Quantifying Effectiveness of Red Flashing LEDs around WRONG-WAY Signs in Deterring Wrong-way Driving: A Before and After Study

by

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ABSTRACT

Wrong-way driving (WWD) crashes are a significant safety concern due to their high fatality rates. Traditional countermeasures like static WRONG WAY (WW) signs have shown limited effectiveness. This study evaluates the additional impact of red flashing LEDs around WW sign borders on deterring WWD incidents at a university campus area. Using a Wrong Way Alert System with radar detectors, cameras, and flashing LED-equipped signs, 416 WWD incidents were analyzed over 29 months, comparing periods with LEDs activated and deactivated.

The Two-Proportion Z-Test showed a 20% higher driver turnaround rate with LEDs activated ($p<0.001$). A Random Forest model identified LED status as the most influential factor, followed by time of day, day of week, and academic calendar period. Results highlight the LED's enhanced effectiveness during specific contexts. Recommendations include AI-driven enhancements and pavement marking implementation to reduce system false positives and prevent drivers entering the wrong direction.

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List of Abbreviations

AI	Artificial Intelligence
AUC	Area Under the Curve
DNE	DO NOT ENTER
CTDOT	Connecticut Department of Transportation
DSRC	Dedicated Short-Range Communication
DUI	Driving Under the Influence
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
HCTRA	Harris County Toll Road Authority
ITS	Intelligence Transportation System
LEDs	Light-Emitting Diodes
MassDOT	Massachusetts Department of Transportation
MDOT	Michigan Department of Transportation
ME	Margin of Error
MUTCD	Manual on Uniform Traffic Control Devices
NCDOT	North Carolina Department of Transportation
NTSB	National Transportation Safety Board
ODOT	Ohio Department of Transportation
ODOT	Oklahoma Department of Transportation
PDP	Partial Dependence Plot
PennDOT	Pennsylvania Department of Transportation
RIDOT	Rhode Island Department of Transportation
TxDOT	Texas Department of Transportation
WW	WRONG WAY
WWD	Wrong Way Driving

Chapter 1 INTRODUCTION

Wrong-way driving (WWD) is defined as the act of driving a motor vehicle against the direction of traffic, typically occurring on divided highways (Zhou, et al., 2023). While WWD crashes occur less frequently than other types of crashes, they often tend to be more severe, resulting in a higher likelihood of injuries and fatalities (Chang, 2022). According to the U.S. Department of Transportation Federal Highway Administration (Federal Highway Administration, 2024), total traffic fatalities increased yearly from 36,835 in 2018 to 42,514 in 2022. Among these fatalities, WWD traffic fatalities increased from 445 to 704, increasing their proportion from 1.2% to 1.7%.

Transportation agencies and policymakers have implemented various countermeasures to mitigate WWD crashes and incidents (Jones, 2012; Kayes, Al-Deek, & Sandt, 2022; Pour-Rouholamin, Zhou, & Shaw, 2014). Despite efforts involving traditional measures such as deploying and modifying WRONG WAY (WW), DO NOT ENTER (DNE), and ONE WAY signs, WWD crashes persist, particularly during nighttime hours and among impaired drivers. The challenges in alerting drivers under the influence (DUI) of alcohol or drugs, who may have diminished cognitive and visual abilities, limit the effectiveness of conventional signage.

To enhance the visibility and effectiveness of warning signs, recent advancements have incorporated Intelligent Transportation System (ITS) technologies (Hosseini, Jalayer, Zhou, & Atiquzzaman, 2022). A significant improvement over conventional signage is the addition of supplemental flashing LEDs around sign borders, aiming to increase sign conspicuity and attract drivers' attention. For instance, in 2012, the Illinois Center for Transportation analyzed wrong-way crashes on freeways over six years (Zhou, et al., 2012). It is recommended that enhanced WRONG

WAY signs with flashing LEDs be installed at high-frequency crash locations. The Wisconsin Department of Transportation (WisDOT) deployed solar-powered WRONG WAY signs with flashing LEDs around the borders during twilight hours at two ramps in late 2012 (Jones, 2012). In 2011, the Harris County Toll Road Authority (HCTRA) invested approximately $38,788 per mile in a wrong-way driver detection system, incorporating flashing LED signs as a critical feature (ITS International, 2010). The Texas Department of Transportation (TxDOT) also implemented two signs on each exit ramp along a selected 15-mile corridor of US 281 from I-35 to just north of Loop 1604 in San Antonio (Finley, et al., 2014).

These ITS solutions often integrate real-time detection mechanisms, dynamic signage, and communication technologies to immediately warn wrong-way drivers and alert traffic management centers. However, empirical evaluations of these systems are limited, partly due to the challenges in collecting comprehensive before-and-after data, especially at the same locations.

In this context, our research team collaborated with TAPCO company to test its Wrong WAY Alert System, an ITS designed to enhance WWD prevention efforts. This collaboration provided a unique opportunity to evaluate the system in a real-world setting over an extended period. As shown in **Figure 1**, the system consists of radar detectors, front and rear cameras, illumination, three WRONG WAY signs with flashing LEDs around the borders installed on three poles, and an operation cabinet that controls and transmits the captured incident to a cloud database. The system functions by detecting wrong-way vehicles and activating visual alert (red flashing LEDs) to prompt drivers to self-correct. It also captures detailed incident data, including timestamps, vehicle images, and video clips that contain drivers' behavioral responses, enabling a thorough analysis of driver reactions and system effectiveness.

Figure 1 Configuration of the Wrong Way Alert System

Beyond the system itself, the study location presents several notable features that add valuable context. The system was installed on Auburn University's campus, adjacent to a one-way road specifically designed for university transit buses (as illustrated in **Figure 2**). This road supports over 10 routes, with each route serviced by 2 to 3 buses that pick up and drop off students at a nearby bus station before using the one-way road to exit campus (**Figure 3**). On average, a bus travels along this road approximately every 5 minutes, ensuring consistent and frequent service throughout the day. Additionally, the one-way road ends at a signalized intersection, which is equipped with DO NOT ENTER signs on both sides of the road and NO TURN signs mounted on the traffic light poles. Despite these countermeasures, daily observations revealed a high frequency of WWD incidents at this location, highlighting the need for additional safety interventions.

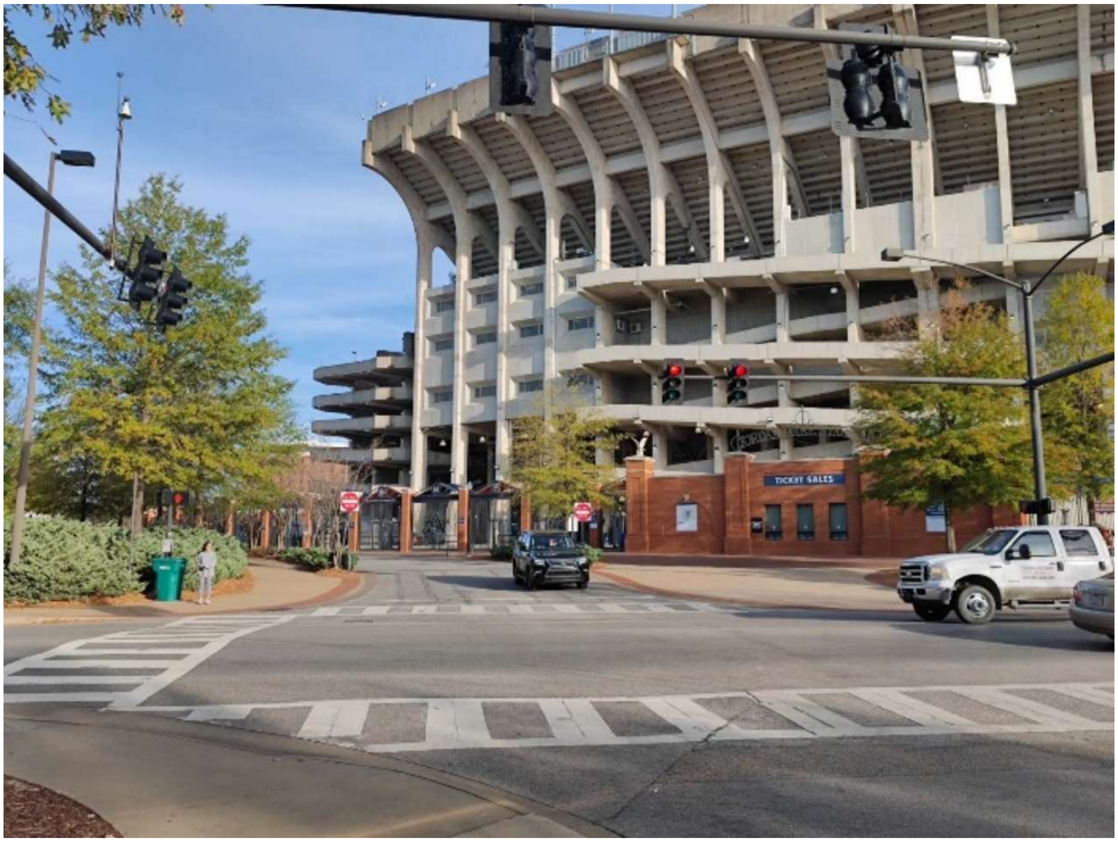

Figure 2 Downstream Signalized Intersection of Study One-Way Road

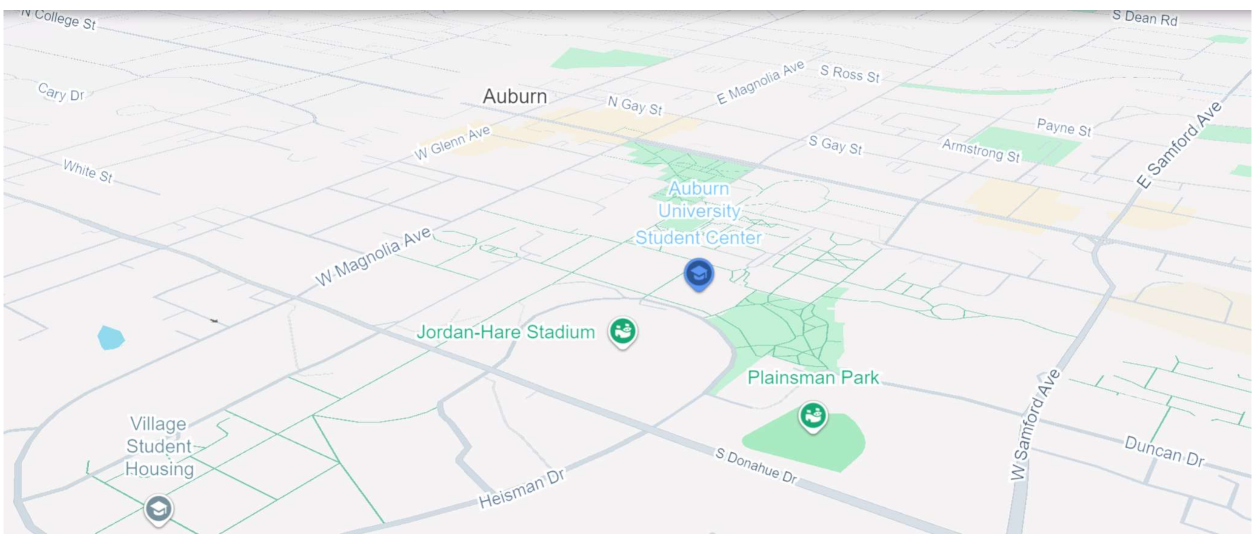

Figure 3 Map Around the Study Location

The objective of this study is to quantify the effectiveness of red flashing LEDs around WRONG WAY sign borders in deterring WWD incidents by analyzing drivers' turnaround rates before and after LED activation, while keeping all other system functionalities unchanged. The findings aim to deepen the understanding of advanced WWD countermeasures, provide evidence of the additional impact of red flashing LEDs on traditional static WRONG WAY signs, and offer insights for future system enhancements. These enhancements could include reducing false positives and extending the product's operational lifespan to improve efficiency and effectiveness.

Chapter 2 LITERATURE REVIEW

Wrong-way driving (WWD) incidents pose a significant safety concern due to their high fatality rates compared to other types of crashes. Traditional countermeasures, such as deploying standard WRONG WAY (WW), DO NOT ENTER (DNE), and ONE WAY signs, have been widely implemented across various roadways and facilities. Transportation agencies have sought to enhance these traditional signs by adjusting their mounting heights, increasing their sizes, and improving their retro-reflectivity to enhance visibility, especially during nighttime conditions (Pour-Rouholamin, Zhou, & Shaw, 2014; Cooner, Cothron, & Ranft, 2004; Sandt & Al-Deek, 2018). Despite these efforts, the effectiveness of traditional signs remains limited, particularly in alerting impaired drivers.

The evolution of wrong-way related signs in the Manual on Uniform Traffic Control Devices (MUTCD) reflects ongoing efforts to improve the effectiveness of traffic control measures for preventing WWD incidents (Federal Highway Administration, 2023). **Table 1** summarizes the key provisions and updates related to WWD signage in the MUTCD over the years.

Table 1 Evolution of Wrong-Way Related Signs in the MUTCD

Year	Provisions Update	Year	Provisions Update
1935	ONE-WAY sign	1988	Larger size of DNE sign
1942	-	2000	More details regarding DNE signs and WW signs
1948	DO NOT ENTER (DNE) sign	2003	-
1961	One standard has changed to a recommendation	2009	Relocation of WW traffic control information from “guide signs” to “regulatory signs” Lower mounting height of DNE signs and WW signs
1971	Modification of DNE sign and WRONG-WAY (WW) sign	2023	Provisions allowing the use of light-emitting diodes (LEDs) within the borders of WW and DNE signs

1978	WW traffic control sign standards were divided into two sections: Section 2A.31 and 2E.41		

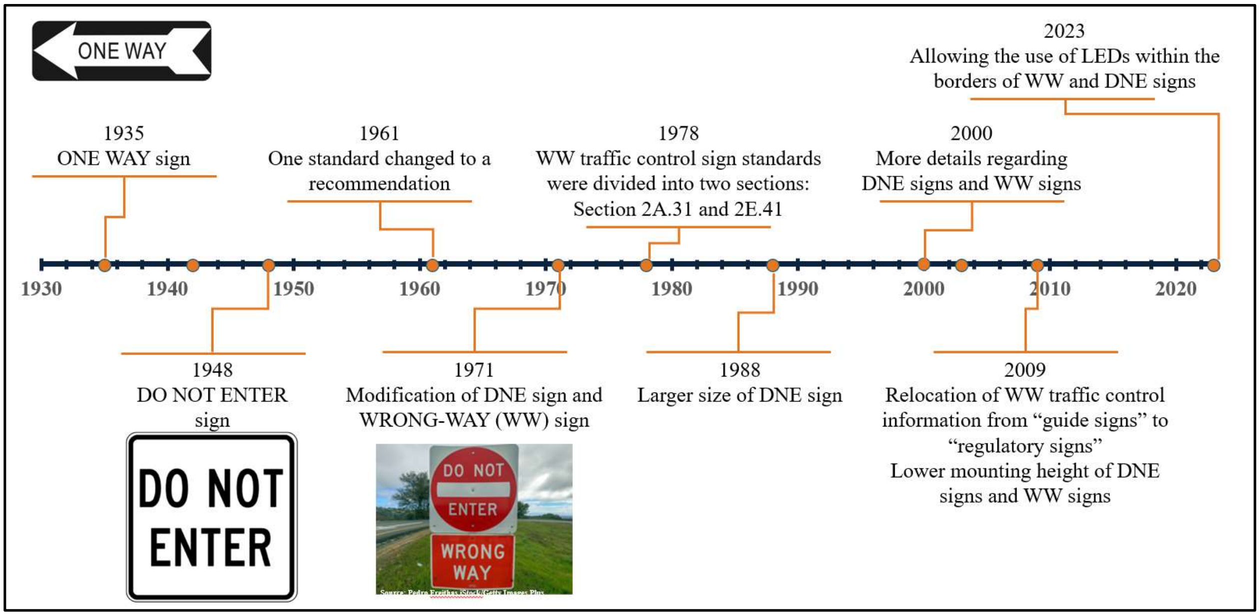

Figure 4 Evolution of wrong-way related signs in the MUTCD

These updates demonstrate a progressive recognition of the need for more conspicuous and effective signage to prevent WWD incidents. The initial introduction of the ONE WAY and DNE signs provided fundamental tools for directing traffic flow. Subsequent modifications, such as increasing sign sizes and adjustments of mounting heights, aimed to enhance visibility, especially during nighttime conditions when a substantial proportion of WWD incidents occur (**Figure 4**). Research indicates that many WWD incidents are associated with drivers under the influence of alcohol, who may have reduced cognitive abilities and diminished responsiveness to traditional traffic signs. This necessitates the development of more conspicuous and attention-grabbing countermeasures (Pour-Rouholamin & Zhou, 2016; National Transportation Safety Board (NTSB), 2012; Zhou, Zhao, Pour-Rouholamin, & Tobias, 2015; Finley & Miles, 2018).

In response to this need, the latest 11th edition of the MUTCD in 2023 introduced new provisions allowing the use of light-emitting diodes (LEDs) within the borders of WW and DNE signs to enhance their visibility. This update represents a significant advancement, reflecting governmental acknowledgement of the potential effectiveness of LED-enhanced signage in mitigating WWD incidents by capturing the attention of impaired drivers.

Several studies have explored the efficacy of improved signage incorporating flashing LEDs. Pour-Rouholamin et al. surveyed during the first National Wrong-Way Driving Summit in 2013, involving representatives from 16 states responsible for half of the WWD fatalities from 2004 to 2011 (Pour-Rouholamin, Zhou, & Shaw, 2014). The survey revealed that 15.4% of respondents from these states had already implemented border-illuminated signs, while 7.7% had installed red or yellow flashing beacons on their signs. At that time, most implementations focused on adding a second identical sign to the left-hand side of the roadway and increasing the size of existing signs. These findings suggest that LED enhancements to traditional signs may serve as practical countermeasures to WWD incidents.

Similarly, Song conducted a driving simulator study using eye-tracking technology to analyze drivers' behavioral responses to different signage (Song, 2023). The study compared regular WW signs, DNE signs, and WW signs with flashing LEDs in terms of the number of WWD events, fixation duration on signs, and braking behavior. The results indicated that WW signs with flashing LEDs deterred more WWD events than regular WW and DNE signs when drivers encountered a single sign. Notably, drivers under the influence of alcohol demonstrated quicker comprehension of the flashing LED signage and applied the brakes earlier upon approaching these signs, highlighting the potential effectiveness of LED enhancements in capturing the attention of impaired drivers.

In real-world settings, Golias et al. investigated WWD prevention systems by installing three different brands of ITS at exit ramps near Nashville, Tennessee, for 30 days (Golias, Mishra, & Ngo, 2021). Each system utilized radar or lidar technology to trigger flashing LEDs on WW signs and recorded short video clips of the events. The evaluation reported no missed or false detections when the systems operated normally, demonstrating the feasibility and reliability of such ITS deployments in actual traffic conditions.

Building on these findings, transportation agencies and state governments have increasingly implemented ITS technologies incorporating flashing LEDs on WW signs at highway exit ramps prone to WWD incidents. **Table 2** summarizes emerging WWD countermeasure technologies adopted by various State Departments of Transportation (DOTs).

These implementations demonstrate a nationwide trend toward adopting advanced technologies to mitigate WWD incidents. For instance, the Rhode Island Department of Transportation (RIDOT) has installed radar-based detection systems that trigger flashing LEDs and record incidents via cameras. Similarly, the Texas Department of Transportation (TxDOT) utilizes Dedicated Short-Range Communication (DSRC) radios and flashing signs to detect wrong-way entries, activate warnings, and notify authorities. Adopting such technologies underscores state agencies' commitment to enhancing road safety through innovative solutions.

Table 2 Applications of Emerging WWD Countermeasure Technologies by State DOTs

DOT	Technology	Installation Locations	Key Features
RIDOT	WWD detection with flashing LEDs	Selected ramps	Radar detects WW vehicles; Flashing LEDs alert driver; Camera records incident (Vanasse Hangen Brustlin, Inc, 2022; Kayes, Al-Deek, & Sandt, 2022)
MassDOT		16 high-risk highway off-ramps	
FDOT		44 exit ramps across three expressways	
CTDOT	Sensors and lights	Multiple exits on I-84, Route 2, I-95; 15 more locations in 2023	Motion sensors trigger flashing red lights to alert wrong-way drivers (Connecticut's Official State Website, 2024)
MDOT	Sensors and flashing LEDs	Off-ramps on US-131 in Grand Rapids	Sensors trigger LEDs; Cameras record events; Police notification for rapid response (MDOT Grand Region Media, 2023)
PennDOT	Sensors, detectors, and cameras	Pittsburgh to Harmar/910 interchange	Automated alerts; Flashing lights; Exploring driver awareness signs (City of Pittsburgh, 2023)
NCDOT	SMART Traffic Solution with analytics	12 key state highways	Advanced analytics support Vision Zero initiatives (Chase, Cunningham, Yang, Poslusny, & Xu, 2021)
TxDOT	DSRC radios and flashing signs	-	Activates signs; In-vehicle warnings; Alerts Traffic Management Center and police (Finley, et al., 2014)
ODOT	Thermal cameras and flashing signs	6 ramps along I-40 in eastern Oklahoma	- (Oklahoma Department of Transportation, 2022)
ODOT	Detection systems and flashing signs	22-mile stretch on I-71 and I-90; 50 devices at 25 locations	- (American Association of State Highway and Transportation Officials, 2022)

Empirical studies have further assessed the effectiveness of these implementations. Finley et al. conducted a before-and-after evaluation with yoked comparisons to examine the impact of WW signs with flashing red LEDs on WWD incidents along the US 281 corridor in San Antonio, Texas (Finley & Miles, 2018). By analyzing 911 call logs over a 14-month before period and a 22-

month after period, the study observed a 38% reduction in WWD incidents and a 31% decrease in the average monthly rate of WWD events on US 281. In contrast, the rest of the city experienced a 9% increase in WWD incidents during the same period, suggesting that the LED-enhanced signs significantly reduced WWD events in the test corridor.

Similarly, Kayes reported a significant reduction in WWD events in South Florida following the implementation of flashing LED signs (Kayes, Al-Deek, & Sandt, 2022). The study found a 49% reduction in WWD-related 911 calls and a 38% reduction in combined WWD 911 calls, indicating the effectiveness of the countermeasure in a real-world context.

While these studies underscore the potential benefits of flashing LED signs in deterring WWD incidents, they often face limitations due to challenges in experimental design and data collection. Specifically, the lack of comprehensive before-period WWD incident data hinders the ability to conduct robust before-and-after comparisons at the same location. Data collection is inherently time-consuming, and installations of ITS countermeasures are often reactive and implemented in response to identified problems, which makes prospective data collection difficult. Moreover, previous empirical studies conducted before-and-after evaluations typically introduced multiple changes simultaneously. They either added WRONG WAY signs with flashing red LEDs to supplement existing static signs, replaced existing static WRONG WAY signs with LED-enhanced versions, or implemented WRONG WAY signs where none existed in the before period. This approach makes it challenging to isolate the specific effect of the flashing LEDs from other variables, potentially confounding the results.

In contrast to previous studies, the current research leverages a unique opportunity presented by installing a WWD detection system on a university campus. The controlled environment and the proactive research design allowed for the collection of both before and after WWD incident data at the same location, with the only variable manipulated being the activation status of the red flashing LEDs around the borders of existing WRONG WAY signs. All other factors, including the static signs themselves and the surrounding environment, remained constant. This approach enables a more rigorous evaluation of red flashing LEDs' effectiveness in deterring WWD incidents, eliminating confounding variables present in prior studies. Additionally, the campus setting facilitated the accumulation of a larger dataset within a shorter timeframe due to higher traffic volumes and the prevalence of WWD incidents in the area. This abundance of data supports the application of more robust and complex statistical analyses to examine the results comprehensively. By building upon previous research findings and addressing the limitations inherent in prior studies, this study aims to provide a more definitive assessment of the impact of flashing LED-enhanced WRONG WAY signs on driver behavior, particularly in reducing WWD incidents.

Chapter 3 METHODOLOGY

This study's methodology is structured into four main parts: (1) an overview of the research design, including the definition of the before and after periods; (2) a detailed explanation of the experimental design and the variables used; (3) a description of the data collection methods, highlighting how the variables were obtained; and (4) a discussion of the statistical analyses applied to the collected data.

3.1 Research Design

The primary aim of this study is to quantify the effectiveness of red flashing LEDs installed around "WRONG WAY" sign borders in deterring WWD behavior by increasing drivers' turnaround decisions. To achieve this, a before-and-after study design was implemented, comprising two continuous periods:

- **Before Period**: Lasted for 13 months, from January 2022 to January 2023. During this period, the flashing LEDs were fully operational and were activated by the system whenever a WWD vehicle was detected.
- **After Period**: Extended for 16 months, from February 2023 to May 2024. In this period, the flashing LEDs were manually deactivated by disconnecting the power supply, while all other system functionalities remained unchanged.

This design ensures that the only variable altered between the two periods is the operation of the flashing LEDs, allowing for a controlled assessment of their impact on driver behavior. **Figure 5** illustrates the appearance of the "WRONG WAY" signs with the LEDs activated and deactivated.

Figure 5 (a) WRONG WAY sign with flashing LEDs activated; (b) WRONG WAY sign with LEDs deactivated.

3.2 Data Collection Methods

Data were collected using an Intelligent Transportation System (ITS), specifically a wrong-way alert system installed at the study location on 157 Heisman Drive in Auburn, Alabama. The system operates continuously, 24 hours a day, seven days a week, powered by a consistent power supply. It was fully installed in December 2021, underwent a one-week testing phase, and became operational in early January 2022.

3.2.1 System Installation and Configuration

The system is installed approximately 400 feet upstream of a signalized intersection at the end of a one-way road. This one-way road is primarily designed for university transit buses, with more than 20 lines that operate both on and off-campus for Auburn University students, faculty, and staff. During the fall and spring semesters, Tiger Transit operates Monday to Friday, from 7:00 am to 8:00 pm. In the summer semester, all lines run Monday to Friday, from 7:00 am to 5:00 pm. There is no transit service on weekends and during semester breaks.

At the terminus of the one-way road, the signalized intersection is equipped with DO NOT ENTER signs on both sides. Recently, additional NO RIGHT TURN and NO LEFT TURN signs were installed to reinforce the prohibition of wrong-way driving.

3.2.2 Detection Mechanism

The wrong-way alert system consists of:

- **Radar Detectors**: These detect vehicles entering the `sign activation zone`, which starts from the detector pole's location and extends about 100 feet downstream following the correct traffic direction.
- **Front and Rear Cameras**: Activated simultaneously with the radar detectors to capture images and videos of the WWD event.
- **Three "WRONG WAY" Signs with Flashing LEDs**: Installed on three poles (detector pole and two secondary poles, as illustrated in **Figure 6**), these signs have LEDs around their borders that flash when activated. A consistent power supply powers the primary sign, while the two additional signs are powered by solar energy.
- **Operation Cabinet**: Controls the system's operations and transmits captured incidents to a cloud database via BlinkLink, a remote management platform that notifies officials.

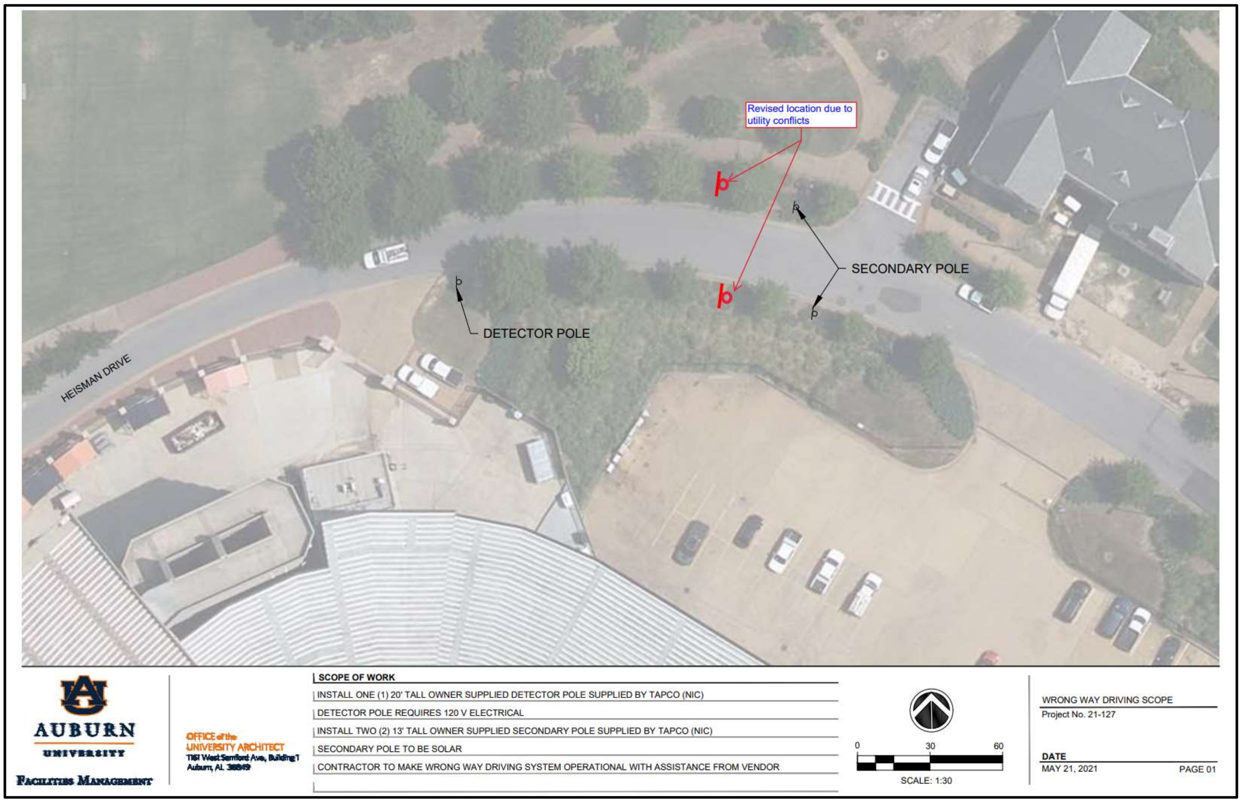

Figure 6 Wrong-Way Alert System Layout Plan

3.2.3 System Functionality

When a vehicle enters the activation zone traveling in the wrong direction, the radar detectors trigger the flashing LEDs on the "WRONG WAY" signs to alert and encourage the driver to self-correct. Simultaneously, the front and rear cameras record the incident, and an alert is sent to BlinkLink for real-time monitoring and response.

3.2.4 Data Acquisition

Data acquisition was conducted via BlinkLink, a remote system management platform that automatically sends notifications to officials upon detecting a WWD incident. BlinkLink stores all captured data, including classified alerts after manual review and labeling, and provides logs of incident alerts containing:

- **Incident Date and Time**: Timestamps are accurate to the second.
- **Visual Evidence**: Fifteen consecutive images and a fixed two-minute video clip capturing the entire WWD event.

The collected data allowed for the extraction of various variables. Temporal variables such as incident period, time of day, and day of the week were derived from the timestamp information. Each incident's images and video were manually reviewed to classify the incidents accurately. Leveraging predefined labels provided by the BlinkLink platform, incidents were categorized into:

- **Continued Wrong-Way**: Vehicles that continued without any evidence of self-correction.
- **Self-Corrected Wrong-Way**: Vehicles that were visually confirmed to have corrected their direction (**Figure 7**).
- **Authorized Vehicles**: Vehicles (such as pickup trucks and golf carts) permitted by the university to use the wrong-way route for service purposes.
- **Emergency Response Vehicles**: Police cars, ambulances, and fire trucks performing official duties.
- **Pedestrians**: Including e-scooter users due to their standing-riding mode resembling pedestrians.
- **Bicycles**

Figure 7 Example of a Confirmed Self-Correcting Vehicle

This meticulous data collection and classification process prepared a comprehensive dataset for subsequent statistical analysis. It is worth noting that several driveways are located along this one-way road, and near the bus stop, there is sufficient space for vehicles of all types to execute a U-turn. However, all these areas fall outside the camera's field of view. As a result, it is unfortunately not feasible to determine where WWD drivers most frequently perform U-turns.

3.3 Experimental Design

With the collected data and identified variables, the experimental design was formulated to analyze the relationship between drivers' turnaround decisions and various influencing factors. The primary outcome of interest is the driver's turnaround decision, classified into two categories:

- **Continued Wrong-Way**: Vehicles that continued without any evidence of self-correction.
- **Self-Corrected Wrong-Way**: Vehicles that were visually confirmed to have corrected their direction.

Several independent variables were examined for their potential influence on the driver's decision to self-correct:

1. **LED Status**: Categorized as functional (LEDs operational and flashing during the before period) and malfunction (deactivated during the after period).
2. **Incident Period**: Classified into four categories based on the university academic calendar—spring semester, summer semester, fall semester, and break periods outside the regular semesters.
3. **Day of the Week**: Recorded from Monday through Sunday, with each day spanning from 00:00 to 23:59 local time.
4. **Time of Day**: The 24-hour period each day was divided into three categories: Daytime (5 am – 5:59 pm), Nighttime (6 pm – 9:59 pm), and Late Night (10 pm – 4:59 am). The classification of Late Night was specifically designed to account for dark driving conditions, which can vary due to seasonal changes such as winter and summer daylight savings. Unlike a simple 6 am to 6 pm division, this approach ensures that the evaluation of the red flashing LEDs' impact during low visibility conditions is appropriately emphasized, regardless of seasonal effects at the different time of year. Additionally, this designed classification ensures that each category contains sufficient incidents for meaningful statistical analysis, avoiding overly sparse data in any time class.
5. **Transit Service Status**: A binary variable indicating whether the university transit service was operational at the time of the incident. Classified as "Yes" during transit service hours and "No" outside of those hours, based on the transit schedule mentioned earlier.

6. **Weather Conditions**: Classified as clear (good weather conditions with no impediments to visibility or road conditions) and adverse (conditions such as fog, rain, strong winds, wet roads, or ice that could increase driving hazards).
7. **Vehicle Type**: Classified based on design and size into four categories—sedan, SUV, pickup truck, and commercial truck. This classification combines the Federal Highway Administration (FHWA) 13 Vehicle Category Classification with empirical observations of all system-captured WWD vehicles in the study. The categorization considers that longer and larger vehicles may find it more challenging to execute turnaround maneuvers, which could influence a driver's willingness to self-correct.

By establishing these variables based on the data collected, the experimental design provides a structured approach to analyze the factors influencing drivers' turnaround decisions.

3.4 Statistical Analysis

With the comprehensive dataset and defined variables, appropriate statistical methods were applied to explore the relationships between LED status, other influencing factors, and drivers' WWD behavior.

3.4.1 Two-Proportion Z-Test

To assess whether the functionality of the LEDs had a significant impact on drivers' turnaround decisions, the Two-Proportion Z-Test was employed. This test compares the proportions of a binary outcome between two independent groups—in this case, the proportion of drivers who self-corrected during periods when LEDs were activated versus when they were deactivated.

The Two-Proportion Z-Test determines if there is a statistically significant difference between the two proportions and provides a confidence interval for the difference. The test results offer insights into the magnitude and direction of the effect of the LED status on drivers' self-correction rates. The test is appropriate here because it directly addresses the research question and provides interpretable results that quantify the impact of LEDs functionality.

However, the Two-Proportion Z-Test is limited to comparing two groups and does not account for other potential influencing factors. Multiple variables may influence drivers' turnaround decisions, including incident period, day of the week, time of day, weather conditions, transit service status, and vehicle types. Therefore, while the Two-Proportion Z-Test provides valuable initial insights, it cannot capture multiple variables' effects and interactions.

3.4.2 Logistic Regression

Considering the binary nature of the outcome (self-corrected or continued WWD) and the presence of multiple influencing factors, logistic regression was considered due to its strength in handling binary dependent variables and providing interpretable coefficients that indicate the statistical significance of predictors. However, logistic regression assumes a linear relationship between the log odds of the outcome and the independent variables. In this study, most predictors are categorical and may exhibit nonlinear relationships with the outcome, violating logistic regression assumptions and making it less suitable for analysis.

3.4.3 Random Forest Model

Given the limitations of logistic regression in this context, a Random Forest model was employed. Random Forest is a robust, non-parametric ensemble learning method capable of handling complex nonlinear relationships and interactions between variables, especially categorical ones. It constructs multiple decision trees during training and outputs the class, that is, the mode of the classes (classification) or mean prediction (regression) of the individual trees. This approach allows the modeling of intricate patterns without relying on linearity assumptions. Moreover, Random Forest is adept at handling class imbalances inherent in the dataset, such as the potential predominance of certain WWD incidents (for instance, in this study, more drivers executed intentional WWD behavior, meaning there were fewer self-correcting WWD incidents). It can adjust for imbalance through bootstrapping techniques and improve model sensitivity and prediction accuracy by tuning classification thresholds. Another advantage of Random Forest is its ability to assess variable importance. While it does not provide p-values or confidence intervals like logistic regression, it ranks variables based on their contribution to the model's predictive accuracy. This feature is valuable for identifying which factors most significantly influence drivers' turnaround behavior.

In summary, the Random Forest model is well-suited to the study's needs due to its flexibility in handling categorical variables, ability to capture complex interactions, robustness against class imbalance, and valuable insights into variable importance. This approach enables a comprehensive examination of the factors affecting drivers' WWD behavior, facilitating more informed system maintenance and improvement recommendations.

Chapter 4 RESULTS AND DISCUSSION

This section presents a comprehensive analysis of the Wrong Way Alert System's performance, the data processing steps undertaken, and the statistical analyses conducted. The objectives are to evaluate the system's detection precision, assess the proportion of true WWD incidents (which will be explained in the following sections), process the raw data for accuracy, and apply statistical methods to understand the factors influencing drivers' turnaround decisions.

4.1 Wrong-Way Alert System Performance

4.1.1 Detection Precision

The initial evaluation focused on the system's detection precision, which is defined by its ability to accurately detect WWD incidents without missing events or generating false-triggered alerts due to adverse weather conditions or animals. To assess this, a portable camera was installed near the detection system, covering its detection zone, and continuously recorded video footage from September 10th to September 12th, 2023, resulting in 60 hours of data. These dates were selected because they included a Game Day event, which historically exhibits a high number of WWD incidents due to increased traffic from motor vehicles, golf carts, and pedestrians.

A manual review of the video footage revealed no missing events when comparing each detected motor vehicle to the alerts captured by the system. Additionally, during the 29 months of data collection, there were negligible false-triggered alerts caused by adverse weather conditions or animals. The high detection precision—with no missing events or significant false alarms—demonstrates the system's robust performance in accurately detecting WWD incidents.

This level of precision is critical because WWD incidents, though rare, have a high potential for fatality. The ability to quickly detect and respond to such events can prevent them from escalating into severe crashes, justifying the system's installation and maintenance investment.

4.1.2 Proportion of True Wrong-Way Driving Incidents

In this study, a true WWD incident is defined as an event labeled either as continued wrong-way driving or self-corrected wrong-way driving. Given the study location—a university campus environment with significant pedestrian activity and service vehicles—the proportion of true WWD incidents provides direct insight into the events of interest. Mathematically, it is expressed as:

$$Proportion\ of\ True\ WWD = \frac{ContinuedWW + SelfCorrectedW}{Overall\ Incidents} \quad \textbf{Equation 1}$$

Table 3 summarizes the overall distribution of captured and manually labeled incidents across different days of the week.

Table 3 Overall Distribution of Captured Incidents

Resolution Types	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Grand Total
Continued WW	21	36	51	40	63	357	95	663
Self-Corrected WW	19	20	9	5	14	28	27	122
Authorized Vehicle	160	186	154	205	255	1145	158	2263
Emergency Response	19	17	7	10	23	277	36	389
Bicycle	97	72	77	96	83	120	94	639
Pedestrian	122	159	182	129	254	2065	188	3099
Grand Total	438	490	477	484	691	3985	595	7175

Based on **Equation 1**, the proportion of true WWD incidents was found to be 11%. This relatively low percentage is primarily attributed to the high number of authorized vehicles and pedestrians detected by the system. The detection system was initially designed for highway exit ramps, where each WWD incident—including those involving pedestrians or authorized vehicles—is crucial to collect. However, in an urban street context, such as the campus area in this study, the system's broad detection capabilities result in a large number of non-critical alerts.

The frequent triggering of flashing LEDs by non-critical events not only accelerates the wear of the system components but also underscores the need for improvements in detection and classification algorithms to differentiate between true WWD incidents and other activities. Additionally, a low proportion of true WWD incidents leads to increased labor in classifying alerts, and advancements in camera and image recognition technologies corporate with artificial intelligence offer potential solutions. The newer system from the same product company can also automatically classify alerts into categories such as pedestrians, cars, or buses becoming available, which could enhance efficiency.

4.2 Data Processing

To focus the analysis on the incidents of interest and ensure the accuracy of the statistical results, comprehensive data processing was conducted.

4.2.1 Exclusion of Special Event Dates

Firstly, GameDay weekends were excluded from the dataset. These are days when significant sporting events occur at the university, leading to dramatically increased traffic volumes, altered traffic management (such as police barriers and road closures), and an influx of pedestrians and authorized vehicles. Including these dates could bias driver behavior data and the occurrence of WWD incidents. The unusual traffic patterns and conditions during GameDay weekends are not representative of typical driving conditions, and their inclusion could skew the analysis.

4.2.2 Filtering Relevant Incidents

Following the exclusion of GameDay weekends, all incidents were filtered to retain only those classified as continued WWD or self-corrected WWD. Incidents involving authorized vehicles, emergency responses, bicycles, and pedestrians were excluded, as these do not represent true WWD incidents of interest.

4.2.3 Removal of Repeated Vehicles

Additionally, multiple incidents involving the same vehicle were excluded to reduce bias. A manual comparison of vehicle characteristics – such as wheel hub design, presence of sunroof, and decorations – was used to identify repeated incidents by the same vehicle. This step ensures that the dataset focuses on unique events rather than repeat offenders, which could disproportionately influence the results.

In the before period (January 1st, 2022, to February 10th, 2023), 21 WWD incidents were removed due to 14 vehicles appearing multiple times. These removed incidents did not include the first occurrence of each vehicle. All these incidents involved intentional WWD behavior, with one vehicle initially self-correcting but later engaging in intentional WWD. In the after period (February 10th, 2023, to May 31st, 2024), 48 WWD incidents were removed due to 25 vehicles appearing multiple times. Among these, only one incident involved a driver who turned around to correct their direction, while the others displayed intentional WWD behavior. Two vehicles initially self-corrected but subsequently engaged in intentional WWD.

The processed data, presented in **Table 4**, reflects these adjustments and provides a more accurate basis for statistical analysis by minimizing the influence of repeat offenders.

Table 4 WWD Incidents after Preprocessing

	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Grand Total
LED Activated	19	22	23	21	22	37	28	172
ContinuedWW	7	10	16	14	16	29	16	108
Self-Corrected	12	12	7	7	6	8	12	64
LED Deactivated	17	26	25	16	36	80	44	244
ContinuedWW	10	19	23	15	31	67	35	200
Self-Corrected	7	7	2	1	5	13	9	44
Grand Total	36	48	48	37	58	117	72	416

Focusing on true WWD incidents and removing those caused by repeated vehicles or special events, made the dataset more suitable for meaningful statistical analysis. This approach ensured that the findings would accurately reflect the factors influencing drivers' turnaround decisions without bias from anomalies.

4.3 Statistical Analysis

4.3.1 Descriptive Statistics

Descriptive statistics were employed to analyze the processed dataset, providing insights into the patterns of WWD incidents across days of the week and the influence of the LED status on driver behavior.

Figure 8 visualizes the number of WWD incidents across days of the week. Both periods (LEDs activated and deactivated) indicate that Saturday had the highest number of WWD incidents, even after removing Game Day weekends. Additionally, drivers were less likely to self-correct on Saturdays.

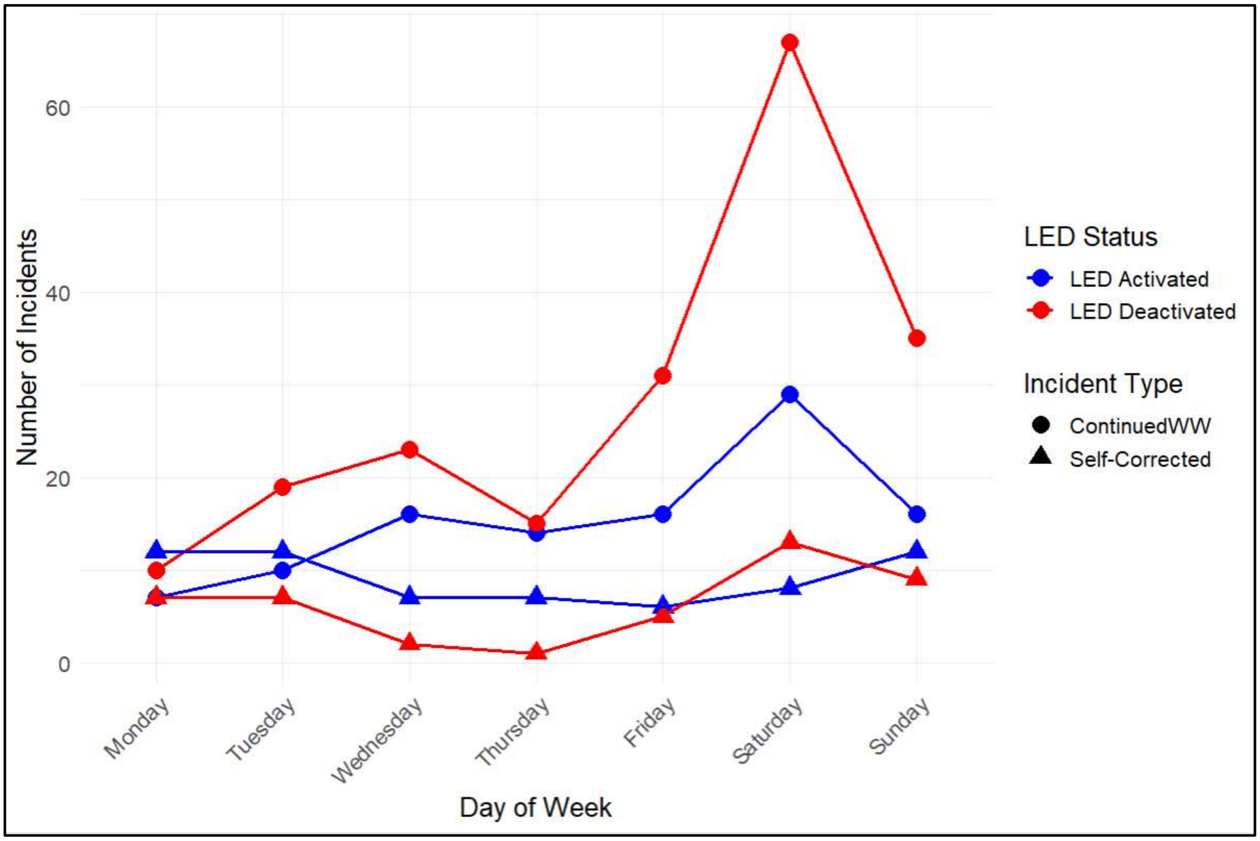

Figure 8 Number of WWD Incidents Across Days of Week

The turnaround rate was calculated to facilitate a meaningful comparison between periods of different lengths, representing the proportion of drivers who self-corrected. It is defined as:

$$Turnaround\ Rate = \frac{Number\ of\ Self-Correct\quad WWD\ Incidents}{Total\ True\ WWD\ Incidents} \qquad \textbf{Equation 2}$$

Figure 9 illustrates that, on average, the period when the LEDs were activated had a higher turnaround rate than when the LEDs were deactivated. The most significant difference was observed on Wednesday, with a 15% higher turnaround rate during the before period.

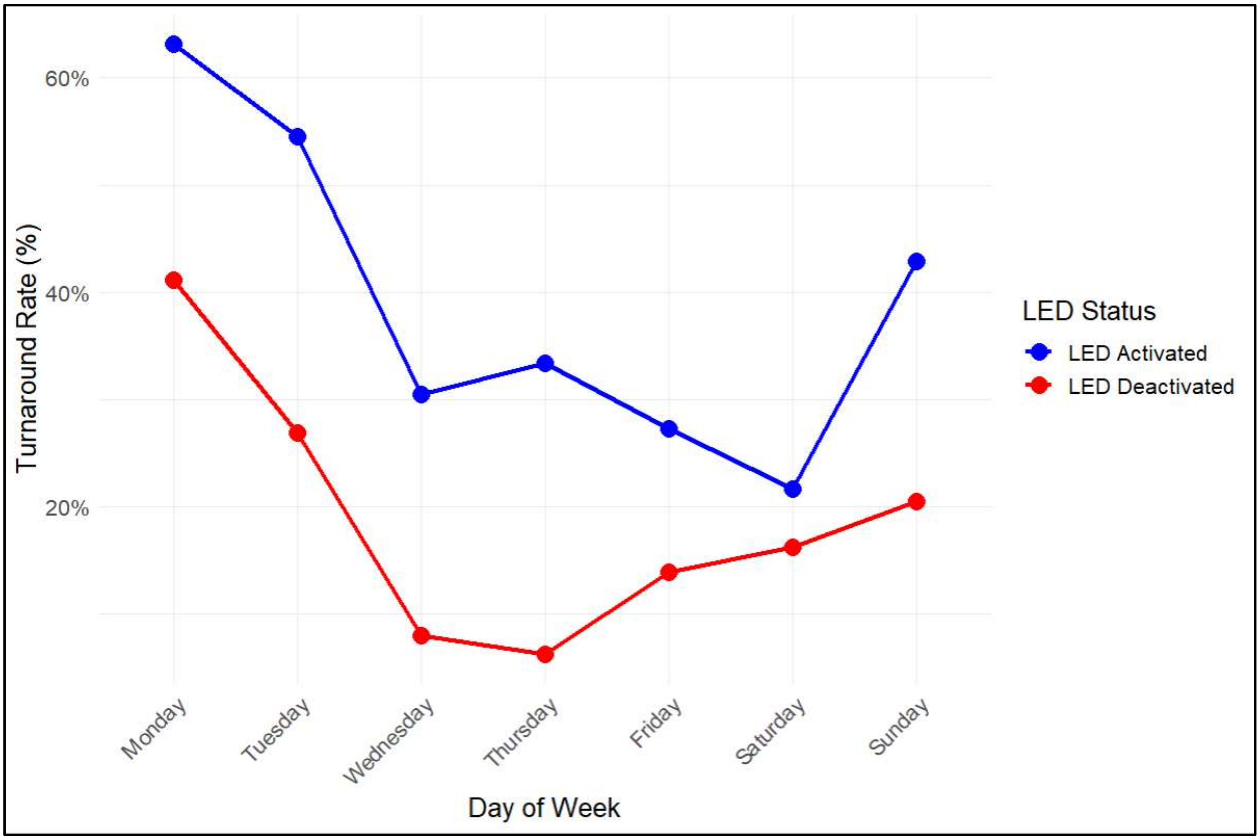

Figure 9 Turnaround Rate of WWD Incidents Across Days of the Week

These descriptive statistics suggest that the functionality of the LEDs positively influences the driver's likelihood to self-correct, with notable variations across different days of the week.

4.3.2 Two-Proportion Z-Test Results

Table 5 shows the contingency table with the number of continued and Self-Corrected WWD incidents during two LED statuses.

Table 5 Contingency Table

LED Status	Continued WW	Self-Corrected WW	Total Incidents	Turnaround Rate (%)
LED Activated	108	64	172	37%
LED Deactivated	200	44	244	18%

A Two-Proportion Z-Test was applied to intuitively show the difference between turnaround rates while LEDs were activated and deactivated. Details about calculations are shown below:

Difference in Turnaround Rates:

$$\Delta p = p_{Activated} - p_{Deactivated} = 0.3721 - 0.1803 = 0.1918\ (or\ 19.18\%) \quad \textbf{Equation 3}$$

Standard Error (SE) of the Difference:

$$SE = \sqrt{\frac{p_{Activated}(1-p_{Activated})}{n_{Activated}} + \frac{p_{Deactivated}(1-p_{Deactivated})}{n_{Deactivated}}} \quad \textbf{Equation 4}$$

$$= \sqrt{\frac{0.3721(1-0.3721)}{172} + \frac{0.1803(1-0.1803)}{244}}$$

$$\approx 0.04432$$

Z-Statistic:

$$z = \frac{\Delta p}{SE} = \frac{0.1918}{0.04432} \approx 4.328 \quad \textbf{Equation 5}$$

A z-score of approximately 4.328 corresponds to a p-value 7.52×10^{-6} in a one-tailed z-test, which is much less than 0.05. Therefore, we can reject the null hypothesis at the 0.05 significance level, concluding that there's a significant statistical increase in driver's turnaround decision when LEDs were activated compared to when they were deactivated.

Margin of Error (ME):

$$ME = z^* \times SE \quad \textbf{Equation 6}$$

For a 95% confidence level, $z^* = 1.96$,

$$ME = 1.96 \times 0.04432 \approx 0.08687 \qquad \textbf{Equation 7}$$

Confidence Interval:

- Lower Limit:

$$\Delta p - ME = 0.1918 - 0.08687 = 0.1049 \qquad \textbf{Equation 8}$$

- Upper Limit:

$$\Delta p + ME = 0.1918 + 0.08687 = 0.2787 \qquad \textbf{Equation 9}$$

The 95% confidence interval for the difference in turnaround rate is 10% to 28%. We're 95% confident that the true difference in self-correction rates between LED-activated and deactivated periods lies within this interval. These results confirm that activating the LEDs significantly increases the likelihood of drivers self-correcting during WWD incidents. The increase of approximately 19% in the turnaround rate is statistically and practically significant. However, recognizing that other factors could impact drivers' turnaround decisions, further analysis using a Random Forest model was conducted to provide deeper insights.

4.3.3 Random Forest Model Analysis

Given the influence of multiple factors on drivers' turnaround behavior, a Random Forest model was applied to further explore these relationships and identify the most influential predictors.

4.3.3.1 Model Performance

The model's performance metrics are summarized in **Table 6**.

Table 6 Model Performance Metrics

Metric	Definition	Value
AUC	Model's ability to distinguish between classes across all classification thresholds	0.909
Sensitivity	Proportion of actual positive cases correctly identified by the model	84.1%
Specificity	Proportion of actual negative cases correctly identified by the model	93.5%
Precision	Accuracy of positive predictions made by the model	81.8%
F1 Score	Harmonic mean of Precision and Sensitivity, providing a balance between the two	83.0%

These metrics were derived from the confusion matrix presented in **Table 7**.

Table 7 Confusion Matrix of Tuned Random Forest Model

	Actual	
Predicted	**ContinuedWW**	**SelfCorrect**
ContinuedWW	289	17
SelfCorrect	20	90

Metric definitions:

$$Sensitivity = \frac{True\ Positive\ (TP)}{TP+False\ Negatives\ (FN)} = \frac{90}{90+17} \approx 84.1\% \quad \textbf{Equation 10}$$

$$Specificity = \frac{True\ Negatives\ (TN)}{TN+False\ Positives\ (FP)} = \frac{289}{289+20} \approx 93.5\% \quad \textbf{Equation 11}$$

$$Precision = \frac{TP}{TP+FP} = \frac{90}{90+20} \approx 81.8\% \quad \textbf{Equation 12}$$

$$F1\ Score = 2 \times \frac{Precision \times Sensitivity}{Precision+Sensitivit} = 2 \times \frac{0.841 \times 0.818}{0.841+0.818} \approx 83.0\% \quad \textbf{Equation 13}$$

The Random Forest model demonstrated excellent discriminative ability, achieving an Area Under the Curve (AUC) of 0.909. At a classification threshold of 0.35—adjusted due to the class imbalance (continued WWD incidents being three times higher than self-corrected incidents)—the model maintained a balance between sensitivity and specificity, accurately identifying a significant proportion of both continued WWD and self-corrected WWD incidents.

4.3.3.2 Variable Importance

The analysis of variable importance, as depicted in **Figure 10**, identified the most influential predictors affecting drivers' turnaround decisions.

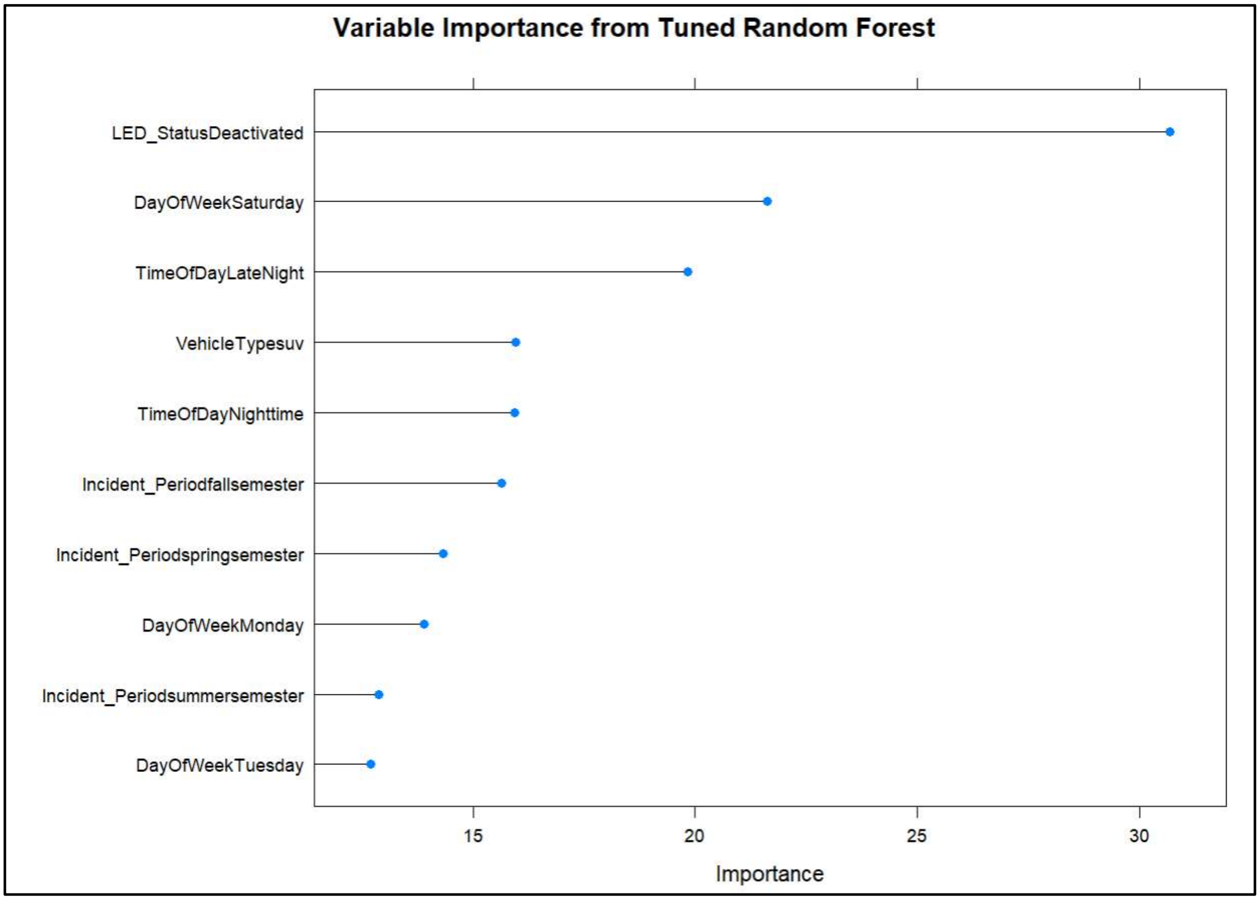

Figure 10 Top10 Variables Importance Rankings from Tuned Random Forest

The Random Forest model's variable importance analysis reveals that `LED_Status_Deactivated` is the most significant predictor in determining driver behavior during wrong-way driving incidents, with an importance index of approximately 31. This high importance score indicates that the status of the LEDs—specifically when they are deactivated—has the greatest influence on whether drivers self-correct or continue driving the wrong way. The next most important variable is `DayOfWeekSaturday`, with an importance index around 22, suggesting that incidents occurring on Saturdays significantly impact driver behavior, possibly due to different traffic patterns or driver activities on that day. Following that, `TimeOfDayLateNight` has an importance index of about 20, highlighting that late-night hours are a crucial factor in predicting driver responses during wrong-way incidents. The other variables in the model have importance indices of 15 or less, indicating they have a comparatively smaller impact on the model's predictive performance.

It's important to understand that these variable importance indices reflect each variable's overall contribution to the model's predictions, including both their individual effects and interactions with other variables. In Random Forest models, variable importance measures like the Mean Decrease in Gini impurity account for how much each variable reduces uncertainty (or impurity) across all the trees in the forest. This means that the importance score for `LED_Status_Deactivated` considers not only its direct influence on the outcome but also how it works in conjunction with other variables to improve the model's accuracy. Therefore, the high importance of LED status suggests it plays a pivotal role both independently and in combination with factors like the day of the week and time of day. Similarly, the importance scores for `DayOfWeekSaturday` and `TimeOfDayLateNight` reflect their overall influence, capturing both their standalone effects and any synergistic interactions that enhance the model's ability to predict driver behavior during WWD incidents.

Additionally, an analysis of the top five and bottom five predicted turnaround rate scenarios provides valuable insights into the key variables influencing driver self-correction during WWD incidents. The best-performing scenarios, with predicted turnaround rates ranging from 95.2% to 100%, consistently feature the activation of LEDs, which underscores their critical role in enhancing driver awareness. These scenarios typically occur during the daytime or nighttime on weekdays (Monday to Wednesday), under clear weather conditions, and involve common vehicle types like sedans, SUVs, and pickup trucks. The presence of bus service is also noted in most high-performing scenarios, suggesting that active bus routes may contribute to heightened driver vigilance. In contrast, the worst-performing scenarios, with predicted turnaround rates close to 0%, often involve deactivated LEDs, highlighting the significant impact of LED status on driver behavior. These scenarios frequently occur during the spring semester or break periods, particularly on weekends (Saturday), when driver familiarity with campus roads may be lower, and attentiveness may decrease due to leisure activities. Adverse factors such as adverse weather conditions and the absence of bus service further diminish the likelihood of drivers self-correcting. Notably, even scenarios with activated LEDs can result in low predicted turnaround rates when combined with unfavorable conditions like adverse weather, weekend days, and the absence of bus services.

4.3.3.3 Interaction Effects

To further understand the nuanced impact of LED status across different contexts, interaction effects were examined using Partial Dependence Plots (PDPs) for LED status in conjunction with incident period, day of the week, and time of day.

Table 8 Distribution of Continued and Self-Corrected WW Incidents by Incident Period with Corresponding Turnaround Rates

Incident Period	LED Activated			LED Deactivated		
	Continued WW	Self-Corrected WW	Turnaround Rate (%)	Continued WW	Self-Corrected WW	Turnaround Rate
Break	13	7	35%	34	4	11%
Fall Semester	45	15	25%	40	12	23%
Spring Semester	55	2	4%	104	20	16%
Summer Semester	17	18	51%	22	8	27%
Grand Total	130	42	24%	200	44	18%

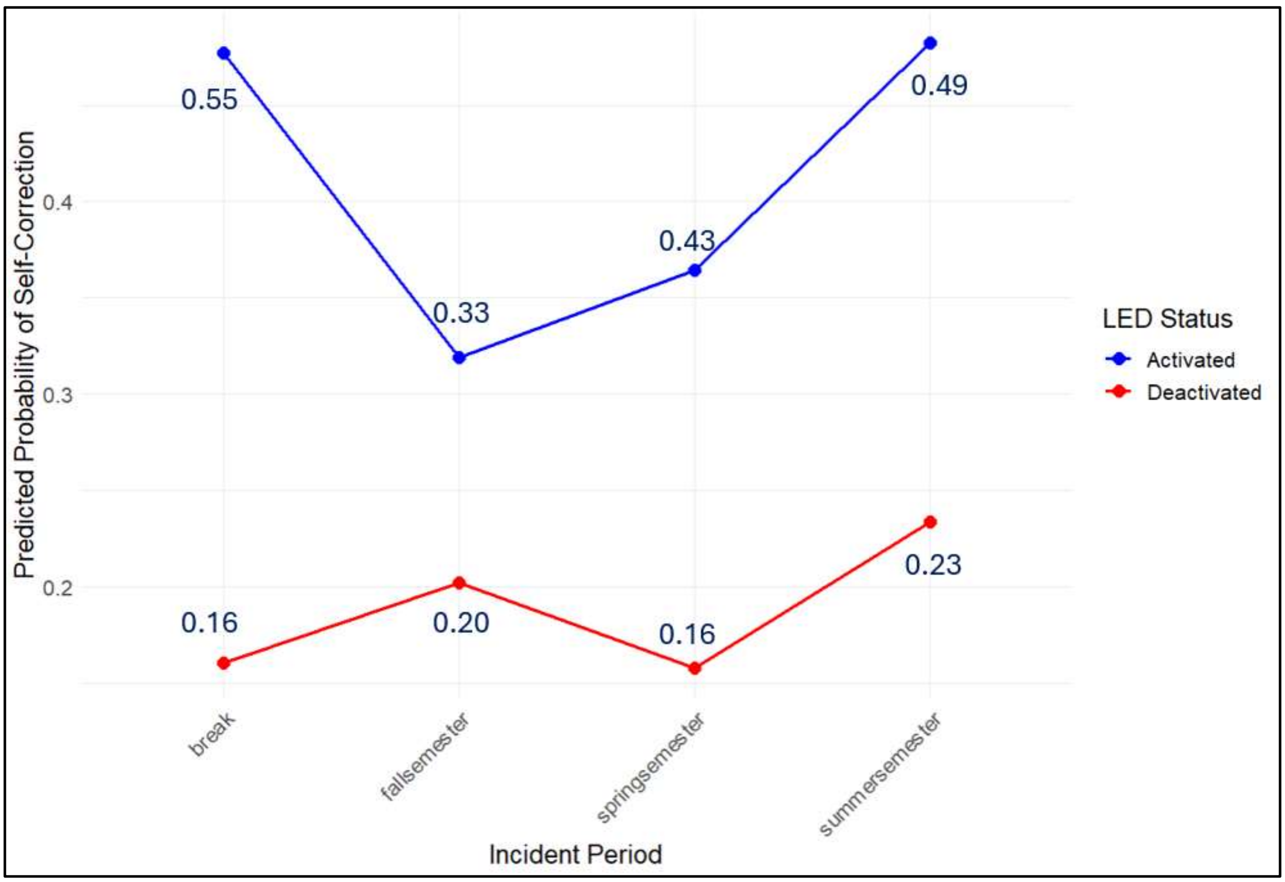

Figure 11 Impact of LED Status on Driver Self-Correction Across Incident Periods

The analysis of WWD incidents across different academic periods reveals significant variations in driver behavior influenced by the activation status of red flashing LEDs and the time of the academic calendar. As illustrated in **Table 8** and **Figure 11**, during break periods, when the LEDs were activated, the turnaround rate increased to 35% (13 Continued WW vs. 7 Self-corrected WW), compared to a markedly lower 11% when LEDs were deactivated (34 Continued vs. 4 Self-corrected). This substantial increase is further supported by the PDP predictions, which estimate a turnaround rate of 55% with LEDs activated versus 16% when deactivated during breaks. Similarly, in the summer semester, the activated LEDs led to a turnaround rate of 51% (17 Continued vs. 18 Self-corrected), surpassing the 27% rate when LEDs were off (22 Continued vs. 8 Self-corrected), with PDP predictions aligning at 49% and 23%, respectively.

In contrast, the fall semester showed a smaller difference between LED statuses, with a 25% turnaround rate when LEDs were activated (45 Continued vs. 15 Self-corrected) and 23% when deactivated (40 Continued vs. 12 Self-corrected), while PDP predictions indicate a rise from 20% to 33% with LED activation. Notably, the spring semester presented an anomaly where the turnaround rate was lower with LEDs activated (4%; 55 Continued vs. 2 Self-corrected) than when deactivated (16%; 104 Continued vs. 20 Self-corrected), despite PDP predictions suggesting an increase from 16% to 43% with activated LEDs.

These results suggest a seasonal effect on the effectiveness of red flashing LEDs in deterring WWD incidents. The heightened effectiveness during break and summer periods may be attributed to an influx of non-local drivers—such as visitors, new students, or staff—who are unfamiliar with campus roadways and thus more responsive to conspicuous warning signals like flashing LEDs. The increased presence of these drivers likely elevates the risk of WWD incidents, but also enhances the impact of visual deterrents. Conversely, during regular semesters, most drivers are familiar with campus routes, potentially reducing the relative effectiveness of the LEDs. The unexpected findings in the spring semester warrant further investigation, as they may result from external factors not accounted for in the model, such as specific campus events or construction activities affecting traffic patterns.

The examination of WWD incidents across different days of the week highlights significant variations in driver behavior influenced by the activation status of red flashing LEDs and daily campus activities. As illustrated in **Table 9** and **Figure 12**, during periods when the LEDs were activated, the highest turnaround rates occurred on Tuesday and Wednesday, with rates of 42% (11 Continued vs. 8 Self-corrected) and 41% (13 Continued vs. 9 Self-corrected), respectively. The PDP predictions support these findings, indicating predicted turnaround rates of 58% for Tuesday and 35% for Wednesday. These elevated rates suggest that midweek days benefit substantially from LED activation, possibly due to increased campus activity, higher traffic volumes of familiar drivers, and greater driver attentiveness during regular academic schedules.

Table 9 Distribution of Continued and Self-Corrected WW Incidents by Day of Week with Corresponding Turnaround Rates

Incident Period	**LED Activated**			**LED Deactivated**		
	Continued WW	Self-Corrected WW	Turnaround Rate (%)	Continued WW	Self-Corrected WW	Turnaround Rate
Monday	21	7	25%	35	9	20%
Tuesday	11	8	42%	10	7	41%
Wednesday	13	9	41%	19	7	27%
Thursday	17	6	26%	23	2	8%
Friday	17	4	19%	15	1	6%
Saturday	18	4	18%	34	5	14%
Sunday	33	4	11%	67	13	16%
Grand Total	130	42	24%	200	44	18%

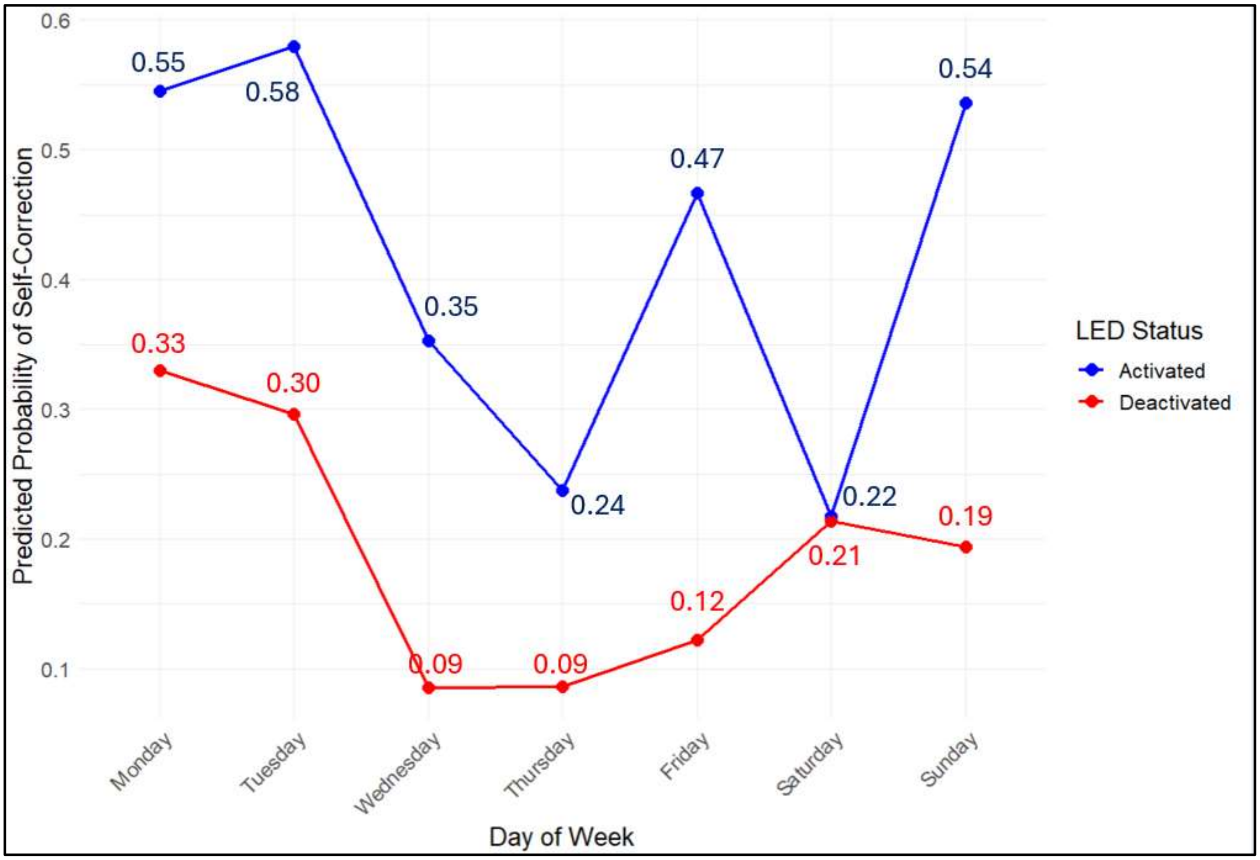

Figure 12 Impact of LED Status on Driver Self-Correction Across Day of Week

In contrast, Thursday and Friday exhibited lower turnaround rates despite LED activation, at 26% (17 Continued vs. 6 Self-corrected) and 19% (17 Continued vs. 4 Self-corrected), with PDP predictions of 24% and 47%, respectively. The diminished effectiveness on these days may be attributed to end-of-week fatigue, increased social activities, or a shift in driver demographics, such as more visitors or non-local drivers less familiar with campus roadways. Saturday showed a particularly low turnaround rate of 18% during LED activation (18 Continued vs. 4 Self-corrected) and 14% when LEDs were deactivated (34 Continued vs. 5 Self-corrected), with PDP predictions remaining relatively constant at 22% and 21%, respectively. This consistency suggests that LED activation has minimal impact on Saturdays, potentially due to leisure activities drawing non-local drivers who may be less responsive to the LEDs or less aware of one-way road systems on campus.

Sunday presented an interesting case where the observed turnaround rate was 11% with LEDs activated (33 Continued vs. 4 Self-corrected) and 16% when deactivated (67 Continued vs. 13 Self-corrected), while PDP predictions indicated a substantial increase from 19% to 54% with LED activation. The discrepancy between observed data and model predictions on Sundays may result from reduced campus activities, lower traffic volumes, or drivers' reduced vigilance at the end of the weekend. Monday displayed a moderate turnaround rate of 25% during LED activation (21 Continued vs. 7 Self-corrected) compared to 20% when deactivated (35 Continued vs. 9 Self-corrected), with PDP predictions showing an increase from 33% to 55%. This suggests that LEDs begin to regain effectiveness at the start of the academic week as drivers resume regular routines.

Overall, the data indicates that the effectiveness of red flashing LEDs in promoting driver self-correction during WWD incidents varies throughout the week, correlating with daily patterns and campus activities. Midweek days, characterized by regular academic schedules and familiar drivers, see enhanced effectiveness of LEDs. In contrast, weekends and end-of-week days like Thursday and Friday exhibit reduced LED impact, likely due to a higher proportion of non-local drivers, social events, and altered traffic patterns. These findings underscore the importance of tailoring safety interventions to account for daily variations in driver behavior and suggest that additional measures—such as increased signage, public awareness campaigns, or enhanced enforcement—may be necessary on weekends to improve road safety and reduce WWD incidents on campus.

The analysis of WWD incidents in relation to time of day and the activation status of red flashing LEDs reveals significant patterns influenced by ambient light conditions and driver activity throughout the day. As illustrated in **Table 10** and **Figure 13**, during daytime hours, when natural lighting is abundant, the activation of LEDs resulted in a turnaround rate of 21% (90

Continued vs. 24 Self-corrected), compared to a lower 14% when LEDs were deactivated (131 Continued vs. 21 Self-corrected). The PDP predictions support this finding, indicating an increase in the predicted turnaround rate from 13% with LEDs deactivated to 33% when activated during daytime. This suggests that even in well-lit conditions, the enhanced visibility provided by flashing LEDs effectively captures drivers' attention, prompting more to recognize their error and self-correct.

Table 10 Distribution of Continued and Self-Corrected WW Incidents by Time of Day with Corresponding Turnaround Rates

Incident Period	**LED Activated**			**LED Deactivated**		
	Continued WW	Self-Corrected WW	Turnaround Rate (%)	Continued WW	Self-Corrected WW	Turnaround Rate
Daytime	90	24	21%	131	21	14%
Nighttime	17	6	26%	45	16	26%
LateNight	23	12	34%	24	7	23%
Grand Total	130	42	24%	200	44	18%

In the nighttime period, characterized by reduced ambient light but not complete darkness, both the observed and predicted turnaround rates showed notable differences with LED activation. The actual turnaround rate remained at 26% regardless of LED status (17 Continued vs. 6 Self-corrected incidents with LEDs activated; 45 Continued vs. 16 Self-corrected with LEDs deactivated). However, the PDP predictions indicate an increase from 27% with LEDs deactivated to 46% when activated at night. The discrepancy between observed and predicted rates may be due to factors such as driver fatigue or decreased traffic volumes, which can influence driver responsiveness to visual cues during nighttime hours.

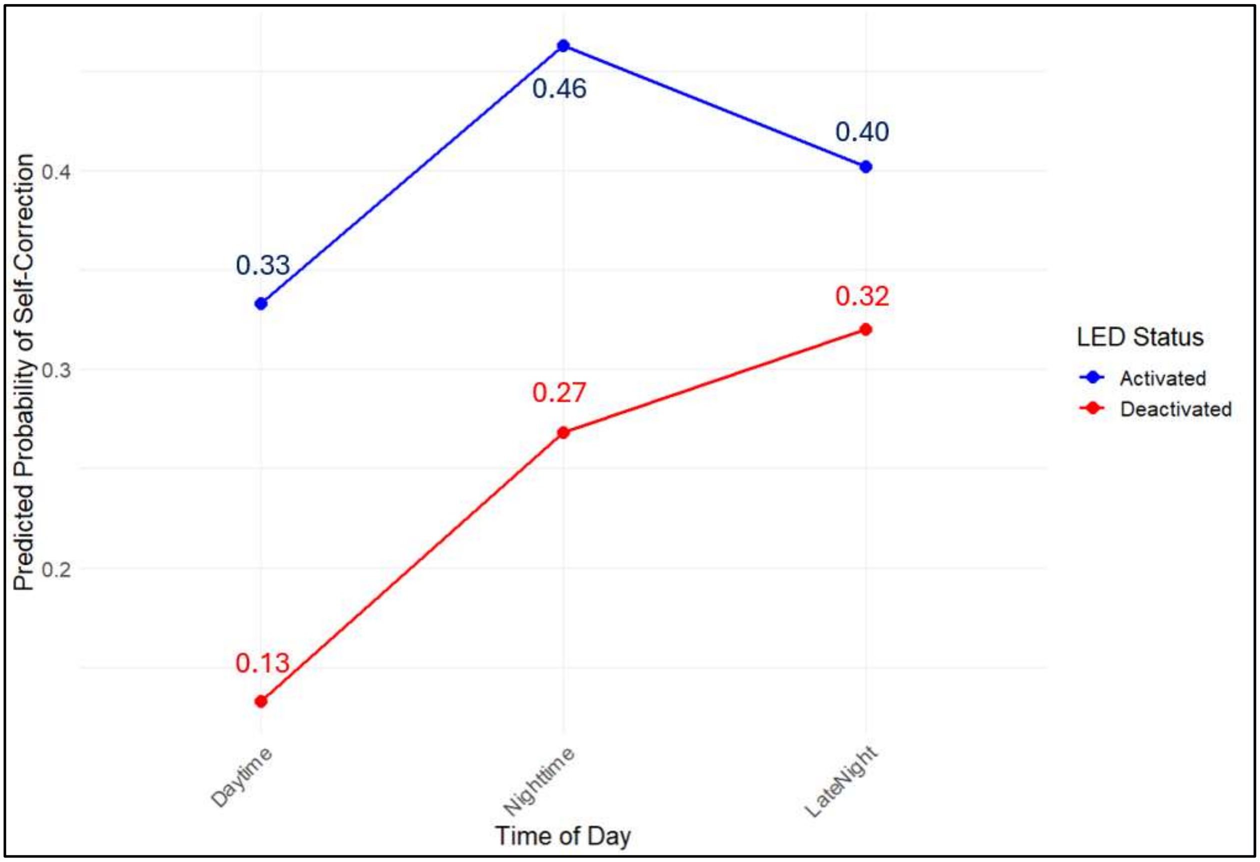

Figure 13 Impact of LED Status on Driver Self-Correction Across Time of Day

During late-night hours, when darkness is at its peak and visibility is significantly reduced, the activation of LEDs had a more pronounced effect. The turnaround rate increased to 34% with LEDs activated (23 Continued vs. 12 Self-corrected) from 23% when LEDs were deactivated (24 Continued vs. 7 Self-corrected). The PDP predictions align with this trend, showing an increase from 32% with LEDs deactivated to 40% when activated during late night. This indicates that in low-light conditions, the red flashing LEDs are particularly effective in enhancing sign conspicuity, aiding drivers in recognizing wrong-way indicators and correcting their course.

These findings underscore the critical role of light conditions and driver activity patterns in the effectiveness of safety interventions like red flashing LEDs. Daytime hours, despite ample natural light, involve higher traffic volumes and potentially more distractions due to increased activity, making additional visual alerts beneficial. Nighttime and late-night periods often see changes in driver behavior, such as increased fatigue or impairment, and lower ambient light levels, which can diminish drivers' ability to perceive standard signage. The enhanced visibility provided by flashing LEDs during these times is crucial in capturing driver attention and preventing WWD incidents.

Overall, the data suggests that while red flashing LEDs improve driver self-correction rates across all times of day, their impact is most significant during late-night hours when darkness impairs visibility. This emphasizes the importance of maintaining and potentially enhancing such warning systems during periods of low light to maximize road safety.

Chapter 5 CONCLUSIONS

This study conducted a comprehensive evaluation of a Wrong-Way Alert System installed on a university campus one-way road, focusing on the effectiveness of red flashing LEDs around WRONG WAY sign border in mitigating drivers' WWD behavior. The research leveraged a unique opportunity to collect extensive before-and-after data at the same location, with the sole variable manipulated being the activation status of the red flashing LEDs around the border of existing WRONG WAY signs. This approach allowed for a precise assessment of the impact of flashing LEDs on drivers' turnaround decisions, addressing limitations in previous studies.

Following is the summary of key findings in this study:

- **High Detection Precision:** The Wrong-Way Alert System demonstrated exceptional detection accuracy, with no missing events and neglectable false-triggered alerts over 29 months of data collection. This level of precision is critical in promptly identifying WWD incidents, which have a high potential for fatality.
- **Effectiveness of Red Flashing LEDs:** Activating the flashing LEDs significantly increased drivers' self-correction rates during WWD incidents. The two-proportion z-test yielded an approximate 20% increase (LED deactivated 18%, LED activated 37%) in the turnaround rate when LEDs were activated compared to deactivated. The 95% confidence interval for this difference ranged from 10% to 28%, indicating a substantial and statistically significant effect. However, the overall low turnaround rate may be attributed to drivers' intentional WWD behavior. Given that the one-way road is wide, and the speed limit is low, drivers may perceive less threat or risk when committing WWD, reducing their incentive to self-correct.

- **Influence of Temporal Factors:**
    - **Incident Period:** During break and summer periods, self-correction rates increased from 11% to over 35% with LED activation, indicating heightened effectiveness among non-local drivers unfamiliar with campus roads.
    - **Day of the Week:** On midweek days like Tuesday and Wednesday, self-correction rates rose above 40% when LEDs were activated, suggesting greater impact during regular academic activities and higher driver attentiveness.
    - **Time of Day:** During late-night hours, the turnaround rate improved from 23% to 34% with LEDs on, highlighting the importance of enhanced visual cues in low-light conditions.
- **Limitations of Current Detection System:** The system, initially designed for highway exit ramps, detected a large number of non-critical alerts in the urban campus environment, including authorized vehicles and pedestrians. This resulted in frequent triggering of LEDs, accelerating system wear and highlighting the need for improved detection and classification algorithms.

Based on the findings, several recommendations are proposed to enhance the effectiveness of the Wrong-Way Alert System and further reduce WWD incidents:

Firstly, improving the detection mechanism by integrating artificial intelligence (AI) or machine learning technologies is crucial. The current system detects more than half of the non-critical events, such as pedestrians and maintenance vehicles (golf carts), leading to frequent and unnecessary activations of the warning signs. By incorporating image recognition technologies, the system can more accurately distinguish between actual wrong-way vehicles and nonthreatening entities. This enhancement will increase detection accuracy, reduce false positives, and extend the product's lifetime.

Secondly, adjusting the flashing patterns of the LEDs, specifically on Saturdays, may address the reduced effectiveness observed on those days. The study suggests that the higher incidence of impaired driving on Saturdays may make drivers less responsive to standard flashing patterns. Modifying the LED sequences to use varying flashing rates, increased brightness, or alternative visual cues could capture the attention of drivers more effectively during these high-risk periods.

Thirdly, implementing enhanced law enforcement measures for repeat offenders is essential. The data revealed drivers repeatedly engaging in WWD, indicating intentional violations that pose significant safety risks. Collaborating with local law enforcement agencies to share information about these repeat offenders can facilitate targeted enforcement actions. Additionally, imposing stricter penalties, such as higher fines, could deter habitual violators. Installing high-resolution cameras capable of capturing plate numbers would support these efforts by enabling the identification and prosecution of repeat offenders.

By focusing on technological enhancements, targeted interventions during high-risk periods, and stronger enforcement measures, these recommendations aim to address the key issues identified in the study. Implementing them can significantly improve the system's effectiveness and contribute to reducing WWD incidents, ultimately enhancing road safety for all user

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