Leveraging a Safe System Approach to Analyze Retrospective Crash Data to Reach Zero

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Abstract Roadway fatalities remain a critical public safety concern, necessitating innovative and data-driven approaches to mitigate risks and prevent severe crashes. The Safe System Approach (SSA) offers a holistic framework for enhancing road safety by recognizing human error and designing transportation systems resilient to such mistakes. This study leverages retrospective crash data from Ohio, USA to examine key risk factors and their interactions within the SSA framework, encompassing People, Vehicles, Roads, and Speed. Using binomial regression and overlap analysis, this research identifies significant contributors to suspected serious and fatal crash outcomes, including impaired driving, seatbelt non-use, older vehicle models, road conditions, and excessive speed. The results highlight that People and Vehicle factors are the most frequent contributors to severe injury outcomes, while multi-factor interactions further increased risk probability. This study underscores the importance of integrating policy interventions, vehicle safety upgrades, infrastructure improvements, and targeted educational campaigns, to drive progress toward zero fatalities. By adopting a systemic approach informed by empirical crash data, transportation planners, policymakers, and safety advocates can implement effective countermeasures to enhance roadway safety and reduce severe crash outcomes.

Keywords Crash Data Analysis, Data-driven Interventions, Roadway Safety, Safe Systems Pyramid, Zero Fatalities

I. INTRODUCTION

Roadway fatalities continue to pose a significant public health challenge, demanding comprehensive strategies that extend beyond traditional driver-focused interventions. Despite advancements in vehicle safety features, infrastructure design, and enforcement policies, serious injury and fatality (SIF) crashes persist, emphasizing the need for a change in basic assumptions in road safety management. The Safe System Approach (SSA) provides a robust framework that acknowledges human fallibility and seeks to minimize crash severity by fostering an inherently safer transportation environment.

Unlike conventional safety models that place primary responsibility on individual road users, SSA emphasizes shared accountability among multiple system components: People, Vehicles, Roads, Speed, and Post-Crash Care. This framework promotes initiative-taking risk mitigation by designing road systems that accommodate inevitable human errors while preventing fatal consequences. Prior to the adoption of the SSA, previous research utilized real-world fatal crash data to analyze systemic contributions to crash outcomes, focusing on interactions between the road user, the vehicle, and the road environment [X 2008]. The findings demonstrated the importance of analyzing crashes as the result of interacting system-level factors, rather than isolated behaviors and found that fatal outcomes were frequently related to intersection of road, vehicle, and road user [X 2008, 2009].

Previous research has demonstrated that SSA-based interventions, such as automated speed enforcement, improved road infrastructure, and enhanced vehicle safety features, have led to significant reductions in crash severity and fatalities [3]. Studies have also shown that seatbelt use is one of the most effective measures in reducing fatal injury risk, with properly restrained occupants experiencing a 45–60% lower likelihood of severe injury [4]. Additionally, previous research highlights that alcohol impairment remains one of the leading causes of fatal crashes, with an estimated 30% of annual roadway deaths in the U.S. involving intoxicated drivers [5].

Furthermore, investigations into vehicle safety improvements, such as electronic stability control and automatic emergency braking, have demonstrated their effectiveness in reducing crash likelihood and severity

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[6–7]. Infrastructure-related studies emphasize the role of road design in mitigating crash outcomes, with elements like median barriers, rumble strips, and roundabouts contributing to lower fatality rates [8]. Speed management strategies, including variable speed limits and traffic calming measures, have also been linked to improved safety outcomes, reinforcing the importance of systemic interventions [9].

Building on foundational studies [1–2], this study applies the SSA framework to analyze retrospective crash data from Ohio's state-level crash database. By examining the interplay between key risk factors—assessed via SSA components, such as people, vehicles, roads, and speed—this research aims to identify high-risk scenarios and inform data-driven interventions. Through statistical modeling and overlap analysis, the study evaluates how these factors contribute to crash severity and highlights actionable strategies for reducing fatalities. By shifting the focus from individual responsibility to systemic resilience, this research supports a holistic safety paradigm that can guide policymakers, transportation planners, and safety advocates in advancing road safety initiatives.

II. METHODS

This study utilized a retrospective approach to analyze crash data sourced from Ohio's state-level crash database (2017–2023), which is compiled from crash reports and submitted by law enforcement to the Ohio Department of Public Safety (ODPS) [10]. A standardized crash report form (OH-1) is used by law enforcement to document key details at the scene using established variables [11]. Variables used in this study were selected from the existing fields recorded on these crash reports and do not reflect author-defined criteria for a safe driver, vehicle, or road. Instead, these variables were assigned to Safe System elements (People, Vehicle, Road, Speed) based on their alignment with SSA component domains for the purpose of risk stratification and outcome modeling.

Vehicles with unit information (type, make, model, model year) that could not be verified via the Vehicle Identification Number (VIN) utilizing the National Highway Traffic Safety Administration (NHTSA) VIN Decoder [12] were excluded from this analysis. All data cleaning, statistical analyses, and data visualization were performed in R v. 4.3.2 [13]. Each row in the resulting database represents a discrete occupant in a unit (vehicle) within a crash, and that occupant is assigned an injury severity level (no apparent injury, possible injury, suspected minor injury, suspected serious injury [referred to as "serious" for the remainder of this manuscript], fatal) at the time of the crash. For this analysis, potential risk factors were assessed at the unit (vehicle) level, by selecting the row representing the driver. A new variable, "Vehicle Severity," was defined as the most severe injury sustained by any occupant within a single vehicle. For example, if a vehicle had three occupants with injury severities of possible injury, minor injury, and serious injury, the Vehicle Severity for that unit would be classified as serious. This approach ensures that the severity classification reflects the highest injury burden associated with each vehicle involved in a crash. The total number of VIN-verified vehicles (n = 2,551,096) was further limited to vehicles with injurious vehicle severity levels (n = 464,788), differentiating vehicles with a non-severe (possible, suspected minor) injury outcome (n = 429,870) from vehicles with an SIF (serious, fatal) injury outcome (n = 34,918). The SIF category was then further differentiated into serious (n = 30,261) and fatal (n = 4,657) vehicle severities.

Data from calendar years 2017–2023 were analyzed, systematically choosing key variables from the Ohio Traffic Crash Report to correspond with dimensions of the SSA framework, excluding Post-Crash Care. These risk factors for SIF were selected from 48 categorical crash data variables. Variables were manually assigned an SSA category of People, Vehicle, Road, or Speed. Crash data variables were assessed as potential predictors of a binary vehicle severity outcome (non-severe/SIF) in binomial regression using a generalized linear model from R base package *stats* [13]. For significant ($p < 0.05$) predictors of a non-severe vs. SIF outcome, the predicted probability of an SIF outcome was estimated using R package *marginaleffects* [14]. These probability estimates were computed as marginal means by averaging predictions across a balanced grid, meaning that each variable level was given equal weight as a predictor of injury outcome. This prevented variable levels with a higher frequency in the dataset from being weighted towards a higher probability of SIF.

Predictor variables were either binary (two levels, e.g., true/false) or contained multiple levels (three or more discrete categorical levels). In addition to estimating the SIF probability of each predictor level, R package *marginaleffects* provided the increase in SIF probability between predictor levels and assessed whether this increase was significant. Binary predictors were selected as risk factors if the significant increase in SIF probability between levels was at least 5% (e.g., comparing "True" vs. "False" levels of predictor "Is Drug Related"). Levels from multi-level variables were selected as discrete risk factors if the significant increase in SIF probability from all less severe levels was at least 5% (e.g., more severe levels of “Head-On” and “Single-Vehicle” vs. less severe levels of predictor “Manner of Crash”). These selections of risk factor variables, and their assignments to Safe System components, are described in the appendix (Tables AI–IV).

An overlap analysis was conducted to assess interactions between the four Safe System components (People, Vehicle, Road, Speed) as defined by their selected risk factor variables. Venn diagrams and upset plots generated using the R package *ComplexUpset* [15] were used to visualize the most frequently occurring intersections of Safe System components among SIF. To further assess injury risk, proportional odds logistic regression was performed using the R package *MASS* [14] to estimate the predicted probability of injury severity (serious injury or fatality, compared to non-severe injury) for each combination of Safe System components. To assess overall injury risk for SIF, a binomial regression was performed using R base package *stats* to estimate the predicted probability of severe compared to non-severe injuries.

Upset plots show intersections between variables, with a layout that can accommodate many more combinations than can be visualized on a Venn Diagram. The abridged exemplar upset plot below (Fig. 1) uses black bars to show the number of serious injuries, and the fraction of all serious injuries, associated with different combinations of Safe System components. The red bars show the predicted probability of serious injury associated with each combination of Safe System components. For example, the first black bar shows that 4,245 serious injuries are associated only with People factors, comprising 14% of all serious injuries. For incidents involving only People factors, the predicted probability of a serious injury, as opposed to a non-severe injury or fatality, is shown by the red bar to be 3.7%. This combination of frequency (black bars) and predicted probability of serious injury (red bars) shows that the most common circumstances are not always the most injurious circumstances. The predicted probability of serious injury increases as more Safe System components are involved in an injurious crash. The highest risk of serious injury, 21.4%, is predicted for incidents that combine People, Vehicle, Road, and Speed factors, even though this combination is relatively rare, representing only 5.6% of all serious injuries.

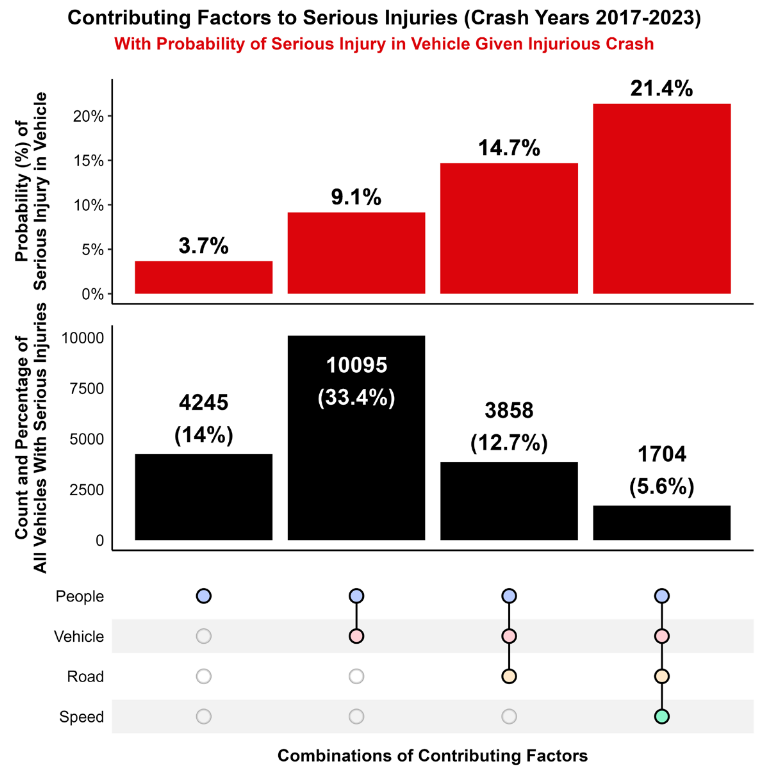

Fig. 1. Simplified upset plot showing increased probability of severe injury (red bars) as more Safe System components combine. For each variable combination, black bars show the number and fraction of vehicles with serious injuries, and red bars show the predicted probability of serious injury.

The Safe Systems Pyramid was employed as a framework to identify evidence-based countermeasures addressing the risk factors identified in this study [17]. This model, adapted from public health principles, prioritizes interventions based on their potential population-level impact and the extent of individual effort required for effectiveness. The pyramid comprises five hierarchical tiers: (1) *Socioeconomic Factors*, which encompass structural policies influencing transportation behaviors, such as the development of affordable housing near transit hubs to reduce reliance on personal vehicles; (2) *Built Environment*, which involves the implementation of infrastructure changes, such as complete streets and protected cycling lanes, to promote safer travel modes; (3) *Latent Safety Measures*, which include passive safety measures, such as the installation of speed-calming devices and roundabouts, to mitigate crash severity; (4) *Active Measures*, which focus on individual-level assessments, and require a large amount of individual effort; such as using seat belts, wearing a motorcycle helmet, or using turn signals; and (5) *Education*, which is typically the least politically controversial and easiest to implement, but are conditional on individual behaviors, such as promoting traffic safety culture or targeted public awareness campaigns addressing high-risk behaviors, such as distracted or impaired driving. By organizing countermeasures within this hierarchical framework, this study provides a structured approach to addressing transportation-related risks.

III. RESULTS

The retrospective analysis of Ohio crash data identified key risk factors contributing to serious injuries and fatalities. Among the four Safe System components utilized in this study, People and Vehicle factors were the most frequent contributors to injury, followed by Road and Speed components.

Serious injuries and fatalities (SIF) showed the highest probability of occurrence when all four Safe System components interacted, with an estimated 25.1% of an SIF outcome (Fig. A2). Examining People-related risk factors as independent predictors, the highest probability of a SIF outcome was associated with seatbelt non-use (28.1% probability) and suspected drug involvement (27.4–27.85% probability) (Table AI). Among Vehicle-related factors, semi-truck-related crashes were the strongest predictor of a SIF outcome (14.03% probability), followed by front deployment of the airbag (12.57% probability) (Table AII). For Road-related factors, wrong way crashes were the best predictors of a SIF outcome (29.68% probability), followed by similar probabilities for driving off the road (14.78% probability), weather conditions of fog, smog, or smoke (13.23% probability), and a curved road contour (12.56% probability) (Table AIII). Speed-related factors were binned to unsafe speed (15.69% probability) when predicting a SIF outcome (Table AIV).

Overlap analysis revealed that crashes involving both People and Vehicle factors accounted for the highest proportion of suspected serious injuries (33.4%), followed by standalone People factors (14%), and then the combination of People, Vehicle, and Road factors (12.7%) (Figs. 2–3). Smaller frequencies of serious injury were observed for standalone Vehicle (3.7%), Speed (0.6%), and Road (0.3%) factors (Figs. 2–3). Although the interaction of all four Safe System components comprised a small fraction of all serious injuries (5.6%), this combination produced the highest risk (21.4% probability) of a serious injury when it did occur (Fig. 3). Intersections between two (4.5–9.1% probability) or three (9.7–14.7% probability) components had a higher risk of serious injury than crashes involving only a single Safe System component (2.7–4.3% probability), but all exceeded the baseline risk of serious injury in crashes with no Safe System factors (1.6% probability) (Fig. 3). Further analysis of the specific high-risk variables within these Safe System components highlighted that the most frequent contributor to serious injury was the combination of pre-crash steady traffic and front airbag deployment (11.8%), followed by pre-crash steady traffic alone (5.7%) (Fig. 4). All other combinations of specific variables comprised a smaller fraction of serious injuries than crashes with no high-risk variable associations (4.2%). In general, the probability of serious injury increased as more high-risk variables were added to the crash, compared to the baseline of crashes with no high-risk variables (1.8% probability). The highest probability of serious injury occurred at the intersection of pre-crash steady traffic, front airbag deployed, single-vehicle crash, no seatbelt used, drug or alcohol related, and drove off road (40.9% probability) (Fig. 4). This was followed by the interaction of pre-crash steady traffic, front airbag deployed, single vehicle collision, unsafe speed related, and no seatbelt used (29.3% probability) (Fig. 4).

The combination of People and Vehicle factors account for the highest portion of fatalities (29.5%), followed by the intersection of People, Vehicle, and Road factors (17.6%) and People, Vehicle, and Speed factors (13.9%) (Figs. 5–6). As with serious injury, the predicted risk of a fatal outcome was highest when all four Safe System components intersected (3.9% probability), but any single or combined instance of these components exceeded the baseline risk of fatality when no components were present (0.2% probability) (Fig. 6). An in-depth analysis of the upset plots for variables within these Safe System components revealed key interactions that significantly increased the probability of a fatal outcome (Fig. 7). Similar to serious injuries, pre-crash steady traffic and front airbag deployment accounted for the highest proportion of fatalities (3.4%) (Fig. 7). The intersection of pre-crash steady traffic, front airbag deployed, drug or alcohol related, no seatbelt used, single-vehicle crash, and drove off road was the second most common combination of factors for fatality (2.4%) (Fig. 7). Unlike serious injuries, the fraction of fatalities with no high-risk variables was low (0.9%). The highest probability of fatality occurred at the intersection of pre-crash steady traffic, front airbag deployed, drug or alcohol related, no seatbelt used, head-on crash, and left of center (21.1% probability) (Fig. 7). The second highest probability of fatality was observed at the intersection of pre-crash steady traffic, front airbag deployed, drug or alcohol related, no seatbelt used, single-vehicle crash, unsafe speed related, and drove off road (13.9% probability) (Fig. 7). The analysis demonstrated that People and Vehicle factors were the dominant contributors in most fatal crashes, often interacting with Road and Speed elements. Notably, all high-risk variable combinations with a fatal probability of at least 10% involved crashes in steady traffic, a crash severe enough to deploy the front airbag, where drugs or alcohol were involved, and no seatbelt was used. This highlights the compounded risk when multiple high-risk behaviors interact (Fig. 7).

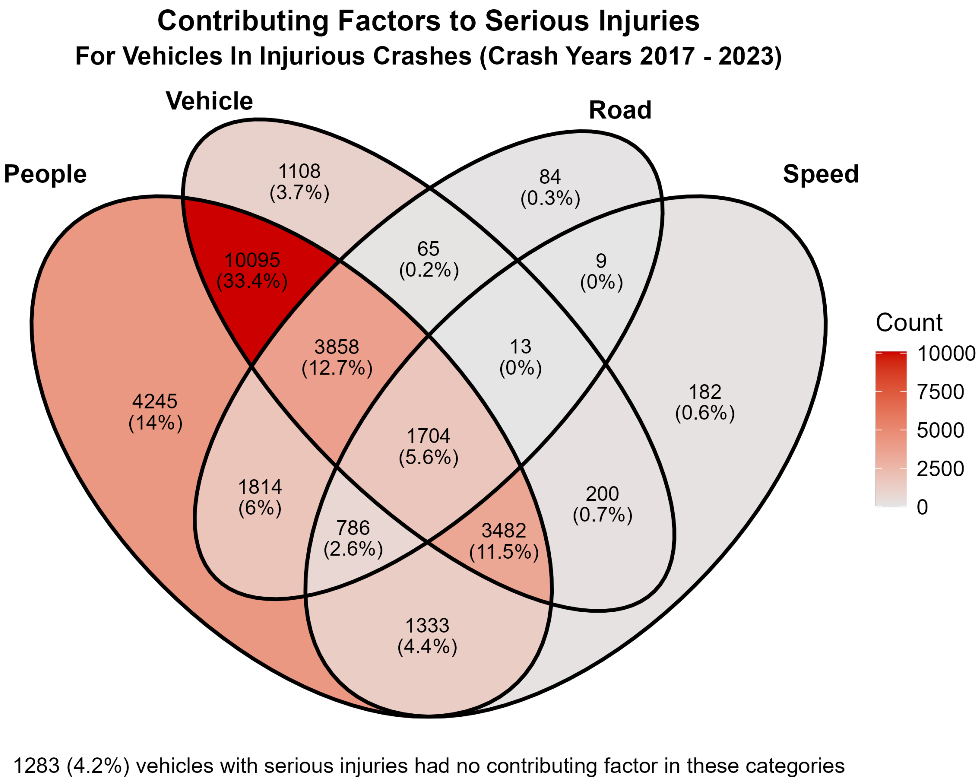

Fig. 2. Venn diagram of serious injuries associated with Safe System components, with each intersection shown as a count and as a percentage of all vehicles with serious injuries.

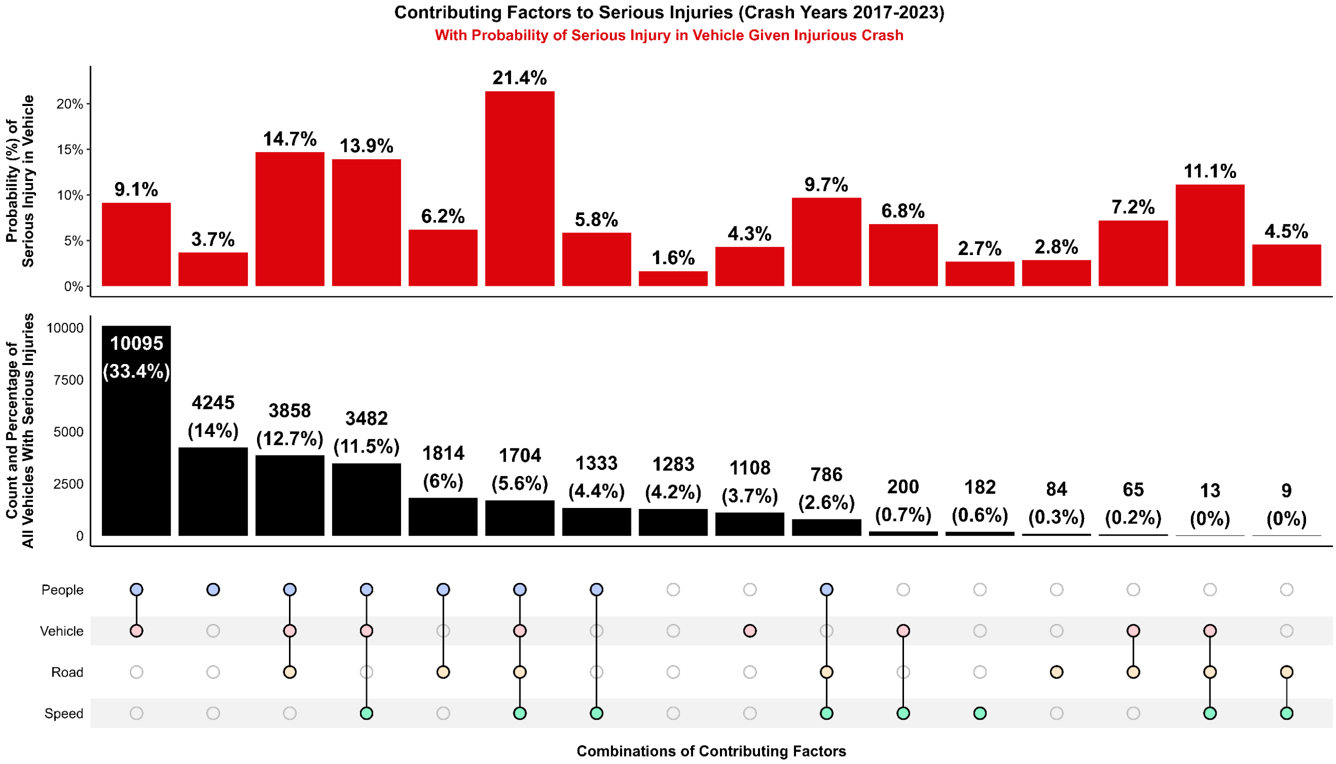

Fig. 3. Upset plot of serious injuries associated with Safe System components (colored dots) and their intersections (black lines). The column with blank dots indicates vehicles with serious injuries but no Safe System association. For each variable combination, black bars show the number and fraction of vehicles with serious injuries, and red bars show the predicted probability of serious injury.

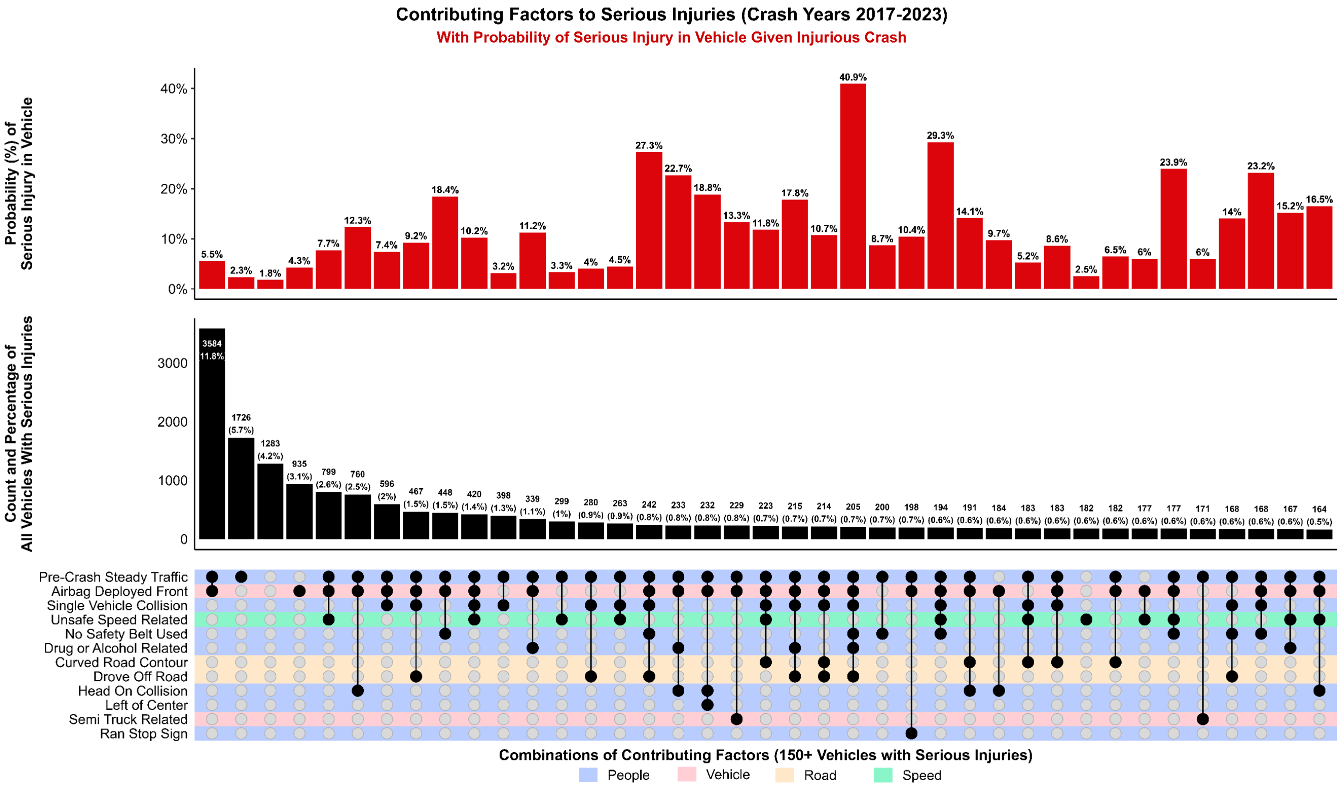

Fig. 4. Upset plot of serious injuries associated with high-risk variables (black dots) within each Safe System component (colored rows) and their intersections (black lines). The column with blank dots indicates vehicles with serious injuries but no Safe System association. For each variable combination, black bars show the number and fraction of vehicles with serious injuries, and red bars show the predicted probability of serious injury.

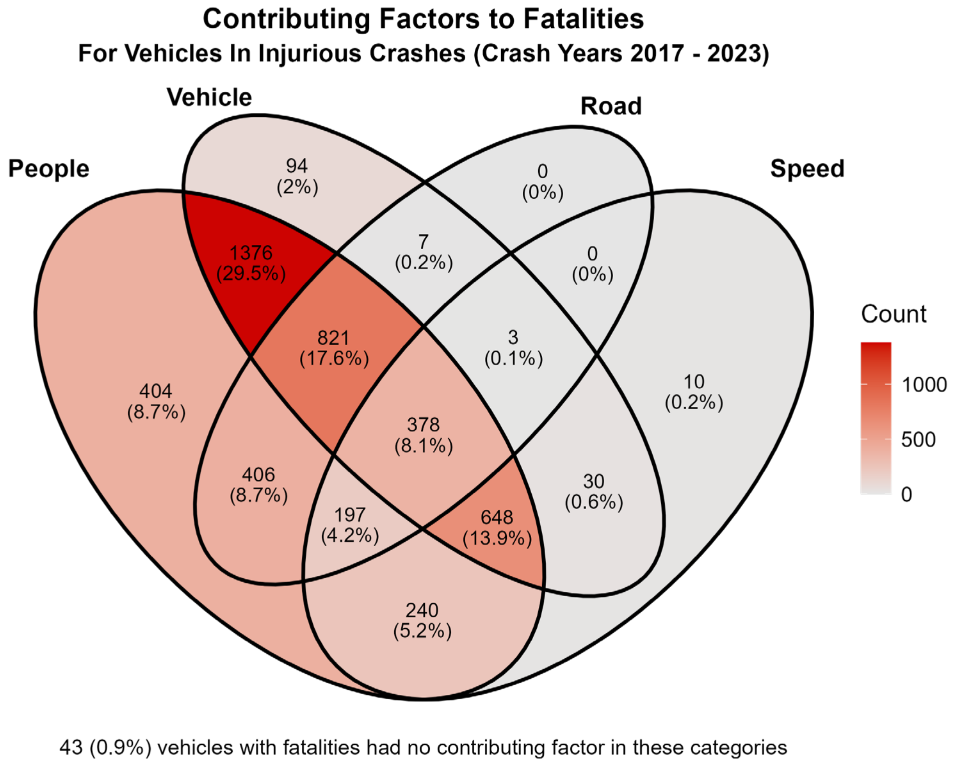

Fig. 5. Venn diagram of fatalities associated with Safe System components, with each intersection shown as a count and as a percentage of all vehicles with fatalities.

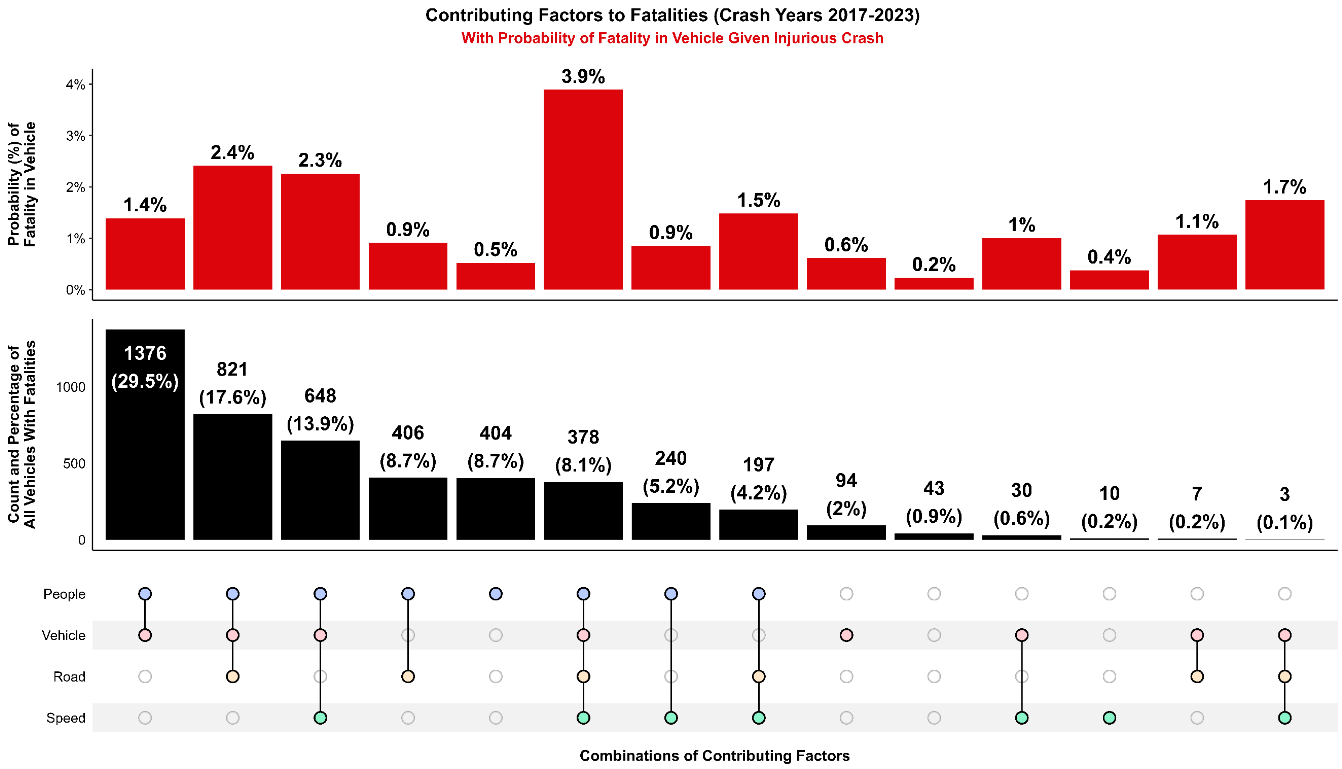

Fig. 6. Upset plot of fatalities associated with Safe System components (colored dots) and their intersections (black lines). The column with blank dots indicates vehicles with fatalities but no Safe System association. For each variable combination, black bars show the number and fraction of vehicles with fatalities, and red bars show the predicted probability of fatality.

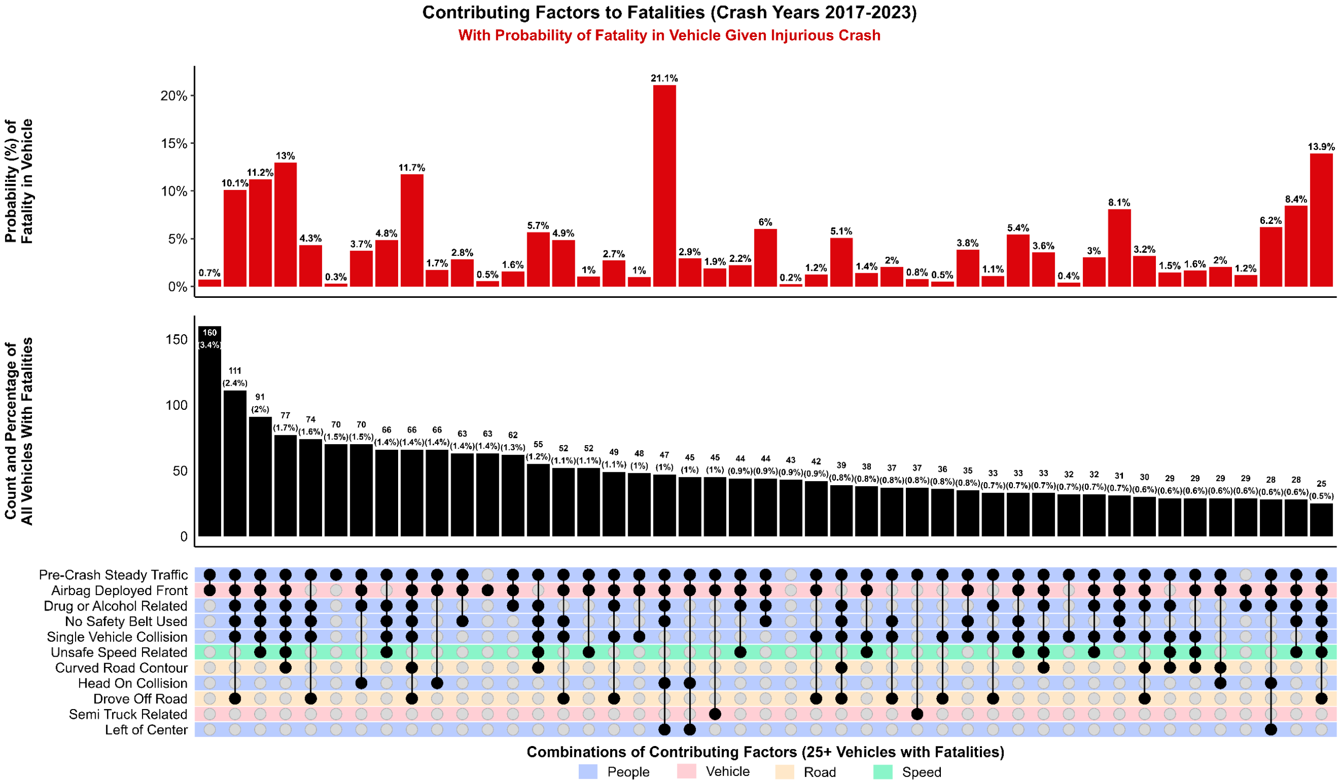

Fig. 7. Upset plot of fatalities associated with high-risk variables (black dots) within each Safe System component (colored rows) and their intersections (black lines). The column with blank dots indicates vehicles with fatalities but no Safe System association. For each variable combination, black bars show the number and fraction of vehicles with fatalities, and red bars show the predicted probability of fatality.

IV. DISCUSSION

The results of this study offer insights into the contributions of Safe System components—People, Vehicle, Road, and Speed—to injury frequency in crash data, revealing both distinct and overlapping influences that shape crash outcomes (Figs. 2–7). An integrated Safe System Approach is critical, as the combined effects of these factors increase the probability of serious injuries and fatalities. By implementing targeted measures based on identified risk factors, road safety efforts can be significantly strengthened to reduce serious injuries and fatalities.

The Safe Systems Pyramid is a structured framework used to guide road safety interventions, emphasizing a hierarchy of measures that range from broad systemic changes to individual behavioral interventions [17–18]. It consists of five tiers: *Socioeconomic Factors* (Tier 1), *Built Environment* (Tier 2), *Latent Safety Measures* (Tier 3), *Active Measures* (Tier 4), and *Education* (Tier 5). This framework prioritizes interventions with the greatest population-level impact (Tier 1) while minimizing reliance on individual effort (Tier 5). By integrating these tiers, policymakers and stakeholders can develop comprehensive safety strategies to reduce crash incidence and severity. The application of the Safe System Approach plays a crucial role in translating data-driven insights into practical safety interventions. SSA helps identify high-risk factors and patterns, which can then be addressed through the Safe Systems Pyramid framework. By utilizing SSA to guide the implementation of targeted safety measures—ranging from infrastructure improvements to behavioral interventions—road safety initiatives can be more effectively tailored to mitigate risks at multiple levels, ensuring a broader and more lasting impact.

The results highlight the predominant role of People-related factors in crash and injury outcomes (Figs. 2–7), with specific risk factors such as driver impairment, lack of seatbelt use, and lane departure consistently contributing to serious injuries and fatalities. Previous research has shown that intoxicated drivers are more likely to be young males, emphasizing demographic trends that may influence risky driving behavior [19]. Given these findings, interventions targeting these behaviors are crucial. Educational initiatives (Tier 5) could emphasize the dangers of impaired driving and seatbelt non-use; however, because educational efforts require individual effort and yield limited population-level impact, additional measures are necessary. Active interventions (Tier 4), such as stricter enforcement of seatbelt laws and increased sobriety checkpoints, could further deter risky behavior. Additionally, speed enforcement mechanisms like automated radar signs and law enforcement speed checks may help mitigate unsafe speeds. However, these findings may vary across different regions due to differences in traffic laws, enforcement practices, and driver behaviors. For example, Ohio does not have a primary seatbelt law, meaning law enforcement officers cannot stop drivers solely for failing to wear a seatbelt, potentially contributing to lower seatbelt compliance rates and a higher incidence of severe injuries in unrestrained occupants. This legislative variation underscores the importance of considering regional policy differences when interpreting crash risk factors and designing targeted interventions.

Vehicle-related factors played a significant role in injury risk, particularly when combined with other SSA components. While airbag deployment is associated with increased injury risk in unbelted occupants, research supports its effectiveness when combined with seatbelt use [20–21]. The lack of seatbelt use in this study may exacerbate injuries from airbag deployment, underscoring the importance of occupant restraint. However, airbag deployment is a proxy for a more severe crash rather than a direct cause of injury, as airbags tend to deploy in high-impact collisions where the potential for severe injury is already elevated. Latent safety measures (Tier 3) that could reduce crash injuries include advanced driver assistance systems, such as lane departure warnings and automated emergency braking. Implementing alcohol ignition interlocks could also reduce impaired driving incidents, specifically for repeat offenders. Ohio Bureau of Motor Vehicles (BMV) records have shown that 38% of people arrested for impaired driving in 2023 had a prior impaired driving charge at some point in their lifetime. Socioeconomic factors (Tier 1) may be the most impactful intervention strategy due to their broad population-level influence with minimal individual effort. Lower-income drivers are disproportionately involved in crashes [22–23], often due to older vehicles lacking advanced safety features. Financial incentives, such as tax benefits and insurance discounts for newer, safer vehicles, could help mitigate this issue. However, while financial incentives for purchasing newer vehicles could facilitate the widespread adoption of these safety technologies, this option is not equitable. It would once again make safety a privilege, accessible primarily to those who can afford the higher upfront costs, thus failing to guarantee safety for all road users, particularly those from lower socioeconomic backgrounds. However, this is not solely a socioeconomic issue, as the average age of cars and light trucks on US roads has reached a record high of 12.6 years [24]. Encouraging the widespread adoption of updated vehicle safety technologies would address risks associated with vehicle-related risk factors, but ensuring equitable access to these technologies requires broader systemic solutions.

While Road and Speed components individually contributed less frequently, their interactions with Vehicle and People factors amplified the risk of severe outcomes, as seen in multi-factor combinations like Vehicle, People, and Road. This study found driving off road, unsafe speeds, and curved road contour to be prevalent Road- and Speed-related factors. These trends are demonstrated in the literature, specifically highlighting the role of unsafe speeds [25–26], lane departure [25–26], and curved road contours [27]. To mitigate road-related risks, infrastructural changes (Tier 4) could include the expansion of guardrails and road shoulders to prevent vehicles from veering off-road. Increasing the use of rumble strips along road edges and medians could reduce lane departure crashes, a primary contributor to fatalities. Additionally, curved road safety could be enhanced by adding convex mirrors and barriers. Speed mitigation strategies such as speed bumps and automated radar signs in high-traffic areas may further decrease speed-related crashes. Several studies have found that higher traffic intensities are associated with an increased risk of crashes [22], while a greater proportion of individuals working from home or having shorter commutes can reduce overall crash risk [23]. Rush hour has been linked to a 28% increase in fatal crashes, with factors such as aggressive driving behavior and precipitation further elevating crash and injury risks [28]. To address higher traffic intensities within the Safe Systems Pyramid framework, a combination of interventions across multiple tiers is needed. At the socioeconomic level (Tier 1), promoting urban planning and development that reduces commute times, expanding public transportation, and encouraging telecommuting can reduce reliance on high-traffic roads. Built environment (Tier 2) interventions, like congestion pricing or toll systems in high-traffic areas can incentivize reduced vehicle volumes and smoother traffic flow. Latent safety measures (Tier 3), such as the use of advanced traffic management systems and adaptive traffic signals, can optimize traffic flow and minimize congestion-related risks. Active measures (Tier 4) include infrastructure enhancements like expanding road capacity, improving intersections, and implementing speed enforcement or traffic-calming measures to reduce crash severity in congested areas. Lastly, educational interventions (Tier 5) can promote safe driving behaviors, raise awareness of the risks in high-density traffic, and encourage carpooling or ridesharing to reduce the number of vehicles on the road. By implementing these strategies across the Safe Systems Pyramid, the risks associated with higher traffic intensities can be mitigated, leading to reduced crash frequency and severity.

Socioeconomic factors (Tier 1) may be the most impactful intervention strategy due to their broad population-level influence with minimal individual effort. Lower-income drivers are disproportionately involved in incidents of crashes in lower-income areas [22] and the higher likelihood of being the at-fault driver [23]. Additional socioeconomic barriers to road safety include the high cost of driver training, expensive insurance premiums, and poor public transportation infrastructure, all of which disproportionately impact lower-income individuals. Limited access to safe and affordable transportation options may force individuals to rely on older, less safe vehicles or engage in riskier driving behaviors. Addressing these disparities requires investment in alternative transportation solutions, such as improved public transit systems, increased pedestrian and cyclist infrastructure, and financial support for driver education programs. By implementing these measures, road safety improvements can be made more accessible and equitable for all road users.

This study underscores the necessity of a holistic Safe System Approach, integrating People, Vehicle, Road, and Speed factors to understand and mitigate crash-related injuries. The results highlight how specific risk factors are frequently observed in serious injuries and fatalities. While single-vehicle crashes were more closely linked to serious injuries, head-on crashes emerged as a significant predictor of fatalities. The overlap of these risk factors across Safe System components reinforces the need for integrated, multi-tiered interventions guided by the Safe Systems Pyramid. By leveraging systemic safety measures, infrastructural improvements, technological advancements in vehicles, and targeted enforcement strategies, policymakers can create a safer road environment. Addressing socioeconomic barriers, such as access to safer vehicles, driver training, and improved public transportation, will further ensure that safety interventions are equitable and effective. Through the strategic application of these measures, road safety efforts can be significantly strengthened, reducing serious injuries and fatalities.

V. CONCLUSION

This study provides a comprehensive assessment of the factors contributing to serious and fatal crashes through the lens of the Safe System Approach. The analysis of Ohio crash data from 2017–2023 underscores the significant impact of People and Vehicle-related risk factors, with impaired driving and seatbelt non-use emerging as dominant contributors to SIF outcomes. Road and Speed factors, while less frequent as isolated contributors, exacerbate crash severity when combined with other elements.

The findings reinforce the importance of a systemic approach to road safety that prioritizes preventive measures and structural interventions. Strategies such as stricter enforcement of seatbelt laws, increased public awareness of impaired driving risks, incentives for adopting newer vehicle safety technologies, and infrastructure modifications (e.g., improved road design, speed management measures) are critical in mitigating crash severity.

By moving beyond reactive safety measures and embracing a proactive, data-driven framework, policymakers and safety professionals can develop more effective strategies to reduce roadway fatalities. The Safe Systems Pyramid provides a structured approach to this goal, integrating interventions across socioeconomic, systemic, latent, active, and educational levels. This approach ensures that targeted measures are applied at multiple tiers, addressing both the root causes and immediate factors contributing to crashes. By focusing on systemic improvements, such as expanded public transportation, infrastructure enhancements, and increased vehicle safety technologies, and by addressing the socioeconomic disparities that limit access to safety measures, road safety can be significantly strengthened. Through the strategic application of these measures, the goal of reducing serious injuries and fatalities is within reach. The integration of multi-faceted interventions and systemic improvements, guided by the Safe Systems Pyramid, will play a crucial role in advancing the vision of zero fatalities on roadways.

VI. ACKNOWLEDGEMENTS

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VIII. APPENDIX

TABLE AI
SELECTED VARIABLE LEVELS ASSOCIATED WITH RISK GROUP 'PEOPLE'

Predictor Name	Predictor Level	% of All Injuries	% of Severe Injuries	Predicted Probability (%) of Severe Injury	Probability (%) Increase Over Other Outcome(s)
Combined As Variable "Drug or Alcohol Related"					
Is Drug Related	True	3.21	11.70	27.40	20.54
Is Marijuana Suspected	True	0.54	2.02	27.85	20.45
Is Other Drug Suspected	True	1.84	5.41	22.09	14.85
Condition[1]	Under the Influence	5.61	17.22	19.95	14.25
Is DUI21 Related	True	0.37	1.06	21.45	13.99
Is Alcohol Related	True	6.42	17.15	20.06	13.41
Individual Variables					
Seatbelt Used	No Belt Used	7.17	28.40	28.10	22.55
Contributing Circumstance[2]	Left of Center	3.97	17.32	22.83	18.32
Condition[1]	Physical Impairment	1.08	3.60	19.50	13.80
Number Of Occupants (Binned)[3]	8+ Occupants	0.03	0.08	20.15	12.64
Contributing Circumstance[2]	Improper Passing	0.66	2.15	14.92	10.42
Contributing Circumstance[2]	Stopped or Parked Illegally	0.07	0.23	14.79	10.29
Contributing Circumstance[2]	Improper Lane Change	4.51	13.23	14.54	10.03
Condition[1]	Illness	0.98	2.53	14.93	9.23
Contributing Circumstance[2]	Ran Stop Sign	2.63	7.44	13.41	8.90
Is Pedestrian Related	True	0.16	0.30	14.25	6.74
Condition[1]	Fell Asleep, Fainted, Fatigued	1.85	3.88	12.21	6.51
Manner Of Collision	Head-On	5.65	14.05	18.69	6.01
Pre-Crash Action (Binned)[4]	Steady Traffic	70.00	86.32	9.18	5.79
Manner Of Collision	Single-Vehicle	22.64	38.21	12.68	5.75

1. Variable "Condition" was assessed by comparing instances of the named driver condition (e.g., "Under the Influence") to instances of the driver condition "None."
2. Variable "Contributing Circumstance" was assessed by comparing instances of the named contributing circumstance (e.g., "Left of Center") to instances of the contributing circumstance "None."
3. Binned comparison for "Number of Occupants" is 1-7 Occupants vs. 8+ Occupants
4. Binned comparison for "Pre-Crash Action" is "Steady Traffic" (Combined Levels: Entering Traffic Lane, Changing Lanes, Straight Ahead, Negotiating a Curve, Leaving Traffic Lane, Overtaking/Passing) vs. "Slow Traffic" (Combined Levels: Slowing or Stopped in Traffic, Making Right Turn, Parked, Backing, Making Left Turn, Making U-Turn)

TABLE AII
SELECTED VARIABLE LEVELS ASSOCIATED WITH RISK GROUP 'VEHICLE'

Predictor Name	Predictor Level	% of All Injuries	% of Severe Injuries	Predicted Probability (%) of Severe Injury	Probability (%) Increase Over Other Outcome(s)
Is Semi Truck Related	True	3.32	6.20	14.03	6.74
Contributing Circumstance[1]	Load Shifting, Falling, Spilling	0.06	0.15	10.96	6.45
Airbag Usage (Binned)[2]	Deployed Front	39.84	67.59	12.57	5.26

1. Variable "Contributing Circumstance" was assessed by comparing instances of the named contributing circumstance (e.g., "Load Shifting, Falling, Spilling") to instances of the contributing circumstance "None."
2. Binned comparison for "Airbag Usage" is "Deployed Front" (Combined Levels: Deployed Front, Deployed Front/Side) vs. "Deployed Side Only" vs. "Not Deployed"

TABLE AIII
SELECTED VARIABLE LEVELS ASSOCIATED WITH RISK GROUP 'ROAD'

Predictor Name	Predictor Level	% of All Injuries	% of Severe Injuries	Predicted Probability (%) of Severe Injury	Probability (%) Increase Over Other Outcome(s)
Contributing Circumstance[1]	Wrong Way	0.40	2.55	29.68	25.17
Contributing Circumstance[1]	Drove Off Road	12.50	31.90	14.78	10.27
Road Contour (Binned)[2]	Curve	10.57	17.68	12.56	5.65
Weather	Fog, Smog, Smoke	0.48	0.85	13.23	5.43

1. Variable "Contributing Circumstance" was assessed by comparing instances of the named contributing circumstance (e.g., "Load Shifting, Falling, Spilling") to instances of the contributing circumstance "None."
2. Binned comparison for "Road Contour" is "Curve" (Combined Levels: Curve Grade, Curve Level) vs. "Straight" (Combined Levels: Straight Grade, Straight level)

TABLE AIV
SELECTED VARIABLE LEVELS ASSOCIATED WITH RISK GROUP 'SPEED'

Predictor Name	Predictor Level	% of All Injuries	% of Severe Injuries	Predicted Probability (%) of Severe Injury	Probability (%) Increase Over Other Outcome(s)
Combined As Variable "Unsafe Speed Related"					
Contributing Circumstance[2]	Unsafe Speed	7.63	22.33	15.69	11.18
Is Speed Related	True	15.47	26.39	12.81	6.27

1. Variable "Contributing Circumstance" was assessed by comparing instances of the named contributing circumstance (e.g., "Unsafe Speed") to instances of the contributing circumstance "None"

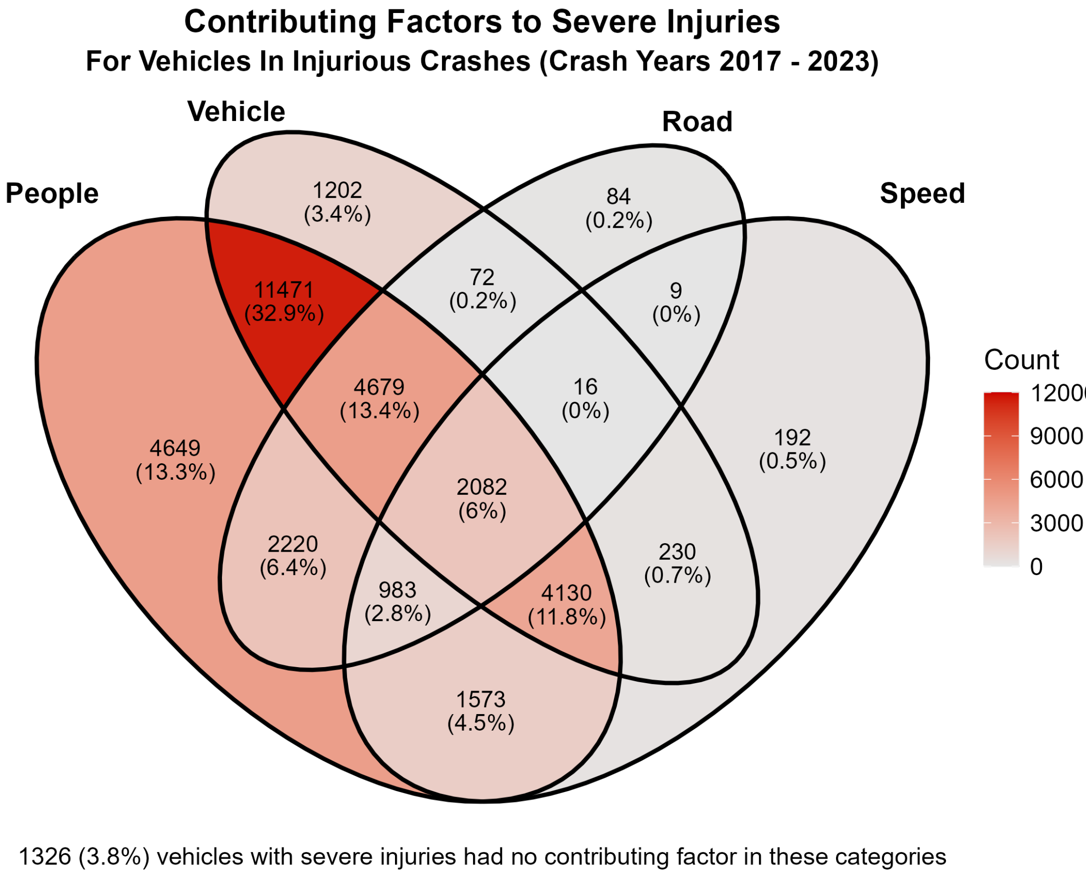

Fig. A1. Venn diagram of severe injuries (serious or fatal) associated with Safe System components, with each intersection shown as a count and as a percentage of all vehicles with severe injuries.

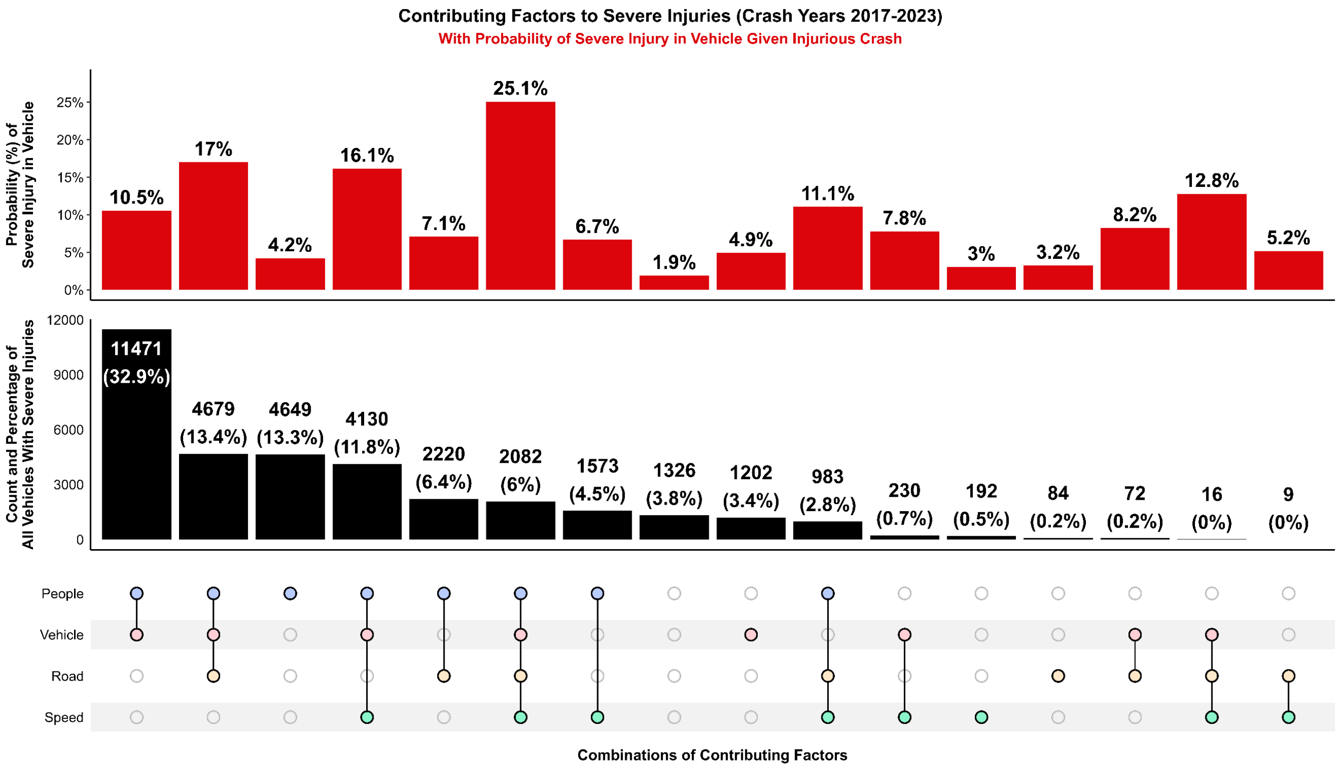

Fig. A2. Upset plot of severe injuries (serious or fatal) associated with Safe System components (colored dots) and their intersections (black lines). The column with blank dots indicates vehicles with severe injuries but no Safe System association. Gray bars show the number and fraction of vehicles with severe injuries associated with each combination. Red bars show the predicted probability of severe injury for each combination.

1

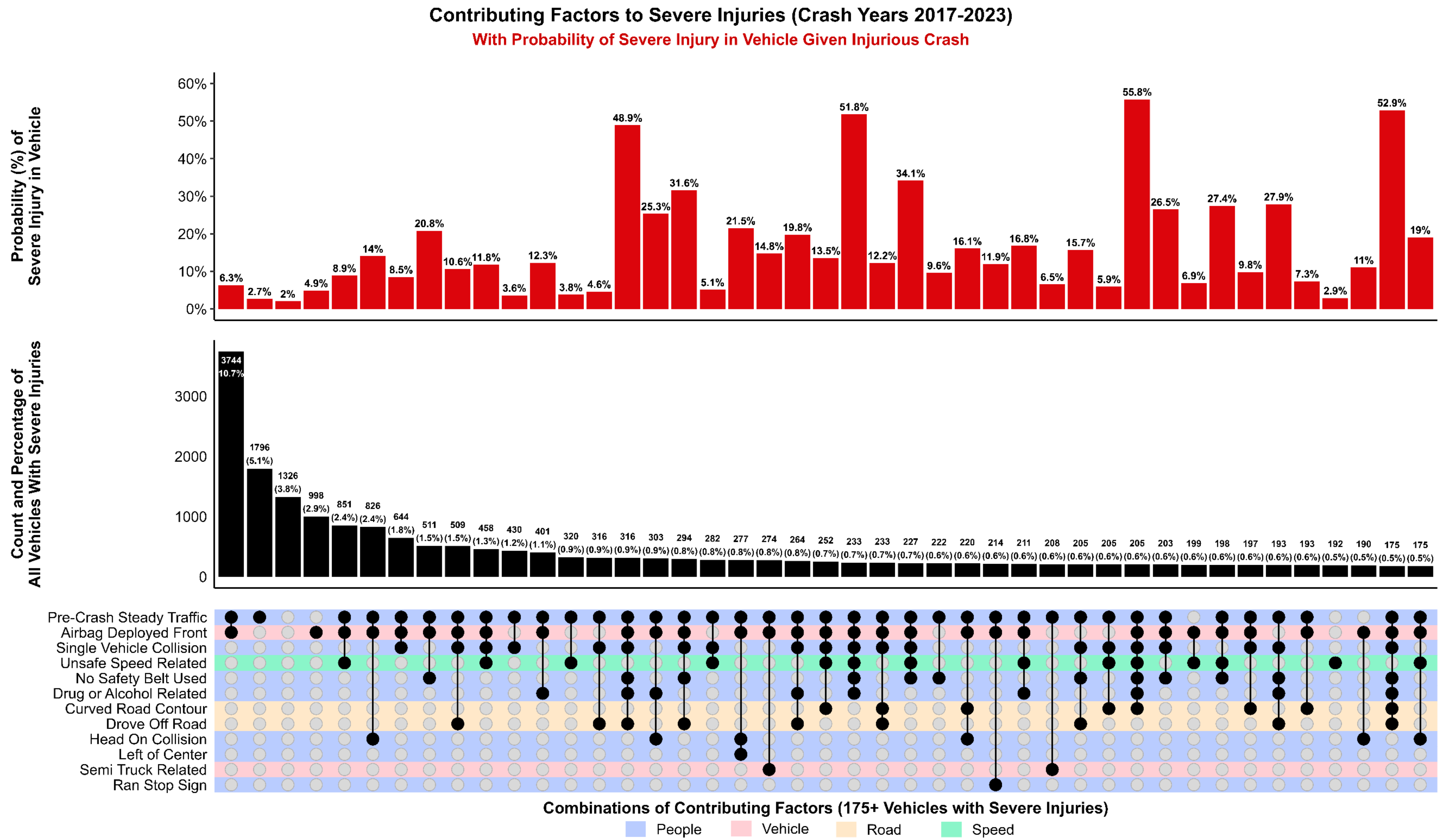

Fig. A3. Upset plot of severe injuries (serious or fatal) associated with high-risk variables (black dots) within each Safe System component (colored rows) and their intersections (black lines). The column with blank dots indicates vehicles with severe injuries but no Safe System association. For each variable combination, black bars show the number and fraction of vehicles with severe injuries, and red bars show the predicted probability of severe injury.

2