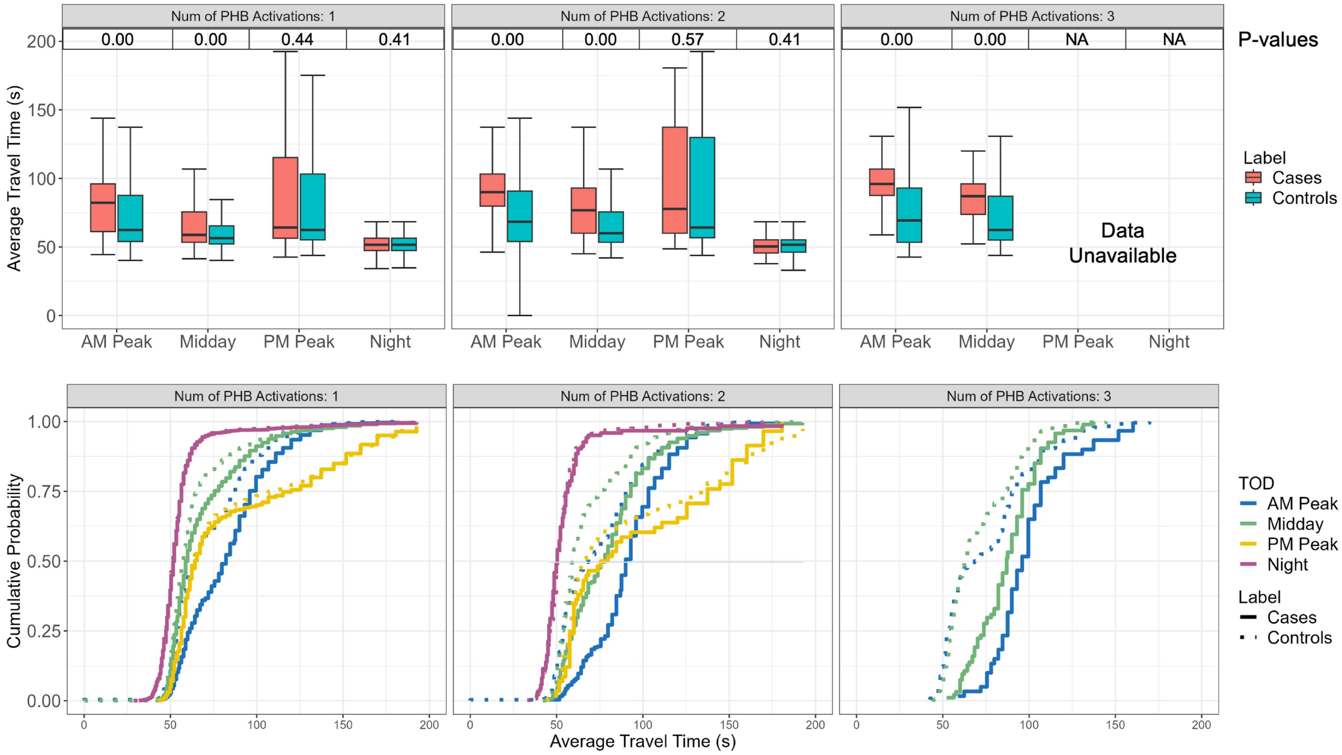

Fig. 5. Boxplots and cumulative distribution function plots for average travel time on segments with PHB installed.

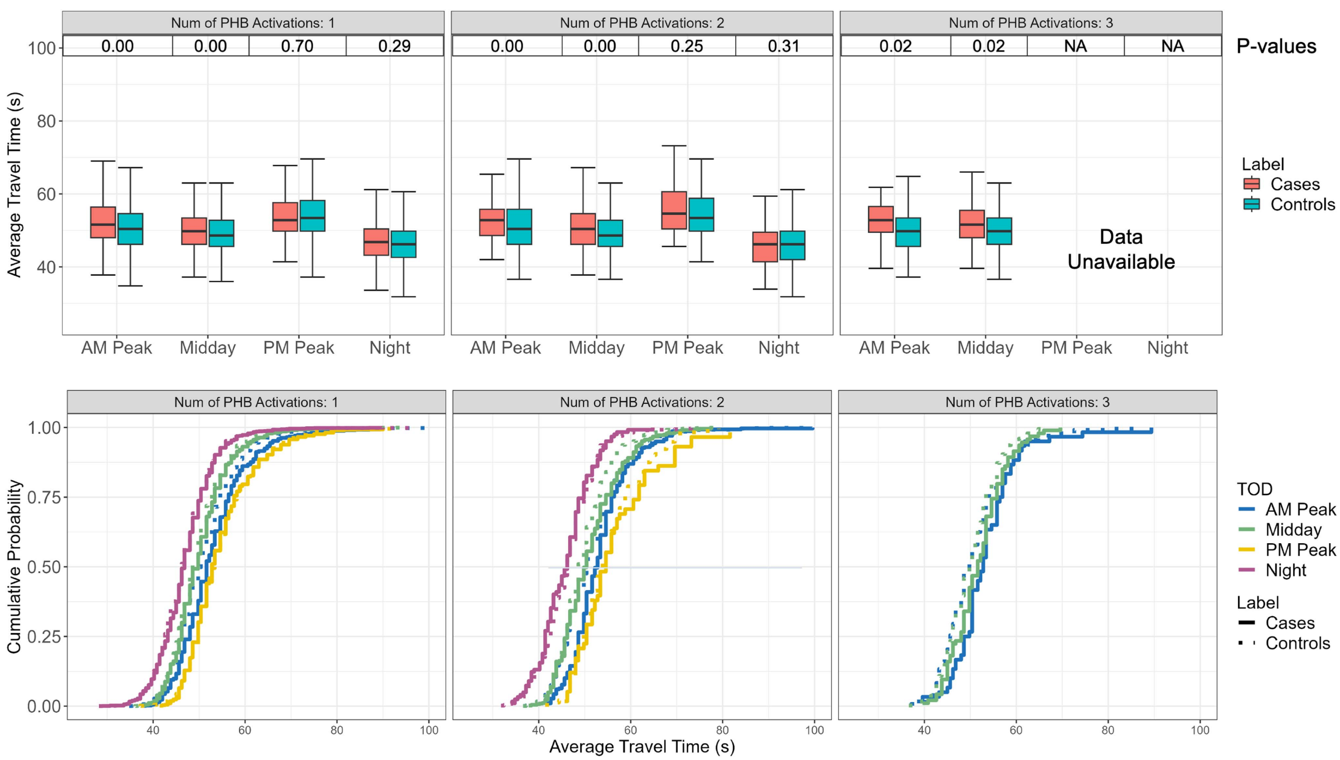

Fig. 6. Boxplots and cumulative distribution function plots for average travel time on downstream segments.

major roads at upstream and downstream signalized intersections, number of pushbutton activations at upstream and downstream signalized intersections, day of the week, evaluation period (AM and PM peak, Midday, and Night), segment length, and segment location (upstream, downstream, and the segment with PHB installed) were considered. The variation inflation factor (VIF) was calculated to verify the absence of multicollinearity and to ensure no significant correlations between predictors in the data. Total green time, segment length, and segment location were excluded because VIF values were larger than four.

Table 2. Results of model assessment measures

Models	Lognormal	Weibull	Finite mixture (normal-normal)	Finite mixture (lognormal-lognormal)
		Upstream segments		
McFadden pseudo R^2	0.45	0.06	0.11	0.21
AIC	66	1,940	1,611	270
MAD	21	34	47	32
MSPE	2,941	3,519	6,821	4,217
		Segments with PHB installed		
McFadden pseudo R^2	0.54	0.06	0.08	0.19
AIC	92	1,952	1,713	214
MAD	25	34	41	31
MSPE	2,597	2,825	4,579	3,382

Note: PHB = pedestrian hybrid beacon; AIC = Akaike information criterion; MAD = mean absolute deviance; and MSPE = mean square prediction error.

Regression models were separately developed for the upstream segments and segments with PHB installed. Four distributions, that is, lognormal, Weibull, mixture normal-normal, and mixture lognormal-lognormal, were explored in the regression models. The McFadden pseudo R^2 and AIC were used to evaluate model fits, whereas MAD and MSPE were used to assess the prediction performance. Table 2 shows the results of the model comparisons. In both upstream segments and segments with PHB installed, lognormal regression models exhibited a higher McFadden pseudo R^2 and lower AIC, MAD, and MSPE values. Therefore, lognormal regression models were employed to assess the impact of the selected predictors on travel time for both upstream segments and segments with PHB installed.

Results for Upstream Segments

The lognormal regression model results for upstream segments are presented in Table 3. The reference groups for the time of day and day of the week variables are night and typical weekdays (Tuesdays to Thursdays), respectively. The results show that, as the number of PHB activations increased, upstream segments experienced longer travel time. Given a one-unit increase in the number of PHB activations every 15 minutes, the average travel time in the upstream segments increased by approximately 3.3%. To some extent, these findings are consistent with previous research that evaluated the mobility impact of PHBs on adjacent signalized intersections without ATCSs (Teketi and Pulugurtha 2020). Although it was unclear whether the signalized intersection was upstream or downstream of the PHB, Teketi and Pulugurtha (2020) suggested that increased pedestrian volume at PHB locations could increase the delay and queue length at an adjacent signalized intersection. This queue length and delay at a signalized intersection could cause longer travel times on segments upstream of the PHB location. Another potential reason is that PHBs could be associated with spillover or spillback effects at adjacent intersections. Unlike the previous study, the effects of the PHB impact in this study were based on the actual activations rather than pedestrian volume considering that multiple pedestrians can cross a street at a single activation.

The number of pushbutton activations at signalized intersections was positively related to the average travel time, with the most impact by pushbutton activations (1.9%) at the nearby intersection from minor directions. This could be because a higher number of pushbutton activations at signalized intersections, particularly from minor directions, could disrupt the coordination of major directions, leading to increased travel time. In contrast, the increase in approach volume from both major and minor sides had a minimal impact on travel time. Given a one-unit increase in major approach volume and maximum minor approach volume, the average travel time on the upstream segments increased by approximately 0.06% and 0.13%, respectively. One potential reason for this could be that the optimization algorithm of the ATCS is primarily focused on maximizing throughputs.

Table 3. Summary of model results

Predictors	Upstream segments Coef.	Upstream segments Std. error	Upstream segments P-value	Segments with PHB installed Coef.	Segments with PHB installed Std. error	Segments with PHB installed P-value
Constant	5.9940**	0.1631	0.0000	4.817**	0.0029	0.0000
Number of PHB activations	0.0325**	0.0019	0.0000	0.0674**	0.0018	0.0000
Major approach volume	0.0006**	0.0000	0.0000	0.0008**	0.0000	0.0000
Maximum minor approach volume	0.0013**	0.0000	0.0000	0.0010**	0.0000	0.0000
Number of pushbutton activations at signalized intersections						
Cross major road at the nearby intersection	0.0181**	0.0020	0.0000	0.0078**	0.0020	0.0000
Cross minor road at the nearby intersection	0.0195**	0.0017	0.0000	0.0081**	0.0016	0.0000
Cross major road at the distant intersection	0.0050**	0.0021	0.0200	0.0134**	0.0020	0.0000
Cross minor road at the distant intersection	0.0110**	0.0017	0.0000	0.0214**	0.0017	0.0000
Four evaluation periods						
Midday	−0.0510**	0.0043	0.0000	−0.0300**	0.0040	0.0000
AM peak	0.0733**	0.0065	0.0000	0.0391**	0.0060	0.0000
PM peak	0.1044**	0.0066	0.0000	0.1379**	0.0062	0.0000
Time of day						
Monday	−0.0240**	0.0049	0.0000	−0.0178**	0.0047	0.0000
Friday	0.0113**	0.0048	0.0200	0.0046	0.0046	0.3300

Note: **Statistically significant at the 95% confidence level; Coef. = coefficient; and Std. error = standard error.

Relative to the Night periods, AM and PM peaks were associated with an increase in travel time by approximately 7.3% and 10.4%, respectively. Typically, heavier traffic occurs during AM and PM peaks than during Night periods, resulting in higher travel time than at nighttime. However, Midday periods were associated with a decrease in travel time by approximately 5.1%. Additionally, compared to typical weekdays, Mondays were associated with a decrease in travel time by approximately 2.4%, whereas Fridays were associated with an increase in travel time by 1.1%. Fridays commonly experience higher travel volumes than other weekdays, potentially increasing travel time. Mondays unexpectedly showed shorter travel times than those on typical weekdays in the regression analysis; however, this corridor previously displayed a pattern of slightly shorter travel time on Mondays.

Results for Segments with PHB Installed

The lognormal regression model results for segments with PHB installed are presented in Table 3. The reference groups for the time of day and day of the week variables are night and typical weekdays (Tuesdays to Thursdays), respectively. As the number of PHB activations increased for the segments with PHB installed, the segments experienced longer travel time. Given a one-unit increase in the number of PHB activations every 15 minutes, the average travel time in the segments with PHB installed increased by approximately 6.7%. The number of pushbutton activations at signalized intersections was positively related to the average travel time, with the most impact by pushbutton activations (2.1%) at the distant intersection from minor directions. Similarly, given a one-unit increase in major approach volume and maximum minor approach volume, the average travel time increased by approximately 0.08% and 0.01%, respectively. Relative to Night periods, Midday periods were associated with a decrease in travel time of approximately 3%. However, AM and PM peaks were associated with increased travel time by approximately 3.9% and 13.8%, respectively. Additionally, compared to typical weekdays, Mondays were associated with a decrease in travel time by approximately 1.8%, whereas Fridays were not statistically significant in the model. The findings from the segments with PHB installed exhibited a similarity to the findings regarding the impact on upstream segments.

Conclusions

Adaptive traffic control systems (ATCSs) have observed widespread deployment and have demonstrated remarkable effectiveness in enhancing traffic mobility. However, various factors, including detection layouts, traffic conditions, network types, urban settings, and daily monitoring, can influence the extent of mobility improvements achieved by ATCSs. Although PHBs serve as crucial pedestrian control devices utilized nationwide, their impact on the mobility performance of ATCSs has gone unexplored. One potential reason for this gap was the lack of valuable PHB activation data because not all agencies collect such information.

Understanding the influence of PHBs on the mobility performance of ATCSs is critical for identifying appropriate locations for ATCS installations, given that the implementation of specialized traffic control devices, such as PHBs, can present challenges for certain ATCSs. This study employed descriptive and lognormal regression analyses utilizing PHB activation data to evaluate the mobility effects of PHB activations on road segments next to signalized intersections with ATCSs. The descriptive analysis considered segments with installed PHBs and upstream and downstream segments. Regression models were developed for segments with PHBs installed and upstream segments.

The descriptive findings revealed a consistent trend in which the average travel time was longer with PHB activations than periods without activations, particularly during AM peaks. Specifically, two activations within five minutes resulted in a 126% (90 s) increase in travel time for upstream segments, whereas three activations within the same timeframe led to a 38.5% (27 s) increase for segments with PHBs. During Midday, segments with PHBs exhibited a 39.5% (25 s) average travel time difference between periods with and without PHB activations. Regression analysis further supported these findings, indicating that an increase of one PHB activation every 15 min corresponded to an approximate 3.3% and 6.7% increase in travel time for upstream road segments and segments with PHB installed, respectively.

Moreover, using pushbuttons at the signalized intersections, particularly from minor directions, increases travel time for upstream PHB segments and segments with PHB installed. Traffic volume had a limited impact on travel time for these road segments. Regarding time of day, during AM and PM peaks, travel time for upstream segments and segments with PHB installed was typically higher than that for Night periods. Regarding the day of the week, Mondays generally saw shorter travel times, and Fridays generally saw longer travel times than typical weekdays (Tuesdays to Thursdays) for upstream segments and segments with PHB installed.

The observed trends in this study indicate that PHB activations notably influenced travel time, particularly in upstream segments and segments with PHB installed. When practitioners select sites for deploying ATCSs, incorporating PHB usage as a crucial factor may help ensure optimal performance. It is also critical to account for the PHB operational characteristics, including the crossing time, interval length, and lockout durations, which could affect vehicle delays and travel times. Optimizing these PHB operational characteristics based on location-specific factors such as geometry, pedestrian volume, and demographics may help balance pedestrian safety and traffic mobility.

Additionally, practitioners may account for the mobility effects of PHBs when designing systems or refining algorithms. Incorporating the pushbutton information of PHBs into ATCS algorithms, especially by syncing PHB pushbutton data with the closest upstream and downstream vehicle signals, may enable better coordination between PHBs and vehicle signals. Furthermore, installing pedestrian detection systems at PHB locations to track whether pedestrians have crossed the road and synchronizing this detection information with the traffic controller or ATCS optimization algorithms may reduce unnecessary pedestrian clearance time, balancing pedestrian safety and traffic mobility.

This study acknowledges several limitations, including the lack of diverse scenarios, such as multiple PHBs installed on segments, several evaluation sites, and corridor-level assessments. Analysis of the PHB effects on different site characteristics could enhance the comprehensiveness of the evaluation. This study also focused on a single type of ATCS specific to the corridor; incorporating a variety of ATCS types could reveal different trends in how PHBs influence operational performance. Furthermore, the detection layout of the ATCS was not disclosed by the vendor. Accessing and utilizing information on the detection layout of the adaptive layout could be a focus of future studies and could provide further insights into the interaction between PHBs and the ATCS. Comparing the results of adaptive operations with those of similar coordinated operations could be a valuable future direction, especially for evaluating whether adaptive systems provide additional advantages. Nevertheless, this study contributes to the body of knowledge by demonstrating the notable impact of PHBs on corridors with ATCSs. These results could help agencies consider the deployments and configurations of PHBs and ATCSs.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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