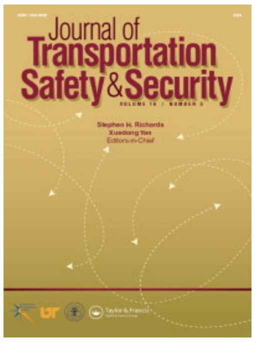

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Influential factors of pedestrian and bicycle crashes near Pedestrian Hybrid Beacons: Observing trends through an applied analysis

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ABSTRACT

Pedestrian Hybrid Beacons (PHBs) facilitate safe pedestrian crossings at marked crosswalks in unsignalized locations. However, few studies have recognized situations in which individuals may cross roads without PHB activation, potentially raising safety concerns. The influential factors contributing to pedestrian and bicycle crashes near PHBs remain insufficiently investigated. This study identifies characteristics of pedestrians and bicyclists prone to crossing without PHB activation. Additionally, this study uncovers differences between crash-prone and non-crash-prone PHB locations. Furthermore, this investigation examines the diverse factors that impact pedestrian and bicycle crashes in proximity to activated PHBs and accessible PHBs in Tucson, Arizona. Descriptive analysis and Bayesian multilevel Poisson-Lognormal regressions are conducted. Results indicate that young individuals (minimum age 13 and median age 29) and males were more likely to cross when PHBs were not activated. Moreover, the odds of pedestrian and bicycle crashes near PHBs increased when approach speeds decreased 5 to 10 minutes before crashes and at night (even with activated PHBs), while they decreased in regions with a greater proportion of non-White individuals and higher household incomes. These findings provide insights for transportation agencies, enabling them to implement targeted education and supplementary traffic control strategies to improve pedestrian and bicycle safety near PHBs.

KEYWORDS

Pedestrian Hybrid Beacon; pedestrian and bicycle crash; event-based data; Bayesian Multilevel Poisson-Lognormal regression; influential factors

1. Introduction

Walking and bicycling have been promoted by public agencies as they are environmentally sustainable and physically and mentally beneficial (APHA et al., 2018; Giles-Corti et al., 2016). According to data from the National Household Transportation Survey, walking comprised 10.5% of trips and bicycling accounted for 1% in 2017 in the US (McGuckin & Fucci, 2018).

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Notably, pedestrians and bicyclists are more vulnerable than other travelers, e.g., drivers, because they have less protection (Behnood & Mannering, 2016). In 2021, the National Highway Traffic Safety Administration (NHTSA) reported that pedestrian fatalities in the US increased by 13% to 7,388 fatalities in one year, while bicyclist fatalities rose by 2% to 966 fatalities in one year (Stewart, 2023).

To enhance the safety of pedestrians and bicyclists, previous studies have examined factors impacting the frequency (Amoh-Gyimah et al., 2016; Cheng et al., 2018; Haddad et al., 2023; Zhu et al., 2023) and severity (Hussain et al., 2019; Paudel et al., 2022; Sun et al., 2019; Zamani et al., 2021) of pedestrian and bicycle crashes at signalized intersections and on arterials. However, there have been limited studies investigating pedestrian and bicyclist safety at or near Pedestrian Hybrid Beacons (PHBs). PHBs, formerly known as High-Intensity Activated CrossWalK (HAWK) signals, are used to warn and control traffic at unsignalized locations to assist pedestrians in safely crossing streets or highways at marked crosswalks (MUTCD, 2009). Several US states, including Georgia, Minnesota, Florida, Michigan, Virginia, Alaska, Delaware, North Carolina, and Kansas, have implemented PHBs since their original installation in Tucson, Arizona (Chalmers, 2010; Pulugurtha et al., 2018).

PHBs, as shown in Figure 1, comprise of a circular yellow signal indication at the center, with two horizontally aligned circular red signal indications above. The vehicular display faces of PHBs are usually positioned on mast arms over the main approaches. When not activated by a pedestrian, the PHB indications remain dark. Upon pedestrian actuation, the PHB displays a flashing circular yellow signal, followed by a steady circular yellow signal to alert drivers to prepare for a pedestrian crossing. At that time, both steady circular red signals are activated during the pedestrian walk interval. Following, alternating flashing circular red signals are displayed

Figure 1. Pedestrian Hybrid Beacon installed in Tucson, Arizona (photo by Xi Zhang).

during the pedestrian clearance interval, functioning similarly to a stop sign. Once the pedestrian clearance interval concludes, the PHB signals return to a dark state (MUTCD, 2009).

Several studies have assessed motorist compliance and the safety effectiveness of PHBs. Fitzpatrick et al. evaluated yielding rates for staged pedestrians and the general population at five PHB locations in Tucson, Arizona. The staged pedestrian crossings were conducted in 2003 for this study, while the video recordings were reviewed in 2004. The results showed yielding rates were between 94% to 100% for staged pedestrians and 98% to 100% for the general population (Fitzpatrick et al., 2006). In an expanded study at 20 PHB locations, data was collected in 2014 for Austin, Texas, at eight sites and in 2015 for Tucson, Arizona, at 12 sites. Tucson, Arizona, exhibited an average yielding rate of 97% for the general population, whereas Austin, Texas, showed a yielding rate of 94% (Fitzpatrick et al., 2016). Other studies have also indicated that drivers tend to yield to pedestrians and bicycles at activated PHBs in the last decade and a half of research (Arhin & Noel, 2010; Fitzpatrick et al., 2014). Thus, it has been shown that activating PHBs before crossing roads could enhance the safety of pedestrians and bicyclists while crossing, highlighting the need to increase the appropriate usage of PHBs in locations where they are installed. Effective educational programs have been shown to potentially encourage the proper use of PHBs (Godavarthy & Russell, 2016; Hunter-Zaworski & Mueller, 2012), and the activation rate of PHBs reached up to 91% at 20 PHB locations (Fitzpatrick et al., 2016) in cases when the general public was well-educated and used to PHBs. Of note, it is potentially worth further increasing the activation rate of PHBs as safety for pedestrians and bicyclists could be increased accordingly.

Educational campaigns have the potential to increase the activation rate of PHBs. However, certain general educational campaigns focused on road safety have not yielded conclusive evidence of improved traffic safety (Hoekstra & Wegman, 2011). This may be attributed to their potential deficiency in setting strategic, measurable, achievable, realistic, and time-bound objectives (Bayne et al., 2020). Moreover, public awareness campaigns incurred exorbitant costs (Active Trans, 2016). Therefore, rather than focusing solely on educating the general public in cities with relatively high activation rates, it may be more beneficial to target specific groups, such as different genders and age groups, who are more likely to cross when PHBs are not activated. Tailored educational resources for these specific demographic groups may yield more effective results (Boslaugh et al., 2005). However, few studies have identified these specific groups mentioned above.

In terms of safety study at PHBs, Eapen evaluated the safety effectiveness of PHBs from 2012 to 2013 at one location in Las Vegas, Nevada.

Evaluation of the observations generally concluded that PHBs improved pedestrian safety after installation and continued benefiting pedestrian safety one year later (Eapen, 2014). The assessment carried out in this study was restricted due to the limited number of study locations. To perform a more rigorous evaluation of the safety effectiveness of PHBs, Fitzpatrick et al. conducted an Empirical Bayes before-after study in Tucson, Arizona, using six-year crash data (ranging from 1999 to 2007, depending on the installation date) collected at 21 PHB locations. The evaluation results indicated that total crashes and pedestrian crashes decreased by 29% and 69%, respectively. Severe crashes also showed a 15% reduction, but it was not statistically significant (Fitzpatrick & Park, 2010).

Aside from conducting before-after studies, several studies have also identified the influential factors contributing to pedestrian and bicycle crashes at PHB locations. Pulugurtha et al. utilized Pearson correlation tests to examine the association between the number of all crashes and predictors, such as demographic and on-network characteristics, at 13 PHB locations in Charlotte, North Carolina. Crash data was collected from 2011 to 2014. The findings concluded that high traffic volume, high speed, wide roads, near office, multi-family, retail, and vertical mixed land-use areas would result in a rise in the number of all crashes (Pulugurtha et al., 2018). However, the correlation test used in the study cannot precisely determine the extent of a predictor's impact on the number of crashes. Fitzpatrick et al. conducted a cross-sectional study analyzing 186 PHB locations in Arizona. Crash data was collected from 2007 to 2017. They found that an increase in the number of lanes and a shorter distance between traffic control signals and PHBs increased the number of crashes. Conversely, the presence of a bike lane, a raised median, and a pedestrian refuge island reduced the total number of crashes (Fitzpatrick et al., 2021). Nevertheless, none of these studies thoroughly examined the influential factors contributing to pedestrian and bicycle crashes near PHB locations, particularly when PHBs were activated, but pedestrians and bicyclists were involved in crashes. Further, the transportation field has observed a change in driver behavior since the 2020 COVID-19 pandemic, resulting in higher speeding rates (NHTSA, 2022a), among other violations. This change in behavior has not been accounted for in any PHB study to date.

When evaluating the influential factors of crashes, generalized linear models, such as Poisson models and negative binomial models, may not adequately account for unobserved heterogeneity existing in predictors, such as traffic conditions, roadway characteristics, and human elements (Huang & Abdel-Aty, 2010; Mannering et al., 2016; Xie et al., 2013). Unobserved heterogeneity describes the existence of unmeasured differences between crashes that are associated with predictors of interest. Failing to consider unobserved heterogeneity in predictors may result in a biased and inefficient estimation of model parameters (Mannering et al., 2016). Several studies have utilized Bayesian multilevel models to address potential heterogeneity in predictors (Cheng et al., 2018; Huang & Abdel-Aty, 2010; Wang et al., 2015; Xie et al., 2013). Bayesian multilevel models provide outstanding explanatory power and can effectively estimate the multilevel structure of data by incorporating predictors (Gelman & Hill, 2006; Xie et al., 2013). Moreover, the effects of predictors can also be independently examined by including predictors at different levels (Gelman & Hill, 2006). However, there is a lack of research applying Bayesian multilevel models to examine the influential factors of pedestrian and bicycle crashes near PHB locations.

To address the aforementioned research gaps, this study aims to achieve the following three objectives: 1) identify circumstances in which people tended to cross roads when PHBs were not activated and subsequently experienced crashes, targeting specific groups for education and awareness efforts, and 2) analyze varying crash frequencies near different PHB locations to understand differences. An observation from this study is that certain PHB locations had pedestrian and bicycle crashes reported from 2018 to 2021 while others had not. In this study, PHB locations with reported pedestrian and bicycle crashes are labeled crash-prone, while those without such reported crashes are termed non-crash-prone. Finally, the last objective (3) is to investigate factors contributing to pedestrian and bicycle crashes near activated PHBs during road crossings and all available PHBs in this study to assist in developing policies and research topics that can lead to better safety near PHB locations.

Descriptive and statistical analyses are conducted in this study to assist in facilitating the accomplishment of the three objectives. The descriptive analysis visually examines situations, including demographic factors and traffic conditions, in which people tend to cross roads without activated PHBs and experience crashes. It also observes characteristics of crash-prone and non-crash-prone PHB locations. The statistical analysis provides insight into the degree to which a specific predictor affects the number of pedestrian and bicycle crashes near activated and all PHB locations. Multilevel Poisson-Lognormal regression models incorporated into a full Bayesian framework are utilized to carry out the statistical analysis. The models are estimated at both intersection and individual levels. In addition, various influential factors, such as traffic conditions (i.e., approach speed and approach speed standard deviation), population density, the proportion of White individuals, household income, and lighting conditions, are evaluated. Moreover, recommendations are provided to assist transportation agencies in enhancing pedestrian and bicyclist safety near PHB locations.

2. Data description

Since the late 1990s, Tucson, Arizona has implemented approximately 150 PHBs (Nassi & Barton, 2008; Nassi et al., 2023). The coordinates of PHB locations for this study were obtained from Google Maps (Google, 2023), and their IDs were acquired from the MAXVIEW Advanced Traffic Management System (ATMS) platform to facilitate this study. MAXVIEW ATMS offers real-time data collection and analysis capabilities for traffic signal networks and ITS infrastructure (Q-Free, 2023). For this study, 112 out of the 150 PHB locations connected to the MAXVIEW ATMS platform were selected for analysis, depicted in Figure 2. These 112 PHB locations were classified into three groups to serve different analysis purposes in this study:

- Group 1: 71 PHB locations with no reported pedestrian and bicycle crashes from 2018 to 2021.
- Group 2: 24 PHB locations with reported pedestrian and bicycle crashes from 2018 to 2021, but no controller event-based data (hereafter, "event-based data") was logged at these locations.
- Group 3: 17 PHB locations with reported pedestrian and bicycle crashes from 2018 to 2021, and event-based data was logged at these locations.

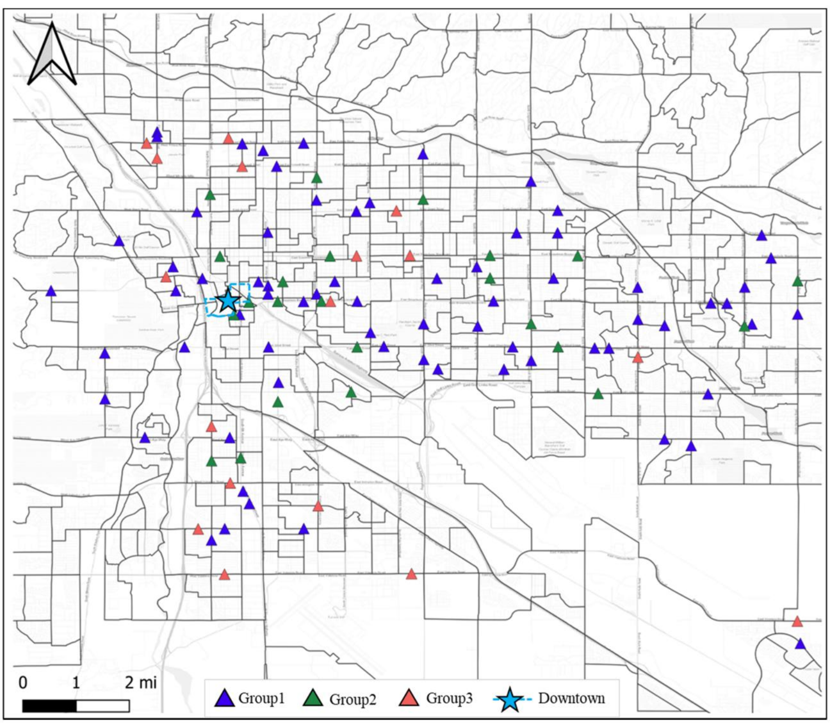


Figure 2. Locations of Pedestrian Hybrid Beacons in Tucson, Arizona.

2.1. Crash data

Four years of crash data (from 2018 to 2021) was collected from the Arizona Crash Information System (ACIS), which is maintained by the Arizona Department of Transportation (ADOT) (ADOT, 2023). The ACIS dataset provides various details about crashes, including driver, pedestrian, and bicyclist information, environmental factors, and geometrical information. To define the influential safety area associated with PHB locations, a 300 ft radius was used as a buffer. This radius is commonly used in transportation literature to identify areas of interest (Ryan et al., 2022). Pedestrian and bicycle crashes beyond this 300 ft buffer were excluded since they were judged to be less influenced by PHBs. A total of 76 pedestrian and bicycle crashes were reported near the 112 PHB locations during the study period.

2.2. Event-based data

High-resolution event-based data is informative and can be accessed through traffic controllers (Li & Wu, 2021; Zhang et al., 2023). When a pedestrian or bicyclist activates the pushbutton at a PHB location, the traffic controller will log the events, such as "Pedestrian Call Registered," "Walk," and "Flashing Don't Walk," for each phase until the PHB signal is not activated (Li & Wu, 2021). However, the event-based data at PHBs is rare because not all agencies are archiving this data due to limitations in their databases, concerns about cost-effectiveness, or the perception that such data collection may not be particularly useful or aligned with their operational goals. Despite these challenges, the research team has been collecting and archiving event-based data at over 60 PHBs in Tucson, Arizona, since 2018.

The event-based data was used in this study to identify whether the PHBs were activated when pedestrian and bicycle crashes happened. Crash reports may be inaccurate or incomplete due to time restrictions and the limited experience of some police officers (Imprialou & Quddus, 2019; Lopez et al., 2022). Additionally, police-reported crash locations are prone to inaccuracies (Lopez et al., 2022), and the reported crash time may not align precisely with the actual time of the crash (Imprialou & Quddus, 2019). Thus, it is challenging to accurately capture whether PHBs are activated when crashes happen. Given the typically low volume of pedestrian traffic near PHB locations in Tucson (Fitzpatrick et al., 2019), if PHBs were activated shortly before crashes, it is more likely that crashes occurred while PHBs were activated.

This study conducted a sensitivity analysis to estimate if PHBs were activated when crashes happened near PHB locations. Two types of time buffers were applied: minutes before the reported crash time (ranging from 5 to 30 minutes in 5-minute increments) and minutes after the reported crash time (ranging from 1 to 5 minutes in 1-minute increments). Due to limited event-based data availability, the analysis focused on 30 crashes from 17 PHB locations (Group 3 in Figure 2). For example, if a crash was reported at 8 am, the event-based data from 7:35 to 8:01 am was examined, assuming the actual crash time falls within this interval. If PHB activation was detected within this period, the crash was labeled as occurring during PHB activation.

Various combinations of time buffers were tested, and no considerable variation was observed in the results across time buffers. Specifically, the results obtained 25 minutes and 30 minutes before the reported crash time were found to be identical. For the "Activated" sample, which represents crashes that occurred while PHBs were activated, the sample size was 15 for the loosest buffers (30 minutes before and 5 minutes after the reported crash time). Likewise, the sample size was 11 for the tightest buffers (5 minutes before and 1 minute after the reported crash time). Therefore, 15 samples labeled as "Activated" within the time window of 25 minutes before and 1 minute after the reported crash time were selected for this study.

2.3. INRIX speed data

Approximately 74 percent of pedestrian fatalities occur at non-intersection locations, with vehicle speed often playing a crucial role (FHWA, 2021; NHTSA, 2022b). However, limited studies have evaluated how vehicle speed impacts pedestrian and bicycle safety near PHBs. This study accessed the citywide speed data from the INRIX dataset. INRIX data aggregates information from millions of GPS-enabled vehicles, mobile devices, conventional road sensors, and numerous other sources (INRIX, 2023). Research has demonstrated that INRIX data offers accurate speed data for traffic operations and research purposes (Kim & Coifman, 2014).

2.4. Variable statistics

The variables used in this study comprised several factors, including traffic conditions, demographic and socioeconomic data, and lighting conditions. These factors were believed to be influential in pedestrian and bicycle safety, yet they have not been specifically evaluated near PHBs. Table 1 summarizes the statistics of these selected variables. Census block group data was downloaded from the AZGeo Data Search platform (AGIC, 2023).

Table 1. Summary of variables' descriptive statistics.

Variables	Descriptions	Min	Max	Mean	Std. dev.	Count (proportion)
Group 1: PHBs have no pedestrian and bicycle crashes reported from 2018 to 2022 (71 PHB locations)						
Approach speed	Hourly average speed (mph)	17.0	45.0	31	5.0	–
Std. dev. of approach speed	Standard deviation of approach speed (mph)	0.4	11.2	2.2	0.8	–
Population density	Density of population (per sqmi)	111.4	20560.6	4311.9	2971.3	–
Proportion of White	Percentage of White per block group	24.3%	82.4%	60.8%	15.3%	–
Proportion of Hispanic	Percentage of Hispanic per block group	12.5%	89.6%	31.8%	21.7%	–
Median household income	Median household income per block group	14544	113906	51555	24061	–
Group 2: PHBs have pedestrian and bicycle crashes reported without event-based data available from 2018 to 2022 (24 PHB locations and 46 crashes)						
Approach speed	Hourly average speed (mph)	16.0	41.0	30.0	4.8	
Std. dev. of approach speed	Standard deviation of speed per hour (mph)	0.4	4.7	2.2	0.7	–
Population density	Density of population (per sqmi)	1598.3	8646.3	3970.74	2439.1	–
Proportion of White	Percentage of White per block group	23.3	81.5	58.4	16.4	–
Proportion of Hispanic	Percentage of Hispanic per block group	12.8	87.0	31.3	21.4	–
Median household income	Median household income per block group	17688	77539	47712	15106	–
Pedestrian or bicyclist information						
Age	Age of pedestrian or bicyclist involved in a crash	2	73	34	19.4	–
Female	Gender of pedestrian or bicyclist	–	–	–	–	22 (34.4%)
Male	involved in a crash	–	–	–	–	42 (65.6%)
Lighting conditions						
Dawn	Natural lighting conditions when a	–	–	–	–	1 (1.6%)
Daylight	crash happened	–	–	–	–	34 (53.1%)
Dusk		–	–	–	–	0 (0%)
Night		–	–	–	–	29 (45.3%)

(*continued*)

Table 1. Continued.

Variables	Descriptions	Min	Max	Mean	Std. dev.	Count (proportion)
Group 3: PHBs have pedestrian and bicycle crashes reported, with event-based data available from 2018 to 2022 (17 PHB locations and 30 crashes)						
Pre-crash approach speed	Average speed 5-min to 10-min before a crash happened (mph)	21.5	44.8	31.8	4.6	–
Pre-crash std. dev. of approach speed	Standard deviation of speed 5-min to 10-min before a crash happened (mph)	0	8.0	3.5	1.9	–
Speed limit	Posted speed of major road (mph)	25	45	35	–	–
Population density	Density of population (per sqmi)	388.0	11036.0	5622.0	2758.6	–
Proportion of White	Percentage of White per block group	24.5	76.2	42.5	16.7	–
Proportion of Hispanic	Percentage of Hispanic per block group	17.3	88.5	50.3	26.4	–
Median household income	Median household income per block group	24358	77712	37955	18841	–
Pedestrian or bicyclist information						
Age	Age of pedestrian or bicyclist involved in a crash	2	73	37	20.2	–
Female	Gender of pedestrian or bicyclist	–	–	–	–	12 (36.4%)
Male	involved in a crash	–	–	–	–	21 (63.6%)
Lighting conditions						
Dawn	Natural lighting conditions when a	–	–	–	–	1 (3.0%)
Daylight	crash happened	–	–	–	–	16 (48.5%)
Dusk		–	–	–	–	0 (0%)
Night		–	–	–	–	16 (48.5%)

Natural lighting conditions were collected from the Sunrise & Sunset Times website (Times, 2022).

3. Methodology

This study analyzed influential factors affecting pedestrian and bicycle crashes near PHB locations in Tucson, Arizona. The predictors examined include traffic conditions (approach speed and approach speed standard deviation), speed limit on major roads, population density, proportion of White and Hispanic individuals, household income, lighting conditions, and more. These factors were considered influential in pedestrian and bicycle safety but have not undergone specific evaluation near PHBs. This study did not include certain factors, such as pedestrian volume, due to a lack of available data.

The data was observed a two-level structure, namely, intersection-level and individual-level predictors. To account for unobserved heterogeneity and model the multilevel data structure, Multilevel Poisson-Lognormal regression models (Aitchison & Ho, 1989) were employed to reveal the extent to which a specific predictor would affect the number of pedestrian and bicycle crashes at each PHB location. These models were incorporated into a full Bayesian framework for estimation, which effectively captures complex correlations in multilevel structured data (Cheng et al., 2018).

3.1. Multilevel Poisson-Lognormal models

Although some studies assumed that crash data follows a negative binomial distribution (Xie et al., 2013; Zhang et al., 2023), given the small sample size in this study, the response variable, i.e., the number of pedestrian and bicycle crashes near each PHB location, was assumed to follow a Poisson-Lognormal distribution. This choice is due to the Poisson-Lognormal distribution's ability to handle small sample sizes and overdispersion in crash data more effectively than a negative binomial distribution (Cheng et al., 2018). In Poisson-Lognormal regression models, the observed crash frequency is modeled as a Poisson distribution, while the random effects are modeled as a Lognormal distribution. Additionally, the crash counts across PHB locations are assumed to be independent. The base Poisson-Lognormal model is described below:

Assume that the response variable Y_i, i.e., the predicted crash frequency for each PHB location i is independent Poisson distributed with a mean parameter θ_i :

$$Y_i \sim Poisson(\theta_i) \tag{1}$$

To address overdispersion for unobserved heterogeneity and the random effect across individuals or PHB locations (Wang et al., 2015), it assumes that:

$$\theta_i = \mu_i \exp(\varepsilon_i) \tag{2}$$

$$\text{Log}\ (\mu_i) = \beta_0 + \beta X_i \tag{3}$$

where X_i represents the predictors (e.g., approach speed) for PHB location i, β_0 is the intercept, β is a vector of regression parameters that need to be estimated, the unobserved heterogeneity ε_i is assumed to be uncorrelated with the predictors, the term $\exp(\varepsilon_i)$ is a multiplicative random effect, and it assumes a lognormal distribution:

$$\exp\ (\varepsilon_i) \sim \mathit{Lognormal}\ \left(0, \sigma_\varepsilon^2\right), \mathit{or}\ \ \varepsilon_i \sim N(0, \sigma_\varepsilon^2) \tag{4}$$

where the unobserved heterogeneity ε_i is assumed to be multivariate, normally distributed with mean equals 0 and variance σ_ε^2, the variance parameter, $1/\sigma_\varepsilon^2$, is specified as Gamma prior distribution (0.001, 0.001).

To accommodate the hierarchical structure of the data and unobserved heterogeneity, multilevel Poisson-Lognormal regression models were employed and described as follows (Huang & Abdel-Aty, 2010; Wang et al., 2015; Xie et al., 2013):

Individual-level model (Wang et al., 2015):

$$\text{Log}\ (\theta_i) = \beta_0^{L1} + \beta^{L1} X^{L1} + \varepsilon^{L1} \tag{5}$$

where X^{L1} is the vector of individual-level variables, e.g., traffic conditions, β^{L1} is the vector of coefficients estimated for individual-level variables, ε^{L1} is the random effect of the individual-level model and explains the between-individual variation, and $\exp(\varepsilon^{L1})$ follows a Lognormal distribution.

Intersection-level model (Wang et al., 2015):

$$\beta_0^{L1} = \beta_{00}^{L2} + \beta_0^{L2} X^{L2} + \varepsilon^{L2} \tag{6}$$

where β_{00}^{L2} is the intercept of the intersection-level model, β_0^{L2} is the vector of coefficients estimated for intersection-level variables, e.g., population density, X^{L2} is the vector of intersection-level variables, ε^{L2} is the random effect of the intersection-level model and explains the between-intersection variation, and $\exp(\varepsilon^{L2})$ follows a Lognormal distribution.

The individual-level model was combined with the intersection-level model by substitution to create the combined model:

$$\text{Log}\ (\theta_i) = \beta_{00}^{L2} + \beta_0^{L2} X^{L2} + \varepsilon^{L2} + \beta^{L1} X^{L1} + \varepsilon^{L1} \tag{7}$$

3.2. Bayesian inference and implementation

In the full Bayesian approach, parameters are considered random variables represented by prior distributions. The approach utilizes observed data and prior distributions to calculate posterior distributions for the parameters. Priors capture existing knowledge of the parameters, which can be updated based on the observed sample and the relationship between explanatory and response variables. A few studies set the priors based on their experience, while several studies suggested that priors derived using maximum likelihood estimation can improve model fitting performance more effectively than methods based on moments or expert experience (Wang et al., 2015). In this study, the maximum likelihood method was used to estimate the parameters of negative binomial models. The mean and variance estimates were then utilized to construct a normal distribution for the variables, which served as the prior distribution in the Bayesian multilevel regression analysis. The model estimations were conducted using the "brms" package in R (Bürkner, 2017).

However, several limitations of the Bayesian multilevel Poisson-Lognormal regression model are noted. One key aspect is how the chosen priors can impact the model outcomes. Moreover, this model assumes an absence of spatial correlation among PHB locations, ignoring the potential impact of unobserved variables that might significantly affect crash frequency in nearby PHB sites. Additionally, the computational costs tied to maximum likelihood estimation add to the challenges.

3.3. Model assessment

Leave-One-Out cross-validation (LOO-CV) was used to assess the performance of different Bayesian models due to its greater robustness compared to the Watanabe-Akaike information criterion (WAIC) and the deviance information criterion (DIC), especially in cases of finite samples with weak priors or influential observations (Gelman et al., 2013). In addition, LOO-CV can capture the uncertainty in the estimates of the model parameters and can be used for models with complex hierarchical structures. The detailed LOO-CV process can be found in (Gelman et al., 2013). A lower Leave-One-Out Information Criterion (LOOIC) value indicates a better model fit, but it can be sensitive to the choice of prior distributions (Bürkner, 2017). The LOO-CV process was carried out through the "loo" package in R. Moreover, Mean Absolute Deviation (MAD) and Mean Squared Predicted Error (MSPE) were employed to evaluate the model's accuracy.

4. Results and discussion

The section discussed the situations in which individuals tended to cross roads when PHBs were not activated and consequently involved in crashes.

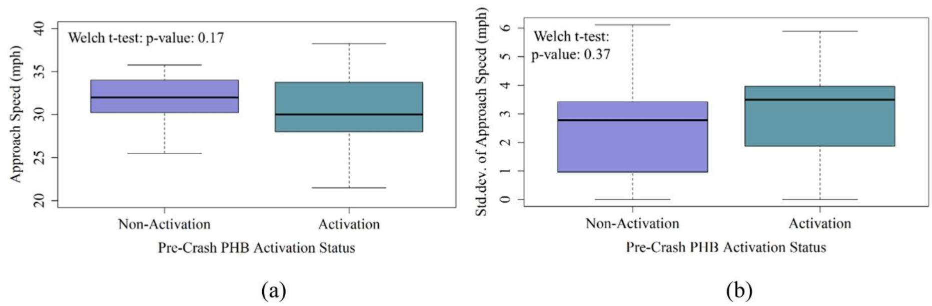


Figure 3. Boxplots for approach speed and standard deviation of approach speed.

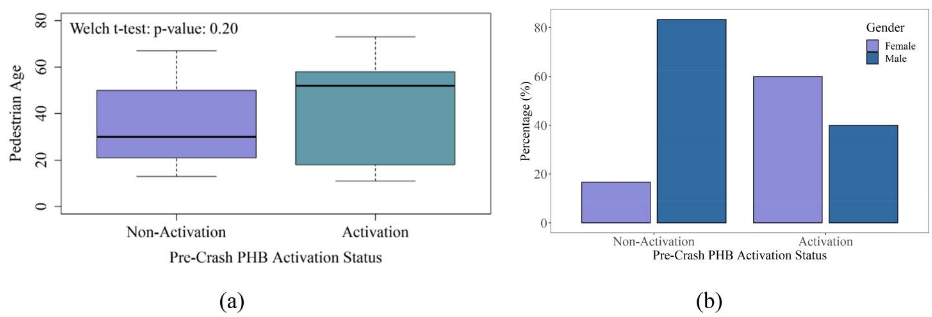


Figure 4. Age and gender of pedestrians and bicyclists.

Then, this section observed differences in characteristics between crash-prone and non-crash-prone PHB locations. Lastly, factors contributing to pedestrian and bicycle crashes near both activated and all available PHB locations were analyzed. The study justified grouping pedestrian and bicycle crashes due to similar crossing behaviors near PHB locations and the presence of lane markings for bicyclists at some PHB locations in Tucson, Arizona (Nassi et al., 2023).

4.1. Descriptive analysis

4.1.1. Characteristics behind non-activation of PHBs and resulting crashes

Data from Group 3 in Figure 2 was used for this section. Figure 3 displays boxplots for approach speed and approach speed standard deviation. The results show that the PHB non-activation group generally had a higher median approach speed than the PHB-activation group while also displaying a smaller variation in approach speed. When approach speeds were around 30 to 35 mph, and the median standard deviation of approach speeds was around 2.8 mph, individuals tended to cross roads near PHB locations when PHBs were not activated and experienced crashes.

Figure 4(a) illustrates that young individuals, with a median age of 29, tended to cross roads near PHB locations when PHBs were not activated

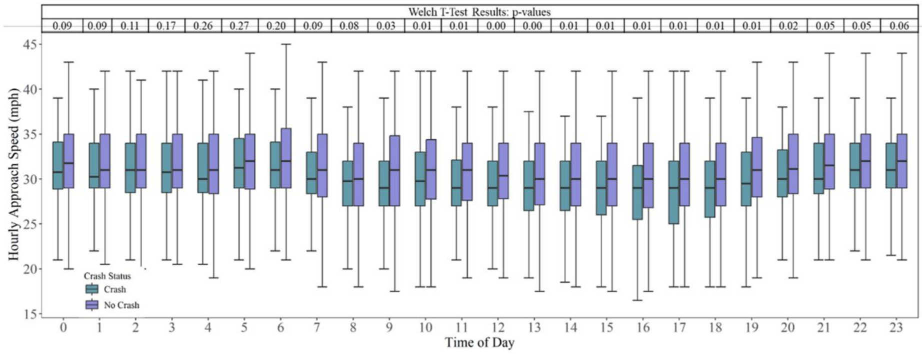


Figure 5. Hourly approach speeds by time of day of PHB locations with/without pedestrian and bicycle crashes reported.

and experienced crashes. As noted, adolescents and young adults may exhibit a proclivity towards taking risks on the road, such as engaging in dangerous pedestrian behaviors (Wang et al., 2022). In addition, Figure 4(b) shows that males were more prone to cross roads near PHB locations when PHBs were not activated and ended in crashes. This finding was consistent with previous studies that found male pedestrians were more risk-taking than female pedestrians, as they committed significantly more violations than females (Chai et al., 2016).

4.1.2. Differences in PHB locations with/without pedestrian and bicycle crashes reported

This section examined the difference between PHB locations with reported crashes (Groups 2 and 3 in Figure 2) and those without reported crashes (Group 1 in Figure 2). Figure 5 displays the distribution of hourly approach speeds for both crash-prone PHB locations (labeled as "Crash" in Figure 5) and non-crash-prone PHB locations (labeled as "No Crash" in Figure 5), and the corresponding results of Welch t-tests. In general, from 9 am to 10 pm, the approach speeds at crash-prone PHB locations ranged from the 25th percentile at 25 mph to the 75th percentile at 33 mph. These speeds were statistically different from the approach speeds observed at non-crash-prone PHB locations, which ranged from the 25th percentile at 27 mph to the 75th percentile at 35 mph. Moreover, crash-prone PHB locations exhibited higher standard deviation in approach speed compared to those without reported crashes, as shown in Figure 6. This trend showed that a higher variation in approach speed may contribute to an increased frequency of pedestrian and bicycle crashes near these PHB locations.

The population density, proportion of White individuals, and household income for crash-prone and non-crash-prone PHB locations were also evaluated. There was no significant difference between the two groups of

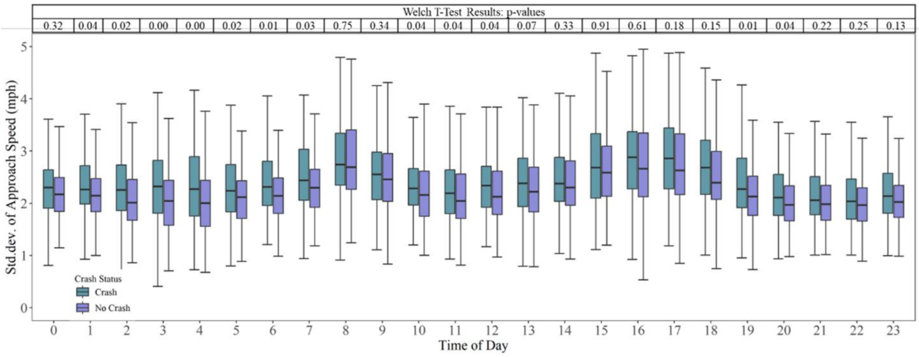


Figure 6. Standard deviation of approach speed by time of day of PHB locations with/without pedestrian and bicycle crashes reported.

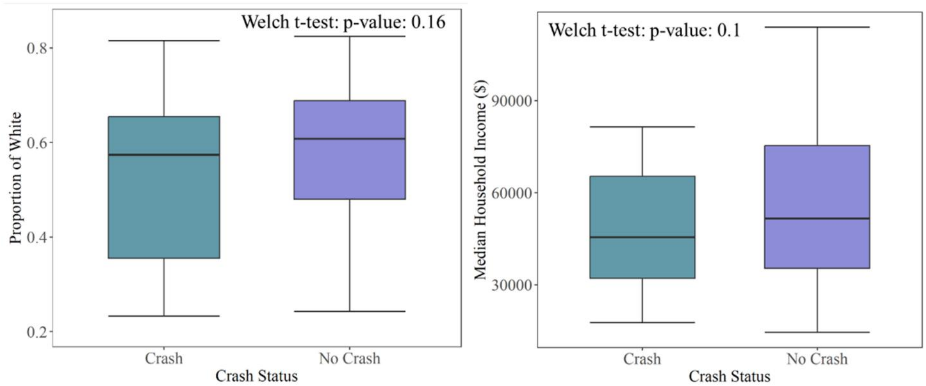
locations in population density. However, there was a slight variation in the proportion of White individuals between the two groups, as shown in Figure 7(a). Locations with a higher proportion of White individuals tended to have a lower frequency of pedestrian and bicycle crashes, aligning with previous literature indicating disparities in traffic injuries among non-White individuals (Haddad et al., 2023; Ryan et al., 2021). Additionally, locations with a higher household income tended to have a lower frequency of pedestrian and bicycle crashes, as shown in Figure 7(b).

4.2. Statistical analysis

Bayesian multilevel Poisson-Lognormal regression analysis was conducted to examine the factors influencing the frequency of pedestrian and bicycle crashes near PHBs. The first section explored potential reasons for crashes during road crossings with activated PHBs, and the subsequent section observed potential reasons behind pedestrian and bicycle crashes near all available PHB locations in this study.

4.2.1. Influential factors of crashes with activation of PHBs

Both crash and non-crash events, when PHBs were activated, were utilized in this investigation. To obtain the non-crash events, a matched case-control design was applied (Wali et al., 2018; Yu & Abdel-Aty, 2013). This design is an effective method for studying rare events (Zheng et al., 2010). Each crash event was matched with four non-crash events (Zheng et al., 2010), ensuring they occurred at the same PHB location, on the same day of the week, and the PHB was activated. A total of 75 records (15 crash events collected from Group 3 in Figure 2 and 60 non-crash events) were included for analysis.



(a) (b)

Figure 7. Boxplots for proportion of white individuals and household incomes near all PHB locations.

Initially, various predictors, such as traffic conditions, speed limit, population density, proportions of White and Hispanic individuals, household income, and lighting conditions, were considered. The Pearson test was conducted to ensure multicollinearity and a high correlation between predictors was not present in the data. Table 2 presents the correlation coefficients of the Pearson test. The speed limit was positively correlated with approach speed, while the proportion of Hispanic individuals was negatively correlated with the proportion of White individuals. Thus, one out of two predictors was selected in the model estimation process. The variance inflation factor (VIF) test was also performed to ensure no multicollinearity between all chosen predictors. All VIF values are less than four in this study, which is acceptable in previous transportation-related studies (Haule et al., 2021; Zhou et al., 2022).

Additionally, traffic conditions contain random effects that were assumed to vary across different records within each PHB location. However, fixed effects, like the proportion of White people and population density, would remain unchanged within records at the same PHB location but differ between PHB locations.

Different predictor combinations were tested before model estimation, and goodness-of-fit was evaluated using LOOIC, MAD, and MSPE. Models accounting for random effects showed better fit (lower LOOIC values) and higher accuracy (lower MAD and MSPE values) overall, as shown in Table 3.

Model estimation results are presented in Table 4. The reference group for lighting conditions was daylight. The results show that the proportion of White individuals and light conditions during the night were statistically significant at 95% Bayesian credible interval (BCI), while the pre-crash/pre-activation approach speed was statistically significant at 90% BCI. However, the standard deviation of approach speed, population density, household income, and light conditions during dawn were not statistically significant.

Table 2. Correlation coefficients of pearson test.

	Approach speed (mph)	Std. dev. of approach speed (mph)	Population density (per sqmi)	Proportion of White	Proportion of Hispanic	Household income ($)	Speed limit (mph)
Approach speed (mph)	1	–	–	–	–	–	–
Std. dev. of approach speed (mph)	−0.07	1	–	–	–	–	–
Population density (per sqmi)	−0.26	0.12	1	–	–	–	–
Proportion of White	0.13	−0.07	−0.12	1	–	–	–
Proportion of Hispanic	−0.12	0.08	0.04	−0. 96	1	–	–
Household income ($)	0.33	−0.15	−0.38	0.44	−0.33	1	
Speed limit (mph)	0.58	−0.09	−0.17	0.04	−0.09	0.33	1

Table 3. Model assessments.

	Without accounting for random effects			Account for random effects		
	LOOIC (SE)	MAD	MSPE	LOOIC (SE)	MAD	MSPE
Model 1	85.80 (12.83)	0.32	0.16	81.55 (11.91)	0.32	0.16
Model 2	88.75 (13.51)	0.31	0.15	82.02 (12.09)	0.31	0.15
Model 3	88.58 (13.48)	0.32	0.15	82.08 (12.12)	0.31	0.16
Model 4	7.38 (2.77)	4.86	3.55	6.54 (3.3)	4.00	3.19
Model 5	3.83 (1.66)	15.3	32.9	2.39 (1.21)	1.97	7.29
Model 6	80.83 (13.48)	0.27	0.13	74.77 (12.24)	0.27	0.13

Notes: LOOIC: Leave-One-Out Information Criterion; MAD: Mean Absolute Deviation; MSPE: Mean Squared Predicted Error; SE: standard error; Model 1 to Model 6: the predictors containing fixed effects are approach speed, std. dev. of approach speed, proportion of White, population density, household income, and lighting conditions, respectively.

When the PHB was activated, an observed trend indicates that a higher proportion of White individuals tended to correlate with a roughly 46% decrease in crash odds. This may be due to regions with more non-White residents experiencing higher crash rates, likely because of transportation system inequalities (Ryan et al., 2021). Lower education levels in these regions may also contribute to increased crash risk (Liu et al., 2022). Moreover, nighttime tended to experience more crashes near the PHB location than daylight, even with the activated PHB. Reduced visibility for drivers, pedestrians, and bicyclists could be the potential reason. Additionally, an observation is that with a one-unit increase in approach speed 5 to 10 minutes prior to crashes, the odds of crashes occurring near PHB locations decreased by around 2%. This could potentially be because a lower approach speed may be associated with a higher volume, and a higher volume of traffic was always linked to higher crash risks (Fitzpatrick et al., 2021). This finding was in line with (Yu et al., 2013): the likelihood of motor-vehicle crashes increased when the average speed decreased 5 to 10 minutes before crashes occurred.

4.2.2. Influential factors of crashes near 112 PHB locations

The analysis was conducted using the data collected at 112 PHB locations, as shown in Groups 1, 2, and 3 in Figure 2. 76 pedestrian and bicycle crashes were

Table 4. Summary of model results.

Results	Predictors	Mean	Std. dev.	95% BCI	Odd ratio (95% CI)
Influential factors of pedestrian and bicycle crashes near activated PHBs	Approach speed 5 to 10 minutes before crash/activation (mph)	−0.02	0.05	(−0.12, −0.004)*	0.98 (0.89, 1.00)
	Std. dev. of approach speed (mph)	0.05	0.18	(−0.32, 0.41)	1.05 (0.72, 1.45)
	Proportion of White	−0.61	2.05	(−4.77, −0.08)	0.54 (0.007, 0.93)
	Population density (per sqmi)	−0.001	0.01	(−0.02, 0.02)	0.99 (0.97, 1.02)
	Household income ($)	−0.0001	0.00	(−0.009, 0.0002)	0.997 (0.991,1)
	Lighting (Dawn)	0.65	0.89	(−1.13, 2.04)	1.91 (0.31, 9.66)
	Lighting (Night)	1.56	0.57	(0.46, 2.66)	4.74 (1.52, 14.39)
Influential factors of pedestrian and bicycle crashes near 112 PHB locations	Hourly approach speed (mph)	−0.26	0.16	(−0.55, −0.16)	0.77 (0.58, 0.85)
	Std. dev. of approach speed (mph)	0.08	0.35	(−0.54, 0.58)	1.07 (0.58, 1.78)
	Proportion of White	−6.57	3.97	(−8.87, −6.56)*	0.0014 (0.00, 1.37)
	Population density (per sqmi)	−0.01	0.02	(−0.05, 0.01)	0.99 (0.96, 1.00)
	Household income ($)	−0.0001	0.0001	(−0.0006, 0.0002)	0.99 (0.99, 1.00)

Notes: BCI: Bayesian credible interval, *: 90% BCI, CI: confidence interval.

reported near 41 PHB locations (Groups 2 and 3 in Figure 2), while no crash was reported near 71 PHB locations (Group 1 in Figure 2) from 2018 to 2021.

The results of the model estimation are presented in Table 4. The results show that pedestrians and bicyclists in regions with lower proportions of White individuals tended to be involved in crashes near PHB locations. Specifically, with a one unit increase in the proportion of White individuals, the odds of crashes occurring decreased by approximately 99%. Furthermore, with a one unit increase in approach speed, the odds of crashes occurring near PHB locations decreased by around 23%. This could be because the driver's yielding rate could be above 95 percent for PHBs on major streets with higher speeds (Fitzpatrick et al., 2006).

5. Conclusions

Pedestrian Hybrid Beacons (PHBs) assist pedestrians in safely crossing unsignalized streets or highways at marked crosswalks by warning and controlling traffic. To increase PHB usage and and improve pedestrian and bicyclist safety near PHB locations, this study employed descriptive and Bayesian multilevel Poisson-Lognormal regression analyses. The objectives of this study were to 1) understand when people tended to cross when PHBs were not activated and ended in crashes; 2) examine varying crash frequencies near different PHB locations to understand differences; and 3) investigate factors that contributed to pedestrian and bicycle crashes during road crossings near activated PHBs and all available PHBs in this study.

The primary observations and contributions of this study include:

- When the approach speeds were around 30 to 35 mph, with a median standard deviation of approximately 2.8 mph, pedestrians and bicyclists tended to cross when PHBs were not activated.

- Young individuals (with a minimum age of 13 and a median age of 29) and males tended to cross when PHBs were not activated compared to other population groups. This aligns with previous findings that reported males and teenagers were less likely to press pushbuttons at signalized intersections (Kutela & Teng, 2020).
- Approach speeds at crash-prone PHB locations (ranging from the 25th percentile at 25 mph to the 75th percentile at 33 mph) were statistically different from non-crash-prone ones (with approach speeds ranging from the 25th percentile at 27 mph to the 75th percentile at 35 mph) between 9 am to 10 pm.
- The odds of pedestrian and bicycle crashes occurring near PHB locations increased when approach speeds decreased 5 to 10 minutes before the crashes. This finding is consistent with conclusions from the literature, such as a study by Yu et al. (2013), which indicated that the likelihood of motor vehicle crashes increased when the average speeds decreased 5 to 10 minutes before the crashes occurred (Yu et al., 2013).
- Regions with a greater proportion of non-White individuals and lower household incomes tended to experience more pedestrian and bicycle crashes near PHB locations.
- Pedestrian and bicycle crashes were more likely to occur at PHB locations during nighttime compared to daytime, even when the PHBs were activated.

The findings suggest that, in addition to providing general guidance on PHB usage, policymakers may benefit from targeted education efforts aimed at young individuals, males, and residents in areas with low proportions of White individuals and lower household income. Such initiatives could potentially boost PHB utilization and enhance pedestrian and bicyclist safety in proximity to PHB locations. Furthermore, particular attention was found to be most helpful when traffic speeds are about 30 to 35 mph and lower, when traffic conditions are unpredictable, and when pedestrians cross during nighttime. These factors may elevate the risk of pedestrian and bicycle crashes near PHB locations. Consequently, implementing supplementary safety countermeasures and developing strategies to improve pedestrian and bicyclist safety near PHB locations with the aforementioned traffic conditions and lighting situations may be advisable. Based on the findings of this study, traffic engineers and urban planners could improve lighting conditions, signage application, and enhance unpredictable traffic volumes by optimizing signal timings of adjacent signalized intersections to improve the safety of pedestrians and bicyclists near PHB locations.

The study acknowledges several limitations. First, due to the constraints of our sample size, pedestrian and bicycle crashes were combined for analysis. Future studies with larger samples may allow for separate examinations of the influential factors of pedestrian and bicycle crashes. Second, the absence of information on factors such as roadway geometries resulted in their omission from this study. These factors could potentially affect pedestrian and bicyclist safety near PHB locations and need to be considered in future work. Lastly, it is worth noting that the data is limited to Tucson, Arizona, which may impact the generalizability of our findings.

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Disclosure statement

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