Are We Ready for Automated Vehicles? Evaluating Automated Driving Systems' Safety and Reliability Using Propensity Score Matching

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ABSTRACT

Automated Driving Systems (ADS) promise transformative changes in transportation by enhancing road safety, efficiency, and accessibility. However, integrating ADS into existing traffic systems introduces new safety challenges, particularly concerning remote driver/operator involvement. Analyzing the National Highway Traffic Safety Administration's ADS crash data from July 2021 to March 2024 (N=580), the study investigates remote driver/operator involvement in crash injuries using the Propensity Score Matching while controlling for confounding factors. The study's findings indicate that a remote driver/operator, as opposed to other drivers, is associated with a significantly higher likelihood of injury in ADS-related crashes, with an odds ratio of 1.310. Crashes involving remote drivers/operators have a higher injury rate (22.95%) than those without remote involvement (8.52%). The study also highlights the association of other controlling factors with ADS crash outcomes. Crashes involving vulnerable road users, like pedestrians and cyclists, significantly increase the injury risk (odds ratio 4.338). Higher pre-crash speeds are strongly associated with increased injury likelihood, with odds ratios of 2.593 for speeds > 25 mph. Rear-end collisions show a pronounced effect on injury risk (odds ratio 5.983). Other key factors positively associated with ADS injury crashes are crashes on highways/freeways and intersections, dark lighting and non-clear weather conditions, and collisions involving trucks. These findings underscore the need for improvements in ADS technology to enhance safety. The study provides insights for manufacturers, planners, and policymakers, guiding future advancements and safety protocols to better integrate ADS into existing transportation systems.

Keywords: Autonomous vehicles (AVs), Automated driving systems (ADS), Crash injury, Remote driver/operator, Causal inference, Propensity Score Matching (PSM), National Highway Traffic Safety Administration (NHTSA) crash data, Vulnerable road users, Roadway Type, Pre-crash speed

INTRODUCTION

Traffic crashes are a major concern in transportation systems. Around 40,000 fatalities and millions of other injuries occur annually in road crashes in the United States (*1*). The emergence of automated vehicles (AVs), also known as self-driving vehicles, is reshaping transportation, indicating a major shift in how we think about driving, mobility, safety, and traffic flow. They promise transformative changes to our transportation systems, potentially enhancing road safety, efficiency, and accessibility (*2-5*). There are five levels of driving automation. The lower two levels are called 'Advanced Driver Assistance System (ADAS),' which include 'driver assistance,' and 'partial automation.' The upper three levels are called 'Automated Driving Systems (ADS),' and they include 'conditional automation,' 'high automation,' and 'full automation.' These vehicles integrate sensors, cameras, and artificial intelligence (AI) to navigate roads with minimal or no human intervention (*6-9*). As they evolve, ADS vehicles promise to mitigate road traffic crashes, alleviate congestion, and improve mobility and safety, especially for those unable to drive (*10-13*). However, the integration of these ADS vehicles into our current traffic system emerges new safety and reliability challenges, particularly in the context of crash scenarios, due to their independent operation, such as driver's over-reliance on ADS and a propensity for more risk-taking behaviors, possibly due to the perceived security these systems offer (*14-16*). Since humans do the programming of these ADS vehicles, it can have errors. These errors include vehicle disengagements, loss of control by the remote driver, and other safety-related issues (*17-19*). According to the National Highway Traffic Safety Administration (NHTSA), a total of 1,141 ADS crashes were reported by automobile manufacturers and operators across the United States from July 2021 to March 2024 (*20*).

As we advance towards the full automation of vehicles, aiming for driverless technology and the complete remote control of vehicles, it becomes crucial to evaluate the safety and reliability of current ADS vehicles by examining the factors associated with injury crashes. The role of the remote driver/operator becomes particularly significant as the driving element is expected to be eliminated in fully automated vehicles. Ensuring that current remote driver/operator technology is reliable enough to safely operate vehicles without causing injury crashes is essential. Causal inference is a robust method to determine whether observed associations reflect a true cause-and-effect relationship (*21; 22*). This research aims to identify the cause-and-effect relationship between injury crashes and the involvement of remote drivers/operators while controlling for other key variables to assess the reliability of current ADS technology. The findings are anticipated to provide valuable insights for automated vehicle manufacturers, transportation planners, and policymakers, informing them about the current safety status of automated driving systems. This will support the development of enhanced safety protocols and human-machine interfaces, facilitating the safer integration of ADS into existing traffic systems.

LITERATURE REVIEW

The synthesis of past studies indicates that while automated vehicles promise transformative changes in transportation systems, their safety and reliability remain areas of significant concern. Numerous studies have analyzed and quantified the impact of various factors contributing to AV crashes. Research has shown that AVs are not necessarily safer than conventional vehicles; for instance, rear-end collisions are more frequent in AVs, and the overall crash rates are higher than those involving human-driven vehicles (*13; 23-28*). This underscores the need for a deeper understanding of the factors contributing to AV injury crashes, particularly in the context of fully automated vehicles and the role of remote drivers/operators. The detection capabilities of AVs, particularly concerning vulnerable road users (VRUs), including pedestrians, bicyclists, motorcyclists, and other non-motorized road users, and adverse weather conditions, have been pinpointed as critical areas for improvement compared to human-driven (*29; 30*). This is supported by the findings of (*31*), those who utilized ordinal logistic regression and Classification And Regression Tree (CART) analyses to reveal that the driving mode and interactions with VRUs, such as pedestrians/cyclists, significantly influence AV collision types. In addition to the challenges inherent in integrating AVs into the current transportation system, recent studies have investigated the specifics of crash patterns and contributory factors. (*32*) found that rear-end collisions are notably more common in AV-involved incidents than those involving only human-operated vehicles, with the likelihood of such crashes increasing alongside speed gap ratios and being higher on highways and rural roads. This suggests that differences in speed and driving patterns between AVs and conventional vehicles are significant factors in crash occurrence. Complementing these findings, (*33*) identified the vehicle's automation level, speed limits, and the vehicle's operational speed as critical predictors of crash patterns, underscoring the complex interplay between AV technology and traditional traffic environments. Further exploring the nuances of AV interactions, (*34*) observed that human operators are more likely to initiate disengagements in mixed traffic scenarios. Disengagements often arise from discrepancies in the planning and execution of maneuvers by ADS, as well as hardware and software limitations. Such disengagements are more frequently initiated by the ADS on streets and roads, contrasting with the more predictable environment of high-speed facilities. Analysis of crash narratives and reports has provided insights into the factors contributing to AV/ ADS crashes (*13; 19; 27; 31; 33; 35-37*). For instance, (*13*) employed text mining techniques to analyze AV crash narratives, revealing that rear-end crashes were the most common collision type, and AVs were often rear-ended more frequently at intersections and one-way streets, particularly where higher speed limits and poor lane markings were present. These findings correlate with the detailed statistical analysis presented by (*38*), who identified driving mode, stopping, and turning maneuvers as critical factors affecting AV crash patterns. Furthermore, human drivers' unexpected responses to AV actions, such as braking at intersections, have led to a higher incidence of AVs being rear-ended (*24*). This is compounded by the conservative behavior of AVs, which may not align with human driving expectations, leading to conflicts and collisions. (*31*) developed a CART model to visualize the hierarchical structure of factors contributing to AV crashes, providing a comprehensive understanding of AV crash mechanisms. (*39*) extended this analysis using a Bayesian latent class model, finding that turning movements, multi-vehicle collisions, and adverse lighting conditions correlate with higher injury severity levels.

The literature review further reveals that ADS injury crashes are associated with numerous factors, including automated driving modes (remote driver/operator or in-vehicle driver), interactions with VRUs (such as pedestrians and cyclists), pre-crash movements and speed of the subject vehicle, roadway geometrics, crash location, collision type, vehicle damage area, weather conditions, lighting conditions, and roadside parking, etc., (*30; 33; 38*). These studies highlight the multifaceted nature of AV safety and the importance of considering factors such as road type, traffic conditions, and the maturity of ADS technology in developing and assessing AV systems. In AV safety research, publication bias may exist, with studies showcasing AV benefits potentially being more appealing to journals and readers. While past studies do not explicitly reveal publication bias, the significant impact of AV technology on public safety, environmental outcomes, and urban planning underscores the importance of both positive and negative findings. Reports yielding unexpected results are crucial as they offer insights into AV limitations and risks, enhancing safety regulations and technological advancements.

Causal inference and treatment effect methodologies have been widely applied in various studies, including intelligent transportation systems and transportation safety studies, to analyze traffic flow and identify factors contributing to road injury crashes and their severities (*21; 22; 40-43*). Propensity Score Matching (PSM), a popular causal inference method, has been utilized in several studies (*21; 44-47*). Despite the robustness of this methodology, its application in AV and ADS/ADAS crash studies remains limited. Furthermore, past studies on AV/ADS crashes have predominantly focused on California-specific data, which limits the understanding of outcomes on a national scale. This regional concentration overlooks the diverse traffic conditions and demographics across the United States, potentially masking crucial factors. By utilizing the NHTSA's latest data on ADS crashes nationwide across the United States, this study seeks to bridge the gap by employing a causal inference approach to assess the efficacy of remote driver/operator technology in automated vehicles. By evaluating key factors associated with ADS injury crashes, the study aims to provide critical insights into the current state of ADS technology and its implications for road safety.

METHODOLOGY

Data Source and Description

The National Highway Traffic Safety Administration (NHTSA) has issued a Standing General Order requiring specified automobile manufacturers and operators across the United States to report crashes involving Automated Driving Systems (ADS) and Advanced Driver Assistance Systems (ADAS) since July 2021. This study focuses on ADS crashes, defined as incidents where the ADS was active at any time within 30 seconds of the crash, resulting in property damage or injury. These crashes correspond to the Society of Automotive Engineers (SAE) Level 3 or higher, where vehicles are designed to independently manage all driving operations over extended periods within specific operational parameters without requiring driver interaction. From July 2021 to March 2024, 1,141 ADS crash reports were recorded. After downloading the data from the NHTSA website, a three-step process was undertaken to clean and screen the data, addressing duplicates and missing values. The original dataset contained multiple versions of reports for single crashes, identifiable by 'Report ID' and 'Report Version.' In the first step, duplicate reports were removed based on 'Report ID' and 'Report Version' using the latest version of the statistical software R-studio. A total of 250 crash reports were identified as duplicates and removed, retaining the latest version of each report. In the second step, a similar procedure was applied to remove duplicate crash reports based on ‘Mileage’ and ‘VIN,’ removing 311 additional duplicate reports. In the third step, missing and unknown values were addressed by referring to crash narratives or imputing them with the mode or most frequent category. The final dataset comprises 580 valid ADS crash reports recorded across the United States. The subsequent analysis of this study was conducted based on these reports.

Conceptual Framework

Figure 1 represents the study’s conceptual framework, designed to evaluate the safety and reliability of Automated Driving Systems by employing a causal inference method, specifically Propensity Score Matching (PSM). The study utilizes a unique latest dataset of the NHTSA, comprising 1,141 ADS crash reports from across the United States, spanning July 2021 to March 2024. After a meticulous data-cleaning process involving the removal of duplicates, the final dataset comprised 580 unique and valid ADS crash reports. The primary outcome variable selected is ‘ADS Crash Injury,’ categorized as a binary variable (Yes/ No). The treatment variable under investigation, ‘Remote Driver/Operator,’ categorizes crashes based on the involvement of a remote driver/operator. The remote driver/ operator is defined as an individual, other than a consumer, not located within the subject vehicle but capable of providing remote driving, fallback operation, and assistance in any part of the dynamic driving task (DDT) at the time of the incident. The ‘base’ category of this variable includes drivers other than remote drivers/operators, such as consumer drivers, in-vehicle commercial/test drivers, a combination of both remote drivers/operators and in-vehicle drivers, or none (no individual is responsible for any part of the DDT at the time of the incident). The ‘Remote Driver/Operator’ refers to crashes involving ADS technology and level 4 driving automation (high automation). This level of ADS crashes is commonly observed in ‘Robotaxis’ manufactured by companies such as Cruise (General Motors), Waymo (Google), Zoox (Amazon), and Mercedes Benz, and testing conducted by vehicle manufacturers. Most of these crashes occurred in four major cities in the USA: San Francisco and Los Angeles (California), Phoenix (Arizona), and Las Vegas (Nevada).

To control for potential confounders, several control variables are included, such as ‘Roadway Type,’ ‘Lighting Condition,’ ‘Weather Condition,’ ‘Crash with (vulnerable road users (VRU), trucks, or others including passenger cars, buses, fixed objects, etc.), ‘Subject Vehicle (SV) Pre-crash Speed,’ and ‘SV Contact Area.’ The study employs Propensity Score Matching (PSM) to estimate the causal effect of having a remote driver/operator on the likelihood of injury in ADS crashes. PSM helps to create a matched sample of crashes with and without remote drivers/operators, similar to the control variables. The matched sample is then analyzed to determine the impact of the remote driver/operator on crash injuries, providing insights into the safety and reliability of current ADS technology.

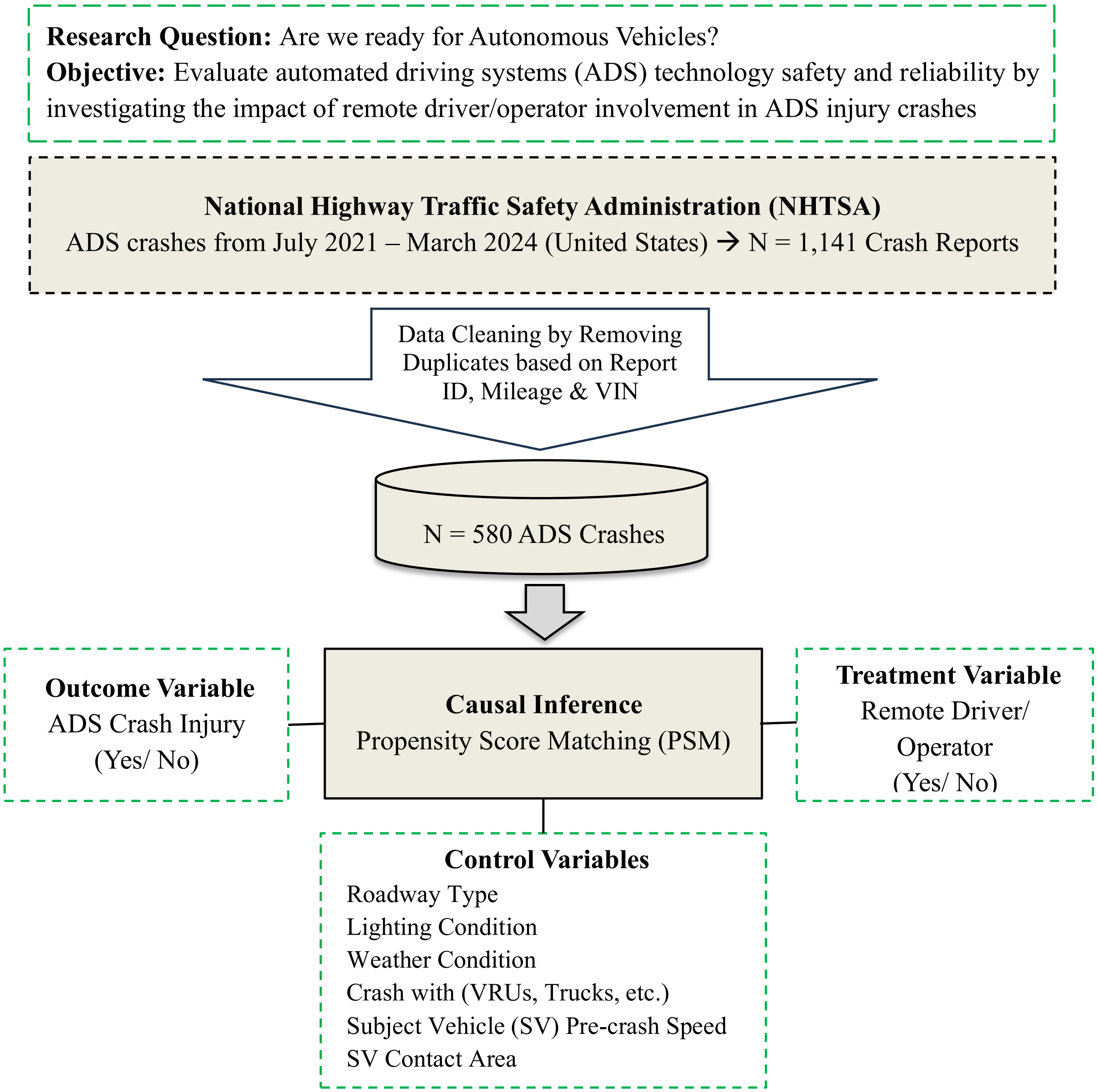

Figure 1 Conceptual Framework of the Study

Casual Inference – Propensity Score Matching

Rosenbaum and Rubin introduced the propensity score matching (PSM) method to address the issue of creating comparable groups in observational studies (*47*). PSM is a statistical technique used to estimate the causal effect of a treatment by accounting for covariates that predict receiving the treatment. This method is particularly useful in observational studies where randomized controlled trials are not feasible. PSM aims to reduce selection bias by equating groups based on these covariates. In a randomized experiment, the treatment status T_i is unconditionally independent of the potential outcomes Y_i. However, in non-randomized observational data, such independence cannot be achieved due to confounding factors X, which affect both the probability of treatment exposure and potential outcomes. Consequently, simple comparisons of mean outcomes between treated and untreated groups generally do not reveal the causal effect. However, conditional independence of potential outcomes and treatment status can be ensured by adjusting for the vector of the covariates X. This adjustment allows for consistent causal estimates of treatment effects. The propensity score $e(X)$ is the conditional probability of receiving the treatment given a vector of observed covariates X. Mathematically, it is expressed as:

$$e(X) = P(T = 1|X) \quad (1)$$

where T is a binary indicator of treatment status (1 if the subject receives the treatment, 0 otherwise). The propensity score is typically estimated using logistic regression:

$$logit\big(e(X)\big) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \quad (2)$$

Once the propensity scores are estimated, the next step is to match the treatment group with the control group 'based' on similar propensity scores. This matching process aims to create a balanced dataset where the distribution of covariates is similar between the treatment and control groups, thus mimicking a randomized experiment. PSM has been extensively studied and applied in various evaluations of social, economic, and medical programs and can be consulted for further details on the method (*44-46; 48-52*)

RESULTS

Descriptive Statistics

Table 1 presents the descriptive statistics of key variables used in the study, providing a comprehensive overview of the dataset comprising 580 ADS crash reports across the United States. The binary outcome variable, 'Crash Injury,' indicates whether a crash resulted in injury. Of the crashes, 11.55% resulted in injuries, while 88.45% did not. The treatment variable, 'Remote Driver/Operator,' categorizes crashes based on the involvement of a remote driver/operator. The 'base' category of this variable includes drivers other than remote drivers/operators, such as consumer drivers, in-vehicle commercial/test drivers, a combination of both remote drivers/operators and in-vehicle drivers, or none (no individual is responsible for any part of the dynamic driving task at the time of the incident). In the dataset, 21.72% of the crashes involved a remote driver/operator, while 78.28% did not.

Various control variables are also summarized. The 'Roadway Type' variable shows that 7.59% of the crashes occurred on highways/freeways, 42.76% at intersections, and 49.66% on other road types. The 'Roadway Surface Condition' indicates that most crashes (93.97%) happened on dry surfaces, with only 6.03% on wet surfaces. The 'Posted Speed Limit' variable reveals that 6.55% of the crashes occurred in areas with speed limits over 45 mph, 24.66% in areas with speed limits between 25 and 45 mph, and 68.79% in areas with speed limits of 25 mph or less. The 'Lighting Condition' shows that 62.76% of crashes happened during daylight/dawn/dusk, while 37.24% occurred in dark conditions. Regarding 'Weather Condition,' 83.62% of the crashes happened under clear weather, with 16.38% in not clear conditions (e.g., snow, fog, rain). The variable 'Crash With' indicates that 16.72% of crashes involved vulnerable road users (VRU)/ non-motorists (pedestrians, cyclists, etc.), 21.03% involved trucks, and 62.24% involved other vehicles or objects. The 'Subject Vehicle Pre-crash Movement' shows that 40.86% of the vehicles proceeded straight, 13.97% made turning maneuvers, 38.45% stopped, and 6.72% were involved in other movements. The 'Subject Vehicle Pre-crash Speed' indicates that 8.10% of the crashes involved vehicles moving at speeds greater than 25 mph, while 47.76% involved vehicles moving between 1 to 25 mph, and 44.14% involved stationary vehicles. Finally, the 'Subject Vehicle Contact Area on Impact' variable reveals that 13.45% of the crashes involved the vehicle's front end, 27.24% involved the rear end, 3.45% involved sideswipe, and 45.86% involved other areas.

Table 2 presents the relationship between the outcome variable, crash injury, and the treatment variable, remote driver/operator involvement. It reveals that crashes involving remote drivers/operators resulted in more injury crashes than those without remote driver/operator involvement. Specifically, 22.95% (28 out of 126) of crashes with remote drivers/operators resulted in injuries, whereas only 8.52% (39 out of 454) of crashes without remote drivers/operators led to injuries, as shown in Figure 2. The higher injury rate in the remote driver/operator group suggests that remote operation results in more injury crashes than non-remote operations. This critical finding will be further analyzed and discussed in subsequent sections to provide a comprehensive understanding of its implications for ADS technology and traffic safety protocols.

TABLE 1 Descriptive Statistics of Key Variables

Variables *(Including Dummy Variables)*	**Descriptive Statistics (N = 580)**	
	Frequency	**Percentage (%)**
Crash Injury (1_Injury, 0_Non-injury) ***(Outcome Variable)***		
Injury	67	11.55
No injury	513	88.45
Remote Driver/ Operator (1_Remote, 0_Others) ***(Treatment Variable)***		
Remote Driver/ Operator (Commercial/ Test)	126	21.72
Others (Consumer, In-Vehicle (Commercial/ Test), In-Vehicle & Remote (Commercial/ Test), None)	454	78.28
Roadway Type		
Highway/ Freeway	44	7.59
Intersection	248	42.76

Others (Street, Parking Lot, Traffic Circle, etc.)	288	49.66
Roadway Surface Condition		
Dry	545	93.97
Wet	35	6.03
Posted Speed Limit (mph)		
> 45 mph	38	6.55
> 25 ≤ 45 mph	143	24.66
≤ 25 mph	399	68.79
Lighting Condition		
Daylight/ Dawn/Dusk	364	62.76
Dark (Dark-Lighted, Dark-Not-Lighted)	216	37.24
Weather Condition		
Clear	485	83.62
Not Clear (Snow, Cloudy, Fog/Smoke, Rain, Severe Wind)	95	16.38
Crash With		
Vulnerable Road Users/ Non-motorists (Pedestrians, Motorcyclists, Cyclists, etc.)	97	16.72
Trucks	122	21.03
Others (Animals, Buses, Passenger Cars, Poles/Trees, Other Fixed Objects)	361	62.24
Subject Vehicle Pre-crash Movement		
Proceeding Straight	237	40.86
Turning Maneuvers	81	13.97
Stopping	223	38.45
Others (Backing, Parking Maneuver, etc.)	39	6.72
Subject Vehicle Pre-crash Speed (mph)		
> 25 mph	47	8.10
1 – 25 mph	277	47.76
0 mph (Stationary Vehicle)	256	44.14
Subject Vehicle Contact Area on Impact		

Front End	78	13.45
Rear End	158	27.24
Sideswipe	78	3.45
Others (Top, Bottom, etc.)	266	45.86

TABLE 2 Outcome Variable (Crash Injury) vs Treatment Variable (Remote Driver/ Operator)

		Remote Driver/ Operator		Total
		Yes (Frequency/ Percent)	No (Frequency/ Percent)	
Crash Injury	Injury	28 (22.95%)	39 (8.52%)	67
	No Injury	98 (77.05%)	415 (91.48%)	513
Total		126 (100%)	454 (100%)	**580**

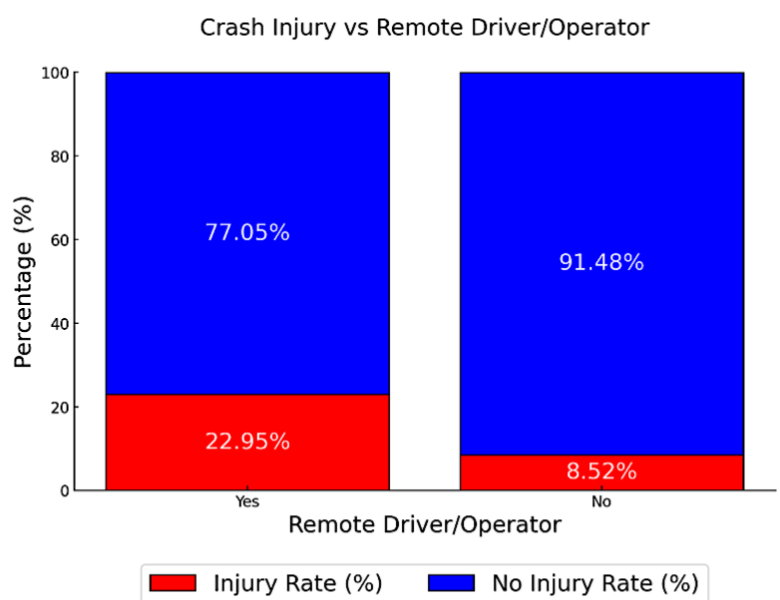

Figure 2 Graphical Visualization of Crash Injury vs Remote Driver/ Operator

Measure of Collinearity

In statistical modeling for this study, special attention is given to the potential issue of collinearity among explanatory variables, which can complicate model estimation. Cramer’s V is applied to assess the degree of association among categorical variables that feature two or more distinct values. This statistic ranges from ‘0’, indicating no association, to ‘1’, indicating a perfect association. For the explanatory variables considered in our study, Cramer's V values are observed to be low to moderate, all below the threshold of $\pm$ 0.75. Notably, the relationship between 'SV pre-crash movement' and 'SV pre-crash speed' yields a Cramer's V of 0.6157, suggesting a moderate association. The Variance Inflation Factor (VIF) is calculated to supplement this finding, with a resulting value of 2.85, which is below the commonly accepted threshold of 5. This suggests that the observed correlation is moderate and does not necessitate remedial actions within the model.

Causal Inference – Propensity Score Matching

The results of the causal inference analysis using Propensity Score Matching (PSM) are presented in Table 3. The analysis is conducted using logistic regression to estimate the propensity scores and match the treated and control groups based on these scores. Remote driver/ operator has been selected as the treatment variable while controlling for various other factors. The average treatment effect of remote driver/operator (treatment variable) shows a significant positive coefficient (0.2698), with an odds ratio of 1.310 and a t-statistic of 3.59 ($p < 0.001$). This indicates that remote driver/operator involvement is associated with a higher likelihood of injury in ADS crashes compared to scenarios without remote driver/operator involvement.

Control variables were included in the model to account for confounding factors. These variables reveal additional insights. Crashes on highways/freeways and intersections showed significant coefficients (0.9141 and 0.1085, respectively) with p-values < 0.01, indicating that these locations are associated with injury outcomes compared to other road types. Daylight conditions significantly reduce injury likelihood compared to dark conditions, evidenced by a negative coefficient (-0.9703) and odds ratio of 0.379. Non-clear weather conditions (e.g., snow, rain) increase the odds of injury crashes (coefficient 0.0561, odds ratio 1.058 with p-value < 0.05). Crashes involving vulnerable road users such as pedestrians, motorcyclists, or cyclists markedly increase injury odds (coefficient 1.4673, odds ratio 4.338), as do collisions with trucks (coefficient 0.6816, odds ratio 1.977), with both p-values < 0.001. Higher pre-crash speeds are also significantly associated with increased injury likelihood, with odds ratios of 2.593 for speeds > 25 mph and 1.423 for speeds between 1 and 25 mph (p-values < 0.001), capturing the non-linear effect of speed on injury outcomes. Crashes where the front or rear ends of the subject vehicle are impacted show a higher likelihood of injury, with odds ratios of 2.050 for front-end impacts and 5.983 for rear-end impacts (both p-values < 0.001), indicating a significant increase in injury risk, with rear-end impacts having a more pronounced effect (Table 3).

The model's fit statistics demonstrate its robustness, with 580 observations, a log-likelihood at the convergence of – 241.2435, a pseudo-R-square value of 0.2053, and an LR Chi-square of 124.65 ($p < 0.0001$). The Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) are 506.487 and 558.843, respectively. Figure 3 shows the distribution of propensity scores for the treated (remote driver/operator involvement) and untreated groups. The blue bars represent the untreated group, the red bars represent the treated group on support, and the green bars represent the treated group off support. The overlap between the treated and untreated groups, as indicated by the red and blue bars, suggests that the matching process effectively created comparable groups based on the observed covariates. Most units (574 out of

580) fall within the common support region, meaning their propensity scores overlap, which allows for a meaningful comparison between the treated and untreated groups. However, a few treated units (6), shown in green, are off-support, indicating that their propensity scores do not overlap with any units in the untreated group. These off-support treated units were excluded from the analysis to maintain the validity of the comparison.

TABLE 3 Causal Inference (Propensity Score Matching) – Results

Variables	Coefficient	Odds Ratio	t-stat[#]	P-Value
Treatment Variable – Remote Driver/ Operator Average Treatment Effect (ATE) *(Base: Others = 0), Remote Driver =1*	0.2698	1.310	3.59*	0.000
Control Variables				
Roadway Type				
Highway/ Freeway	0.9141	2.495	2.82*	0.007
Intersection	0.1085	1.115	3.06*	0.000
Others (Street, Parking Lot, etc.) *(Base condition)*				
Lighting Condition *(Base: Dark = 0), Daylight=1*	– 0.9703	0.379	– 7.12*	0.000
Weather Condition *(Base: Clear = 0), Not Clear = 1*	0.0561	1.058	1.98*	0.047
Crash With				
Vulnerable Road Users/ Non-motorists (Pedestrian, Motorcyclist, Cyclist, etc.)	1.4673	4.338	4.76*	0.000
Trucks	0.6816	1.977	3.95*	0.000
Others (Animals, Buses, Passenger Cars, Trees/ Poles, Fixed Objects, etc.) *(Base condition)*				
Subject Vehicle (SV) Pre-crash Speed (mph)				

> 25 mph	0.953	2.593	5.89*	0.000
1 – 25 mph	0.353	1.423	3.27*	0.000
0 mph (Stationary Vehicle) *(Base condition)*				
Subject Vehicle Contact Area on Impact				
Front End	0.718	2.050	2.86*	0.000
Rear End	1.789	5.983	4.92*	0.018
Sideswipes	0.225	1.252	1.16	0.245
Others (Top, Bottom, etc.) *(Base condition)*				
Constant	–1.127	0.324	–5.76	0.000
Model Fit Statistics				
Number of Observations	580			
Log-likelihood at Null	– 303.5687			
Log-likelihood at Convergence (Model)	– 241.2435			
Pseudo R-square Value	0.2053			
LR Chi^2 (11)	124.65			
Prob > Chi^2	0.0000			
Akaike's Information Criterion (AIC)	506.487			
Bayesian Information Criterion (BIC)	558.843			

** Indicates parameter is significant at 0.05.*
[#] t-stats are calculated at a 95% confidence level.

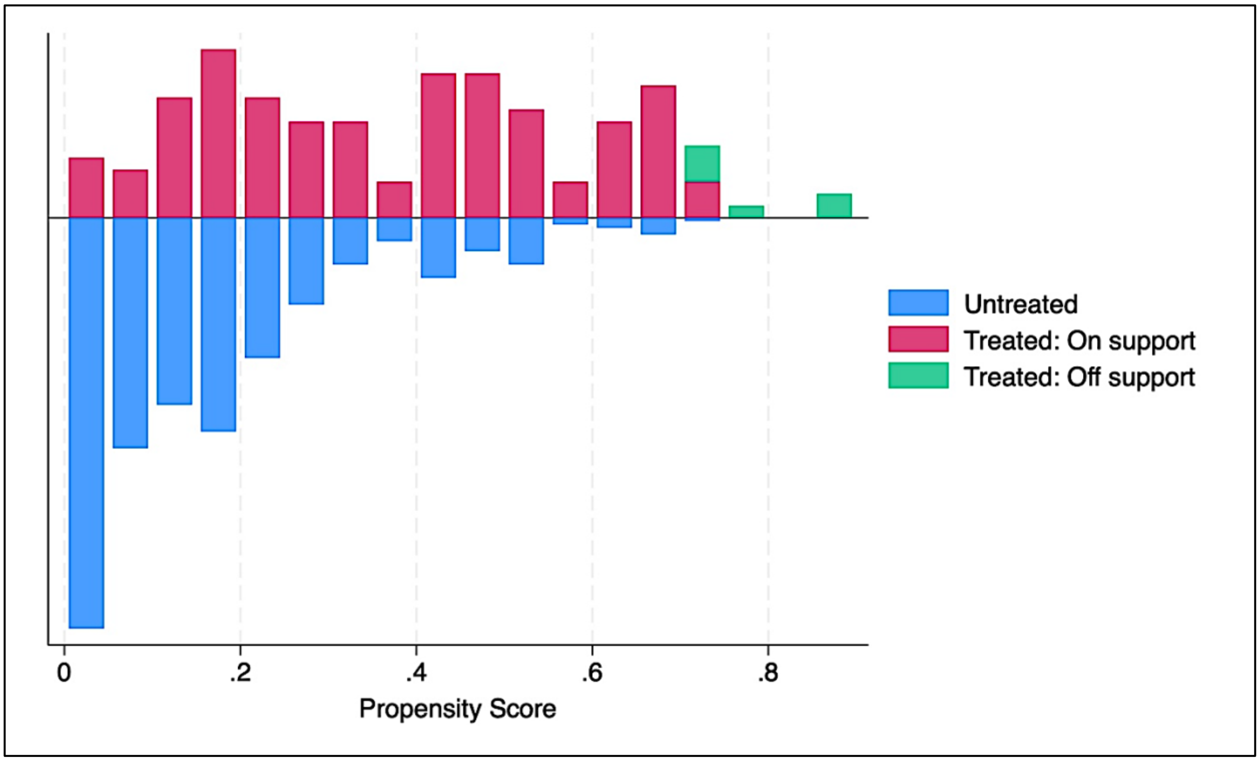

Figure 3 Propensity Score Distribution

DISCUSSION

The study's findings provide significant insights into the correlates of injury outcomes in ADS-related crashes, focusing on the involvement of remote drivers/operators. The findings indicate that remote drivers/ operators in ADS-involved vehicles are associated with a higher risk of injury crashes. This can be attributed to potential delays in response times from remote operators and the possible inadequacy of in-vehicle drivers to override automated systems and take control effectively in safety-critical events. This suggests the current readiness for remote driving may not be adequate. It further emphasizes the risk associated with over-reliance on technology by drivers, which resonates with findings from prior research (*18; 19; 34; 53; 54*).

The analysis of control variables further reveals the conditions under which injury likelihood increases. Crashes on highways/freeways and intersections are significantly associated with higher injury odds. High-speed environments, such as highways, carry a higher risk, which may be intensified by the high velocities involved in ADS operations. Similarly, the complex navigational challenges at intersections likely contribute to injury crashes, as observed in past studies (*5; 38; 39*). Crashes involving vulnerable road users, such as pedestrians, motorcyclists, or cyclists, increase the likelihood of injury by 4.338 times, highlighting the critical need for ADS to improve detection and response strategies. The higher odds ratio suggests that ADS-equipped vehicles may still face challenges in detecting and appropriately responding to the unpredictable movements of these users, especially in the dark when it becomes difficult to observe them, as indicated by the literature (*29; 30*). Collisions with trucks have an odds ratio of 1.977, indicating a higher likelihood of injury in such incidents, likely due to the significant mass and force involved, which corroborates findings from (*30*). Adverse weather conditions, such as snow or rain, significantly increase injury odds (odds ratio 1.058), highlighting ADS's challenges in adverse weather (*55*). Subject vehicles with higher pre-crash speeds, particularly those exceeding 25 mph, are strongly associated with increased injury risk, as indicated by an odds ratio of 2.593. This result also highlights a non-linear effect of speed on injury outcomes, with even moderate speeds (1 – 25 mph) showing a significant increase in injury risk, reflected by an odds ratio of 1.423. This non-linear relationship indicates that the likelihood of injury crashes increases with the increase in the speed of the subject vehicle. This finding aligns with past studies (*30; 56*). The impact area of the subject vehicle also affects injury outcomes. Front-end and rear-end collisions are particularly hazardous, with odds ratios of 2.050 and 5.983, respectively. The pronounced effect of rear-end impacts on injury crashes aligns with past studies (*24; 32*). These findings emphasize the critical need for ADS systems to enhance performance across various environmental conditions and crash scenarios. This underscores the necessity for ongoing technological advancements and safety measures to improve ADS reliability and ensure better occupant protection.

LIMITATIONS

The study has several limitations that should be acknowledged. The data utilized in this analysis is restricted to reported ADS crashes from July 2021 to March 2024, potentially omitting unreported incidents, thus limiting the comprehensiveness of the dataset. A limited sample size also constrains the study's findings due to the scarcity of ADS crash reports, which may impact the validity of the model's results. Further, the integrity of the data depends on the accuracy of crash reports submitted by automobile manufacturers and operators, potentially introducing bias in the information, such as bias in reporting the crash severity. Given that this data represents the early stages of real-world ADS testing and considering the rapid pace at which ADS technology advances, the characteristics and trends of crashes involving ADS may change over time. Additionally, while robust, the propensity score matching methodology cannot entirely eliminate unobserved confounding variables that might influence injury outcomes. Future research should aim to address these limitations by incorporating more extensive and diverse data, improving the accuracy of reporting mechanisms, and exploring the impact of evolving ADS technologies over time.

CONCLUSIONS

The study applies Propensity Score Matching (PSM), a robust causal inference methodology, on NHTSA's newly released nationwide data on ADS crashes from July 2021 to March 2024. After a comprehensive data cleaning process, the final dataset comprises 580 ADS crashes. This methodology evaluates the impact of remote driver/operator involvement on injury outcomes in automated vehicle crashes. The findings indicate that the presence of a remote driver/operator significantly increases the likelihood of injury in ADS-related crashes, with an odds ratio of 1.310 and a positive coefficient of 0.2698. This suggests that current ADS systems require further refinement before fully ready for widespread implementation. Additionally, these results highlight the complexities and challenges of human interaction with automated technologies, emphasizing the need for continued advancements in ADS technology to improve safety and reliability.

The study highlights that crashes on highways/freeways and intersections significantly correlate with injury outcomes, with odds ratios of 2.495 and 1.115, respectively, indicating higher risks due to their complexity and traffic volume. Lighting conditions play a significant role, with crashes in daylight less likely to result in injuries compared to dark conditions (odds ratio 0.379). Non-clear weather conditions, such as snow or rain, increase the likelihood of injury in ADS crashes (odds ratio 1.058). Crashes involving vulnerable road users, such as pedestrians and cyclists, significantly increase the risk of injury (odds ratio 4.338), emphasizing the need for improved detection and response strategies in ADS. Higher pre-crash speeds are significantly associated with increased injury likelihood, with odds ratios of 2.593 for speeds > 25 mph and 1.423 for speeds between 1 and 25 mph. The impact area of the subject vehicle also affects injury outcomes, with rear-end collisions showing a more pronounced effect (odds ratio 5.983), highlighting the need for enhanced safety protocols and vehicle design considerations. Additionally, crashes involving trucks are associated with injury in ADS crashes.

The findings of this study are critically important for policymakers and automobile manufacturers developing automated vehicles, emphasizing the necessity of advancing safety protocols and refining the human-machine interface in ADS, such as pedestrian detection (PD) systems and automated emergency braking systems. For future research, a larger and more diverse dataset encompassing a range of socio-economic and spatial contexts should be collected to enhance the robustness and validity of the models and their findings. Implementing symmetrical reporting standards for ADS crashes and introducing third-party validation can address biases in crash severity reporting. This is essential for ensuring the safe integration of ADS into our transportation infrastructure.

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AUTHORS CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: *Study Conception and Design:* Muhammad Adeel, Asad J. Khattak; *Data Collection and Preliminary Analysis:* Muhammad Adeel; *Analysis and Interpretation of Results:* Muhammad Adeel, Asad J. Khattak, Sheikh M. Usman, Nastaran Moradloo; *Draft Manuscript Preparation:* Muhammad Adeel, Asad J. Khattak. All authors reviewed the results and approved the final version of the manuscript.

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