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Driver Injury Severity in Road Accidents: A Comprehensive Review of Key Influencing Factors

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Abstract

This review provides a comprehensive analysis of the factors contributing to driver injury severity (DIS) in road traffic accidents, structured around five main domains: driver, vehicle, environmental and temporal, roadway, and accident-specific characteristics. A systematic literature search, guided by PRISMA methodology, identified 133 studies published between 2000 and 2025. This review shows that the most used model in the reviewed studies was the mixed logit model (MLM), applied 22 times, followed by its extension, the MLM-Extension (20 times), and Machine Learning models (15 times). Additionally, the results demonstrate that older people, female drivers and those involved in a head-on collision or rolling over accident have an increased risk of severe injury. For vehicle factors, vehicle age and type are major determinants of injury severity, with older vehicles and two-wheeled vehicles having higher risks. Environmental factors such as night time driving, bad weather and rural roads also significantly affect DIS. The review identifies important gaps in the current literature, which include the absence of integrated research investigations and data availability in the lower-middle-income countries (like India) with its different road infrastructure and peculiar traffic scenarios compared to what is available from high-income countries. Addressing these weaknesses, results from our study highlight the need for regional-relevant research to help us understand how different local patterns are affecting DIS. This review proposes that specific interventions aimed at controlling these determinants would mitigate DIS rates worldwide.

Keywords

Driver injury severity; Mixed logit model; Vehicle; Environmental and temporal; Roadway; Accident-specific.

1. Introduction

Road traffic accidents (RTAs) continue to pose a major threat to global public health, leading to many injuries and loss of lives and imposing substantial economic burdens on nations. According to the World Health Organization (2023), an estimated 1.19 million lives were lost globally due to RTAs in the year 2021, ranking them as the 12th leading cause of death across all age groups (WHO, 2023). This alarming statistic underscores the severity of the issue on a global scale. For comparison, in 2023, it was approximately 40,901 road traffic fatalities in the US, and about 20,400 in the European Union, reflecting persistent issues even in high-income regions with mature infrastructure (European Commission, 2024; NHTSA, 2025). In the case of low- and middle-income countries like Iraq, rapid motorization and urban expansion have significantly complicated the road safety issue. RTA studies from low-income countries have demonstrated remarkable regional variation in the statistics and the effect of the driver on the risk of such accidents, with younger age groups disproportionately affected by fatal and injury accidents (Latief et al., 2023). In the context of India, the situation is equally concerning. In 2022 alone, the country recorded a total of 4,61,312 road accidents, of which 33.8% resulted in fatalities, as reported by the Ministry of Road Transport and Highways (MoRTH, 2022). Furthermore, India experienced a notable 11.9% increase in the number of road accidents compared to 2021. This surge can largely be attributed to the rapid pace of motorization and urban expansion, which have introduced greater complexity and risk to road environments. Several studies on RTAs (Duddu et al., 2018; Dzinyela et al., 2023; Sutantaviboon & Kanitpong, 2026; Wali et al., 2018) have highlighted that a significant proportion of fatal accidents were caused by drivers at fault, emphasizing the critical role of driver behaviour and characteristics in the occurrence and severity of accidents. Therefore, understanding injury severity of drivers involved in RTAs becomes a crucial aspect for developing effective road safety strategies. Driver injury Severity (DIS) is the extent of physical harm to drivers in RTAs, and it is measured using ordinal scales including KABCO (Killed, Incapacitating injury, Non-incapacitating injury, Possible injury, No injury) or MAIS (Maximum Abbreviated Injury Scale). DIS is of critical importance as it causes not only direct harm to public health, incurs additional costs such as medical bills and productivity loss, and impacts road safety policy development. Its relevance lies in establishing modifiable factors for prevention of serious outcomes, this information would then guide the implementation of focused interventions, i.e., improved vehicle safety regulations and driver education programs.

Over the years, researchers have made a great effort to improve understanding of the factors that influence driver injury severity (DIS). For instance, some studies indicated that middle-aged drivers were less vulnerable to severe injuries than older and younger drivers, while other studies highlighted gender differences, such as increased risks for female drivers in certain accident conditions (Adanu et al., 2021; M. Islam et al., 2024; Zambon & Hasselberg, 2006). Older vehicles and motorcycles exhibited higher risks, while SUVs and heavy-duty vehicles provided greater protection for occupants but posed a danger to other road users (Fang et al., 2024; Ren et al., 2024; Yasmin, Eluru, Pinjari, et al., 2014; M. Yu et al., 2021). In general, night accidents, limited visibility, and bad weather conditions caused severe injuries (W. H. Chen & Jovanis, 2000; Z. Li, Chen, Wu, et al., 2018; Zou et al., 2023), though some studies suggested that cautious driving in difficult conditions could reduce their severity (C. Chen, Zhang, Cathy, et al., 2016). Road characteristics, such as pavement conditions, nature of curves (horizontal and vertical), number of lanes, and urban versus rural roadways, affected accident severity (Fang et al., 2024; Gray et al., 2008; Zhu & Srinivasan, 2011). In rural areas, curved, graded roads and dirt roads were often linked with higher chances of fatality and serious injury (Dissanayake & Lu, 2002; Schneider et al., 2009; Zou et al., 2023). The types of accidents and the cause of accidents were directly responsible for the progression in injury severity. Among all the accident types, head-on collisions and overturn accidents were considered to be the most severe due to the direct impact and involvement of high-energy transfer (Kockelman & Kweon, 2002; Sorum & Pal, 2024b; Zeng et al., 2016).

Despite the substantial number of studies investigating DIS, a systematic and well-documented study regarding DIS has been missed by the researchers in previous studies. Moreover, most existing literature addresses only isolated factors such as driver characteristics or vehicle type without offering an integrated understanding of how multiple variables interact to influence DIS outcomes. Additionally, most of these studies are based in high-income nations, particularly the United States and Europe, limiting their applicability to lower-middle-income nations like India, where road infrastructure, traffic behaviour, and enforcement systems differ significantly. There is a pressing need for a comprehensive synthesis that not only categorizes the contributing factors into structured domains but also compares and contrasts their effects using findings from diverse geographical and methodological contexts. This review addresses these gaps through the following objectives: (i) To systematically categorize DIS factors into five key domains i.e., driver, vehicle, environmental and temporal, roadway, and accident-specific characteristics derived from well-established frameworks in road safety research to enable a more integrated analysis than previous isolated-factor studies; (ii) To critically evaluate the influence of these domains on DIS outcomes; (iii) To identify patterns, inconsistencies, and gaps in existing studies through comparative analysis; and (iv) To emphasize the lack of integrated DIS studies in low-income countries and call for region-specific research.

2. Study Method

This review adhered to the important features of the PRISMA 2009 statement (Preferred Reporting Items for Systematic Reviews and Meta-Analyses; Moher et al., 2009) to ensure transparency and replicability when identifying and synthesizing literature; however, it was not prospectively registered as a systematic review protocol. PRISMA 2009 sets out a standardized framework (27-item checklist and four-phase flow diagram) for reporting systematic reviews and meta-analyses. While the present work is a comprehensive literature review employing narrative synthesis (and not quantitative meta-analysis), its important methodological elements have been adopted as well, such as using a structured electronic search strategy with backward snowballing, explicit inclusion/exclusion criteria, plus four-stage screening procedures (identification, screening, eligibility, and inclusion) (see PRISMA flow diagram Figure 1). This partial use of PRISMA adds methodological rigour and is suitable for a non-meta-analytic review.

2.1. Search Strategy and Data Sources

A full electronic search, guided by the PRISMA statements, was conducted for studies from 2000 to 2025. Key scholarly databases and academic search engines (e.g., multidisciplinary citation indexes, publisher platforms) were searched along with backward snowballing from included papers and relevant reviews. The search string was a combination of keywords related to accidents and injury severity, and the domains and methods for factors, using Boolean operators and truncations, for example: ("driver injury* severity*" OR "injury severity*" OR "accident severity*") AND (driver OR vehicle OR roadway OR environment* OR "accident type") and ("mixed logit" OR "random parameter*" OR "ordered probit" OR "machine learning") AND (accidents OR accident) AND (severity).

2.2. Inclusion and Exclusion criteria

The inclusion criteria for the review encompass observational, experimental, simulation or data-mining studies on the outcome of DIS in RTAs. Eligible work must include quantitative or qualitative findings that connect DIS to the driver, vehicle, environmental/temporal, roadway or accident-specific factors. Only English-language, peer-reviewed publications such as journal articles, conference papers or book chapters published from 2000 to 2025 are considered. The exclusion criteria eliminate studies that do not focus on DIS, including those centred solely on pedestrian or cyclist injury severity, unless DIS is discussed. Editorials, theses, policy briefs and non-empirical reviews without primary data are excluded. Duplicates or records with no available full-texts are also excluded.

2.3. Study Selection and Screening Process

Screening was performed according to four PRISMA stages- identification, screening, eligibility, and inclusion. Titles and abstracts were initially screened for eligibility, then assessed full text on potentially eligible records. 133 studies were eligible and included in the synthesis.

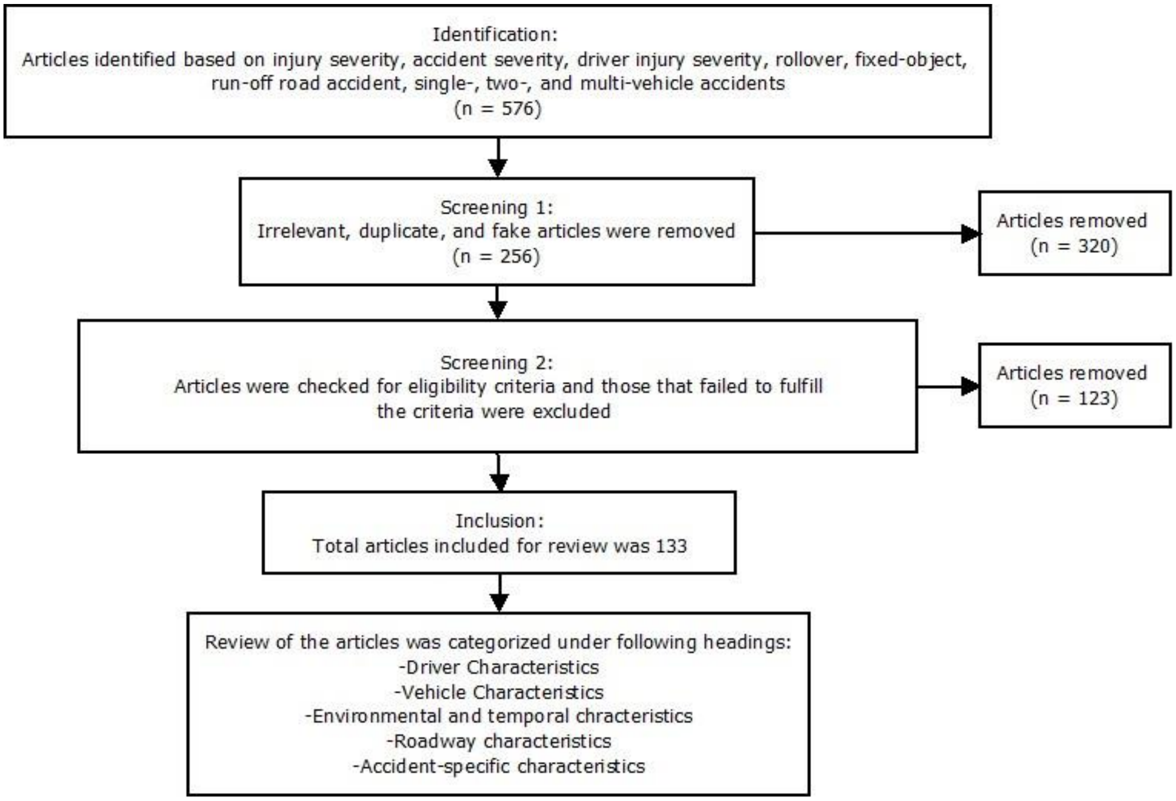

Figure 1: PRISMA flow diagram outlining the selection process

2.4. Data Extraction and Categorization

A structured coding sheet was used for consistent extraction across studies:

1) Study profile: authors, year, country/region, data source and period.

2) Outcome definition: injury severity scale (e.g., binary, ordered categories, MAIS, KABCO).

3) Predictor domains: Driver (age, gender, condition, restraint use, experience, etc.), Vehicle (type, age, damage, safety systems/airbags), Environmental/temporal (lighting, weather, time of day/day of week), Roadway (functional class, rural/urban, curvature/grade, lanes, surface), Accident-specific (collision type: head-on, side, rear-end, rollover/run-off; contributing factors: speeding, distraction, alcohol), Methods: model class (e.g., mixed logit and its extensions, ordered models, latent-class approaches, ML), sample size, handling of heterogeneity/temporal stability, Key findings: direction/magnitude (e.g., marginal effects, odds ratios), notable heterogeneities (by age, gender, context).

For interpretability, studies were organized into the five DIS domains above and, where relevant, into methodological clusters (traditional econometric, latent/heterogeneity models, and ML approaches) to support cross-study comparison of patterns and effect consistency. A detailed summary is presented in Tables 1-5, organized chronologically by publication year.

2.5. Methodological Considerations

Despite the substantial heterogeneity of the studies, namely in injury severity scales (e.g., binary, ordinal KABCO, MAIS), accident contexts (single- vs. multi-vehicle, regional differences), definitions of covariates, and modelling approaches, a quantitative meta-analysis was not feasible. Narrative synthesis was thus used to facilitate qualitative comparison, pattern identification, and critical appraisal of findings. Although narrative synthesis can be more representative and facilitate richer contextual interpretation than meta-analysis, it has drawbacks such as a higher likelihood of reviewer bias in interpretation, reduced ability to quantify pooled effect sizes, and challenges in systematically assessing publication bias. These limitations were mitigated by adhering to structured data extraction, explicit domain categorization, and transparent reporting of conflicting findings according to study context and methodology.

3. Driver Characteristics

Driver characteristics regarding age, gender, physical and emotional condition, driving experience, education level, and use of safety restraints are very important in determining DIS in RTAs because they directly affect their assessment of risk, reaction time, physical resilience, and compliance with safety measures and can be used as the primary targets for personalized road safety interventions and policy development.

3.1. Driver Age

Several studies consistently report that older drivers are more prone to severe injuries in RTAs. In the United States, Lai et al. (2012) found that drivers over 66 were 1.98 times more likely to suffer serious injuries, while Mooradian et al. (2013) also observed increased severity among those aged 65 and older. C. Chen, Zhang, Qian, et al. (2016) reported a 148.53% higher severe injury risk for older drivers. Similar findings have been reported globally, including studies from the United States (Abdel-Aty, 2003; J. C. Anderson & Dong, 2017; Delen et al., 2006; Duddu et al., 2018; Dzinyela et al., 2023; Hanrahan et al., 2009; Hao & Daniel, 2014; Hosseinpour & Haleem, 2021; Khales et al., 2020; Marcoux et al., 2018; Osman et al., 2018; Xie et al., 2012), China (Hou et al., 2019; Ren et al., 2024; Ren & Xu, 2023; Wang et al., 2021; H. Yu et al., 2021; Zeng et al., 2016), Canada (Amiri et al., 2020; Lee & Li, 2015; Yasmin, Eluru, Bhat, et al., 2014), Thailand (Se et al., 2021), South Korea (Kim et al., 2013), the United Kingdom (Pai & Saleh, 2007), and India (Sorum & Pal, 2023). Wang et al. (2021) reported that older drivers' fatality odds were 4.973 times that of middle-aged drivers. Dzinyela et al. (2023) noted increased injury or killed probabilities by 3.27% in single-vehicle accidents (SVAs) and 6.5% in multi-vehicle accidents (MVAs) for drivers aged 65-75. Chamroeun Se et al. (2023) and Sorum and Pal (2024b) also found a greater severity risk for those over 40 compared to middle-aged drivers. However, some studies highlighted middle-aged drivers as more vulnerable. M. Yu et al. (2020) found that drivers aged 30-50 had a higher severe injury than those under 30 in China. Islam et al. (2024) observed that drivers aged 35-45 were more likely to be severely injured in SVAs when speeding.

Meanwhile, young drivers were also frequently associated with high injury severity. In Sweden, Zambon & Hasselberg (2006) found that low socioeconomic status young drivers had 2.5 times higher severity than their high socioeconomic status counterparts. Paleti et al. (2010) reported that drivers aged 16-17 had a higher injury risk than older groups. Kabli et al. (2020) linked young drivers with severe head/abdomen injuries. Haq et al. (2021) reported that drivers (<25 years) in speeding accidents had a 10.32% higher risk. These findings are supported by some United States studies (Adanu et al., 2021; C. Chen, Zhang, Tian, et al., 2015; Z. Li, Chen, Ci, et al., 2018; Savolainen & Ghosh, 2008) and Canadian studies (Lee & Li, 2014).

3.2. Driver Gender

Some studies have shown that female drivers have serious injuries compared to male drivers. Abdel-Aty (2003) found that women were more likely to sustain serious injuries in roadway sections and signalized intersections, while Donmez & Liu (2015) reported an odds ratio of 1.19 for severe injuries among female drivers compared to males. Similar findings were noted across region from the United States (Duddu et al., 2018; Hao & Daniel, 2016; Kockelman & Kweon, 2002; Marcoux et al., 2018; Schneider et al., 2009; Zhang et al., 2020; Zhao & Khattak, 2015), China (F. Chen et al., 2019; Hou et al., 2019; Ren & Xu, 2023; Zeng et al., 2016), Canada (Eluru et al., 2012; Yasmin, Eluru, Bhat, et al., 2014), and Denmark (Hels et al., 2013). Yasmin, Eluru, Bhat, et al. (2014) showed that women's injury severity in rear-end collisions was higher by 46.3%, while Hao & Daniel (2016) reported that women were at a greater risk of fatalities under adverse weather conditions. Using a mixed logit model (MLM), Marcoux et al. (2018) found that female drivers had a 33.8 times higher risk of fatal injuries compared with males. Ren & Xu (2023) mentioned that the increase in riskiness of females was 20.5% frontal collision cases. Dzinyela et al. (2024) further noted that airbag deployment increased serious injury risk for female drivers by 6.8%. On the other hand, several other studies had reported that females had less severe injuries compared to males (Al-bdairi et al., 2020; Boufous et al., 2008; Lai et al., 2012; H. Yu et al., 2020; M. Yu et al., 2020).

Male drivers were reported to have a higher injury severity in some studies. In Denmark, Abay et al. (2013) concluded that male drivers were prone to suffer greater injury compared to their female counterparts due to aggressive driving. Kim et al. (2013) found a 107% higher fatal injury risk for male drivers compared to females. Hao et al. (2015) reported that younger male drivers were more likely to be severely injured during rush hours when speeding through unpaved highway-rail crossings. The same results were reported from the United States (Dzinyela et al., 2023; Kabli et al., 2020; X. Li et al., 2021; Viano & Parenteau, 2012), China (Yan et al., 2021; M. Yu et al., 2020), United Kingdom (Pai & Saleh, 2007), New Zealand (Weiss et al., 2014), and Thailand (Se et al., 2024). Dzinyela et al. (2023) observed that older male drivers were more likely to be involved in fatal injury outcome accidents compared to their female counterparts. Similarly, Chamroeun Se et al. (2024) indicated that male drivers had a 46.85% higher chance of fatal or serious injuries when speed limits were exceeded.

3.3. Driver Condition, Ejection, and Trapped

Many studies have reported that the poor physical and emotional condition of drivers leads to an elevated injury severity or fatality (Behnood & Mannering, 2015; Dissanayake & Lu, 2002; S. Islam & Mannering, 2006; Se et al., 2023). Dissanayake & Lu (2002) linked poor health in older drivers to higher DIS, while Peng & Boyle (2012) reported a 5.8-fold increase under fatigue. Abegaz et al. (2014) found sleeping drivers were 1.31 times more likely to be seriously injured, and Duddu et al. (2018) noted that unfit at-fault drivers doubled the injury risk for others. Dabbour et al. (2020) confirmed impairment raised DIS for both parties, and Dzinyela et al. (2023) found fatigue in older drivers increased serious injury odds by 11%. In contrast, A. Behnood & Mannering (2015) and M. Islam & Mannering (2021) showed that unimpaired drivers had lower injury risks. Driver ejection and entrapment greatly increase injury severity. Dissanayake and Lu (2002) found fatal injury risk was 2.789 times higher for ejected drivers. S. Islam & Mannering (2006) reported fatality risks rising by 389% for drivers aged 16-24 and 506% for those aged 25-64. Xie et al. (2012) found that fatal injury probabilities increased by 248.1% (multinomial logit model) and 469.5% (LCM), while Kabli et al. (2020) noted severe upper-extremity injuries in ejected drivers. Trapped drivers also faced extreme risks: S. Islam & Mannering (2006) found fatal injury odds rose by 524% for middle-aged and 10,158% for older drivers; Zhao & Khattak (2015) observed that trapped drivers in train collisions had higher fatality risks than those ejected, and Hosseinpour & Haleem (2021) confirmed that the drivers trapped inside the vehicle increased the serious injury by 9.79%.

3.4. Driver Experience and Education

Christoforou et al. (2010) reported that drivers with less experience were associated with higher injury severity under adverse weather conditions. Similarly, Weiss et al. (2014) noticed in their study that the chance of injury severity in SVAs increased by 85.9% when the drivers were inexperienced. Hou et al. (2019) noted that drivers having driving experience of more than 10 years were less likely to suffer from minor or severe SVAs than mid-experienced drivers (4-10 years). In another study, Wang et al. (2021) reported that drivers having less than 6 years of driving experience reduced fatality risk by 52.7%. On the contrary, drivers with more than 17 years of experience did not significantly impact fatality risk. Furthermore, Bunn et al. (2022) reported that 52% of the DIS in heavy trucks were related to drivers who had less than 1 year of experience. Rahimi et al. (2020) found that the college degree-possessed drivers had a lower probability of being severely injured or killed in the SVAs compared to the truck drivers who had an education level up to high school.

3.5. Seatbelt and Helmet Usage

Numerous studies have shown that wearing seatbelts and helmets greatly reduces DIS and fatalities (Abdelwahab & Abdel-Aty, 2001; Donmez & Liu, 2015; Hosseinpour & Haleem, 2021; Ren et al., 2024; Savolainen & Ghosh, 2008; Xie et al., 2012). Abdelwahab & Abdel-Aty (2001) found 14.7% of unbelted drivers sustained fatal or disabling injuries, while seatbelt use reduced DIS by 82% (Savolainen & Ghosh, 2008), by 180.1% (MNL) and 285.9% (LCL) (Xie et al., 2012), by 60% (Kim et al., 2013), by 74.2% (Wu, Zhang, Ci, et al., 2016), by 2.9% (C. Chen, Zhang, Cathy, et al., 2016), by 85.1% (Wali et al., 2018), by 205.2% (M. Islam & Mannering, 2020), by 22.5% (Se et al., 2021), by 35.71% (Hosseinpour & Haleem, 2021), by 25.5% (Se et al., 2022), and by 36% (Ren et al., 2024). Some studies have reported that unbelted drivers increased their injury severity by 97.4% (Paleti et al., 2010), by 1,778.35% (Weiss et al., 2014), by 49.1% (Yasmin, Eluru, Bhat, et al., 2014), by 778.69% (C. Chen, Zhang, Qian, et al., 2016), by 265.43% (MLM) and 318.38% (LCM) (Z. Li, Ci, et al., 2019), by 204.08% (Osman et al., 2018), by 1,540.07% (Zou et al., 2023), and 19.6% (Dzinyela et al., 2024). Seatbelt effectiveness was different for occupant position and across collision types and when varying temporal scenarios. Abdel-Aty (2003) reported that the severity coefficients of unbelted drivers were greater for roadway segments (0.553), signalized intersection sections (0.648), and toll plazas (1.506). Ren & Xu (2023) found that seatbelt wearing can decrease injury by up to 35.9%. Demographic effects were also noted. Hanrahan et al. (2009) and Amarasingha & Dissanayake (2014) observed benefits at all ages, with older drivers receiving the greatest protection. Chamroeun Se et al. (2024) and Habib et al. (2025) also found that universal seatbelt use reduced the overall likelihood of severe injuries among all terrains and age groups. X. Li et al. (2021) found that helmet use reduced DIS by 15.3%, but helmet type mattered: riders wearing half helmets were 6.5% more likely to be seriously injured. Reinforcing helmet effectiveness, Weiss et al. (2014) found that 71.8% of non-helmeted riders faced fatal injury risk, while helmeted riders had significantly lower severity.

Overall, older and younger drivers, impaired or ejected drivers, those with limited experience, non-users of seatbelts or helmets are consistently at increased risk of injury severity, while when properly restrained, individuals from various demographics have substantial protection, thus necessitating targeted driver education, enforcement, and age-specific safety programs.

Table 1: Summary of DIS studies based on driver characteristics

Author and country name	Study year and country	Used model	Considered variable	Key findings
Schneider et al. (2009)	(1997-2001), United States	MNL	Driver age	A 1% increase in the age of older drivers raised the probability of incapacitating and fatal injuries by 0.9% (small radius) and 03% (large radius).
Yasmin, Eluru, Bhat, et al. (2014)	(2006-2010), Australia	LSGOL	Driver gender	Female drivers were associated with a higher injury risk (26.8%) than their male counterparts.
Ali Behnood & Mannering (2017)	(2004-2012), United States	MLM-Extension	Driver gender	For female drivers with male passengers, the likelihood of no injury decreased by 0.0107, indicating a higher risk of severe injury.
Dabbour et al. (2020)	(2004-2015), United States	BLR	Driver gender	Female drivers faced higher injury risks in rear-end collisions but had little impact on the other drivers involved.
Se et al. (2020)	(2011-2017), Thailand	BLR	Driver condition	Under fatigue, younger drivers (<26) had a 7.5% higher fatality risk, slightly more than older drivers (>26) at 7.3%
Adanu et al. (2021)	(2012-2016), United States	MLM-Extension	Seatbelt usage	Failing to use seatbelts increased injury risk by 0.0045 for younger drivers and 0.0015 for older drivers.
Jayaraman et al. (2022)	(2011-2020), India	BLR	Driver age	Older drivers aged above 55 years had higher odds of sustaining MAIS+2 injuries compared to younger drivers.
Ren & Xu (2023)	(2015-2017), United States	MLM-Extension	Driver age	Severe injury risk increased by 27.7% in left side and 33.8% in right-side accidents involving older drivers (>50 years).

Note: - MNL: Multinomial Logit Model, LSGOL: Latent Segmentation-based Generalized Ordered Logit Model, MLM-Extension: Random Parameters Logit Model with Heterogeneity in Means/ in Means & Variances, BLR: Binary Logistic Regression Model.

4. Vehicle Characteristics

Vehicle features (e.g., age, type, extent of damage, and safety features such as airbags) are critical in determining injury severity, influencing crashworthiness, energy absorption, and occupant protection levels and are vital drivers for vehicle design regulations, fleet modernization, and safety technology adoption.

4.1. Vehicle Age

Older vehicles were consistently associated with increased DIS. Kockelman & Kweon (2002) noticed a significant association between older vehicles and DIS with a coefficient of 0.0071. S. Islam & Mannering (2006) found that older drivers in vehicles less than five years old had a 216% higher fatality risk, while Kim et al. (2013) observed an 83% increased risk of fatal injuries when older drivers operated older vehicles (≥ 11 years old). Similarly, Yasmin, Eluru, Pinjari, et al. (2014) found that vehicles ≥11 years old were 9.2% more likely to cause severe injuries. Consistent results were reported across multiple countries, including the United States (Alogaili & Mannering, 2020; M. Islam et al., 2024; Kabli et al., 2023; X. Li et al., 2021), China (F. Chen et al., 2019; Ren et al., 2024; Ren & Xu, 2023; H. Yu et al., 2021), Australia (R. W. G. Anderson & Searson, 2015), and Canada (Dabbour et al., 2020). A few studies indicated a significant increase in DIS with older vehicles in different accident types (F. Chen et al., 2019), in side accidents (Ren & Xu, 2023), and for both striking and struck drivers (Dabbour et al., 2020). M. Yu et al. (2021) recorded a 3.49% risk of severe injury for vehicles older than 16 years, whereas that for newer vehicles is only 1.23%. However, a few studies observed that DIS rate was lower in newer vehicles (Donmez & Liu 2015; Marcoux et al., 2018; Zeng et al., 2016).

4.2. Vehicle Type

The vehicle type factor was significant in deciding the level of DIS. A few studies reported that passenger cars were more likely to have high DIS compared with other vehicle types. Dabbour et al. (2020) found that the DIS was higher for driver in passenger car but lower severity level for drivers of collided vehicles. Zou et al. (2023) also pointed out that drivers in passenger cars hit by light trucks were 125.35% more likely to suffer severe injuries. Additional studies, however, have found lower DIS for passenger cars (Braver & Kyrychenko, 2004; Savolainen & Ghosh 2008; A. Behnood & Mannering, 2015). Dzinyela et al. (2024) observed that in passenger cars through airbag deployment, injury severity decreased by 1.8% and without airbags the decrease was 7.6%. Protection was better in SUVs versus passenger cars. Kockelman & Kweon (2002) and H. Yu et al. (2020) found that SUVs were associated with a lower injury severity risk, with coefficients of -0.2220 and -0.0042 in two cases, respectively. However, C. Se et al. (2020) also found that SUVs raised fatal injury severity by 4.9% for middle-aged drivers (26-50 years) and 4.6 % for older drivers (>50 years). The risk of injury severity was substantially elevated for the drivers in pickup trucks. Kweon & Kockelman (2003) reported young and female pickup drivers suffer 6.462% more injury risk. C. Se et al. (2021) observed that pickup trucks raised the odds of severe injury outcomes by 17.6%. However, conflicting results were reported from some studies. Marcoux et al. (2018) observed reductions in driver injury severity of 41.5% for pick-ups and vans. M. Islam & Mannering (2021) found that male pickup drivers had a decreased risk of severe injury and Kabli et al. (2023) showed that light trucks offer more protection than passenger cars, and reduce the risk of injury to the head, thorax and extremities.

Effects on DIS have been observed to be mixed in studies of buses, trucks and heavy vehicles. W. H. Chen & Jovanis (2000) found that 32 % of bus drivers died or were injured in crashes with large trucks/ tractor-trailers. Duddu et al. (2018) indicated that non-at-fault bus drivers were less likely to be injured, with an odds ratio of 0.21 compared with car drivers. Conversely, some studies identified a large DIS of heavy trucks. Boufous et al. (2008) witnessed more severe injuries among truck drivers relative to car drivers. F. Chen & Chen (2011) estimated that single-unit trucks raised driver DIS in MVAs by 37.9%, while Lee & Li (2014) found a.43 unit increase in DIS for heavy truck drivers. This observation was supported by Haq et al. (2021), M. Islam (2022), and Chamroeun Se et al. (2023). But some studies found that bigger, heavier vehicles protect occupants better. Zhao & Khattak (2015) demonstrated that larger vehicles sustained fewer injurious outcomes in crashes with trains, and C. Chen, Zhang, Huang, et al. (2016) concluded that reduced DIS was caused by the rigidity of heavy vehicles. These results were confirmed by some other research (Hou et al., 2019; Ma et al., 2016; Wang et al., 2021). Rahimi et al. (2020) reported a 0.029 decrease in the probability of fatal injury for heavier trucks. However, Sun et al. (2022) reported contrasting results, with fatal injury risk increased by 191.5% in urban areas and 79.1% in suburban ones imposed by heavy trucks.

Motorcycles were the most vulnerable vehicle type, consistently exhibiting the highest injury severity risks (Schneider et al., 2009; Wu et al., 2014). Huang et al. (2008) found that two-wheelers were at 263% higher risk of sustaining severe injuries. Schneider et al. (2009) observed a 560% increased risk of fatal injuries for motorcyclists. Abegaz et al. (2014) observed that two- and three-wheelers had the highest severity levels, and Qiong Wu et al. (2014) reported a 6.5% fatality risk in motorcycle accidents. Yan et al. (2021) found fatal injury risks of 30.1% for male and 25.7% for female riders. M. Islam et al. (2024) showed that speeding motorcyclists were twice as likely to suffer severe injuries, and Fang et al. (2024) confirmed motorcycles had the strongest impact on DIS. In contrast, Wei et al. (2024) reported that pedal motorcycles reduced the prospects of fatal injuries.

4.3. Vehicle Damage and Airbag Deployment

The functional damage and disabled vehicle damage were found to have an increased DIS. C. Chen, Zhang, Tarefder, et al. (2015) found that disabled vehicle damage increased fatal injury risk by a coefficient of 3.7. In a subsequent study, C. Chen, Zhang, Tian, et al. (2015) reported that such damage raised incapacitating or fatal injury odds by an extraordinary 13,199.89%. Similarly, C. Chen, Zhang, Cathy, et al. (2016) found that functional damage raised severe injury likelihood by 235% and was 44 times more probable in vehicles with disabled damage. C. Chen, Zhang, Huang, et al. (2016) further confirmed that disabled vehicle damage was strongly associated with more severe injuries, reflecting the accident's intensity. Some studies have confirmed that airbags reduce driver injuries and fatalities in vehicle accidents. Braver & Kyrychenko (2004) found that side airbags reduced driver death risk by 45% (risk ratio = 0.55). Mafi et al. (2018) found large decreases for younger drivers. F. Chen et al. (2019) found that DIS was reduced in cars when front airbags were active. Some studies, however, had negative results. Savolainen & Ghosh (2008) stated that airbags reduced severe/fatal crash involvement by drivers but raised moderate injury risk by 340%. H. Yu et al. (2020) associated the deployment of front airbags with a 135.92% increase in serious injury/fatality. Dzinyela et al. (2023) found a 4.2% increase in DIS, and Dzinyela et al. (2024) reported an 11% increase in DIS with airbag deployment versus 3.5% without. Recently, Adanu et al. (2025) found that SUV accidents with deployed airbags in 2010 and 2018 had higher DIS compared to similar accidents in 2014 and 2022.

Overall, older vehicles and motorcycles are reliably associated with higher injury severity due to reduced structural protection and outdated safety features, whereas larger vehicles such as SUVs and heavy trucks generally have better occupant protection (with mixed airbag effects), illustrating the role of promoting newer, safer vehicle designs.

5. Environmental and Temporal Characteristics

The environmental and temporal features such as time of day, lighting, weather conditions, and day of the week, are important to investigate because they impact visibility, road friction, and driver behaviour that all affect the possibility and severity of injuries and can guide time-specific strategies such as better lighting and weather-adaptive alerts.

Table 2: Summary of DIS studies based on vehicle characteristics

Author name	Study year and Country	Model Used	Variable Considered	Key findings
Delen et al. (2006)	(1995-2000), United States	ML	Vehicle type	Vehicle type did not have much effect on accidents involving fatality outcomes.
Zhu & Srinivasan (2011)	(2001-2003), United States	OPM	Vehicle type	Single-unit trucks were associated with lower injury severity to drivers than large truck trailers.
Xie et al. (2012)	(2005), United States	LCM and MNL	Airbag deployment	Airbag deployment reduced fatality risk in less severe accidents but had mixed effects based on collision severity.
Xiong & Mannering (2013)	(1995-1999), United States	LC-RPP	Vehicle type	In areas with over 10% large trucks, severe injury risk was 10.4% with guardian supervision, compared to 24.5% without it.
Lee & Li (2015)	(2004-2008), Canada	ML	Vehicle type	A higher percentage of trucks in road traffic increased the chances of injury severity of truck drivers, especially in the case of two-vehicle accidents.
Cong Chen, Zhang, Qian, et al. (2016)	(2010-2011), United States	ML	Vehicle action	Vehicles with frequent acceleration or deceleration had a 24.14% higher risk of severe injury than those driving straight.
Kabli et al. (2020)	(2005-2015), United States	RP-GOPM	Vehicle age	Newer vehicles had better protection against injuries compared to older vehicles.
Hosseinpour & Haleem (2021)	(2015-2019), United States	RP-OPM	Vehicle type	Drivers involved in accidents related to single-unit trucks increased the injury severity risk by 0.05%.

Note: - ML: Machine Learning, LCM: Latent Class Model, LC-RPP: Latent Class Random Parameters Probit Model, RP-GOPM: Random Parameters Multivariate Generalized Ordered Probit Model, and RP-OPM: Random Parameters Ordered Probit Model.

5.1. Time of Accident

Several studies reported that nighttime accidents were consistently associated with increased DIS. W. H. Chen & Jovanis (2000) found that 58% of bus drivers in Taiwan involved in nighttime accidents (11pm-5am) suffered severe or fatal injuries. Pai & Saleh (2007) reported a 55.21% DIS increase for accidents between 12 am-6:50 am, while Gray et al. (2008) found a 23% higher fatality likelihood for accidents from 12am-6:59am. Similar results were found in studies from the United States (Behnood et al., 2014; Harland et al., 2018; Marcoux et al., 2018; Pervaz et al., 2024; Pour-Rouholamin & Zhou, 2016; Zhao & Khattak, 2015), Thailand (Se et al., 2020), and India (Sorum & Pal, 2024a). Zhao & Khattak (2015) confirmed higher DIS during night or dawn across multiple models. Harland et al. (2018) reported that 42% of alcohol-impaired accidents occurred between 6pm-11:59pm. Marcoux et al. (2018) observed that nighttime accidents on unlit highways raised male and female driver injury risks by 14.5% and 18.7%, respectively. Sorum & Pal (2024a) also reported higher DIS between midnight and 6 am, and M. Islam et al. (2024) attributed similar increases to speeding during those hours. In contrast, C. Chen, Zhang, Cathy, et al. (2016) reported that nighttime accidents had a 15.53% decreased probability of DIS. M. Islam & Mannering (2021) found that male drivers were more likely to sustain severe injuries between midnight and 5:59 a.m., while female drivers faced higher risks around noon. Chamroeun Se et al. (2024) noted that large injury risk was dominant among older drivers in morning peaks, while severe injuries were predominant in evening peaks for younger drivers. Nighttime dark conditions with no streetlights greatly enhanced DIS (Hao & Daniel, 2014; Kim et al., 2013; Xie et al., 2012; Zhao & Khattak, 2015). Adanu et al. (2021) found that younger drivers were less likely to be injured during the day, while older drivers were at a greater risk on unlit roads. C. Se et al. (2020) reported that DIS was 12.4% lower in night accidents with street light and 20.3% higher under unlit conditions. Zou et al. (2023) observed a 20.08% increase in DIS under similar conditions.

Mixed outcomes were reported in the case of morning-hour accidents. Khorashadi et al. (2005) found fatal injuries decreased by 4.3% in rural and 37.1% in urban morning rush hours (5:31-8:00am), while Lee & Li (2014) reported daytime driving reduced DIS by 0.29 units. In contrast, several studies found the opposite trend (J. C. Anderson & Dong, 2017; Hao et al., 2016; Ren & Xu, 2023; Wen & Xue, 2020). W. Hao et al. (2016) showed that morning hours (5-9:59am) had the highest fatality rate (9.14%) at highway-rail crossings, whereas J. C. Anderson & Dong (2017) noted lower severe injury risks for heavy vehicles at the same time. Wen & Xue (2020) found early morning accidents increased fatal injury likelihood by 21.6% for familiar and 28.9% for unfamiliar drivers. Similarly, Ren & Xu (2023) found that early morning (12am to 5:59am) accidents resulted in a 24.6% higher likelihood of DIS in right-side accidents and 15.2% in centre accidents.

5.2. Weather Conditions

Numerous studies have shown that weather conditions significantly affect DIS. S. Islam & Mannering (2006) noted foggy weather drastically increased fatalities, especially in older female drivers. Dabbour (2017) found clear or cloudy increased DIS for light-duty vehicles in train-vehicle collisions, while Kim et al. (2013) observed a 24% rise in fatal injuries under cloudy conditions. Several studies linked snow and rain to higher DIS (Mooradian et al., 2013; Qiong Wu et al., 2014; Yasmin, Eluru, Pinjari, et al., 2014; Abegaz et al., 2014; M. Yu et al., 2020). W. Hao et al. (2016) found snow increased DIS by 4.29% in early mornings. Qiong Wu, Zhang, Zhu, et al. (2016) linked rural DIS increases with rain, and M. Islam & Mannering (2021) found that rain worsened DIS for speeding male drivers. Wen & Xue (2020) found increased DIS in familiar drivers during rain (22.3%), fog (21.2%), and snow (20.7%). In contrast, some studies found that snowy or rainy weather reduced DIS. Eluru et al. (2012) reported snow lowered severe injury risk by 198.6% and 28.9%. Zhang et al. (2020) reported that clear weather reduced DIS by 0.06 and snow by 0.3. Studies on clear weather showed mixed results. Pai & Saleh (2007) found an 8.59% higher DIS in clear conditions. Schneider et al. (2009) noted that clear daylight raised DIS by 46% in small-radius and 27.6% in large-radius curves. S. Islam et al. (2023) found that fatal/serious injury to drivers increased by 19.3% (males) and 23.4% (females) in clear weather.

Wei Hao & Daniel (2014) highlighted adverse weather risks at highway-rail crossings: sleet raised fatalities by up to 2.3% and snow by 1.7%. Cong Chen, Zhang, Qian, et al. (2016) found that adverse conditions raised DIS probability by 31.4%. Haq et al. (2021) noted an 8.01% higher risk when drivers failed to maintain lanes in poor weather. Yan et al. (2021) found an enhanced risk of injury in females (18.6%) and males (22.4%).Sun et al. (2022) and Fang et al. (2024) associated unfavourable weather conditions with higher DIS, particularly in the suburban areas. However, decreased DIS was reported in other studies under poor weather conditions: Donmez & Liu (2015) found a decrease of 14% for severe injuries during rain/snow. Likewise, C. Chen, Zhang, Yang, et al. (2016), Wali et al. (2018), and Mohamed Osman et al. (2019) showed lower severity risk in adverse weather and a 15.57% reduction in DIS.

5.3. Day of Accident

Temporal factors such as weekdays and weekends significantly affect DIS. Gray et al. (2008) found a 14% higher fatality risk on Saturdays, while Kim et al. (2013) reported a 21% DIS increase on weekends compared to weekdays. Similar results were observed by J. C. Anderson & Dong (2017), Mohamed Osman et al. (2019), Zhang et al. (2020), C. Se et al. (2020), Yan et al. (2021), and Wei et al. (2024), all noting higher DIS during weekend accidents. However, Christoforou et al. (2010) and Fang et al. (2024) found that weekend accidents had lower DIS than weekday ones. Among weekdays, F. Chen et al. (2019) identified Mondays, and M. Islam (2022) found Tuesdays, as the days with the highest DIS. More recently, Tamakloe et al. (2025) reported weekday taxi driver at-fault accidents increased the probability of fatal and severely injured outcomes by 0.0076.

Collectively, nighttime accidents, adverse weather, poor lighting, and weekend periods commonly increase the severity of driver injuries due to diminished visibility and increased behavioural hazards; however, risk-aware driving adjustments during adverse conditions have the potential to alleviate some consequences, highlighting the significance of temporal and environmental safety planning.

Table 3: Summary of DIS studies based on environmental and temporal characteristics

Author name	Study year and country	Used Model	Variable considered	Key findings
Wei Hao & Daniel (2016)	(2002-2011), United States	MLM	Time of accident	Peak-hour accidents were associated with an increased fatality of 15.3% under fog conditions.
Zhao & Khattak (2015)	(2009-2013), United States	OPM, MNL, MLM	Time of accident	Daylight and dusk conditions led to lower severe injury outcomes compared to night and dawn conditions.
F. Chen et al. (2019)	(2011-2015), United States	RPB-OPM	Time of accident	Both rear and front vehicles had a higher possibility of suffering severe injuries during nighttime.
Dabbour et al. (2020)	(2004-2015), United States	BLR	Time of accident	Injury severity decreased during peak PM hours (4–8 pm) but increased during darkness.
Khales et al. (2020)	(2008-2017), United States	MLM	Weather	Adverse weather, like rain, fog, or snow, increased driver fatality risk at passive warning devices.
Wei et al. (2024)	(2014-2018), China	ML	Day of accident	Weekends were associated with a higher risk of motorcyclist injuries compared to weekdays.
Tamakloe et al. (2025)	(2017-2023), South Korea	MLM	Time of accident	Taxi driver at-fault accidents between 12-3am and 4-7am significantly increased the risk of fatal or severe injuries.

Note: - RPB-OPM: Random Parameters Bivariate Ordered Probit Model.

6. Roadway Characteristics

Roadway attributes such as pavement condition, curvature, lane count, urban/rural classification, and lighting infrastructure deserve in-depth exploration, as they determine vehicle stability, sight distance, and hazard exposure and provide necessary inputs for infrastructure upgrades that can address differences in severity of accidents between regions.

6.1. Pavement Condition

Several studies have found that wet road conditions often lead to reduced DIS, likely due to more cautious driving behaviour. Zhu & Srinivasan (2011) found lower severity on wet pavements, while Kim et al. (2013) reported 33% and 29% decreases in fatal and severe injuries. Pour-Rouholamin & Zhou (2016) observed a 35.5% reduction, and C. Chen, Zhang, Cathy, et al. (2016) and Marcoux et al. (2018) found 55.2% and 9.4% decreases, respectively. Similar findings were reported by Mohamed Osman et al. (2019) (35.47% reduction), H. Yu et al. (2020) (25.31% reduction), Dzinyela et al. (2024) (8.9% reduction), and Ren et al. (2024) (25% reduction). In contrast, wet pavements are frequently associated with larger DIS. Christoforou et al. (2010) found a higher probability of being seriously injured on dry roads, and the same was supported by Qiong Wu et al. (2014), who found a 2.5% increase in mortalities due to fatality. Hosseinpour & Haleem (2021) noted an increase of 0.02% in DIS during dry conditions and Ali Behnood et al. (2014), Qiong Wu, Zhang, Chen, et al. (2016), Al-bdairi et al. (2020), and Zhang et al. (2020) reported increases of 76.7%, 186.67%, 8%, and 8%, respectively.

DIS was differently influenced by snowy and icy roads. Several studies have found that DIS decreased under such conditions (J. C. Anderson & Dong, 2017; F. Chen et al., 2019; Wu, Zhang, Zhu, et al., 2016; H. Yu et al., 2020; M. Yu et al., 2020). However, F. Chen & Chen (2011) showed that snow-covered roads raised DIS for MVAs but lowered it for SVAs. Morgan & Mannering (2011) also pointed out that snow/ice effects varied with age and gender: male drivers under the age of 45 experienced reduced severe injury risk on snow/ice, while no difference was found for older males, also female drivers showed a higher DIS in both categories. Effect of Unpaved/Gravel Roads on DIS. The impact of unpaved and gravel roads has had mixed effects on DIS. Several studies associated them with increased DIS from poor traction and inconsistent surfaces. Thompson et al. (2013) found unsealed roads contributed to 9.5% of fatal injuries, especially for older rural drivers (OR = 2.22).

6.2. Roadway Curves and Lanes

Several studies have shown that curved roads are associated with an increased DIS relative to straight segments. C. Chen, Zhang, Cathy, et al. (2016) found a 36.8% increase in DIS on rural highway curves in line with M. Yu et al. (2020).

Wen & Xue (2020) observed an increase of 25.4% on long downhill curves, Christoforou et al. (2010) confirmed vertical curvature effects. Rahimi et al. (2020) also found an elevated fatality risk on unlevelled curved roads, and Zou et al. (2023) reported a 304.69% increase. Driver demographics and characteristics had a significant effect on injuries occurring in curvature sections. Mohamed Osman et al. (2019) reported that older age group drivers (≥65) were 108.13% more likely to have severe injuries compared with the younger ones (≤25). M. Islam & Mannering (2021) found that males had a higher likelihood of severe injury both sexes more minor injuries, particularly on right curves. Risks were also elevated by environmental and alignment variables. Zhenning Li, Ci, et al. (2019) showed that during rain, curved roads increased fatal injury likelihood by 84.14% (MLM) and 20.13% (LCM). Over time, C. Se et al. (2020) observed DIS rising by 19.3% in 2016 and 21.8% in 2017 for such accidents, and Chamroeun Se et al. (2024) found that speeding on curved roads in Thailand raised severe injury risks for all ages. Conversely, Haq et al. (2021) reported an 11.49% DIS reduction on curved roads, indicating possible mitigating factors needing further study.

Zhenning Li, Wu, et al. (2019) found that multiple lanes increased DIS in SVAs by 5.40% in the MLM and 23.88% in the LCM. Similar findings were observed in some studies (Duddu et al., 2018; Gray et al., 2008; Wu, Zhang, Chen, et al., 2016). Gray et al. (2008) observed that single carriageways caused more severe injuries than dual carriageways, while Duddu et al. (2018) noted that at-fault drivers were 1.81 times, and not-at-fault drivers 1.31 times, more likely to sustain severe injuries on two-way roads. H. Yu et al. (2020) found that 3-4 lane roads raised severe injury likelihood by 0.0046, and M. Islam (2022) reported higher DIS for heavy trucks changing lanes on multi-lane highways. Conversely, Chamroeun Se et al. (2024) reported that middle-aged drivers involved in 4-lane accidents had a 7.27% reduction in DIS.

6.3. Roadway Types

Several studies indicated that the DIS on rural roads was greater than on urban roads. Abdelwahab & Abdel-Aty (2001) reported that Rural intersections were found to have more severe. Boufous et al. (2008) and Yuan et al. (2021) also reported that 66.6% of rural accidents led to severe or fatal injuries. Zhenning Li, Ci, et al. (2019) showed that male heavy vehicle drivers on rural curved roads were at a higher risk of fatality, especially during poor lighting or in the case of drunk driving. Yan et al. (2021) reported that female drivers on rural two-lane highways had a 19.3% increased risk, while male drivers on urban freeways had an average reduction of 13.2%. The results are mainly supported by Pai & Saleh (2007) (increase by 350%), Wei Hao & Kamga (2015) (by 2.3%), Qiong Wu, Zhang, Zhu, et al. (2016) (by 649.9%), and Cong Chen, Zhang, Qian, et al. (2016) (by 35.48%). In contrast, Mooradian et al. (2013) and Rahimi et al. (2020) found a greater DIS in urban regions.

Accident patterns between urban and rural areas have been compared in many studies. Fang et al. (2024) reported that 87.17% of rural angle accidents resulted in severe driver injuries, and M. Yu et al. (2020) obtained negative fatality odds (− 0.0059) for urban run-off-road accidents. Pervaz et al. (2024) revealed that DIS was higher in urban compared with rural accidents for head-on and sideswipe types, whereas rural accidents showed higher DIS for head-on and SVAs. These patterns were supported by temporal and regional analyses. Dabbour (2017) revealed that rural roads continually had more DIS: 8.24% and 6.32% (2007); 6.62%, and 4.73% (2013). Wang et al. (2021) observed reductions in driver mortality by 81.8% on urban and 65.5% on rural roads relative to national/provincial roads. Behavioural differences were also evident. M. Islam & Mannering (2020) reported that aggressive urban drivers are approximately 0.0092 more likely to be severely injured, while Duddu et al. (2018) reported that non-at-fault drivers would tend to suffer severe injuries on urban roadways. M. Islam (2022) found similar patterns in work-zone fatal and severe injury crashes on rural interstates involving large trucks, where they analysed such RTAs as 14 times more likely to lead to severe injury than those that are non-work zones.

Road functional classification and land use structure and environment further influence the patterns of the two urban/rural contexts, with freeways and arterials (often in mixed urban/suburban contexts) having varying severity due to higher speeds and multi-vehicle interactions, while collector and local streets in dense land-use areas can induce lower speeds and more potential for conflicts (Pervaz et al., 2024; Fang et al., 2024). Land types (residential, commercial, industrial) indirectly account for accident causation and severity by influencing traffic composition, pedestrian presence, and access points, yet the direct DIS relationship is lacking in the studies involved.

6.4. Roadway Lighting Condition

Many studies demonstrated the very important effect that roadway lighting had on DIS. Pai & Saleh (2007) observed a 36.2% DIS increase when processing night captures from unlit streets, while Gray et al. (2008) observed 30% higher DIS values in darkness than during daylight. Fang et al. (2024) reported 78.71% of DIS with dim light and 81.48% in total darkness. Chamroeun Se et al. (2024) also linked nighttime accidents to greater fatality risk. Street lighting was shown to reduce such risks. Xiong & Mannering (2013) found less severe outcomes in lit nighttime accidents among adolescents, and Pour-Rouholamin & Zhou (2016) showed DIS increases dropped from 35% (unlit) to 12.7% (lit). Regional effects also mattered. Wei Hao & Kamga (2015) observed DIS increases of 2.1% (rural) and 1.1% (urban) under poor lighting. Wei Hao & Daniel (2016) observed DIS of 13.2% under fog and 11.9% under snow in low-light. C. Chen, Zhang, Tarefder, et al. (2015) confirmed that darkness heightened fatal injury risk, while Dabbour (2017) found DIS increased by 9.59% in 2007 and 7.23% in 2013 due to poor lighting.

Work zones are not frequently studied in DIS literature but represent another road condition that carries great risk. Temporary geometric alterations such as lane shifts or narrowed configurations in work zones also tend to significantly increase severe and fatal injury outcomes, particularly for large trucks on rural interstates where such crashes are estimated 14 times more likely than non-work zones to result in serious injuries (Islam, 2022). These higher chances of injury because of interaction with speeds, driving behaviour, fewer gaps for error in altered alignments, emphasise once again the need for special temporary signage, speed controls and geometric smoothing during maintenance work.

Overall, curved roads, multi-lane configurations, rural settings, and poor lighting are universally associated with an increase in DIS, driven by a combination of increased complexity and decreased safety margins, while wet or icy pavements may encourage compensatory cautious behaviour that reduces severity, suggesting the need for a particular roadway engineering and maintenance improvements.

Table 4: Summary of DIS studies based on roadway characteristics

Author name	Study year and country	Model used	Considered variable	Key findings
Savolainen & Ghosh (2008)	(2004-2005), United States	MLM	Roadway lighting	Dark conditions without lighting decreased DIS by 46.9%.
Wali et al. (2018)	(2013), United States	CBOR	Roadway type	Rural road accidents significantly raised serious and fatal injury risks for at-fault (0.730) and not-at-fault drivers (0.572).
H. Yu et al. (2020)	(2014-2017), United States	HOPIT	Horizontal and vertical curves	Curved road alignment raised severe injury risk of drivers by 0.0038 across all yearly models.
Khales et al. (2020)	(2008-2017), United States	MLM	Roadway lighting	Poor lighting conditions during no daylight at Passive Warning Devices resulted in a significant fatality risk of 27.8%.
Adanu et al. (2021)	(2012-2016), United States	MLM-Extension	Number of lanes	Younger drivers faced major injuries on six-lane highways, while older drivers experienced these mainly during overtaking on two-lane highways.
X. Li et al. (2021)	(1999-2018), United States	GTWOLR	Roadway type	Accidents taking place on interstates increased the risk of sustaining serious injuries by 6%.
Sun et al. (2022)	(2014-2015), China	MLM, ML	Roadway lighting	Poor lighting conditions were a key factor in increased fatality risk.
S. Islam et al. (2023)	(2012-2016), United States	MLM, ML	Horizontal and vertical curves	Horizontal curves increased fatal or incapacitating injury risk for 35% of the sample.

Note: - CBOR: Copula-based bivariate ordinal regression; HOPIT: Hierarchical Ordered Probit Model, GTWOLR: Geographically-Temporally Weighted Ordered Logistic Regression Model.

7. Accident-Specific Characteristics

Accident-specific characteristics, such as collision type and contributing causes including speeding, distraction, and alcohol impairment, are central to understanding DIS, because these determine impact energy transfer, force distribution, and fault-related outcomes, and accordingly the enforcement priorities and behavioural strategies.

7.1. Type of Accidents

Head-on collisions are consistently identified as one of the most severe accident types, with extensive evidence linking them to high DIS (Delen et al., 2006; Dissanayake & Lu, 2002; Kockelman & Kweon, 2002). Kockelman & Kweon (2002) found coefficients above 0.6483 for head-on impacts, while Dissanayake & Lu (2002) reported that such accidents increased DIS by 3.028 times. Pai & Saleh (2007) showed motorcyclists in head-on collisions faced a 50.31% higher fatality risk than in other accident types. Several studies (Chang & Chien, 2013; Lee & Li, 2014; Viano & Parenteau, 2012; Zeng et al., 2016) supported these findings. Chang & Chien (2013) reported an 11.11% DIS increase in head-on accidents, marking them as the deadliest collision form. Zhang et al. (2020) observed a 35% increase in DIS and Pervaz et al. (2024) had demonstrated that excessive speed contributed to the severity of such accidents. Sorum & Pal (2024b) indicated that accidents of head-on collision and side impact ranged between 26-32% for fatal crashes in Itanagar and were highest in Imphal.

Dzinyela et al. (2023) reported that the DIS rates were higher for side-impact accidents in MVAs. The same observation was noticed by Abdelwahab & Abdel-Aty (2001) and Kabli et al. (2023), where side accidents were reported to be more severe, resulting in direct application of impact forces on sensitive body parts such as head, face and upper limbs. However, Adanu et al. (2021) reported an opposite outcome, that younger drivers were less likely to be severely injured in side-impact accidents. W. H. Chen & Jovanis (2000) determined that rear-end collisions were the most dangerous crash type, and 49% of drivers were either killed or seriously injured. Viano & Parenteau (2012) reported that rear-impacted drivers had a 0.290% risk of severe-to-fatal injury compared to a risk of 0.058 % for front-impacting vehicle drivers. Dzinyela et al. (2023) reported that rear-end collisions comprised 23.1% of MVAs, often resulting in serious injuries to drivers. In contrast, some studies reported lower DIS. Zhu & Srinivasan (2011) found that truck-car rear-end accidents had the lowest injury severity compared to head-on or fixed-object collisions. Mooradian et al. (2013) found rear-end collisions were less likely to result in severe injuries. Harland et al. (2018) further reported that fatality likelihood in rear-end accidents was only half that of non-collision incidents.

Chamroeun Se et al. (2023) concluded that drivers involved in run-off-road (ROR) accidents on vehicles faced a higher risk of fatal injuries. Some other studies verified the same (Schneider et al., 2009; Se et al., 2020). In contrast, Rahimi et al. (2020) found that the probability of DIS in ROR accidents was reduced by 0.019. Consistent findings were reported for rollover and overturned accidents. Kockelman & Kweon (2002) identified rollover accidents as the most severe contributor to DIS. Gray et al. (2008) found a 17% DIS increase from skidding or overturning, while F. Chen & Chen (2011) observed DIS rises of 10.6% in SVAs and 12.2% in MVAs due to overturned trucks. C. Chen, Zhang, Cathy, et al. (2016), Qiong Wu, Zhang, Zhu, et al. (2016), J. C. Anderson & Dong (2017), and Zhenning Li et al. (2018) confirmed that overturn accidents strongly correlated with severe injury to drivers. Recent studies (Dzinyela et al., 2024; M. Islam et al., 2024; Kabli et al., 2023) reinforced these findings. Dzinyela et al. (2024) identified DIS risk increases of 2.2% with airbag deployment and 2.7% without in rollover accidents. Fixed object collisions are strongly linked to increased DIS (Gray et al., 2008; Hosseinpour & Haleem, 2021; Marcoux et al., 2018). S. Islam & Mannering (2006) found fatalities 1407% higher for older females (>65) in such accidents, while Gray et al. (2008) reported a 32% fatality increase among young males. Xie et al. (2012) noted fatal injury to drivers of 121.1% (MNL) and 179.9% (LCL) for fixed-object impacts. Marcoux et al. (2018) observed a 73.9% increase in DIS from collisions with large objects. Hosseinpour & Haleem (2021) reported DIS increases of 0.678% for trees and 0.28% for utility poles. Similar findings were reported in some studies (Eluru et al., 2012; Hou et al., 2019; X. Li et al., 2021; Ren & Xu, 2023; Yan et al., 2021). M. Islam et al. (2024) showed speeding-tree collisions raised severity by 0.0281, while Rahimi et al. (2020) contradicted this, finding a slight DIS decrease (0.033).

7.2. Cause of Accidents

Numerous studies have established a clear link between excessive speed and increased DIS (Abdelwahab & Abdel-Aty, 2001; Boufous et al., 2008; S. Islam et al., 2023; Wei et al., 2024; Zhu & Srinivasan, 2011). Kim et al. (2013) reported that unsafe speeds increased the risk of fatal injury 2-fold and nonfatal injury by 46%. Similar findings were observed in other studies (Abegaz et al., 2014; Thompson et al., 2013; Weiss et al., 2014; Xiong & Mannering, 2013). Wali et al. (2018) found that speeding-at-fault increased the odds of severe/fatal by 0.024 and Duddu et al. (2018) discovered that the odds of serious injury were 3.79 times. M. Islam & Mahmud (2025) recently demonstrated that speed-related heavy-truck accidents are more likely to involve severe and minor injuries. DIS was strongly affected by the environmental and road conditions. Wei Hao & Daniel (2016) noted DIS increases by 132% in fog and 118% in snow, whereas Wei Hao & Kamga (2015) reported rises of 3.9% at rural and 2.7% at urban on speeds higher than 55 mph. Jayaraman et al. (2022) observed the odds of MAIS+2 injury being 11% greater for each additional 1 mph speed interval increase, while Patalak et al. (2020) found an additional 0.045 DIS for each mph for accidents. Ali Behnood et al. (2014) found that alcohol intoxicated drivers engaged in 1.89 times as much driving while distracted, which has led to serious injury risk. Donmez & Liu (2015) also found that cell phone use while driving was cited as the primary cause of severe driver injuries.

There is a strong association between drunken driving and higher DIS across different groups, types of accidents and geographical areas (Amarasingha & Dissanayake, 2014; Khorashadi et al., 2005; Osman et al., 2019; Pervaz et al., 2024; Weiss et al., 2014; Xie et al., 2012). Demographic impacts differ: Hanrahan et al. (2009) reported that younger drunken drivers were at higher risk, whereas Ali Behnood et al. (2014) reported 18.72% severity in elderly males and 13.11% in elderly females. C. Se et al. (2020) found the biggest fatal risk (↑25.9%) in drivers below 26 years. Accident context also played a role: Kockelman & Kweon (2002) reported increases of 41.74% in SVAs and 24.35% in two-vehicle accidents, and Weiss et al. (2014) observed increases of about 85% in both. Contextual differences were also evident: Khorashadi et al. (2005) found risk deaths increasing 797.9%, and 246% for drunk truck drivers in urban and rural areas, respectively, and Qiong Wu, Zhang, Zhu, et al. (2016) reported similar increases in both regions. Combined substance use worsened outcomes: Hels et al. (2013) found alcohol + psychoactive drugs raised DIS 39-fold. However, some studies reported contrasting results. Dissanayake & Lu (2002) found lower injury severity for older impaired drivers. Zeng et al. (2016) found no significant alcohol/drug impact at 95% credibility. M. Islam & Mannering (2021) found alcohol use associated with lower odds of severe and minor injuries in both genders.

Overall, head-on collisions, rollovers, fixed-object impacts, and accidents involving speeding, distraction, or alcohol impairment are reliably associated with the greatest DIS, as they involve the highest kinetic force loading and the least evasive opportunities, whereas rear-end collisions show more variable outcomes, reinforcing the critical need for addressing their preventable contributing causes with rigorous policy actions as well as public education efforts.

Table 5: Summary of DIS studies based on accident-specific characteristics

Author name	Study year and country	Used model	Considered variable	Key findings
Boufous et al. (2008)	(2000-2001), Australia	MVA	Fixed object collision	Vehicle-to-object collisions had a lower DIS than vehicle-to-vehicle.
Chang & Chien (2013)	(2005-2006), Taiwan	ML	Overspeeding	Exceeding the authorized speed limit increased the fatality rate by 17.65%.
Qiong Wu et al. (2014)	(2010-2011), United States	MLM	Overtaking	Overtaking in SVAs increased driver fatality rate by 601.6%.
Ma et al. (2016)	(2012), United States	HFMM	Rollover/Overturn	Rollover accidents increased the fatality risk by 75.3%.
Kabli et al. (2020)	(2005-2015), United States	RP-GOPM	Side collision	Driver-side impacts were linked to abdomen, thorax, and lower extremity injuries, with lower risks for the face and spine.
X. Li et al. (2021)	(1998-2018), United States	GTWOLR	Head-on collision	Head-on collisions increased the risk of severe injury among riders by 12.1%.
Zubaidi et al. (2021)	(2015-2018), Australia	MLM	Rear-end collision	Rear-end collisions increased DIS by 1.56%.
Zou et al. (2023)	(2010-2016), United States	LC-MNL	Drunken driving	Drunken driving increased DIS by 54.11% in rear-end collisions.

Note: - MVA: Multivariate Analysis, LC-MNL: Latent Class-Multinomial Logit Model, HFMM: Hybrid Finite Mixture Model.

8. Discussion

8.1. Statistics on Published Literature

The annual publication trend on DIS is shown in Figure 2, where 2020 had the highest number of studies (14), followed by 2016 and 2021 (12 each). As shown in Figure 3, most studies originated from the United States (80; 60%), followed by China (17; 13%), likely due to the availability of detailed U.S. accident datasets. Table 6 highlights that 37 models have been used for DIS analysis. The most popular models were MLM (22), its various extensions (20) and machine learning (ML) models (15). MLM has gained popularity by capturing unobserved heterogeneity, relaxing the Independence of Irrelevant Alternatives (IIA) assumption and considering cross-alternative correlations (Al-bdairi et al., 2020; Sun et al., 2022). Nevertheless, MLM has shortfalls of high computational load, parameter sensitivity, overfitting risk and convergence issues, particularly from the beginning sample size. To solve these limitations, advanced versions such as MLM with heterogeneity in means and variances and ML approaches have been adopted in recent works (Adanu et al., 2025; Habib et al., 2025; M. Islam & Mahmud, 2025). The MLM-Extension enhances flexibility by allowing both the mean and variance of random parameters to vary with observable characteristics. ML models, on the other hand, outperform traditional MLMs by capturing complex nonlinear patterns, managing large datasets efficiently, and functioning without strict distributional assumptions (Wei et al., 2024).

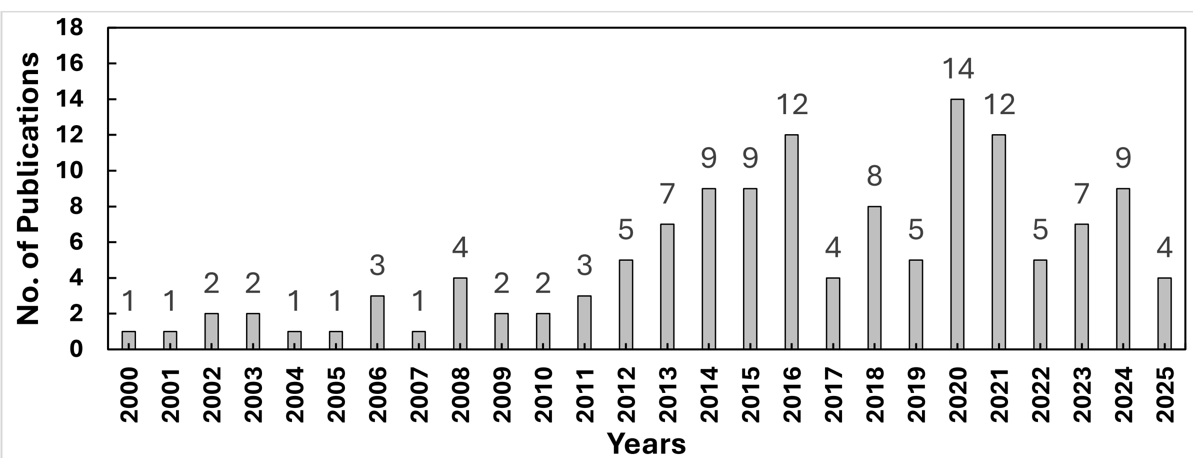

Figure 2: Number of publications per year

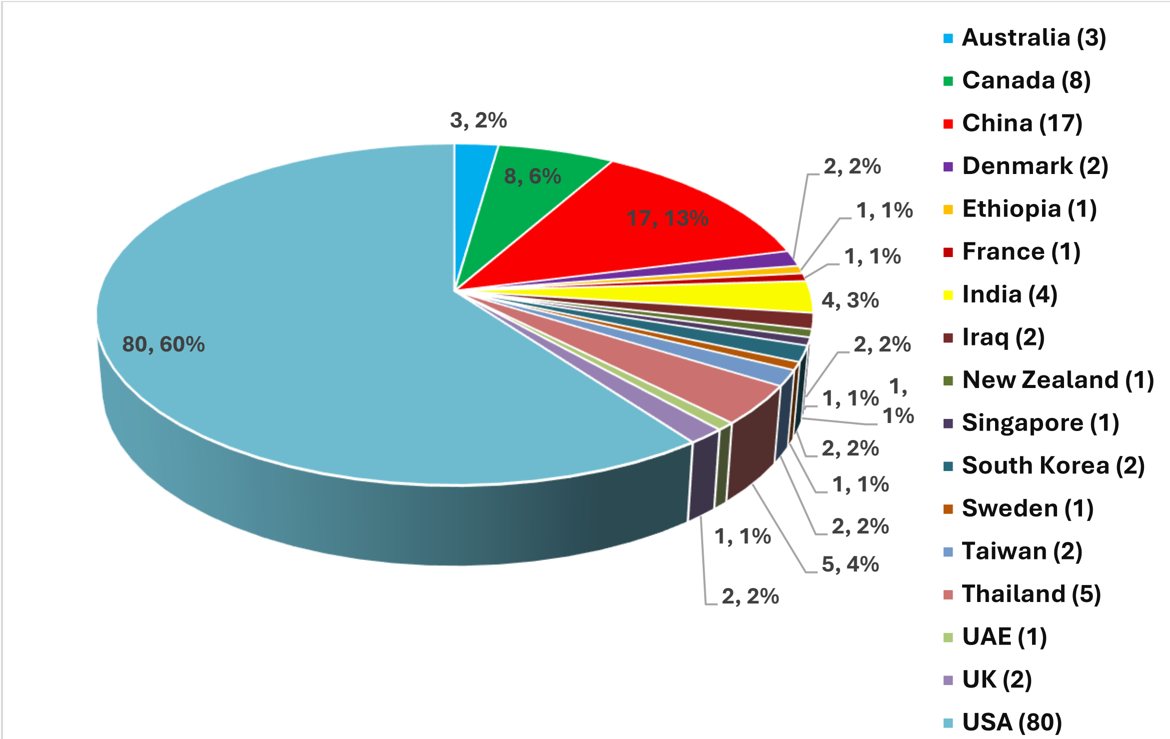

Figure 3: The DIS studies conducted country-wise

8.2. Driver Characteristics

Older drivers who are victims of some accidents have more severe injuries than the younger, reflecting less responsiveness in emergencies (C. Chen, Zhang, Qian, et al., 2016) and lower physiological resilience (Dzinyela et al., 2023; Marcoux et al., 2018; Se et al., 2023). Additionally, decrements in vision, cognition, and physical status with advancing age may further compromise complex driving performance and the ability to withstand forces associated with an RTA. On the other hand, some studies reported that middle-aged drivers present higher injury severity (M. Islam et al., 2024; Wu, Zhang, Zhu, et al., 2016; M. Yu et al., 2020), which may be due to behavioural and exposure factors. Although younger drivers (age <26) tend to be risk takers, middle-aged drivers may feel the need to drive aggressively due to work pressures or driving in locations that pose greater risks, such as on rural/curvy roads (M. Islam et al., 2024; Wu, Zhang, Zhu, et al., 2016). Younger drivers experience greater injury severity due to touchscreen use, due to lapses in attention, and risky driving (particularly when SVAs are concerned) (Adanu et al., 2021; Lee & Li, 2014), and poor seat belt compliance (Haq et al., 2021).

Several studies have examined the gender inequities in DIS outcomes with conflicting results. Some of the empirical evidence suggests that males are harder hit (Al-bdairi et al., 2020; Boufous et al., 2008; Dzinyela et al., 2023; Lai et al., 2012; Z. Li, Chen, Ci, et al., 2018; Paleti et al., 2010; Se et al., 2024; Yan et al., 2021), which are often linked to differences in crash risk, driving behaviour (such as speeding, aggression, and violations) (Dzinyela et al., 2023; Paleti et al., 2010), as well as biomechanical and vehicle-related factors influencing safety system performance (Se et al., 2024). Conversely, some studies found that female drivers were associated with higher injury severity than their male counterparts (Abdel-Aty, 2003; Donmez & Liu, 2015; Hou et al., 2019; Kockelman & Kweon, 2002; Ren & Xu, 2023), which may be due to more cautious or fearful behaviours at high speeds, causing hesitation or delayed responsiveness under emergency conditions (Hou et al., 2019; Ren & Xu, 2023). These inconsistencies arise from methodological and contextual differences. Data source variation (e.g., police vs. hospital-linked records) can bias results, as police data often underreport minor injuries. Model choices, such as controlling for accident type, exposure, and unobserved heterogeneity, also shape findings; for example, males show higher accident involvement, while females often experience greater severity in comparable accidents due in part to vehicle designs. Cultural, socioeconomic, and regional differences, along with temporal changes in safety technologies and behaviours, further contribute to variability. Addressing these issues through meta-analysis or stratified modelling is essential for informing gender-inclusive safety policies.

Table 6: Number of times the models applied

Sl. No	Model name	Abbreviations	No. of times used
1	Mixed logit model (Random parameter logit model)	MLM	22
2	Mixed logit model with heterogeneity in means/Mixed logit model with heterogeneity in means & variances	MLM-extension	20
3	Machine learning	ML	15
4	Binary logistic regression model	BLR	13
5	Multinomial logit model	MNL	11
6	Ordered probit model	OPM	11
7	Latent class model	LCM	5
8	Generalized ordered logit model	GOLM	5
9	Ordered logit model	OLM	4
10	Partial proportional odds model	PPOM	4
11	Random parameters-ordered probit model	RP-OPM	3
12	Joint econometric framework model	-	3
13	Hierarchical bayesian logit model	-	2
14	Hierarchical ordered logit model	-	2
15	Random parameters bivariate-ordered probit model	RPB-OPM	2
16	Hierarchical ordered profit model	HOPIT	2
17	Hierarchical generalized ordered probit model	HG-OPM	2
18	Generalized ordered probit model	GOPM	2
19	Latent class multinomial logit model	LC-MNL	1
20	Latent class random parameters probit model	LC-RPP	1
21	Age-period-cohort model	APC	1
22	Multivariate analysis	MVA	1
23	Log-linear model	-	1
24	Bayesian network model	BNM	1
25	Hierarchical bayesian random model	-	1
26	Heteroscedastic ordered logit model		1
27	Hierarchical multivariate logit model	HML	1
28	Nested logit model	NLM	1
29	Copula-based bivariate ordinal model	-	1
30	Latent segmentation-based generalized ordered logit model	LS-GOLM	1
31	Copula-based joint multinomial ordinal model	-	1
32	Hybrid finite mixture model	HBMM	1
33	Geographically-temporally weighted ordered logit model	GTWOLR	1
34	Random parameters multivariate generalized ordered probit	RP-GOPM	1
35	Latent class mixed logit model	LC-MLM	1
36	Hierarchical Bayesian random model	HBRM	1
37	Hierarchical multivariate logit model	HMLM	1

Note: ML: Machine Learning models including Random Forest, Support Vector Machine, Artificial Neural Network, and Decision Tree.

Similar patterns are observed for other driver factors, including conditions, ejection/entrapment, education experience, and use of a safety device. Drivers in some conditions, with reduced disturbance such as sleepiness, emotional stress, or fatigue, often experience high injury severity (Abegaz et al., 2014; M. Islam & Mannering, 2021; Peng & Boyle, 2012; Se et al., 2023), because low quality of sleep can decrease the reaction time and hazard perception (Abegaz et al., 2014; Peng & Boyle, 2012). Ejected or trapped drivers are also more likely to have higher DIS: ejected drivers may collide with other obstacles outside as well (Dissanayake & Lu, 2002; Osman et al., 2019) and trapped drivers receive severe vehicle distortion, limited escape opportunities and delayed rescue aid (Hosseinpour & Haleem, 2021; Zhao & Khattak, 2015). On one side, education and driving experience can reduce injury severity as educated drivers have less speeding (Rahimi et al., 2020) and experienced drivers were better prepared for emergencies (Wang et al., 2021; Weiss et al., 2014). No such attenuation phenomenon is observed with seatbelt and helmet use: belted drivers incur fewer and less severe injuries from a reduced incidence of ejection, as well as from force sharing (M. Islam & Mannering, 2020; Ren et al., 2024), and head trauma and death risks are decreased for helmeted riders because Helmets absorb a significant portion of the impact forces during an accident, especially to the head (X. Li et al., 2021).

8.3. Vehicle Characteristics

Research consistently indicates that vehicle age is a significant determinant of DIS, with older vehicles more associated with all types and higher severity levels. This can be mainly attributed to not being equipped with recent safety features and having structural degradation, as well as mechanical problems like brake or tyre failure that increase the risk and severity of accidents (Marcoux et al., 2018; H. Yu et al., 2020). Conversely, the more recent vehicles have a reduced DIS on account of an improved level of designed standards and the inclusion of technologies such as electronic stability control (Adanu et al., 2025; Ren et al., 2024).

The effect of the type of vehicle on DIS varies among studies. Some show excessive severity for two-wheelers (Fang et al., 2024; M. Islam et al., 2024; Schneider et al., 2009), others for LMVs (Wali et al., 2018; Zou et al., 2023), and a few for heavy motor vehicles (HMVs) (Haq et al., 2021; M. Islam, 2022; Se et al., 2023). With the least structural protection in two-wheelers, riders (usually classified as vulnerable road users) are exposed to very high levels of impact and thus have the highest DIS (M. Islam et al., 2024). LMVs exhibited a greater DIS than HMVs in some studies, mostly due to their reduced mass and structural strength which makes them less effective at absorbing accident energy, resulting in greater cabin deformation and injury risk (Wali et al., 2018). On the other hand, even though HMVs offer better protection during multi-vehicle accidents, the mass, momentum, and high centre of gravity contribute to increased rollover risk in single-vehicle accidents, particularly on curved or unprotected roads. When HMVs strike fixed objects or overturn, the resulting energy transfer can cause severe injuries, particularly without restraints (Haq et al., 2021; M. Islam, 2022). In contrast, other studies associate LMVs with lower DIS compared to other vehicle types (Dzinyela et al., 2024; Kabli et al., 2023; Savolainen & Ghosh, 2008; H. Yu et al., 2020). Due to smaller size, better safety design, and extensive application of modern accident mitigation technologies, injury severity is usually low in passenger cars, SUVs, and pickup trucks (Dzinyela et al., 2024; H. Yu et al., 2020). These mixed results among vehicle types were due to methodological, data, and contextual differences. Heterogeneity-aware models (for example, copula or random parameters) describe vehicle-specific interactions with accident type, and frequently uncover more severe accidents in LMV, while simpler models may conceal these effects and show lower risk in passenger cars. In-depth data on police or reconstruction focus on two-wheeler risk and HMV rollover, whereas large datasets temper effects by adding low-severity urban LMV accidents with advanced safety features. Further regional traffic mix and emerging vehicle technologies are also involved, and in future DIS analyses accident type, heterogeneity, and technological change should be factored in.

The influence of other vehicle characteristics (vehicle damage, number of vehicles involved, and airbag deployment) is relatively constant. Functional versus severely damaged post-accident vehicles indicated higher DIS; the higher the vehicle damage, the higher was the accident energy. When safety systems cannot take in all this energy, greater force is delivered to the drivers of the vehicles, resulting in additional injury or mortality risk (C. Chen, Zhang, Huang, et al., 2016; C. Chen, Zhang, Tarefder, et al., 2015). The degree of difference in DIS between SVAs and MVAs is dependent on accident dynamics, vehicle type, and driver characteristics (Boufous et al., 2008; Braver & Kyrychenko, 2004; S. Islam et al., 2023; Osman et al., 2019). For MVAs, the effectiveness of airbags can be evidenced by their 53% reduction in fatality rate (Braver & Kyrychenko, 2004). MVAs presented a marginally higher mortality rate (2.8%) compared with SVAs (2%); however, SVAs tended to present with more extensive injuries owing to greater impact forces and rollover behavior (Boufous et al., 2008; Wu et al., 2014). High speeds also increased DIS in MVAs along rural roads (C. Chen, Zhang, Huang, et al., 2016), but some studies reported a 37.49% decrease in DIS, probably as a result of the impact distribution among vehicles (Osman et al., 2019). Male drivers in SVAs were 5.6% exposed to more severe or fatal injuries, probably related to their riskier driving than females (S. Islam et al., 2023). Airbags could reduce acute injury by protecting vehicle occupants from the harsh surfaces of the hard dashboard or steering wheel, reducing the impact force transferred to the body (Dzinyela et al., 2024).

8.4. Environmental and Temporal Characteristics

Several studies have linked nighttime accidents to increased DIS because of decreased alertness, fatigue, and poor visibility, which impair reaction and hazard perception (M. Islam et al., 2024; Marcoux et al., 2018; Pour-Rouholamin & Zhou, 2016). Dim light, poor monitoring and enforcement of the law, and isolated roads result in poorer outcomes, while driving risks such as speeding or impaired driving appear to be more prevalent at night (Marcoux et al., 2018). However, lower DIS was observed during nighttime accidents, likely resulting from more cautious driving to prevent unexpected incidents (C. Chen, Zhang, Yang, et al., 2016). Research on morning-hour accidents has mixed results on DIS. Some claim greater DIS due to more hazardous behaviours such as speeding, fatigue, and drowsiness, along with reduced visibility in the early hours, particularly on poor roads (Ren & Xu, 2023; Wen & Xue, 2020). In contrast, Lee & Li (2014) and Khorashadi et al. (2005) noted lower DIS related to better daylight visibility and increased traffic, as these factors decreased speed and impact forces during a crash. Combined, these factors account for the variability of early morning accidents.

The weather has a mixed impact on DIS. Some investigations associate rainy, snowy, cloudy, and even clear weather with higher DIS because of decreased visibility, lower tire-road friction, and poor vehicle control, resulting in an increased accident impact and injury severity (M. Islam & Mannering, 2021; Kim et al., 2013; Mooradian et al., 2013). Clear weather can also intensify the DIS by making the drivers overly confident to speed and aggressive driving (Dabbour, 2017; Wu et al., 2014; Yasmin, Eluru, Pinjari, et al., 2014). In contrast, in other studies, it has been shown that DIS is lower under equal conditions (J. Anderson & Hernandez, 2017; Eluru et al., 2012; Zhang et al., 2020). In adverse weather, drivers will also compensate by slowing down, increasing following distances, and driving more cautiously, thereby reducing the energy generated and the severity of an accident. Similarly, during clear weather, consistency with safe driving practices can minimize DIS. These inconsistencies arise from methodological, data-related, and contextual factors. Studies using advanced heterogeneity models e.g., random parameters (Islam and Mannering, 2021) capture subgroup-specific weather effects, often revealing higher severity under adverse conditions, whereas simpler models (Eluru et al., 2012) assume homogeneous impacts and may report overall reductions. Data limitations also matter: police-reported datasets may overrepresent severe accidents in clear weather due to higher speeds, while adverse-weather accidents may involve cautious driving or underreported minor incidents. Contextual differences further contribute, including climatic adaptation (e.g., frequent snow in Canada) and culturally driven risk-taking in clear conditions (Dabbour, 2017). Overall, the mixed findings reflect interactions between environmental risk and behavioural compensation, moderated by unobserved heterogeneity.

Regarding weekends and weekdays, weekends have been related to high DIS in some studies (Kim et al., 2013; Wei et al., 2024; Zhang et al., 2020). One of the major contributors is that weekend drivers would experience less traffic congestion than weekday drivers, which results in higher driving speed, increased severity of collisions and increased DIS. Moreover, the increase in recreational travel caused a rise in traffic volume and behavioural variance, which is reflected by a more complex and unpredictable driving process that further exacerbated the DIS (Wei et al., 2024; Zhang et al., 2020).

However, some studies (F. Chen et al., 2019; M. Islam, 2022) have reported contrasting results. Work zone road accidents on Tuesdays significantly increased DIS, probably due to higher traffic loads and operational pressure early in the week (M. Islam, 2022). There were also significant increases in DIS observed between 12:00 pm and 4:00 pm in non-work zones, at which these peak hours of activity would be coupled with driver tiredness. On the weekdays, the additional features of difficult work-zone like lane shifts, increase DIS further.

8.5. Roadway Characteristics

Pavement condition is consistently shown to affect DIS, with wet surfaces associated with lower severity. This decrease is due to behavioural and environmental influences: drivers slow down and exercise additional precaution on wet roads, showing risk-compensating behaviour that reduces the impact of an accident (Z. Li, Ci, et al., 2019; Marcoux et al., 2018). Airbags were also not activated in many wet-surface accidents, indicating lower collision intensity (Dzinyela et al., 2024). In work zones, wet conditions additionally encouraged speed compliance and attentiveness (Osman et al., 2019). Conversely, increased speeds and overconfidence in driving are linked, and often contribute to higher DIS in dry pavement conditions (Hosseinpour & Haleem, 2021; Wu, Zhang, Chen, et al., 2016; Zhang et al., 2020). Dry surfaces contribute to increased rollover risks, and large trucks are more at risk (Qiong Wu, Zhang, Chen, et al., 2016; Hosseinpour & Haleem, 2021) due to lack of environmental caution cues, resulting in greater accident severity outcomes (Zhang et al., 2020). DIS for snowy and icy conditions presents inconsistent results. Many find lower DIS because drivers generally adjust by slowing down, increasing following distance, and avoiding sudden manoeuvres (behaviours indicative of greater caution on slippery roads) (F. Chen et al., 2019; M. Yu et al., 2020). These conditions are powerful environmental signals encouraging safer driving. However, some studies demonstrated greater DIS in conditions like this, especially among older male and female drivers of all ages (Morgan & Mannering, 2011). This can be due to delayed response times, physical vulnerability, and limited ability to adapt to compromised traction. This intersection of environmental threats, human factors, and vehicle behaviour contributes to increased risk for less adaptive or vulnerable drivers.

Mixed effects are achieved in studies of unpaved and gravel roads on DIS. The higher risk for rollover and ROR in rural, curved and undivided roads subject to increased speed limits has resulted in a noticeable rise in the DIS on such roads (Thompson et al., 2013). The higher severity for those accidents, especially those involving heavy vehicles, where limited energy absorption is applied, contributes to a significantly higher effect on the severity of impact (Hao et al., 2016; Dabbour, 2017) due to reduced visibility, low traction, and unstable terrain. In contrast, other analyses found that lower DIS on unpaved and gravel roads, in which drivers slow down and tread cautiously due to a perception of the roadway as unstable, was associated with a lower risk of accidents (Fang et al., 2024; Wu, Zhang, Chen, et al., 2016; Yasmin, Eluru, Bhat, et al., 2014). Horizontal and vertical curves were shown as consistently associated with higher DIS in the multiple studies. Their geometric complexity reduces visibility and vehicle stability, increasing accident risk. Rahimi et al. (2020) stated that vertical and horizontal curves together induced high DIS in SVAs due to limited sight distance, higher rollover potential, and loss of control at high speeds. Similarly, Donmez & Liu (2015) and Wen & Xue (2020) showed that horizontal curves would lead to increasing DIS caused by sudden changes in direction, while vertical curves, particularly crests, will influence forward visibility negatively, so the rear-end and angle collisions will increase as well. Chamroeun Se et al. (2024) also report that older drivers were the most sensitive on horizontal curves on excessive fast driving speed due to slow reaction time and reduced adaptability. However, some studies have also shown mitigating effects, such as reduced severity on certain curved routes where drivers adapt by lowering speeds or in specific contexts like wet weather prompting caution (Haq et al., 2021). There are also inconsistencies in the grades based on interaction with driver demographics (e.g., older males more vulnerable) or environmental factors (Morgan and Mannering, 2011). These geometric inconsistencies underscore the need for context-specific design standards to address unexpected alignments and transitions.

Multiple-lane roads were systematically associated with greater DIS in several of the studies. Zhenning Li, Wu, et al. (2019) found that multilane layouts result in intricate environments with frequent lane changes, varying speed limits, and more turning movements, factors that increase conflict points and DIS, especially during adverse weather. Dual carriageways and multilane roads are also more prone to overtaking manoeuvres, which become more dangerous with additional lanes (Gray et al., 2008). Duddu et al. (2018) have shown it to result in excessive speed and driver overconfidence, causing injury risk. Similarly, H. Yu et al. (2020) reported that multi-lane systems are associated with higher DIS in ROR accidents, especially for male, middle-aged drivers. Higher DIS is consistently associated with rural road characteristics (due to environmental and behavioural factors). It may appear that these roads feature higher speed limits, there is less congestion, and limited safety infrastructure (lighting, lane divisions, or roadside barriers) contribute to an impact of an accident and to a higher chance of serious outcome (Mafi et al., 2018; Yuan et al., 2021). In addition to higher speed of travel, delayed emergency response and reduced driver vigilance in low-traffic areas lead to increased DIS (Wu, Zhang, Zhu, et al., 2016). Nevertheless, urban studies documented increased DIS in communities as a response to the dense condition of the road space, complex geometry, the multitude of interactions and certain risky behaviours (including sudden lane changes and aggressive driving) (Duddu et al., 2018; Mooradian et al., 2013; Rahimi et al., 2020; M. Yu et al., 2020).

In terms of roadway lighting conditions, unlit roads were correlated with increased DIS due to several contributing factors. Bad road lighting weakens visibility, delays reaction time, and hinders drivers' ability to identify hazards, exacerbating DIS (J. C. Anderson & Dong, 2017; Fang et al., 2024; Se et al., 2024; Wen & Xue, 2020). Chamroeun Se et al. (2024) showed that poor lighting had a stronger effect on speeding driving, and in more serious accidents, among young drivers, particularly during morning rush hours. Pour-Rouholamin & Zhou (2016) reported that the injury severity of wrong-way accidents on unlit roads increased by up to 35% because people who have less visibility, fatigue, and impaired driving at night were more likely to injure themselves. Wen & Xue (2020) reported that unfamiliar drivers had a higher risk on dark mountainous driving paths in view of the low safety knowledge and difficulty navigating sharp corners and tunnels.

8.6. Accident-Specific Characteristics

In all accident types (head-on, side, run-off, overturn, rollover, or fixed object), except rear-end collision, higher DIS is consistently associated with each type of accident. The head-on accidents have a big impact because opposing directions of driving vehicles increase the generation of kinetic energy (Marcoux et al., 2018; Pervaz et al., 2024; Zeng et al., 2016). Side impacts cause bigger injuries due to poor lateral protection (Abdelwahab & Abdel-Aty, 2001; Dzinyela et al., 2023; Kabli et al., 2023). ROR and fixed-object accidents also generate high DIS on account of cars hitting rigid objects or going off balance on curvilinear corners, resulting in speeding, fatigue, or alcohol use (Se et al., 2023; Schneider et al., 2009). Overturn and rollover accidents increase DIS by having occupant ejection, roof crushing, and extreme deformation, especially when high-speed single-vehicle rollovers are taking place (F. Chen & Chen, 2011; Haq et al., 2021; S. Islam & Mannering, 2006). Fixed-object collision aggravates the effect of DIS due to concentrating force transfer to occupants from collisions with non-moving objects such as poles or trees, further exacerbated by low friction and immovable barriers, which do not absorb energy (Ren and Xu, 2023; Hosseinpour and Haleem, 2021). These impacts are particularly heavy on rural roads and are characterized by low roadside protection and delayed emergency response (Xie et al., 2012; Yan et al., 2021).

DIS patterns in rear-end collisions are mixed. Other reports show increased DIS associated with compartment intrusion, increased accident energy (delta-V), and occupant impact with interior components (Ma et al., 2016; Viano & Parenteau, 2012). It becomes more severe on straight or divided roads and near ramps, especially with older vehicles, alcohol or drug use, and without seatbelt use (F. Chen et al., 2019; Zubaidi et al., 2021). In contrast, lower DIS has been found in rear-end collisions at low speeds, which cause decreased kinetic energy transfer relative to head-on and side impact (Mooradian et al., 2013; Zhu & Srinivasan, 2011). Traffic in congested or stop-and-go conditions with little speed variation enables crumple zones to absorb energy well and accordingly reduces DIS (Harland et al., 2018). The heterogeneity in studies probably explains these mixed results. Modelling-wise, models which can accommodate unobserved heterogeneity, hybrid finite mixture (Ma et al., 2016) and random parameters bivariate ordered probit models (Chen et al., 2019), usually find higher severity in high-energy rear-end accidents, which may be masked by simpler ordered models (e.g., partial proportional odds in Mooradian et al., 2013), which assume proportional impacts across severity levels. And data source differences matter too: accident reconstruction datasets (e.g., delta-V in Viano and Parenteau, 2012) focus on intrusion risks at higher speeds, while police-reported data (e.g., Zhu and Srinivasan, 2011) risk under-representing low-speed congested accidents, resulting in downward bias in severity. Contextual factors further contribute, including roadway environment (freeway ramps vs. stop-and-go traffic) and behavioural factors (e.g., alcohol impairment increasing risk (Harland et al., 2018)).

All major causes for accidents are related to higher DIS continuously. Over-speeding elevates the energy of the accident thereby increasing DIS, which in turn reduces the time for evasive action and enhances impact forces, especially during head-on collisions (Wali et al., 2018; Wei et al., 2024). Furthermore, speeding in conjunction with bad lighting or alcohol consumption has the potential to have further impact (Alogaili & Mannering, 2020; S. Islam et al., 2023). High-speed driving behaviors, such as tailgating, reckless overtaking, and sudden lane changes, also increase DIS by restricting control and reaction time (Haq et al., 2021; M. Islam et al., 2024). Distracted driving behaviours such as texting or calling lead to heightened DIS through poor attention, delayed braking, and reduced hazard perception, which are more prominent among older individuals (Donmez and Liu, 2015; Behnood et al., 2014). Drunk driving remains recognized as one of the strongest predictors of severe accidents due to its negative implications on vehicle control with impaired judgment, coordination, and reaction time caused by alcohol, thus impaired vehicle control and risk-taking behaviours, which are more prevalent in younger drivers (Pervaz et al., 2024; Xie et al., 2012). The overconfidence and excessive speeding associated with driving under the influence present an especially challenging risk of significant nighttime or weekend accidents in young male drivers (Amarasingha and Dissanayake, 2014; Osman et al., 2019).

9. Summary and Conclusion

9.1. Summary

The review comprehensively investigates the influential factors of DIS in RTAs by identifying them in five key domains: driver, vehicle, environmental and temporal, roadway, and accident-specific factors. The search was conducted in accordance with PRISMA literature review standards, and 133 studies published between 2000 and 2025 were included in this review. These papers were chosen by rigid inclusion criteria for specific accident types, e.g., single-vehicle, two-vehicle, multi-vehicle, ROR, rollover, and speeding-related accidents. The model which was most adopted is mixed logit model, which captures unobserved heterogeneity and cross-alternative correlations well. The main components that contributed to increased DIS, overall, were the drivers (older drivers, females, and the use of seat belts), vehicle (type and age), environmental and temporal (nighttime and adverse weather condition), roadway (rural roadway), and accident-specific characteristics (head-on rollover and drunken driving), which were all discussed in this paper. This review also highlights a lack of comprehensive studies in low and middle-income regions such as India, where traffic patterns and infrastructure differ from high-income countries. It argues that region-specific research is needed to improve knowledge about DIS and emphasizes the necessity of specific safety measures that can respond directly to localized risk factors.

9.2. Conclusions

Older drivers, female drivers, unbelted drivers and inexperienced drivers had a greater risk of severe injuries in road traffic accidents. Age-related decreases in reaction time and physical resilience are contributing factors in explaining the greater severity of injuries among older drivers. Older vehicles and two-wheelers were consistently associated with elevated injury severities due to outdated safety features and a lack of structural protection. SUVs and heavy-duty trucks generally give better occupant protection but are riskier for other road users. Nighttime traffic, bad weather and rural roads all increased the DIS significantly. Higher DIS rates were influenced by poor visibility and hazardous road conditions. Curved, graded, and rural roads were associated with greater injury risks. Drivers' injuries are also affected by the type of pavement and the number of lanes. Most severe accident types were head-on collisions and rollover, attributed in part to energy transfer during impact.

This review underlines key road safety issues and relevance to lower-middle-income countries like India. Heightened risk of injury among older and younger drivers, particularly in unfavourable weather, low light, and curved or rural roads, also provides a rationale for focus on interventions such as age-appropriate driver training, stricter enforcement of seatbelt or helmet use, and physical infrastructure interventions (i.e., improved lighting, curve warnings, and rural pavement maintenance). Given rapid motorization, mixed traffic flow, and variable enforcement, rollover-resistant motorcycle design and tougher speed control on rural highways might reduce severe outcomes if implemented in India. The analysis of identified factor interactions can also inform AI-based driver assistance systems (ADAS) and intelligent transportation systems (ITS), wherein real-time convergence of driver, weather, roadway, and temporal data could facilitate adaptive alerting, speed management, or improved emergency braking in high-risk situations.

Although work on DIS has progressed over the past few decades, many gaps persist. Firstly, most previous research has used conventional statistical models to evaluate the SVA severity. More advanced frameworks, including MLM-Extension, ML, and Deep Learning models, which are gaining significant research interest in the community, are required to investigate further. Second, most DIS research has been conducted in the United States, with relatively small studies in upper-middle-income countries such as China. Of the 133 studies included in this review, approximately 62% are from the United States, 15% from Europe, 18% from upper-middle-income countries (primarily China), and only 5% from low- or lower-middle-income countries. There is a notable lack of comprehensive studies in lower-middle-income countries such as India, where different traffic behaviours, road infrastructure, and enforcement levels exist. More studies tailored to the region are needed to understand the factors affecting DIS in each of these regions. This paper suffers one limitation in that it fails to capture all relevant studies, even though the review has applied extensive search strategies, which used a broad search strategy with multiple logical keywords across multiple scientific databases.

Author Contributions

N.L.: Conceptualization, Data curation, Formal analysis, Investigation, Writing - original draft. **D.P.**: Visualization, Supervision, Writing - review and editing. **N.G.S.**: Formal analysis, Methodology, Writing - original draft. All authors critically reviewed and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Disclosure of Interest

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Data Availability Statement

No data was involved in the study.

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