A Tier-1 University Transportation Center

Effectiveness of Pedestrian Crash Avoidance Technologies: Comparing Day vs. Night Performance

July 2025

A Report from the Center for Pedestrian and Bicyclist Safety

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About the Center for Pedestrian and Bicyclist Safety (CPBS)

The Center for Pedestrian and Bicyclist Safety (CPBS) is a consortium of universities committed to eliminating pedestrian and bicyclist fatalities and injuries through cutting-edge research, workforce development, technology transfer, and education. Consortium members include: The University of New Mexico, San Diego State University, The University of California, Berkeley, The University of Tennessee, Knoxville, and The University of Wisconsin, Milwaukee. More information can be found at: https://pedbikesafety.org

Disclaimer

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- Bayati Z., & A. Khattak, Shedding Light on Safety: Comparing the Collision Likelihood and Impact Severity of Pedestrian Crash Avoidance Systems Across Day and Night Conditions, Presented at Transportation Research Board 104th Annual Meeting, Transportation Research Board, TRBAM-25-03034, 2025 (under review in a journal).
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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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TABLE OF CONTENTS

List of Figures

List of Tables

Acronyms, Abbreviations, and Symbols

P-AEB	Pedestrian Automatic Emergency Braking
AVs	Automated Vehicles
AEB	Automatic Emergency Braking
EVs	Electric Vehicles
IIHS	Insurance Institute for Highway Safety
TTC	Time to Collision
FCW	Forward Collision Warning
VRUs	Vulnerable Road Users
SAE	Society of Automotive Engineers
VLC	Visible Light Cameras
LiDAR	Light Detection and Ranging
LED	Light Emitting Diode

Abstract

Rising pedestrian fatalities and injuries underscore a critical safety concern. With Pedestrian Automatic Emergency Braking (P-AEB) systems increasingly prevalent in vehicles, there is a growing effort to enhance crash avoidance technologies. However, P-AEB performance varies, particularly at nighttime, when most pedestrian fatalities occur. This study evaluates P-AEB systems by analyzing 2,494 test cases (1,654 at night and 840 during the day). Tests involve 42 Society of Automotive Engineers Level 1 automated vehicles, manufactured between 2021 and 2024, conducted by the Insurance Institute for Highway Safety. All tests were conducted with no driver intervention. The research has two parts: the first assesses deceleration and detection rates, while the second focuses on crash occurrences and impact speed. Detection rates were highest during the day (98%), lower at night with low beams (87%), and somewhat improved at night with high beams (93%). Of detected tests, crashes occurred more often at night, 23% with low beams compared to only 10% during daytime, and at higher speeds. Additionally, analysis revealed that low beam halogen headlights significantly reduce detection (up to 43%) compared to daytime, emphasizing the need to enhance P-AEB effectiveness in poor lighting conditions. Extending P-AEB system activation times can reduce crash probabilities by up to 32%. The study also examines how pedestrian behavior and vehicle characteristics, such as size and fuel type, correlate with P-AEB effectiveness. These insights can enhance pedestrian safety by refining P-AEB performance across various lighting conditions, addressing research gaps, and supporting future advancements in vehicle safety technology.

Executive Summary

In recent years, the troubling increase in pedestrian fatalities has highlighted the urgent need for advanced safety technologies. P-AEB systems, crucial components of low-level AVs, play a vital role in reducing both the severity and frequency of pedestrian crashes, thereby enhancing road safety. These systems, representing a significant advancement in modern vehicles with Level 1 automation capabilities, are central to this analysis. Utilizing the comprehensive IIHS dataset, this study examines the detection capabilities, deceleration processes, and resultant crash speeds of P-AEB systems. By offering insights into the operational strengths and areas for improvement, this analysis underscores the potential of P-AEB systems to increase pedestrian safety.

For this study, the primary dataset employed was the IIHS dataset, which provided a comprehensive basis for analyzing the performance of P-AEB systems. The IIHS dataset includes detailed information on vehicle tests conducted under various lighting conditions, which is crucial for evaluating the systems' effectiveness in detecting pedestrians and mitigating or avoiding crashes. This study examines the effectiveness of P-AEB systems across 42 vehicles tested under both day and night conditions. A total of 2,494 tests, with 840 conducted during daylight and 1,654 at night, provide a robust framework for assessing the impact of these systems on pedestrian safety. The method used in this analysis was the random effects-Heckman sample selection model on panel data. The Heckman model accounts for the selection mechanism in cases where detection is conditional for evaluating the declaration after detection. In another application, crash speed is conditional on crash occurrence.

The study focused on two sets of analyses with distinct dependent variables. 1) In this part of the study, the primary dependent variables were the detection success and the deceleration rate. This analysis aimed to understand how well vehicles detected pedestrians and initiated deceleration maneuvers during daylight compared to nighttime conditions. 2) The second analysis focused on actual crash occurrences and the resulting crash speeds. This model examined the instances where the P-AEB system failed to prevent a crash and analyzed the impact speed of such events. All the tests were conducted with no driver intervention. The correlates in this model included vehicle type, test speed, and environmental conditions. These analyses help understand how variables such as lighting conditions, pedestrian movements, and vehicle type are associated with the effectiveness of P-AEB systems in detecting pedestrians and mitigating crash speed impacts. Additionally, this study highlights the critical role of visibility and identifies key areas where P-AEB technology needs improvement to enhance pedestrian safety across different driving conditions.

Detection is the foundational operation of P-AEB systems, where vehicles identify potential pedestrian threats. The analysis of the detection phase is crucial. It involves variables such as the Time-to-Crash (TTC) for Forward Crash Warning (FCW) systems, which measure the time from detecting a pedestrian to the potential crash. This data shows that successful detection rates are high at 98% during the day but drop to 90% at night, indicating a significant reduction in effectiveness under reduced visibility conditions.

Detection effectiveness is further influenced by the type of sensors used, such as radar and cameras, which must operate optimally under various environmental conditions. The challenges of nighttime detection, where lighting impacts sensor performance, are significant. These conditions often require enhanced sensor sensitivity and improved algorithmic interpretation to maintain high detection rates. Moreover, vehicle type plays a role, with larger vehicles, such as SUVs and trucks, generally experiencing more difficulty detecting pedestrians than smaller vehicles, like hatchbacks and sedans. This disparity suggests a need for vehicle-specific adaptations in sensor configurations to improve detection across all vehicle types.

Once a potential crash is detected, P-AEB systems initiate a deceleration process designed to mitigate or avoid the impact. This phase is critical as the effectiveness of the deceleration directly influences the outcome of the encounter. After measuring the average deceleration rate given detection for each test, it is shown that deceleration dynamics vary and are associated with factors such as vehicle speed, fuel type, and the time elapsed between detection and response. Although most vehicles exhibit prompt deceleration, the variability in the intensity and timing of braking highlights the complexity of optimizing these systems for every potential scenario. Sometimes, even with swift detection, the (slow) deceleration may not prevent a crash completely. However, it significantly reduces the impact speed, potentially lowering injury severity.

Reducing crash speed is a fundamental goal of P-AEB systems, and it directly correlates with the severity of pedestrian injuries and fatalities. The IIHS dataset offers extensive data on crash speeds across numerous testing scenarios, enabling a detailed evaluation of system performance in real-world conditions. While P-AEB systems successfully reduced crash speeds in many instances, the extent of this reduction varies widely.

This variation stems from differences in several factors, including vehicle size, pedestrian movement, and lighting. For instance, the data reveals that parallel pedestrian movements often result in higher crash speeds than perpendicular movements, particularly at higher vehicle speeds. This outcome is likely attributable to failures in detection under certain conditions, pointing to a need for improvements in how pedestrian movement is identified and processed by the system. Such enhancements are crucial for reducing crash severity and improving the system's overall effectiveness.

The detailed examination of the IIHS dataset has provided critical insights into the performance of P-AEB systems. Equipped with vehicles with Level 1 automation, these systems have shown a substantial capacity to enhance pedestrian safety. Through rigorous analysis of detection accuracy, deceleration processes, and crash speeds, it is evident that while P-AEB systems significantly bolster pedestrian safety, they also exhibit considerable variability in performance under challenging conditions. This variability underscores the need for ongoing technological enhancements. Advancements in sensor technology, improved object recognition, and better integration of these technologies into overall vehicle systems are paramount. Such developments are not only crucial for enhancing pedestrian safety but are also instrumental in advancing the capabilities of automated driving technologies, thereby fostering the creation of safer, more efficient, and intelligent transportation networks for the future.

Introduction

As urban populations swell and roadways become increasingly busy, the safety of pedestrians, the most vulnerable in the transportation ecosystem, remains a pressing concern. Despite significant advancements in vehicular safety technologies, pedestrian fatalities continue to rise, with a disturbingly high number occurring at night; notably, over 70% of pedestrian deaths occur at nighttime (NHTSA, 2023). This persistent issue highlights a critical gap in our current technological defenses, underscoring the need for effective pedestrian crash avoidance systems, particularly in varied lighting conditions.

P-AEB systems represent a pivotal innovation in this arena, designed to mitigate the risk of crashes by automatically detecting pedestrians and initiating braking when a crash is imminent. These systems are increasingly standard in modern vehicles and are critical for Advanced Driver Assistance Systems (ADAS) (Graziano, 2012). However, their reliance on sensor technologies that interpret visual and spatial data makes their performance susceptible to variations in environmental lighting, which can be profound as the day turns to night (Ahmed et al., 2022; Mehta et al., 2023; Moradloo et al., 2025a; Olleja et al., 2022).

The challenge might be worsened by the inherent limitations of the sensors and algorithms that govern these systems (Haus et al., 2021). During the day, good visibility provides optimal conditions for detection sensors to perform well, accurately detecting obstacles promptly. In contrast, nighttime conditions compromise the ability of these systems to identify and respond effectively to pedestrians (IIHS, 2022). Reduced visibility can delay the detection of pedestrians or, worse, lead to non-detection, increasing the risk of fatal outcomes (Cicchino, 2022; Moradloo et al., 2025a). Furthermore, the integration of these technologies across different vehicle models and types has been uneven, leading to a poorly understood performance disparity (Mahdinia et al., 2022). This disparity raises important questions about the standards and regulations governing the implementation of P-AEB systems and their efficacy in real-world conditions.

This study thoroughly investigates the operational efficacy of pedestrian crash avoidance technologies across different lighting conditions, utilizing empirical research methodologies. It specifically evaluates the performance of P-AEB systems, analyzing four critical aspects: detection, deceleration, crash occurrence, and impact speed during potential crashes. This research examines how these systems initially detect pedestrians, assesses the contributing factors to deceleration rates upon detection, and provides an in-depth look at the performance of vehicle braking systems. It also evaluates the severity of crashes by measuring the impact speed.

The objective is to study the functionality of P-AEB systems under both daylight and nighttime conditions, generating insightful, data-driven recommendations that can guide policy modifications and enhancements in vehicle design. To achieve this, the study estimates a random-effects Heckman sample selection model to evaluate unobserved heterogeneity, alongside a detailed descriptive statistical analysis of recent data from the Insurance Institute for Highway Safety (IIHS). This data encompasses tests on low-level automated vehicles in a range of scenarios defined by the IIHS, based on pedestrian movements, as well as different test speeds, conducted under both daytime and nighttime conditions in controlled settings with no driver intervention. 42 vehicles, commonly tested under both daytime and nighttime conditions, manufactured between 2021 and 2024, are collected for this analysis. Through this comprehensive approach, the research aims to gain nuanced insights into the performance of P-AEB systems and their practical implications for enhancing pedestrian safety.

The goal is to enhance the robustness of pedestrian detection systems, ensuring they provide reliable protection for pedestrians at all times and under all conditions of visibility, thereby making the road safer for all road users, especially vulnerable road users (VRUs). This investigation seeks to highlight discrepancies in current technology and inform future developments in vehicle safety systems. By understanding the variables associated with the performance of P-AEB systems, manufacturers can innovate more effective solutions that reduce pedestrian fatalities, moving closer to the ultimate goal of achieving zero traffic-related pedestrian deaths.

Literature Review

Pedestrian safety remains a significant global challenge in road safety initiatives (WHO, 2023). P-AEB systems represent a vital safeguard against pedestrian crashes, offering a beacon of hope in reducing the incidence of these crashes, which have increased by over 50% in recent years (Haddad et al., 2023). These systems are designed to mitigate the human errors that frequently contribute to accidents, significantly enhancing pedestrian safety (Moradloo et al., 2025b; Shinar, 2019). However, current system capabilities indicate a clear need for technological improvements and updated regulations to ensure consistent performance across different environments.

The efficacy of P-AEB systems varies dramatically with environmental conditions, particularly lighting, and numerous studies have been conducted on this topic, as summarized in Table 1 (Anctil et al., 2023; Bartholomew et al., 2024; Kidd et al., 2024; Moradloo et al., 2025a). Studies consistently show poorer system performance during low-light conditions, such as nighttime or adverse weather, precisely when they are most needed (Combs et al., 2019; Kidd et al., 2024; Utriainen, 2020). While integrating multiple sensor technologies (e.g., Visible Light Cameras (VLC), LiDAR, and radar) has been shown to substantially enhance detection capabilities, even advanced systems struggle with consistent performance across varied lighting scenarios (Haus et al., 2021; Liu et al., 2022). This inconsistency is critical, as most pedestrian fatalities occur at night (Moradloo et al., 2025a).

Research indicates that combining multiple detection technologies can prevent over 90% of pedestrian fatalities, significantly better than the 30% effectiveness observed with standalone VLC systems (Combs et al., 2019). Recommended enhancements include improved deceleration capabilities, wider sensor fields of view, refined lane detection, quicker response times, and improved detection of small pedestrians, such as children (Anctil et al., 2023; Kim & Lee, 2020).

Real-world crash data from sources such as Sweden's STRADA database reveal varied effectiveness of P-AEB systems. These systems reduced pedestrian crash risks by 8% and bicyclist crash risks by 21%, with notably better performance during daylight and twilight compared to darkness, where no significant reduction was observed (Kullgren et al., 2023). Another study suggests fully optimized P-AEB systems could reduce pedestrian crashes by up to 52% and, combined with multiple sensor technologies, prevent over 90% of fatalities (Cicchino, 2022). However, these studies overlook factors such as instances of drivers disabling the P-AEB systems, reliance on rear-end crash data as control cases, and the use of speed limits rather than actual vehicle speeds. Such limitations highlight the need for more robust data collection methods to evaluate real-world effectiveness accurately.

Experimental and simulation-based studies have evaluated system performance under various conditions, such as environmental factors, pedestrian movement scenarios, initial vehicle speed, sensor types, and pedestrian demographics (Charlebois et al., 2023; Gruber et al., 2019; Haus et al., 2021). Some studies used limited experimental methods (e.g., (Charlebois et al., 2023), with only 13 vehicles from 2019-2021), while others relied on simulations (Gruber et al., 2019; Haus et al., 2021). In contrast, the current study utilizes an extensive dataset under controlled conditions for a robust statistical analysis, providing deeper insights into actual P-AEB performance, rather than relying solely on simulations.

The IIHS has conducted rigorous evaluations of P-AEB systems across various vehicle models from 2018 to 2024, revealing that while daytime performance is generally satisfactory, nighttime effectiveness remains inadequate. These studies underscore the need for ongoing improvements in sensor technology and algorithm development to ensure that P-AEB systems operate reliably in all conditions. Furthermore, using the IIHS data, some studies reveal how vehicle characteristics, such as vehicle body size and sensor configurations, contribute to the performance of these systems, suggesting avenues for potential improvements (Cicchino, 2022; Kidd et al., 2024; Mahdinia et al., 2022; Moradloo et al., 2025a). This data also indicates that under nighttime conditions, different types of vehicle lighting, such as LED and halogen, can significantly correlate with the outcomes of crashes (Moradloo et al., 2025a). Although these studies offer important insights, they did not directly compare the effectiveness of systems during daytime and nighttime, nor did they investigate the factors associated with detection and deceleration steps in the P-AEB system across different lighting conditions.

(Kidd et al., 2024) also utilized IIHS test data to investigate how P-AEB systems perform under various lighting conditions—daytime and nighttime, with both low and high beams. Using linear mixed-effects models, they examined outcomes such as Time to Collision (TTC), deceleration, jerk, and braking intensity. Their results showed that better lighting and exceptionally high beams help improve visibility and system performance at night. In contrast, our study takes a different approach. First, we examine factors associated with whether the system detects a pedestrian (using FCW TTC). Then, for cases where detection occurs, we analyze the factors associated with how much the vehicle slows down. We use a two-stage model that accounts for both selection bias and hidden differences between vehicles and scenarios. Notably, (Kidd et al., 2024) used separate one-stage models on the test data. However, the method used in this study links the detection and braking processes. We also incorporate a wider range of lighting conditions, including high and low beams with both Light Emitting Diode (LED) and halogen headlights, along with daytime scenarios and detailed vehicle characteristics. This comprehensive approach enables a deeper understanding of how various lighting environments impact P-AEB system performance.

This study aims to bridge existing knowledge gaps by comprehensively analyzing the effectiveness of P-AEB systems from the initial detection of a potential crash to the application of brakes and the assessment of crash potential and impact speeds. Additionally, it compares the system's performance between daytime and nighttime conditions to understand how varying light environments affect the effectiveness of P-AEB. Utilizing the IIHS dataset, which comprises 42 low-level automated vehicles commonly tested under controlled day and night lighting settings without driver intervention, this research provides a detailed evaluation of their performance. Such an approach not only enhances our understanding of P-AEB systems under varied lighting but also informs future improvements, ensuring these systems can reliably protect pedestrians in all conditions.

The current research underscores the need for further advancements in P-AEB technology, particularly in enhancing the sensitivity and accuracy of sensors under low-light conditions. Enhancing object recognition in darkness could significantly bolster pedestrian safety during nighttime, when the risk of a crash is notably higher. Additionally, there is a critical need for regulatory bodies to establish more stringent performance standards for P-AEB systems. These standards should ensure that systems are thoroughly tested and certified across a broad spectrum of environmental conditions before they are deployed.

Table 1: Summary of some studies on P-AEB systems

Study	Data	Gap Identified	Study Environment
Mahdinia et al. (2022)	IIHS crash test data (daytime)	Focused on daytime; no nighttime evaluation.	Controlled
Moradloo et al. (2025)	IIHS crash test data (nighttime)	Only examines nighttime tests; does not provide daytime comparison.	Controlled
Kidd et al. (2024)	IIHS crash test data (daytime & nighttime)	Analyzed when and how P-AEB systems warn and brake, without addressing unobserved heterogeneity or conditional detection and deceleration factors.	Controlled
Charlebois et al. (2023)	Limited dataset of 13 vehicles	Used a limited sample size (2019-2021).	Controlled
Gruber et al. (2019)	Simulated crash scenarios	Based on simulations (rather than real-world or controlled test data).	Simulated
Haus (2021)	Pedestrian Crash Data	Based on simulations, it assumes P-AEB sensors always detect pedestrians when they are on the road and not obstructed.	Simulated
Kullgren et al. (2023)	Police-reported crash records	Uses relatively older data (2015-2020). Ignores samples where drivers might disable these systems; predominantly featuring Volvo vehicles.	Real-World Data
Cicchino (2022)	Police-reported crashes	The study does not account for system deactivation; it relies on rear-end crashes as a control and speed limits as a proxy for actual speeds.	Real-World Data

Data and Methodology

Methodology

This study evaluates the performance of P-AEB systems, focusing on four key steps: detection capabilities and braking effectiveness, crash occurrence, and crash impact speed resulting from these systems. To ensure an accurate analysis, it is crucial to address specific data characteristics that could bias the results. One primary consideration is sample selection bias, which occurs because deceleration data are only available for instances where the P-AEB system has successfully detected pedestrians. This limitation means that only a subset of all possible scenarios is represented in the dataset, which could skew the analysis if not adequately addressed. Simpler models, such as separate regressions, overlook the conditional link between them and may yield biased results.

To address this, the study employs a two-step Heckman sample selection model (Briggs, 2004), which jointly estimates both the selection and outcome equations, assuming a bivariate normal distribution of errors. This method corrects selection bias and captures unobserved differences across vehicles and test settings. The framework breaks the crash avoidance process into four sequential components: (1) detection rate, referring to whether the system identifies the pedestrian in time, measured using TTC for FCW. This metric, reported by IIHS, indicates the time remaining when the vehicle first issues a warning and detects the pedestrian; (2) average deceleration, which reflects how effectively the vehicle slows down after detection, measured in this study using speed-time data from IIHS; (3) crash occurrence, which indicates whether a crash ultimately happens, determined based on the reported impact speed, where a value of zero shows no crash; and (4) impact speed, representing the speed at impact when avoidance fails and crash happened, also drawn from IIHS test data.

In addition, activation time, represented by TTC for AEB—the time remaining when the system initiates automatic braking—is a key measure of system responsiveness. TTC for FCW, previously used to assess detection rate, also serves as an indicator of detection timing. Both metrics reflect critical timing in the system's response and are included in the analysis to understand better the effectiveness of pedestrian detection and the initiation of braking. By explicitly modeling each of these conditional stages and including effective metrics, the analysis isolates the contribution of each step to overall system performance, offering a more comprehensive understanding of P-AEB behavior and its limitations.

The data is structured in a panel format to effectively manage and control the correlation among tests using the same vehicle. Vehicles are grouped into panels based on their model, year, and specific testing scenarios. The study used 42 vehicles, including 40 unique models, and tested two models with two cars each; for example, two Mercedes-Benz GLCs. Four panels represent each car of a model according to the four scenarios. Therefore, across all models, we have 160 (40 x 4) panels, each containing an average of 15.6 observations, with individual panels ranging from 12 to 27 observations. This panel structure enables controlled comparisons across similar vehicles and test conditions, thereby enhancing the consistency of results. Summary statistics and trends were analyzed at the test level, treating each trial as a separate observation.

In the regression equation (Equation 1), 'i' denotes multiple tests per vehicle and multiple trials per scenario, 't' stands for each observation, y_{it} represents the deceleration rate with β and α as the coefficients for the regression and selection equations, respectively. The errors, ϵ_{nit} at the observation level, are assumed to be bivariate normal and independent of the random effects, enhancing the robustness and reliability of the analysis in assessing P-AEB system performance. are assumed to be bivariate normal and independent of the random effects, enhancing the robustness and reliability of the analysis in assessing P-AEB system performance.

$$\mathbf{y_{it} = x_{it}\beta + v_{1i} + \epsilon_{1it}} \qquad 1$$

Additionally, equation 2 represents the selection equation in the Heckman sample selection, where s_{it} = 1, y_{it} is observed and not observed when s_{it} = 0.

$$\mathbf{s_{it} = 1(z_{it}\alpha + v_{2i} + \epsilon_{2it} > 0)} \qquad 2$$

Here z_{it} is the selection covariate, v_{2i} is panel-level random effect for selection and ϵ_{2it} is the error term for observation-level selection.

$\mathbf{v_{1i}}$ and $\mathbf{v_{2i}}$ are bivariate normal with mean 0 and variance

$$\sum \mathbf{v} = \begin{bmatrix} \sigma_{1v}^2 & \rho_v\sigma_{1v}\sigma_{2v} \\ \rho_v\sigma_{1v}\sigma_{2v} & \sigma_{2v}^2 \end{bmatrix} \qquad 3$$

The binary variable is illustrated in the following Equations for the selection model:

$$\textbf{Event (Yes/No)} \begin{cases} \mathbf{0: No} \\ \mathbf{1: Yes} \end{cases} \qquad 4$$

The log-likelihood for all panels is calculated using the following Equation:

$$\mathbf{lnL = \sum_{i=1}^{N}(ln\sum_{k2=1}^{q}\left[\left\{\prod_{t=1}^{Ni} f((y_{it}, s_{it})|(v_{1i}, v_{2i}) = L\,\alpha_k\right\}\left\{\prod_{s=1}^{n2} w_{k_s}\right\}\right]} \qquad 5$$

Here, α_k and w_{k_s} are adaptive versions of abscissas and weights after an orthogonalizing transformation, which eliminates posterior covariances between elements of the prior density of Ψ_i, a vector of independent standard normal random variables. These calculations happen in the intermediate steps of getting the likelihood of panel i, which is L_i. Also, the conditional mean of y_{it} is shown in the Equation below:

$$\mathbf{E(y_{it}|x_{it})|(x_{it}\beta)} \qquad 6$$

The study also estimates marginal effects to interpret the coefficients derived from the probit model more effectively. For continuous variables, marginal effects quantify how a one-unit increase in each variable is associated with the probability of detection. For categorical variables, these effects determine the change in the likelihood of the outcome when a variable shifts from its baseline category (set as zero) to one, assuming all other variables remain constant.

Additionally, lighting conditions are utilized as a treatment variable in both models, though their role differs between them. In the first model, its contribution to the probability of detection is assessed. In the second model, the association with crash occurrence is analyzed. This dual application enables a comprehensive evaluation of how lighting affects both the detection capabilities and the safety outcomes of the system. Figure 1 illustrates the study's framework, outlining the key components, processes, and analytical steps used throughout the research.

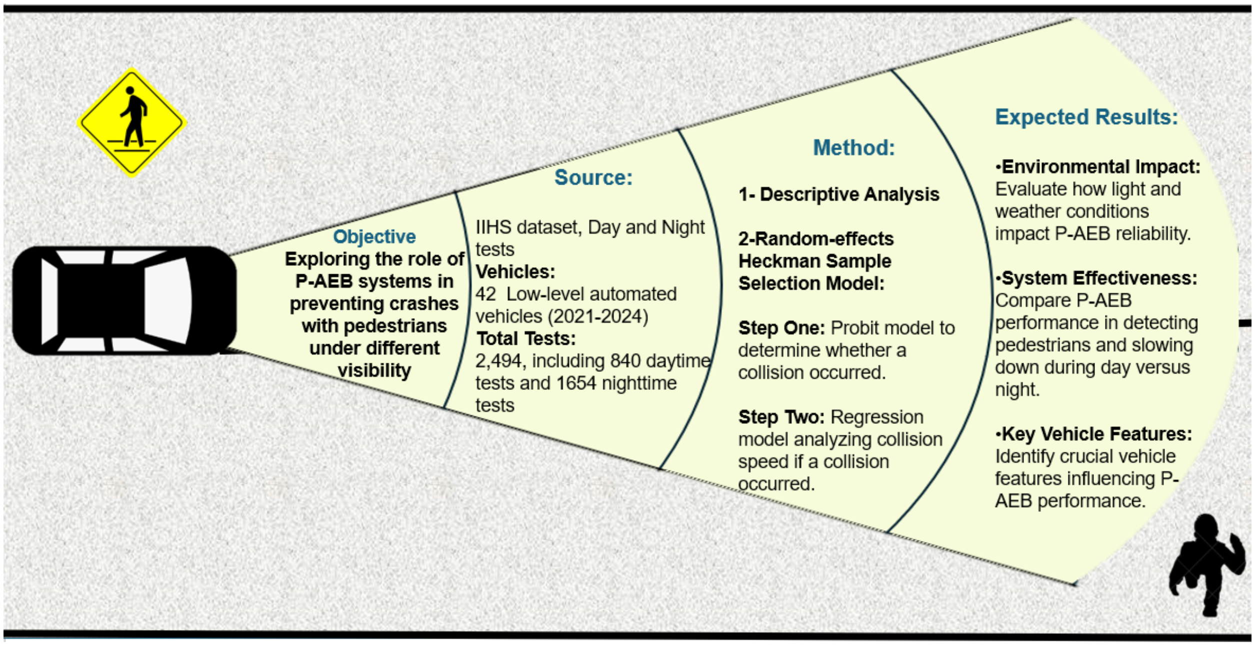

Figure 1: Study Framework

Data

Data collection

This research utilizes the IIHS public datasets to evaluate the performance of P-AEB systems in various lighting conditions (IIHS, 2023). Tests are designed to simulate real-world conditions by considering vehicle specifications, environmental factors, and realistic pedestrian models. The experimental setup accounts for various factors, including vehicle specifications, environmental conditions, and dummy pedestrian characteristics. Vehicle characteristics, such as brand, size, fuel type, brake features, and tire specs, varied across models. Some data were sourced from the IIHS website, while others were obtained using vehicle make, model, trim, and year to extract specifications from manufacturer websites.

Prior to each test, the vehicle undergoes a brake warm-up procedure that involves ten braking actions from a speed of 56 km/h (34.82 mph) at deceleration rates ranging from 0.5 g (16.1 ft/s²) to 0.6 g (19.3 ft/s²). This is followed by three stops from 72 km/h (44.74 mph) to activate the Anti-lock Braking System (ABS). The vehicle is driven at 72 km/h (44.74 mph) for five minutes to ensure the brakes are adequately cooled. If the vehicle remains idle for more than 15 minutes, the brakes are reheated with three additional stops from 72 km/h at a deceleration of 0.7 g. A mandatory three-minute interval is observed between the warm-up phase and the commencement of the test or between successive tests. Depending on the vehicle model, system checks and sensor calibrations may be required, as specified by the manufacturer's instructions. Settings for the P-AEB and Forward Crash Warning (FCW) systems are adjusted to either their middle or slightly higher settings when necessary.

In each trial, the test vehicle begins its approach from a distance of 150 to 200 meters (492 to 656 feet) from the target, accelerating to speeds of 20, 40, or 60 km/h (12.43, 24.85, and 37.28 mph). The commencement of the approach phases is marked at distances of 25, 50, and 75 meters (82, 164, and 246 feet). For a test to be considered valid, the vehicle's speed must remain within ±1.0 km/h (±0.62 mph) of the target speed, its yaw rate within ±1 °/s, and it must keep within 0.1 meters (0.33 feet) of the center of the lane. Activation of the automatic emergency braking is identified when a deceleration of 0.5 m/s^2 (1.64 ft/s^2) is achieved. The system's effectiveness is also evaluated through the timing of audible and visual forward crash warnings, which are recorded for analysis.

Test vehicles have mileage ranging from 200 to 5,000 miles, are equipped with new tires set to the manufacturer's recommended pressure, and are maintained at optimal fluid levels. They also feature sophisticated data recording equipment, including the Oxford RT-Range and Race Logic Video VBOX Pro, to accurately measure speed, acceleration, and the timing of impacts during tests. The test vehicle's weight—including the driver and all equipment—should not exceed its curb weight by more than 200 kg (441 lbs). Details about the vehicle features relevant to the study are provided on the IIHS website.

IIHS employs static and dynamic models that closely replicate human size and motion using dummy pedestrians, ensuring the testing scenarios are robust and realistic. These models, representing adults to maintain consistency, are meticulously checked for any defects that could impact the results. Dynamic models are specifically used to simulate human movement accurately. Throughout the testing, these dummies maintain a steady speed of 5 ± 0.2 km/h (3.1 mph). During nighttime testing, they are dressed in black to simulate the challenges of detecting pedestrians in reduced visibility.

The test environment features a dry asphalt track with clearly marked lane lines and no surrounding obstacles that might interfere with the measurements. Tests are conducted within a temperature range of -6.7°C (20°F) to 37.8°C (100°F), and the layout is designed to minimize interference with the vehicle sensors and the testing apparatus. Nighttime tests are performed under natural darkness, with illumination levels maintained below one lux. In contrast, daytime testing benefits from ample natural lighting that does not affect the sensors.

The scenarios shown in Figure 2 under test include perpendicular (CPNA) and parallel (CPLA) movements, with vehicles moving at 20 km/h (12.43 mph), 40 km/h (24.85 mph), and 60 km/h (37.28 mph). Each test is designed to simulate a specific type of potential crash with a 25% overlap of the vehicle's width impact. In perpendicular scenarios, the target crosses 4 meters from the center of the lane to achieve this overlap, whereas in parallel scenarios, the target is aligned parallel to the vehicle’s path. These controlled conditions are chosen to evaluate P-AEB systems without driver input, which differs from typical driving situations where driver reactions may alter the outcomes. This methodical approach ensures a precise analysis of the systems' detection and response capabilities in various lighting conditions, providing valuable insights into their operational effectiveness (IIHS, 2024).

Data preprocessing was conducted using both Excel and Python to prepare a dataset of 42 vehicles tested under daytime and nighttime conditions. From the original IIHS database, 267 invalid tests labeled 'NA' were removed, resulting in 2,494 valid tests—840 during the day and 1,654 at night, with no missing values. Although IIHS initially conducted a nearly equal number of tests across both lighting conditions, the final daytime test count is lower because child scenarios were excluded, as these are not conducted at night. This exclusion created a difference in scenario frequencies between day and night. In this study, all measurements were standardized using kilometers per hour (km/h) for speed, meters (m) for distance, and meters per second squared (m/s²) for deceleration rates.

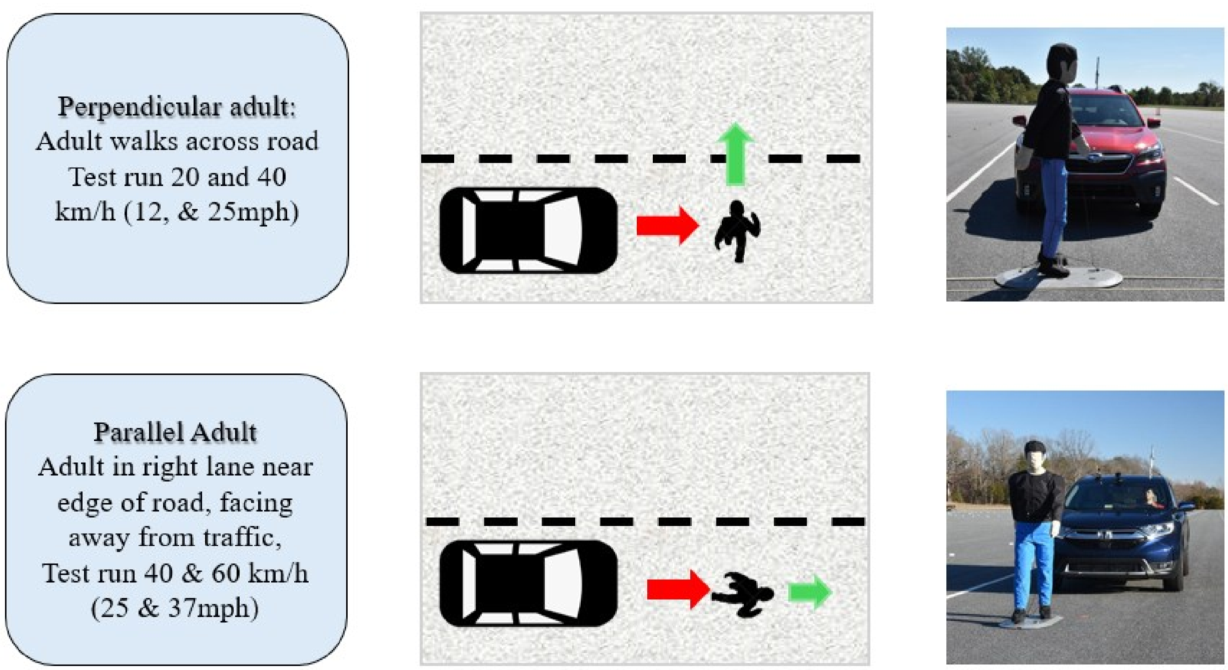

Figure 2: IIHS scenario settings

Data visualization

Detection of pedestrians:

The first step of the analysis is to assess the accuracy of P-AEB systems in detecting pedestrians across different visibility conditions. In the IIHS dataset, direct records of pedestrian detection are absent; thus, we used TTC for FCW as an indirect measure of detection effectiveness. For our analysis, instances where TTC for FCW is zero typically indicate non-detection, often leading to crashes. To verify these non-detections, we checked if maximum deceleration was zero (suggesting no braking response) and if speed reduction was zero, indicating no braking intervention before a crash. Furthermore, TTC for AEB, which should always be shorter than TTC for FCW since it represents the time until braking is activated post-detection, confirms the non-activation of the braking system.

In our findings, 13 tests reported a zero TTC for FCW without a crash and a high average deceleration, which was inconsistent; these were adjusted to the median TTC for FCW of 1.59 seconds. Additionally, 58 other tests with no crash and detection signs deviating from the rest of the data values were adjusted to this median to show successful detection. After corrections, our analysis confirmed 179 detection failures out of 2,494 tests, highlighting critical areas for enhancing the responsiveness and reliability of P-AEB systems to improve pedestrian safety under varied conditions.

Deceleration rate after detection

In this study, the average deceleration rate is measured. We utilized Python scripts to analyze speed data recorded at 0.01-second intervals across all 2,315 tests where detection was confirmed. These scripts helped pinpoint key moments in the deceleration process, including the initiation of braking, the stabilization of deceleration, and the vehicle's eventual stop, as shown in Figure 3. This study focuses on the moment the P-AEB system detects a pedestrian risk, not on vehicle speed before braking or at impact. While IIHS provides initial and impact speeds, we analyzed speed data between those points. We identified when the vehicle transitioned into steady deceleration by detecting a consistent slope in the speed-time curve. In many cases, we also reviewed speed-time plots to confirm this point. This helped us accurately estimate the average deceleration rate during the stable braking phase.

The average deceleration over a series of discrete data points was measured using these identified points. The calculated average deceleration rates were consistent with those reported in the literature, confirming the accuracy of our calculation (AASHTO, 2001; Savolainen et al., 2024). Reference studies suggest that in emergencies, deceleration can exceed 14.4 ft/s² (4.39 m/s²) when the driver is unexpectedly alerted to an event. Despite this, the observed rates in the controlled IIHS environment were typically lower, averaging 3.64 m/s², without exceeding the maximum deceleration recorded. These findings were incorporated into a Heckman regression model to analyze the efficacy of P-AEB systems further, ensuring both the accuracy and relevance of our results in assessing system performance. Additionally, Figure 4 illustrates the distribution of declarations and crash rates in each range. Higher deceleration rates tend to reduce the likelihood of crashes, underscoring the importance of effective braking systems in preventing crashes and informing further safety enhancements.

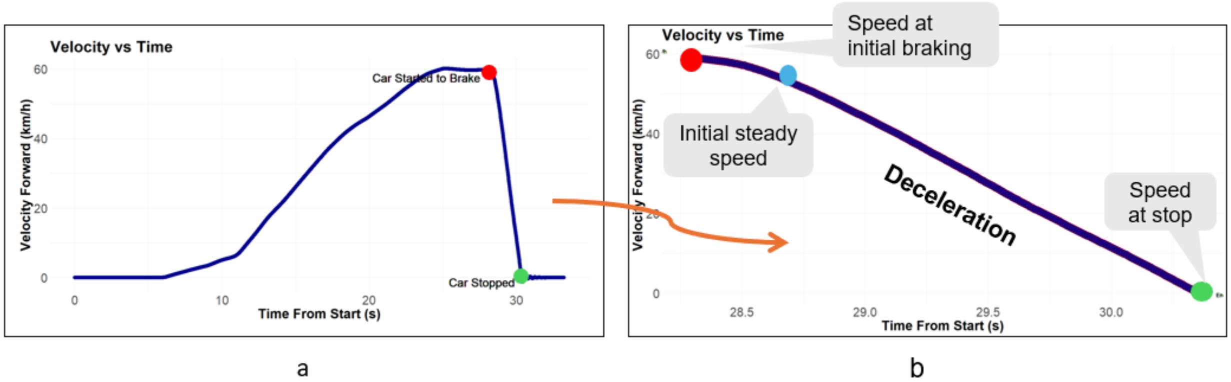

Figure 3: a) Complete Velocity-time Diagram, b) Close-up of Braking & Stopping Points

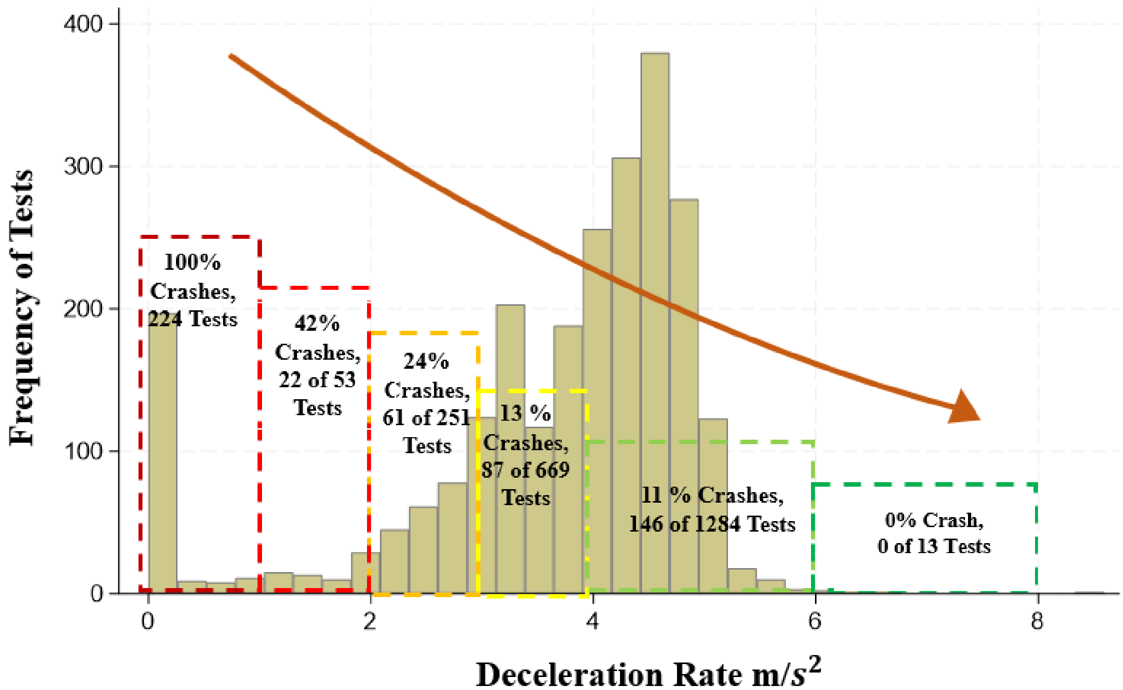

Figure 4: Deceleration Rate Distribution and Associated Crash Frequency

Table 2 represents a comprehensive description of the data under different lighting conditions. Breaking down the data by model car year, the distribution is relatively even across 2021 to 2024, with slight fluctuations in percentages. 2.4% of the tests are conducted by vehicles made in 2021. Most tests conducted during the day and at night were for models from 2022 and 2023, representing approximately 80% of the tests, indicating that newer vehicle models were predominantly used. For models manufactured in 2024, both day and night tests account for approximately 12% of the total.

Although the IIHS tests included minivans, these vehicles were not tested in both daytime and nighttime conditions; therefore, they are not included in this analysis. As a result, the study covers four specific vehicle categories: hatchbacks, sedans, SUVs, and pickup trucks. Among these, SUVs are particularly dominant, accounting for approximately 62% of all tests, underscoring their significant presence.

Regarding the testing scenarios, the tests were equally divided into four categories: CPNA_20, CPNA_40, CPLA_40, and CPLA_60, each representing different test speeds and pedestrian movement patterns. Each category accounts for approximately 25% of the tests conducted in both lighting conditions, demonstrating a balanced approach to testing across various dynamic driving scenarios that comprehensively evaluates the P-AEB systems.

Regarding sensor setups, although the internal processing algorithms of sensors are unavailable, these components are crucial because detection is the first step in activating the P-AEB system. The IIHS tests confirm that the P-AEB systems were active, enabling this research to investigate broad trends in pedestrian detection across different sensor configurations. About 14% of the vehicles tested relied solely on camera-based systems, while the remaining vehicles combined cameras with radar sensors. Although the study cannot directly establish causation, including sensor type as a variable helps explore possible associations with detection effectiveness. Most tested vehicles (around 95%) used LED headlights for both low and high beams, while only about 5% utilized halogen headlights.

Fuel-type analysis reveals that conventional vehicles were most frequently tested, accounting for over 75% of both day and night sessions, followed by EVs and hybrid vehicles. This reflects the current market distribution where gasoline vehicles still dominate, but with a significant representation of EVs and hybrid vehicles to test system efficacy across different powertrains. Additionally, the average curb weight of the vehicles tested is approximately 3,985.21 lbs., ranging from 2,821 to 5,625 lbs. The brake disc sizes average 12.85 inches, ranging from 10.80 to 14.70 inches. Additionally, the average tire aspect ratio is 56.09%, ranging from 40% to 75%, illustrating the diversity of vehicle specifications included in the study.

Table 2: Low Beam (n = 823 Tests), High Beam (n = 831 Tests), and Daytime (n = 840 Tests)

Variable	Category	Low Beam		High Beam		Day	
		Freq	**%**	**Freq**	**%**	**Freq**	**%**
Vehicle model year	**2021**	20	2.43	20	2.41	20	2.38
	2022	341	41.44	340	40.92	339	40.36
	2023	371	45.08	363	43.67	381	45.36
	2024	99	12.03	100	12.03	100	11.91
Scenario	**Perpendicular, 20 km/h test speed**	204	24.78	212	25.51	209	24.88
	Perpendicular, 40 km/h test speed	208	25.27	208	25.03	210	25.00
	Parallel, 40 km/h test speed	206	25.03	205	24.66	211	25.12
	Parallel, 60 km/h test speed	205	24.91	204	24.54	210	25.00
Vehicle Size	**Hatchback**	40	4.86	40	4.81	20	2.38
	Sedan	202	24.54	198	23.82	221	26.31
	SUV	501	60.80	512	61.60	519	61.79
	Pickup Truck	81	9.84	80	9.63	80	9.52
Fuel Type	**Conventional**	623	75.69	631	75.93	638	75.95
	EV	100	12.16	100	12.03	101	12.02
	Hybrids	100	12.16	100	12.03	101	12.02
Sensor Type	**Radar & Camera**	703	85.45	714	85.92	721	85.84
	Camera	121	14.70	116	13.95	119	14.16
Headlight Type	**Halogen**	41	4.98	40	4.81	-	-
	LED	782	95.02	791	95.19	-	-

Variable	**Mean**	**Max.**	**Min.**	**SD**
Brake disc size (in)	12.85	14.70	10.80	0.97
Curb weight (lbs)	3985.21	5625.00	2821.00	639.15
Tire aspect ratio (%)	56.05	75	40	8.09

Table 3 presents a detailed statistical analysis of variables, comparing nighttime low beam, high beam, and daytime datasets containing 823, 831, and 840 tests, respectively. As shown, Driver Alert Time (reported in IIHS data) during the day was slightly higher than at night for both low and high beams, with the lowest average observed under low beam conditions at night, 1.30 seconds. Additionally, average deceleration rates—including 179 zero values for non-detected tests—were slightly higher during the day than at night for both low and high beams, with less variability. This is likely due to earlier detection and quicker braking response in daylight. When excluding zero values and focusing only on detected tests, the average deceleration from brake initiation to stop was, on average, 3.87 m/s^2 for the low beam, 3.80 m/s^2 for the high beam, and 4.04 m/s^2 during the daytime.

The average maximum deceleration values reported in the IIHS data were 8.26 m/s^2 for the nighttime low beam, 9.04 m/s^2 for the nighttime high beam, and 9.66 m/s^2 during the daytime. When excluding tests with no detection (i.e., zero values), the averages increase slightly to 9.51 m/s^2 for low beam, 9.68 m/s^2 for high beam, and 9.80 m/s^2 for daytime. According to the American Association of State Highway and Transportation Officials (AASHTO), the 90th percentile deceleration rate for emergency braking is 3.41 m/s^2 (11.2 ft/s^2). This Greenbook rate is substantially lower than the maximum deceleration rates observed in the data (AASHTO, 2001; Fambro et al., 1997; Savolainen et al., 2024). The minimum was 0 m/s^2 across all conditions, indicating no braking occurred in some tests. Notably, the maximum deceleration rates were always greater than the average deceleration rate post-detection in all tests.

The table also reveals a pedestrian detection rate of approximately 87% at night, using low beam, rising to approximately 98% during the day. Crashes occurred in approximately 34% of nighttime low beam tests and approximately 21% of nighttime high beam tests, compared to approximately 11% during daytime conditions. Overall, vehicles performed better during the day, with higher detection rates, suggesting potentially less severe outcomes for pedestrians in daytime conditions.

Crash Speed data reveals a substantial difference in impact speed during crashes. Daytime crashes occur at significantly lower speeds (average 2.44 km/h) compared to nighttime high beam (average 5.30 km/h) and low beam (average 11.48 km/h), with much higher variability at night (SD of 18.96) than during the day (SD of 8.66). The crash speed metric includes results from all tests, encompassing those that did not result in a crash, where the crash speed is recorded as zero. This suggests that the effectiveness of mitigating impact speeds is diminished under night conditions.

Overall, these metrics indicate that P-AEB systems may respond more quickly during the daytime, and the effectiveness and reliability of these responses are more consistent than at night. This variability underscores the need for improvements in system performance under low-light conditions to ensure better and more consistent safety outcomes.

Table 3: Day vs. Night Vehicle Test Metrics

Variable	Metrics	Low Beam (N = 823 tests)	High Beam (N = 831 tests)	Day (N = 840 tests)
Driver Alert* Time	**Mean**	1.30	1.57	1.70
	Maximum	3.43	3.53	3.55
	Minimum	0.00	0.00	0.00
	SD	0.65	0.66	0.56
Average deceleration (m/s^2)	**Mean**	3.28	3.61	3.97
	Maximum	5.49	5.64	6.62
	Minimum	0.00	0.00	0.00
	SD	1.67	1.05	0.84
Average deceleration from brake initiation to stop (m/s^2)	**Mean**	3.78	3.87	4.04
	Maximum	5.49	5.64	6.62
	Minimum	0.05	0.07	0.20
	SD	1.14	0.95	0.84
Maximum* deceleration (m/s^2)	**Mean**	8.26	9.04	9.66
	Maximum	11.86	12.49	12.06
	Minimum	0.00	0.00	0.00
	SD	3.62	1.33	2.13
Maximum* deceleration (excluding zero value) (m/s^2)	**Mean**	9.51	9.68	9.87
	Maximum	11.86	12.49	12.06
	Minimum	0.79	0.54	1.20
	SD	1.85	1.351	1.72
Impact Speed (km/h) (including no crashes)	**Mean**	11.48	5.30	2.44
	Maximum	60.69	60.89	60.51
	Minimum	0	0	0
	SD	18.96	12.83	8.67
Successful Detection		86.75% (714)	93.26% (775)	98.33% (826)
Crash Occurance		33.65% (277)	20.57% (171)	10.95% (92)

*reported in IIHS data.

Figure 5 classifies all tests into successful or failed detections. When Driver Alert Time was zero, the average crash speed was 42.4 km/h. Of the 179 times the system failed to detect a pedestrian, 165 occurred at night, making up 92% of all detection failure crashes, with 62% of these instances happening under low beams. In contrast, when the system did detect the pedestrian, the average Driver Alert Time was 1.61 seconds, ranging from 0.45 to 2.86 seconds. Still, crashes happened in 15.6% of these cases (361 out of 2,315). Most of these crashes, 78% (283 cases), also happened at night: 46% under low beams and 32% under high beams, showing that high beams led to better system performance.

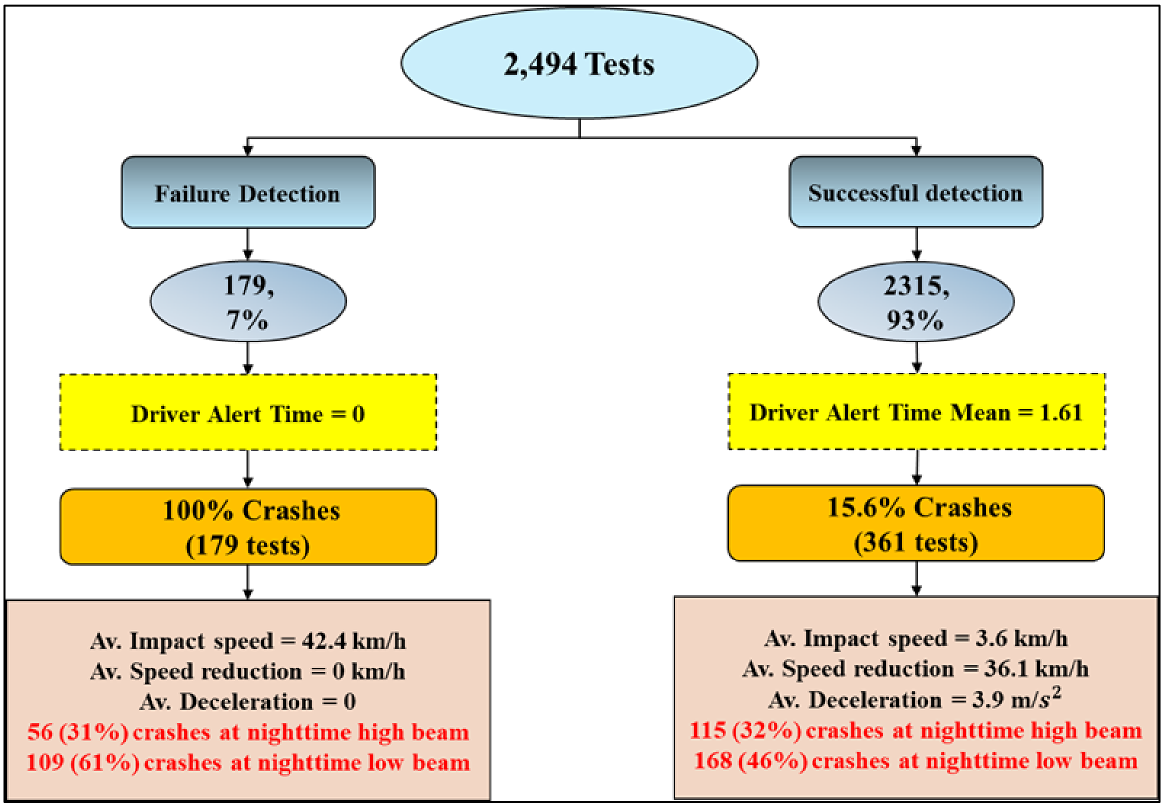

Figure 5: Distribution of Detection Time Across Different Test Speeds

Figure 6 shows that out of the 2315 tests (9% success rate), they were conducted at speeds of 20, 40, and 60 km/h, with detailed insights into Detection Time, average deceleration rates, and crash occurrences. At 20 km/h, covering 589 tests, the average Detection Time is approximately 1.27 seconds, with crashes occurring in 4.7% of cases. For the 40 km/h speed tests, which include both perpendicular and parallel pedestrian movements, the average Detection Time extends to 1.66 seconds, with 10.6% resulting in crashes. At a speed of 60 km/h, the Detection Time further increases to 1.85 seconds, yet 37.3% of these tests result in crashes. Overall, although a longer Driver Alert Time indicates earlier detection, higher vehicle speeds reduce the effectiveness of those alerts. Despite longer alert times at higher speeds, the incidence of crashes substantially increases, indicating a need for more effective deceleration strategies or even longer alert times to prevent crashes at higher speeds.

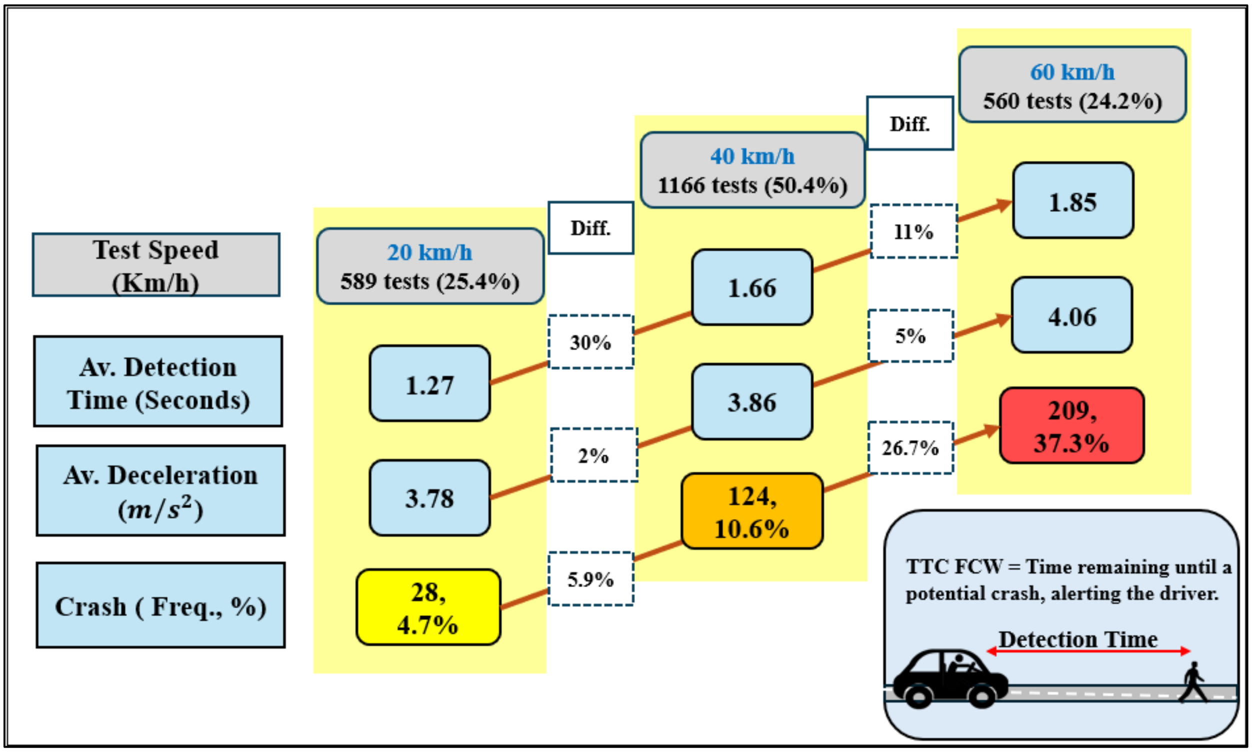

Figure 6: Detailed Analysis of Successfully Detected Tests (N=2315)

Figure 7 presents a detailed analysis of P-AEB system performance, focusing on detection rates and subsequent crash occurrences despite detection. It further explores the crash impact speeds and deceleration rates to provide deeper insights into the system's effectiveness under various conditions. In nighttime low beam tests, dummy pedestrians were not detected in 13% of tests, with an average impact speed of 44.6 km/h and a standard deviation of 13.7, showing high variability in impact speeds. Of the detected cases, 23% resulted in crashes, even after detection, with an average impact speed of 27.3 km/h, a high standard deviation of 15.6, and an average deceleration rate of 3.2 m/s² with a standard deviation of 1.6. For the 77% of detected cases that did not result in a crash, the average deceleration rate was 4.0 m/s² and a lower standard deviation of 0.9.

In nighttime tests under high beams, dummy pedestrians were not detected in 7% of tests, with an average impact speed of 39.0 km/h and a standard deviation of 14.9, indicating considerable speed variability. Of the detected cases, 15% still resulted in crashes, with an average impact speed of 19.4 km/h, a standard deviation of 13.1, and an average deceleration rate of 3.2 m/s² (SD = 1.4). The average deceleration rate for the 85% of detected cases that avoided crashes was 4.0 m/s², with a lower standard deviation of 0.8.

However, during the daytime, dummy pedestrians were not detected in only approximately 2% of tests, with an average impact speed of 38.6 km/h and a standard deviation of 16. Of the detected pedestrians, crashes occurred in 10% of the cases, with an average impact speed of 20.5 km/h, a standard deviation of 12.6, and a deceleration rate of 3.5 m/s^2 with a standard deviation of 1. Notably, in 90% of the detected cases where crashes were avoided, the average deceleration rate was 4.1 m/s^2 with a standard deviation of 0.8, effectively stopping the vehicles before impact. These results, shown in the figure, underscore the critical role of effective detection and deceleration in enhancing pedestrian safety, particularly highlighting how nighttime conditions, especially low beam, challenge the performance of P-AEB systems more than daytime scenarios.

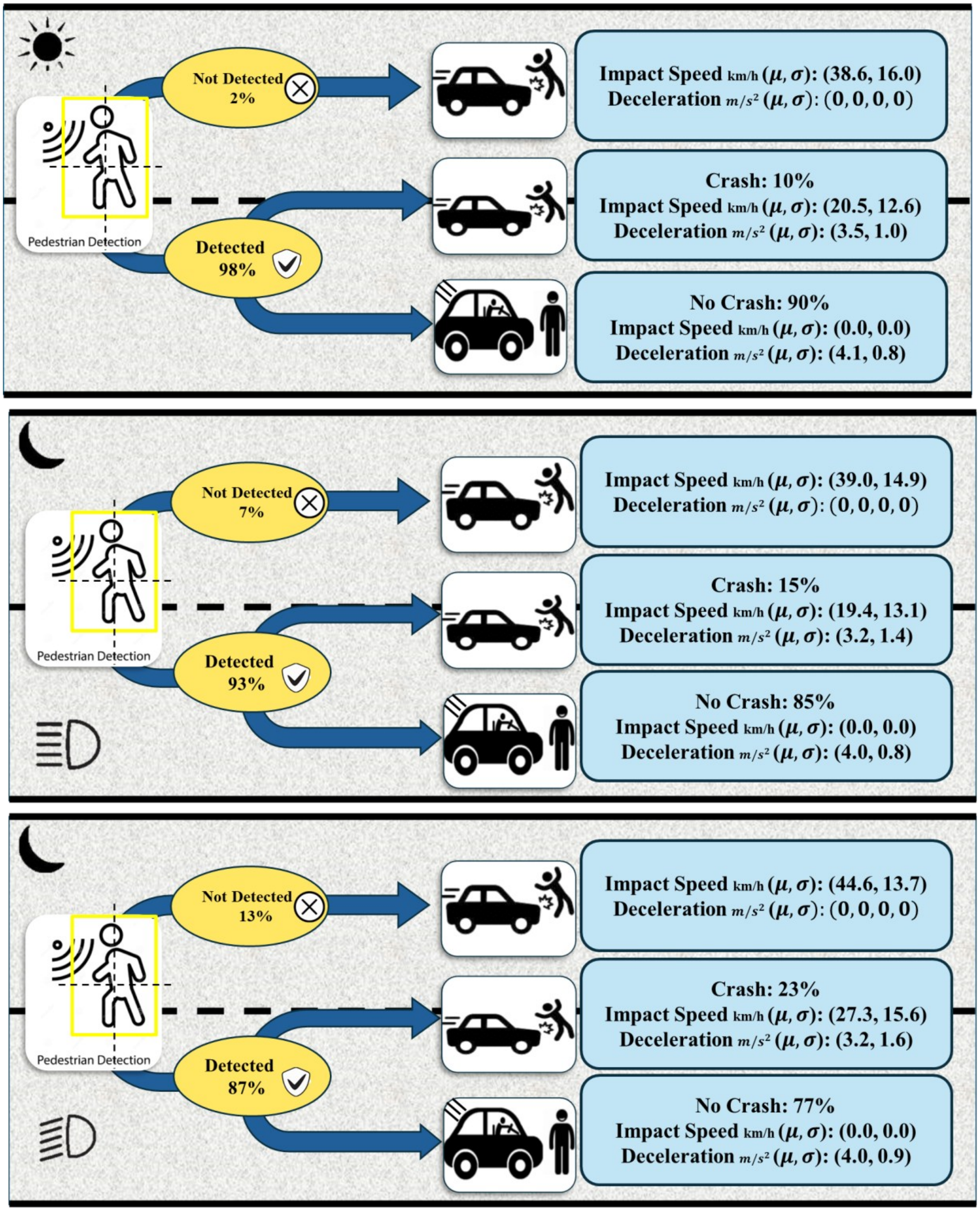

Figure 7: Detection Rates and Crash Occurrence at Daytime & Nighttime

Figure 8 illustrates the performance of P-AEB systems across various scenarios, demonstrating variations in detection rates and impact speeds depending on test speeds and pedestrian movements. Detection failure remains nearly constant in daytime scenarios but varies from 7.9% to 13.4% at night, with the higher rates in scenario 4. Scenario 4 also records the highest average impact speeds, particularly at night, underscoring better system effectiveness in well-lit conditions. The data suggests that visibility significantly contributes to detection rates and system performance.

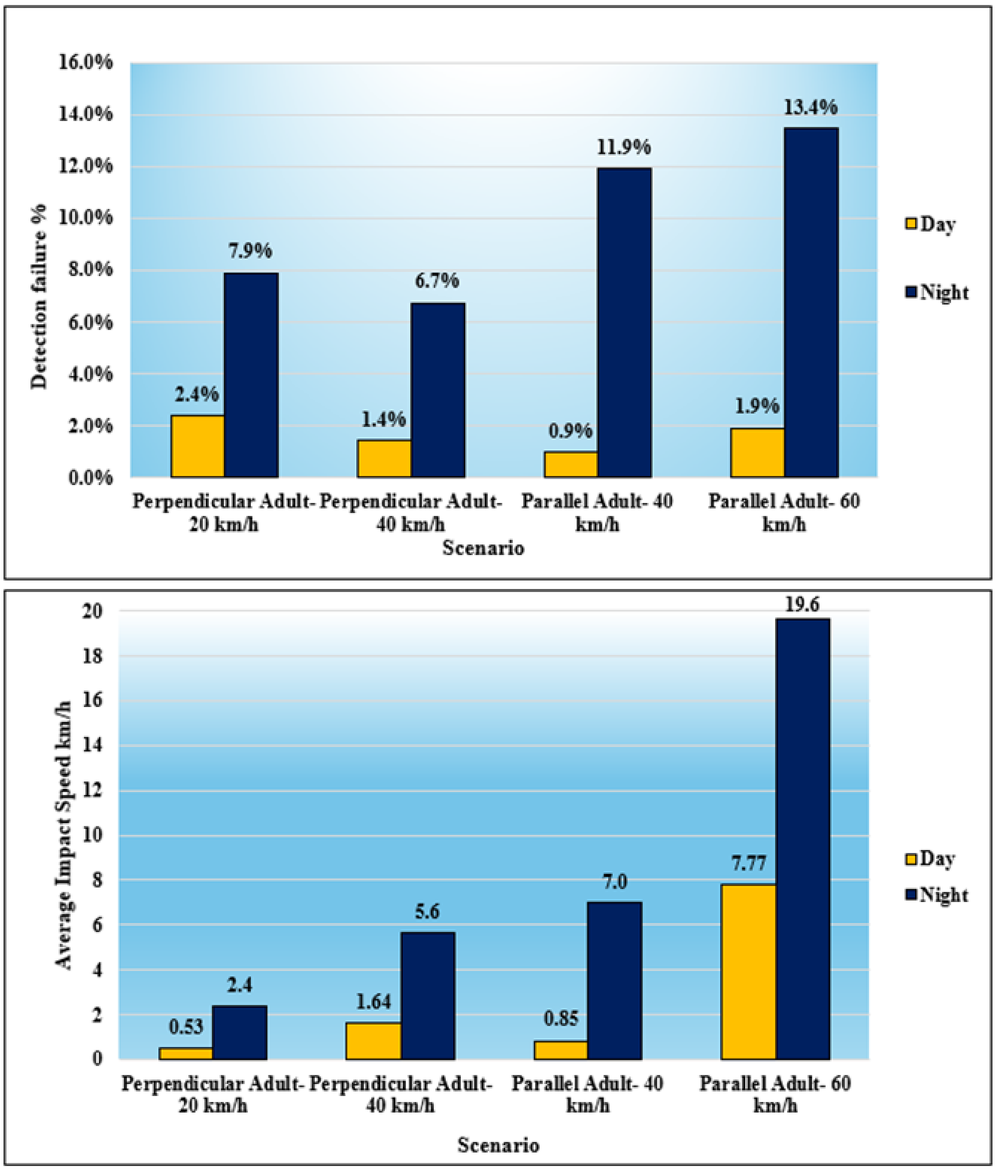

Figure 8: Performance of P-AEB Systems Across Different Scenarios and Lightings

In addition to analyzing detection, the study conducted crash-only tests to assess the impact of lighting and speed on crash outcomes. Figure 9 focuses on 540 crash cases, revealing that only 17% occurred during the day, while 51% happened at night under low-beam lighting conditions, also linked to higher average crash speeds. Crash frequency and speed increased with test speed across all lighting conditions. For example, under high beams, the average crash speed rose from 17.5 km/h at a 20 km/h test speed to 31.4 km/h at a 60 km/h test speed. The most concerning results were under low beams at 60 km/h, with an average crash speed of 40.6 km/h, indicating poor detection and higher impact severity. In contrast, daytime tests consistently showed lower crash speeds, highlighting the role of visibility in reducing crash risks.

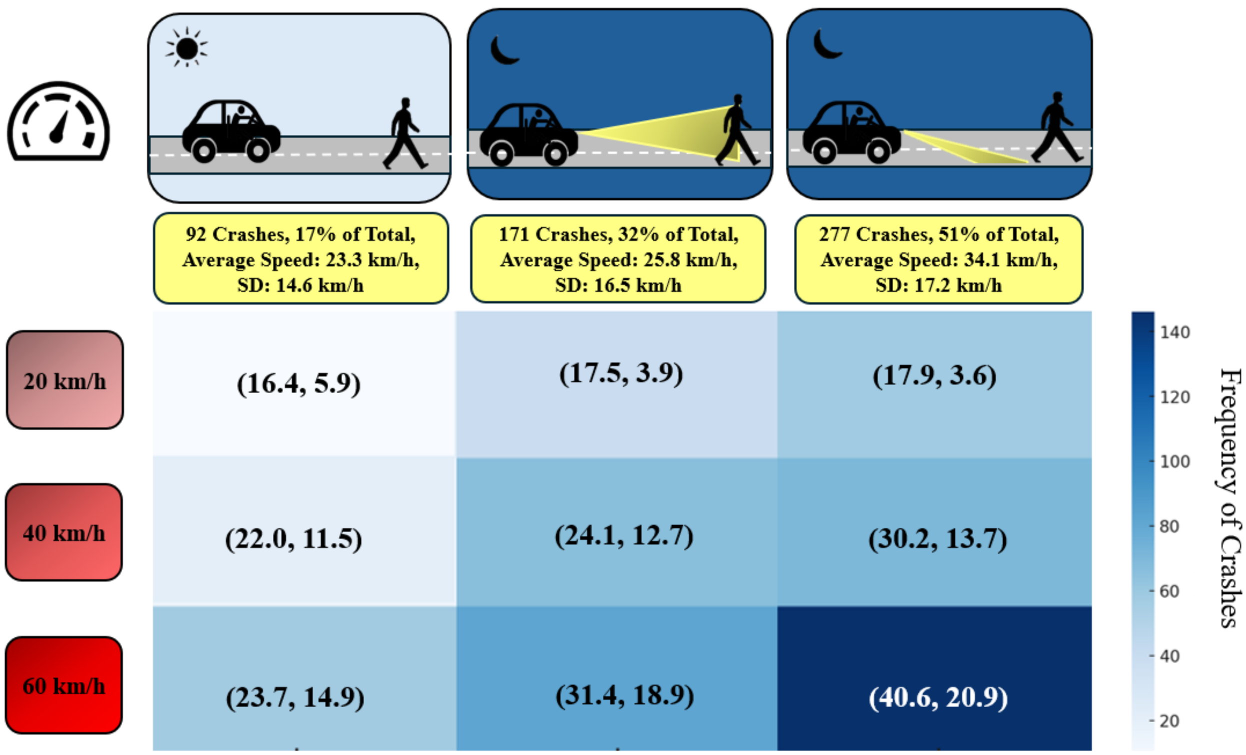

Figure 9: Crash Speed Metrics (μ, σ) For Various Lighting & Test Speeds (Crashes =540)

Figure 10 also presents the kernel density distribution of crash speeds, excluding no-crash tests, across three lighting conditions. Daytime tests (yellow lines) exhibit a consistent pattern, with speeds clustering around 20 km/h and an average crash speed of 23.3 km/h, indicating stable driving behavior during daylight hours. High beam tests (blue lines) reveal slightly higher variability and an average crash speed of 25.8 km/h. In contrast, low beam tests (brown dashed lines) show the widest spread, with multiple peaks and an average speed of 34.1 km/h. This suggests greater inconsistency in driver response and visibility under low-light conditions, contributing to more severe crashes.

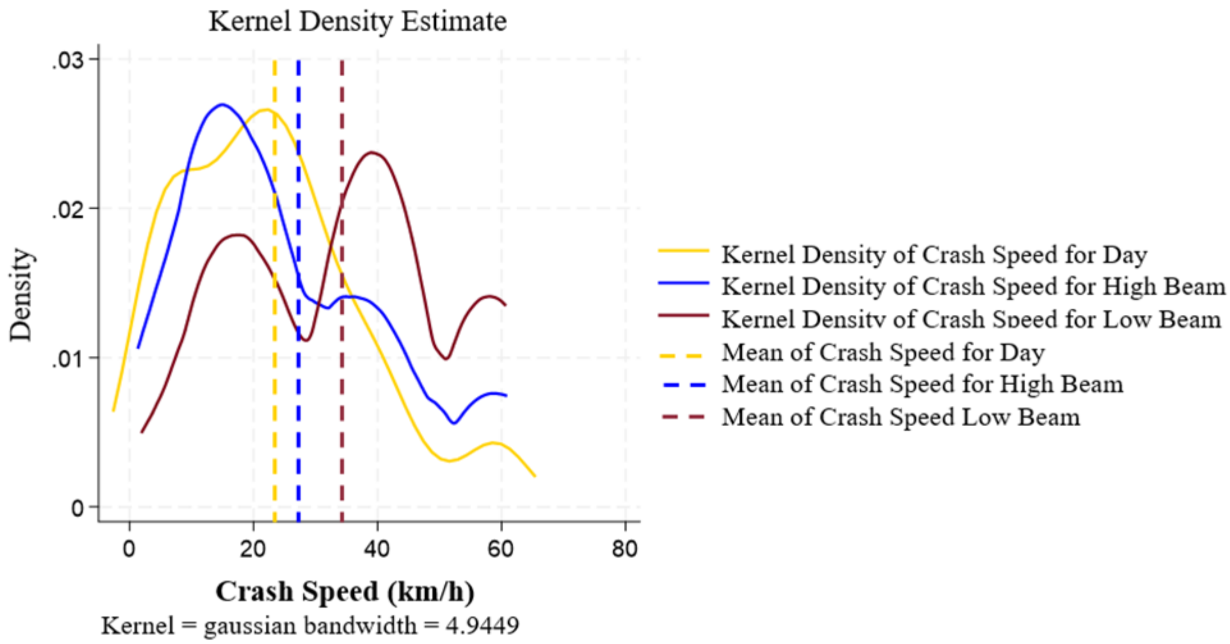

Figure 10: Density Plot of Crash Speed with Mean Lines

Results

The study's results are structured into two distinct sections. Initially, the analysis focuses on the pre-crash phase, examining the detection capabilities and deceleration rates of the P-AEB systems. Subsequently, the study shifts to assessing the crash itself, specifically analyzing the crash occurrence and the speeds involved at the time of impact. This dual-phase approach allows for a comprehensive understanding of both the effectiveness of preventive measures and the dynamics of the crashes.

Vehicle-related factors, such as fuel type, size, sensor type, and model year, are included as fixed effects to capture observable correlations with system performance. The random intercepts at the panel level (vehicle model × scenario) account for unobserved heterogeneity across test conditions. This means the model allows each vehicle-scenario group to have its baseline, helping control for hidden differences not directly measured in the dataset. Together, the fixed and random components provide a more accurate estimate of the parameters.

Detection & Deceleration Section

The result of the random effects Heckman sample selection model with the dependent variable of pedestrian detection in the first step and the average deceleration rate in the second step, where the model focuses on tests where detection occurs, is shown in Table 4 and is explained in detail as follows:

P-AEB system performance, Dependent variable = Detected or Not Detected:
This section examines the correlates of pedestrian detection, including sensor configurations, environmental conditions, and algorithm limitations, each of which plays a crucial role in how automated systems identify nearby pedestrians. Lighting conditions are also strongly associated with detection rates. Compared to daytime, detection drops by 43% under halogen low beams, 20% under LED low beams, 7% under halogen high beams, and 3% under LED high beams, after controlling for other factors.

Detection is further correlated with vehicle speed, with lower speeds improving detection rates relative to the 60 km/h baseline in parallel adult scenarios (as expected). Newer models (2023–2024) showed a 12% increase in detection, and smaller vehicle types (hatchbacks and sedans) were associated with a 7% improvement. Among these, sensor type is especially important: vehicles equipped with both camera and radar showed an 8% higher detection rate than those using camera-only systems, highlighting the benefit of sensor fusion in improving P-AEB performance. These insights underscore the importance of sensor technology and system design in enhancing P-AEB effectiveness.

Braking system performance, Dependent variable = Average deceleration rate:
This section examines key variables that correlate with the average deceleration rate as measured in this study, and their distribution is depicted in Figure 4. The findings indicate that hybrid vehicles tend to have lower deceleration rates than conventional vehicles, with a significant

negative coefficient of -0.52, while EV is marginally significant. Detection Time significantly contributes to deceleration with a coefficient of 0.45, indicating that earlier detection or prolonged detection times in seconds could provide more time for achieving a higher deceleration rate. Larger vehicles exhibit a reduced ability to decelerate quickly, as negative coefficients indicate challenges with rapid braking in heavier vehicles. Improvements in braking are also linked to specific features, such as front brake discs, which positively contribute to deceleration with a coefficient of 0.37. Moreover, tires with lower aspect ratios are marginally associated with improved vehicle handling and stability at high speeds, which enhances deceleration. Lastly, newer vehicle models are shown to have more effective braking systems than older ones.

The model's summary of statistics:
The model calculates variances for error terms in deceleration rates (0.48), panel-level deceleration rates (0.47), and detection (3.50), showing significant correlations between these error terms ($z = -2.15$, $p < 0.001$) and among panel-level results ($z = 2.32$, $p < 0.001$). These findings underscore the importance of considering both selection effects and unobserved heterogeneity in the analysis. Additionally, the model demonstrates a strong fit, evidenced by an R-squared value of 0.22 and a highly significant Wald $\chi2$ statistic of 128.01 ($p < 0.0001$).

Table 4: Result of Detection & Deceleration Rate Model (N=2,494)

Average Deceleration Rate (m/s^2)					
Variable		Coefficient	z	P>|z|	
Fuel type (Base = Conventional vehicles)	**EVs**	-0.34	-1.85	0.07	
	Hybrid Vehicles	-0.52	-2.85	0.00	
Detection Time (seconds)		0.45	9.06	0.00	
Curb Weight (lbs) (Base ≤ 3100)	**3100 - 4900**	0.68	2.40	0.02	
	>4900	1.05	2.61	0.01	
Tire Aspect Ratio		-0.02	-1.85	0.06	
Brake Front Disc		0.37	4.84	0.00	
Newer Vehicles (Base =2021 & 2022)	**2023 & 2024**	0.46	3.84	0.00	
Constant		-0.39	-0.25	0.81	
Selection Model: Detected=1, Not detected=0					dy/dx
Lighting Condition (Base = Daytime)	**Low beam Halogen**	-4.87	-5.94	0.00	-0.43
	High beam Halogen	-3.19	-4.25	0.00	-0.20
	Low beam LED	-1.86	-7.96	0.00	-0.07

Average Deceleration Rate (m/s²)					
Variable		Coefficient	z	P>|z|	
Fuel type (Base = Conventional vehicles)	**EVs**	-0.34	-1.85	0.07	
	Hybrid Vehicles	-0.52	-2.85	0.00	
Detection Time (seconds)		0.45	9.06	0.00	
Curb Weight (lbs) (Base ≤ 3100)	**3100 - 4900**	0.68	2.40	0.02	
	>4900	1.05	2.61	0.01	
Tire Aspect Ratio		-0.02	-1.85	0.06	
Brake Front Disc		0.37	4.84	0.00	
Newer Vehicles (Base =2021 & 2022)	**2023 & 2024**	0.46	3.84	0.00	
Constant		-0.39	-0.25	0.81	
	High beam LED	-1.08	-4.66	0.00	-0.03
Vehicle Model Year (Base = 2021 & 2022)	**2023 & 2024**	2.11	3.80	0.00	0.11
Scenario (Base = CPNA_25, 20 km/h test speed)	**CPNA_25, 40 km/h test speed**	-0.07	-0.10	0.92	-0.0
	CPLA_25, 40 km/h test speed	-1.64	-2.44	0.02	-0.07
	CPLA_25, 60 km/h test speed	-1.70	-2.48	0.01	-0.08
Vehicle Size (Base = SUVs & Pickup Trucks)	**Hatchbacks & Sedans**	1.64	2.46	0.01	0.07
Sensors Type (Base = Camera)	**Camera & Radar**	1.22	2.11	0.04	0.08
Constant		3.42	4.18	0.00	
Var (Error Deceleration Rate)		0.48			
Var (Deceleration Rate [Panel])		0.47			
Var (Detection [Panel])		3.50			
Summary of Statistics					
Ru=0.22			**Prob > χ2 = 0.00**		
Number of observations= 2,494			**Selected = 2315**		
Wald χ2 (8) = 128.01			**Nonelected = 179**		
Observations per group: Min. = 12,	**Mean. = 15.6,**	**Max. = 27**	**Number of groups = 160**		
Corr (Error Detection, Error Deceleration Rate) = -0.27 | z = -2.15, P>|z| = 0.000					

Average Deceleration Rate (m/s²)				
Variable		Coefficient	z	P>|z|
Fuel type (Base = Conventional vehicles)	**EVs**	-0.34	-1.85	0.07
	Hybrid Vehicles	-0.52	-2.85	0.00
Detection Time (seconds)		0.45	9.06	0.00
Curb Weight (lbs) (Base ≤ 3100)	**3100 - 4900**	0.68	2.40	0.02
	>4900	1.05	2.61	0.01
Tire Aspect Ratio		-0.02	-1.85	0.06
Brake Front Disc		0.37	4.84	0.00
Newer Vehicles (Base =2021 & 2022)	**2023 & 2024**	0.46	3.84	0.00
Constant		-0.39	-0.25	0.81
Corr (Detection [Panel], Deceleration Rate [Panel]) = 0.29 | z = 2.32, P>|z| = 0.000				

Crash Occurrence & Impact Speed Section

The result of the random effects Heckman sample selection model with the dependent variable of crash occurrence in the first step and crash speed in the second step, where the model focuses on tests where the crash occurs, is shown in Table 5 and is explained in detail as follows:

P-AEB system performance, Dependent variable = Crash occurrence:

The selection model for crash occurrence in the table uses a logistic regression approach to differentiate between crash (1) and no crash (0) tests, utilizing various predictors such as vehicle type, lighting conditions, and scenario specifics. Notably, nighttime conditions, especially with halogen low beams, significantly increase the probability of a crash by up to 31%. Under LED low beams, the increase is up to 10%. High beams help reduce this risk: the marginal effect drops to 6% with LED high beams and 12% with halogen high beams. The results also highlight the protective effect of newer vehicle models (2023 and 2024), which reduces crash likelihood compared to the baseline years of 2021 and 2022, albeit marginally significant (p = 0.06). Moreover, different vehicle sizes exhibit varied impacts on crash probabilities, with larger vehicles, including SUVs and pickup trucks, showing a higher likelihood of crashes compared to smaller hatchbacks and sedans. The analysis demonstrates that higher test speeds of 40 and 60 km/h significantly increase crash occurrence, boosting the likelihood of crashes by 12% to 46% compared to tests conducted at 20 km/h.

P-AEB system performance, Dependent variable = Impact Speed (km/h):

The crash speed model analysis focuses on the factors contributing to the impact speed. Key findings indicate that the combination of camera and radar performs better, especially during the daytime, compared to camera-only systems at night. Additionally, using only a camera at night is associated with a higher impact speed. Hybrid vehicles typically increase impact speeds by about 4.27 km/h compared to conventional vehicles, while EVs show a marginally significant positive coefficient contributing to a decrease in crash speed. A higher deceleration rate could significantly reduce impact speed, emphasizing its vital role in lessening the severity of crashes. Activation time, notably, has a substantial negative correlation with impact speed, indicating that quicker system response times are crucial for reducing the speed at impact. The analysis across different scenarios reveals notable variations in impact speeds, particularly in tests involving parallel pedestrian movements. Comparing parallel scenarios at a test speed of 40 km/h with the baseline parallel scenario at 20 km/h reveals a potential increase in crash speeds, highlighting how parallel configurations could intensify crash impacts compared to perpendicular configurations at the same speed.

The model's summary of statistics:

The model reveals variances for error terms associated with impact speed (35.53), panel-level impact speed (27.19), and crash occurrence (2.01), with strong correlations demonstrated between these error terms ($z = 2.08$, $p < 0.001$) and among panel-level results ($z = 3.93$, $p < 0.001$). These correlations highlight the importance of considering both selection effects and unobserved heterogeneity in statistical analysis. The model also shows the R-squared value of 0.22 and a highly significant Wald $\chi 2$ of 1174.76 ($p < 0.0001$).

Table 5: Result of Crash Occurrence & Impact Speed Model (N=2,494)

Impact Speed (km/h)					
Variable		**Coefficient**	**z**	**P>|z|**	
Fuel type (Base = Conventional vehicles)	**EVs**	-4.29	-1.80	0.07	
	Hybrid Vehicles	4.27	2.09	0.04	
Deceleration rate (m/s2)		-3.38	-13.86	0.00	
Scenario (Base = CPNA_25, 20 km/h test speed)	**CPNA_25, 40 km/h test speed**	19.70	7.85	0.00	
	CPLA_25, 40 km/h test speed	17.08	6.88	0.00	
	CPLA_25, 60 km/h test speed	34.24	14.28	0.00	
Activation Time (Seconds)		-20.16	-18.22	0.00	
Sensors Type (Base = Camera & Radar - Night)	**Camera & Radar-Night**	2.65	3.27	0.00	
	Camera at Day	4.28	1.05	0.30	
	Camera at Night	9.03	4.28	0.00	
Constant		18.59	7.57	0.00	
Selection Model: Crash =1, No Crash=0					dy/dx
Lighting Condition (Base = Daytime)	**Low beam Halogen**	2.19	2.25	0.03	0.31
	High beam Halogen	1.01	2.03	0.04	0.10
	Low beam LED	1.21	7.34	0.00	0.12
	High beam LED	0.69	4.68	0.00	0.06
Vehicle Model Year (Base =2021 & 2022)	**2023 & 2024**	-1.03	-3.74	0.00	-0.06
Scenario (Base = CPNA_25, 20 km/h test speed)	**CPNA_25, 40 km/h test speed**	2.09	4.78	0.00	0.15
	CPLA_25, 40 km/h test speed	1.86	4.21	0.00	0.12
	CPLA_25, 60 km/h test speed	4.47	9.64	0.00	0.46
Vehicle Size (Base = Hatchbacks & Sedans)	**SUVs**	0.72	2.41	0.02	0.04
	Pickup Trucks	1.49	3.41	0.00	0.20
Activation Time (Seconds)		-3.50	-13.12	0.00	-0.32

Constant	-1.25	-2.66	0.01
Var (Error Impact Speed)	35.53		
Var (Impact Speed [Panel])	27.19		
Var (Collied [Panel])	1.72		
Summary of Statistics			
Ru=0.22			**Prob > χ2 = 0.00**
Number of observations = 2,494			**Selected = 540**
Wald χ2 (8) = 1243.37			**Nonelected = 1954**
Observations per group: Min. = 12, Mean. = 15.6, Max. = 27			**Number of groups = 160**
Corr (Error Detection, Error Deceleration Rate) = 0.25 | z = 2.08, P>|z| = 0.000			
Corr (Detection [Panel], Deceleration Rate [Panel]) = 0.55 | z = 3.93, P>|z| = 0.000			

Discussion

Our research evaluates and compares the performance of P-AEB systems under varying lighting conditions (day versus night) using the IIHS dataset. In the first stage, we examine the systems' effectiveness in detecting pedestrians and initiating deceleration prior to a potential crash. The second stage focuses on analyzing the occurrence of crashes and the resulting crash speeds as outcomes following the detection of an imminent crash. All aspects of P-AEB systems are evaluated and compared in this study, which includes 2,494 tests on 42 low-level automated vehicles equipped with P-AEB, conducted under controlled settings by IIHS. This study aims to provide comprehensive insights into how P-AEB systems perform under various lighting scenarios, which is crucial for enhancing pedestrian safety in real-world driving conditions.

Firstly, the effectiveness of P-AEB systems in detecting pedestrians and preventing crashes varies notably by lighting condition. Detection rates were highest during the day (98%), followed by night with high beams (93%) and low beams (87%). However, detection did not always prevent crashes. Among detected cases, the highest crash rate occurred under low-beam conditions at night (23%), followed by high beam (15%), and daylight (10%). When considering all tests, regardless of detection, the overall crash rates were approximately 11% during the day, increasing to 21% and 34% at night under high and low beams, respectively. These findings highlight the system's reduced effectiveness in low-light conditions. The model's results also confirm the superior performance of P-AEB systems in daytime scenarios.

After analyzing the detection conditions, it was found that out of 540 crashes, 179 were not detected by the P-AEB systems. The remaining 361 crashes, although successfully detected by the P-AEB systems, emphasize the critical importance of not just detection but timely detection. These incidents suggest that while the system was able to recognize the pedestrian, the delay in detection may have limited the system's ability to fully prevent the crash. This highlights a key limitation in current P-AEB performance—detecting too late can still result in a crash, especially at high speeds and under challenging conditions like nighttime driving; notably, among these 361 tests, 283 cases (approximately 78%) occurred during nighttime.

More detailed research on lighting also shows that at night, systems equipped with LED headlights outperformed those with halogen: halogen low beams were associated with up to a 43% increase in non-detection compared to daytime, likely due to poorer illumination and narrower beam patterns, consistent with the findings of (Moradloo et al., 2025a). Regarding impact speed, results showed that impacts were generally lower during the day than at night, with greater variability in daytime conditions, suggesting that daytime collisions may be less severe.

Once the FCW system completes its function, effective braking becomes critical. Observations show that vehicle deceleration is generally stronger and more consistent during the daytime, likely due to improved detection in better lighting conditions. The model analysis highlights the importance of this variable, emphasizing that a reliable braking system plays a key role in preventing crashes. The findings further demonstrate that strong and timely deceleration could significantly reduce crash speeds when they are unavoidable, reinforcing the need for continued improvements in braking technologies to lessen crash severity (Coelingh et al., 2010).

After examining detection performance and vehicle deceleration, it is essential to turn attention to crash speed outcomes, which provide valuable insights into vehicle behavior when crashes cannot be avoided. The analysis of crash speeds reveals that nighttime crashes are more severe than daytime ones. Specifically, the average crash speed at night is 34.1 km/h under low beam lighting and 25.8 km/h under high beam lighting, compared to 23.3 km/h during the day among these 540 crashes. Additionally, crash speeds during the day are more consistent, whereas nighttime tests show greater variation, highlighting increased uncertainties in the performance of the P-AEB system during nighttime conditions. This could be due to the reduced effectiveness of detecting pedestrians in darker situations, consistent with previous studies (Cicchino, 2022; Kullgren et al., 2023).

These findings highlight the challenges that P-AEB systems face in consistently detecting pedestrians and effectively preventing crashes in varying lighting conditions throughout the day and night. The effectiveness of these systems varies significantly between daylight and darkness, underscoring the need for technological improvements that enhance detection accuracy and response efficacy under all conditions. For a deeper understanding of crash prevention and detection, it is important to consider several key variables associated with P-AEB systems' effectiveness.

For instance, when examining the main components of P-AEB systems, it becomes evident that FCW and AEB systems play crucial roles. Their performance is significantly enhanced when they operate earlier and with greater accuracy, leading to more effective outcomes. Early and precise detection and response are crucial in reducing the likelihood and severity of crashes, underscoring the importance of these systems in enhancing road safety (Zhao et al., 2017). To better clarify the importance of these systems, Figure 11 compares crash and non-crash tests under various lighting conditions, focusing on detection time, activation time, and deceleration rate. Even small differences in these metrics significantly impact pedestrian safety. For instance, under high beams, activation time averages 1.10 seconds in non-crash cases versus 0.62 seconds in crash cases—a seemingly minor gap with major safety implications. The findings emphasize that timely detection, rapid activation, and sufficient deceleration are critical in reducing crash severity and improving pedestrian protection.

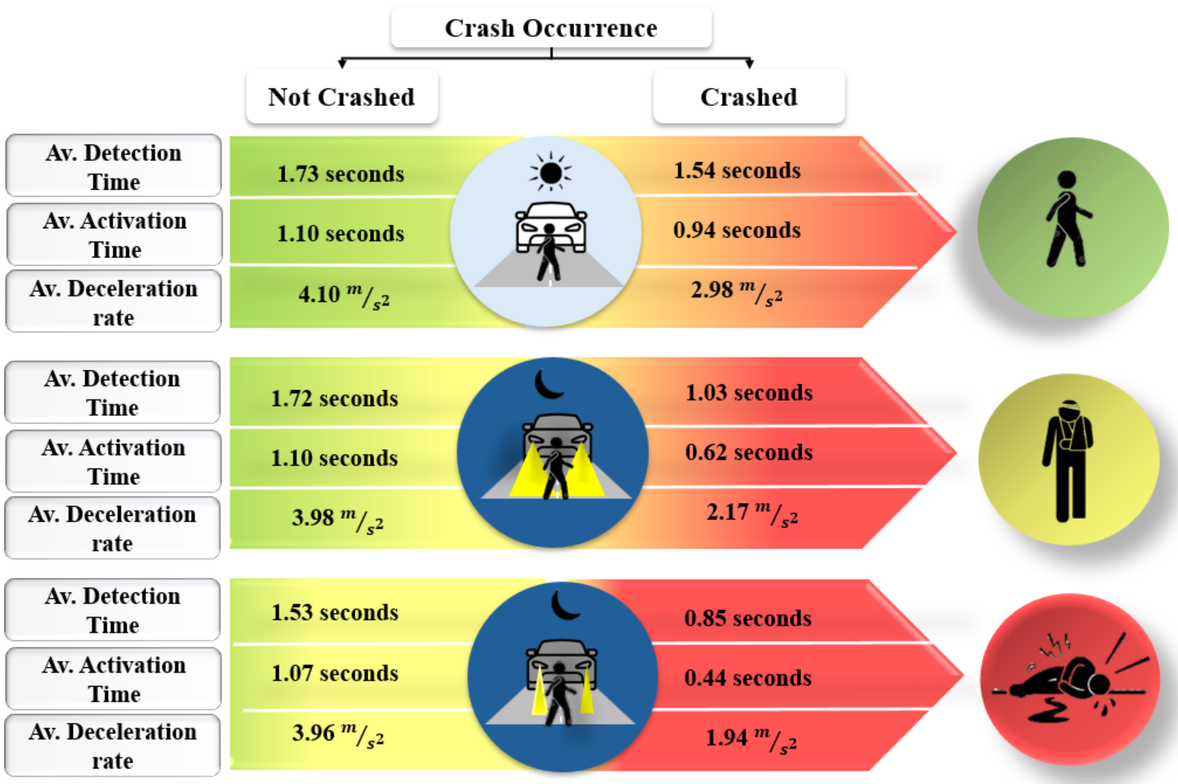

Figure 11: Comparison of P-AEB performance in Terms of Crash Occurrence

In terms of vehicle characteristics, the study highlights significant differences in P-AEB system performance based on vehicle size, braking systems, fuel type, sensor technologies, and model year, as numerous studies suggest (Nogayeva et al., 2021; Rosen et al., 2011). Smaller vehicles, such as hatchbacks and sedans, typically outperform larger ones, like SUVs and pickup trucks, likely due to better sensor placement and design factors, including sensor height (Khattak & Rocha, 2003). Additionally, their lower weight not only contributes to faster braking once a potential hazard is successfully detected, thereby enhancing their overall safety performance but also smaller vehicles, such as hatchbacks and sedans, possess less mass, which reduces their momentum and makes it easier to slow down or stop quickly compared to larger vehicles (Mahdinia et al., 2022; Skrucany et al., 2020).

The strategic installation and dynamic adjustment capabilities of radar sensors enhance the ability of these vehicles to estimate positions under various traffic conditions precisely. This is especially critical in complex driving environments where swift detection and response are necessary (Haus et al., 2021). Additionally, integrating camera systems that provide detailed semantic views complements radar systems, particularly under adverse weather conditions where radar has an advantage. This combination allows for a more comprehensive environmental analysis, enabling the radar to quickly detect an object while the camera confirms its identity, a feat less achievable with cameras alone (Combs et al., 2019; Jannat et al., 2020)

Regarding fuel types, although both hybrid vehicles and EVs tend to exhibit lower deceleration performance compared to conventional vehicles (Previati et al., 2024), their crash outcomes differ. In our analysis, hybrid vehicles were associated with significantly higher impact speeds, which may be explained by their blended braking systems and slightly elevated center of gravity. The brief transition between regenerative and friction braking can introduce lag in brake force delivery, while the added mass of the battery and control hardware can compromise pitch stability during emergency deceleration (Bayar et al., 2013; Li et al., 2024; Vodovozov et al., 2021).

EVs, on the other hand, showed marginally lower impact speeds compared to conventional vehicles despite similar deceleration limitations. This outcome is likely due to design advantages, including floor-mounted battery packs that lower the center of gravity and improve stability (Li et al., 2024; Previati et al., 2024). Additionally, EVs rely on consistent, instantaneous torque delivery and default to conventional hydraulic braking at higher speeds, which may help compensate for the reduced effectiveness of regenerative braking (Fujimoto et al., 2012; Shenberger & Antanaitis, 2018). These distinctions collectively help explain why hybrid vehicles exhibited significantly higher crash impact speeds, while EVs did not.

Consistent with previous studies (Mahdinia et al., 2022; Parekh et al., 2022), the results show that P-AEB systems in vehicles manufactured in recent years exhibit enhanced performance compared to older models, indicating a trend towards more effective vehicle technologies. These improvements are attributed to advancements in pedestrian detection technologies, artificial intelligence systems, sensor quality, and the integration of overall safety systems, including superior braking systems. These developments underscore a promising trend in enhancing vehicle safety features, particularly in protecting VRUs. Key elements like tire aspect ratios and front brake disc sizes are vital for effective deceleration in emergencies. These components are important in enhancing vehicle safety through improved braking performance (Sokolovskij & Žuraulis, 2024).

This study shows that the effectiveness of pedestrian detection is closely linked to both pedestrian movement patterns and vehicle speed. Using three standardized test speeds (20, 40, and 60 km/h) as applied by IIHS, it was observed that detection systems perform best when pedestrians move perpendicularly to the vehicle at lower speeds, such as 20 km/h, likely due to increased reaction time. In contrast, detection becomes less reliable at higher speeds and during parallel pedestrian movement, particularly when pedestrians face away from the vehicle. These dynamics are also associated with crash outcomes—pedestrians moving parallel at 60 km/h were associated with up to a 46% higher crash probability compared to those moving perpendicularly at 20 km/h. Interestingly, at 40 km/h, perpendicular movement resulted in slightly higher crash frequencies and speeds than parallel movement, possibly due to later detection or reduced system sensitivity to sudden lateral motion. These findings highlight the critical role of pedestrian movement and speed in both detection reliability and crash severity, aligning with prior research and emphasizing the need to enhance P-AEB performance across diverse real-world scenarios (Mahdinia et al., 2022).

Improving detection is essential for addressing limitations in sensing and perception technologies, particularly under low-light conditions where P-AEB systems still face challenges. While performance is stronger during the day, enhancing nighttime capabilities is critical for reducing pedestrian crash severity and improving overall safety (Boggs et al., 2020; Moradloo et al., 2024). Advancements in safety features, especially in low-level automated vehicles, play a key role in protecting vulnerable road users and reducing crashes. These systems, which combine automation with active driver involvement, mark an important step toward safer, more efficient transportation, bridging the gap between manual driving and full autonomy.

Conclusions and Recommendations

Recent studies have highlighted a significant rise in pedestrian fatalities and severe injuries, particularly under nighttime conditions, underscoring the urgency for effective safety measures like P-AEB systems. This comprehensive analysis used data from the IIHS, involving 2,494 tests on 42 level 1 automated vehicles from 2021 to 2024, to examine two key aspects of P-AEB performance: pre-impact detection and deceleration, as well as crash occurrence and impact speed capabilities. The study assessed how commercially available P-AEB systems function under different lighting conditions, without driver intervention.

The findings reveal that detection times play a pivotal role in system performance, with quicker detection observed during the day contributing to reduced crash speeds. This timely detection is a key factor in improving crash outcomes by enabling the system to initiate deceleration sooner. Despite successful detections during the day, the risk of crashes remains significantly higher at night, underscoring the urgent need to enhance P-AEB capabilities in low-light conditions. Furthermore, the occurrence of crashes despite a high rate of successful detections highlights the critical impact of the timing of detection—whether early or late—on the outcomes of potential crashes. This emphasizes optimizing detection times to improve overall system effectiveness in preventing crashes. The study suggests that combining radar and camera performs better than using cameras alone, which could improve detection accuracy, particularly in low-visibility conditions. More generally, the use of additional sensors, such as Lidar, could be explored further.

The results also illustrate a distinct difference in system performance between day and night in terms of crash outcomes, with a notable reduction in crash occurrence during the daytime (about 11%) compared to nighttime low beam (about 34%). The results also confirm the critical role of activation time in preventing potential crashes. Longer activation times significantly increase the likelihood of avoiding accidents, with the potential to reduce crash occurrences by up to 40%. This underscores the importance of optimizing system responsiveness to enhance overall safety.

The analysis also underscored the importance of vehicle features and design in improving system responses, with newer vehicles and those equipped with optimized braking systems showing better performance. Additionally, the study identified key factors influencing P-AEB system performance, including vehicle type. Conventional vehicles exhibited higher deceleration rates, likely due to their lighter weight compared to EVs and hybrid vehicles, which are heavier because of battery mass. While EVs showed marginally lower average impact speeds, hybrid vehicles tended to have higher impact speeds than conventional vehicles. Pedestrian movement is another environmental condition that can influence the outcomes of P-AEB systems, emphasizing the need for these systems to detect all types of movements accurately. This highlights the importance of enhancing the P-AEB system's ability to recognize a wide range of pedestrian behaviors to ensure effective operation across various scenarios.

All these findings are relevant for manufacturers and include refining sensor integration and braking mechanisms to ensure robust pedestrian detection and protection across all lighting conditions. Improving these systems could increase pedestrian safety, enhance consumer trust, and facilitate the transition to automation. It is also important to point that while the IIHS tests avoided driver intervention, in real-life situations (especially with close calls) the driver will likely intervene and take over vehicle control for executing evasive actions by addressing these issues, especially considering real-world situations, future research can expand the scope of the study to include a wider range of scenarios and situations and analyze variables correlated with pedestrian safety, such as diverse environmental conditions, pedestrian behaviors, and vehicle types.

The practical implications of this study are significant for enhancing road safety, particularly for VRUs. By pinpointing the variations in P-AEB system effectiveness between daytime and nighttime, manufacturers are provided with clear directions on where improvements are needed, especially in the combination of sensors, such as integrating radar with camera systems rather than relying on cameras alone, for better performance in low-light conditions. Advancements in these areas could lead to P-AEB systems that are more reliable and effective across all lighting conditions, potentially reducing pedestrian fatalities and injuries significantly. Furthermore, this research could influence policy by supporting the development of stricter safety standards and regulations that mandate the inclusion of advanced detection technologies in all new vehicles. Implementing these changes would improve pedestrian safety and help build public trust in emerging automotive technologies, enabling broader acceptance and usage of automated vehicles.

In summary, this research underscores the necessity for advancements in automotive technologies and the development of stringent safety standards and regulations that promote the widespread adoption of effective pedestrian protection technologies. These improvements are essential for enhancing pedestrian safety and advancing the goals of creating safer, more reliable transportation systems.

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