applied sciences

MDPI

Systematic Review

Risky User Behavior at Highway–Rail Grade Crossings: A Systematic Literature Review with Empirical Insights

Imran Badshah [1], Asad Ali [2] and Pan Lu [1,*]

[1] Department of Transportation, Logistics and Finance, North Dakota State University, Fargo, ND 58102, USA; imran.badshah@ndsu.edu
[2] Department of Civil, Construction and Environmental Engineering, North Dakota State University, Fargo, ND 58102, USA; asad.ali@ndsu.edu
* Correspondence: pan.lu@ndsu.edu

Abstract

Highway–rail grade crossings (HRGCs) remain a critical safety problem despite decades of infrastructure investment. Moreover, the relationship between specific driver behaviors and crash severity across different geographic contexts remains poorly quantified. This study aimed to conduct a systematic review to (1) synthesize existing evidence on behavior-specific crash outcomes at HRGCs and (2) empirically validate findings from crash datasets. The study was conducted following PRISMA 2020 guidelines, identifying peer-reviewed studies (2015–2025) through structured searches of electronic databases. Inclusion criteria required studies to report quantitative associations between driver behavior and crash severity at HRGCs. In addition, crash records from two U.S. states (New Jersey and Texas; 2013 to 2022) were analyzed using multinomial logistic regression to assess empirical validity. Multinomial logistic regression analysis reveals that highway user action (HAU = 1) "going around gates" significantly increase the fatal risk. Empirical analysis confirmed these trends but revealed geographic variation: New Jersey showed a fatality odds ratio of 4.490 versus Texas's 3.686 for a fatal risk, i.e., severity level 1. In addition, gender emerged as a significant factor in fatal crash risk, with female drivers facing elevated odds of fatal injury compared to male drivers: 1.464 in New Jersey and 1.817 in Texas. Despite these findings, three critical gaps remain in HRGCs: (1) predictive models focus on crash frequency rather than behavior forecasting, (2) data quality issues compromise of risk predictions, and (3) machine learning approaches lack interpretability for practitioners. This review demonstrates that identical driver behaviors produce different crash outcomes across geographic regions. Effective safety interventions need to address local risk factors instead of relying on a uniform national approach.

Keywords: highway-rail grade crossing; risky behavior; crash severity; empirical analysis

check for updates

Academic Editor: Raffaele Zinno

Received: 5 October 2025
Revised: 24 October 2025
Accepted: 29 October 2025
Published: 12 November 2025

Citation: Badshah, I.; Ali, A.; Lu, P. Risky User Behavior at Highway–Rail Grade Crossings: A Systematic Literature Review with Empirical Insights. *Appl. Sci.* **2025**, *15*, 12021. https://doi.org/10.3390/app152212021

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Highway–rail grade crossings (HRGCs) are critical points where roads and railway tracks meet at the same level [1]. These crossings pose serious safety concerns due to the potential for collisions between vehicles and trains, which often result in severe injuries or fatalities [2]. The combination of different types of transportation at a single point creates a high-risk environment, especially when driver behavior is not aligned with safety guidelines. Crashes at these intersections are often fatal and result in significant damages which raise important public safety concerns and demand immediate attention [3].

Understanding these incidents requires a detailed look at several factors including human actions, road conditions, and how surroundings affect decision-making at crossings.

Studies reveal that one of the key reasons behind crashes at highway–rail crossings is risky behavior by drivers [4]. These behaviors include actions like driving around lowered gates, ignoring warning signs, or stopping on the tracks [4]. These actions are especially common at crossings where road design may not fully account for the realities of local traffic or pedestrian flow. Unexpected changes in track alignment or road layout can increase the likelihood of vehicle hang-ups [5]. Environmental conditions such as bad weather, limited visibility, and off-peak hours, especially during night or early morning, can greatly increase the risk of serious crashes at HRGCs [6]. Stopping distance is a major factor, especially for fast-moving vehicles approaching an active crossing [7]. In areas with limited visibility or higher train frequencies, predicting and preventing crashes becomes more difficult [8]. The challenges of forecasting crash risks at these crossings increase due to changes in traffic and train schedules. The type of crossing, whether it has active signals or passive signs, makes a difference in how drivers respond [9].

Despite extensive research on rail safety [10], few studies have explored all the important factors together. There is a lack of research that connects crash severity, land use patterns around the crossings, and ways to predict dangerous situations in advance. This review aims to bring together studies that focus on each of these areas to better understand the causes and patterns of crashes at HRGCs. It also looks at how recent research uses large transportation datasets to identify risky driving behavior and its outcomes [11]. Such knowledge can help improve warning systems, guide drivers, and support better decisions in road planning and traffic management [12].

This literature study addresses three research questions based on critical gaps in existing knowledge.

RQ1. How do specific driver behaviors affect crash severity across different geographic contexts at highway–rail grade crossings?

RQ 2. Can current predictive models assess the risk levels of different user behaviors across various crossing locations?

This study advances the existing literature by combining systematic review methodology with cross-state empirical validation, directly quantifying geographic variation in behavior severity relationships that previous single-state studies and national aggregate analyses have not examined. This knowledge supports efforts to make crossings safer through improved planning, design, and driver guidance. The study shows how combining behavior analysis, location-based research, and prediction methods can reduce crashes at these sites.

2. Methodology

This systematic literature review adopts the PRISMA 2020 guidelines, (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), an internationally recognized framework for transparent reporting of systematic reviews. To examine risky user behavior at HRGCs, with a particular focus on crash severity, spatial and environmental influences, and predictive modeling. A comprehensive search was conducted using a major academic database, Web of Science, which was selected for its extensive coverage of peer-reviewed research in transportation safety. The review focused on studies published between 2015 and early 2025 to capture both foundational and recent developments in the field.

The search strategy involved a combination of keywords related to HRGCs and safety topics, including terms such as “highway rail grade crossing,” “railroad crossing,” “risky behavior,” “crash severity,” “driver behavior,” and “spatial analysis.” Boolean operators

were used to refine and expand the search scope, ensuring coverage of a broad yet relevant range of studies. The following search query was used:

"highway rail grade crossing OR railroad crossing OR rail crossing OR grade crossing AND behavior OR crash OR safety OR risk OR prediction OR severity".

For literature synthesis, we extracted effect measures where studies reported them. It included odds ratios, and *p*-value. Many studies presented only directional findings, indicating whether a factor increased or decreased crash risk. We recorded these as qualitative results. For our empirical analysis, we calculated odds ratios using multinomial logistic regression. These odds ratios compared fatal and non-fatal injury outcomes against property damage only crashes. The odds ratios showed how much each factor changed the likelihood of different severity levels.

The initial search returned 338 results; a breakdown by year is shown in Figure 1. After removing duplicate and non-review articles, 186 unique articles remained. This set was then filtered by publication year (2015–2025), resulting in 185 review articles. Further refinement based on studies conducted in the United States reduced the number to 150. During screening by title, keywords, and abstract assessment, 49 articles were excluded for not being relevant to HRGCs or lacking sufficient focus on behavior- or crash-related aspects. This left 101 full-text articles to be assessed for eligibility. An additional 61 articles were excluded during full-text review for reasons such as insufficient focus on HRGC safety (n = 22), absence of behavioral analysis (n = 15), lack of crash severity data (n = 12), studies conducted outside the U.S. context (n = 7), and inaccessible full texts (n = 5). This resulted in a final set of 40 articles that met all inclusion criteria, as shown in the PRISMA Flow Diagram in Figure 2. The final set of studies was evaluated using six quality assessment criteria, as outlined in Table 1.

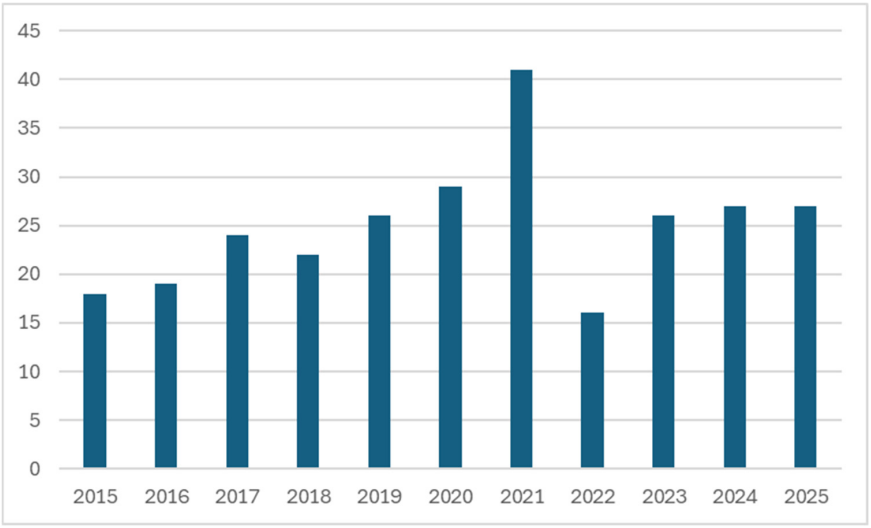


Figure 1. Number of publications per year (2015–2025).

Table 1. Quality Assessment Criteria.

Quality Assessment Criteria	Evaluation Focus
Focus on Highway–Rail Grade Crossings	Does the study specifically address safety at highway–rail grade crossings or level crossings?
Human Behavior Analysis	Is the study related to driver, pedestrian, or cyclist behavior at crossings?
Crash Severity Investigation	Does the study explicitly examine crash severity outcomes or factors influencing severity?
Spatial and Environmental Factors	Does the study investigate location-based influences, land use patterns, or environmental conditions?
Predictive Modeling Approaches	Does the study address risk prediction, forecasting models, or safety assessment methodologies?
Empirical Data and Analysis	Does the study utilize quantitative data analysis, statistical methods, or comprehensive datasets?

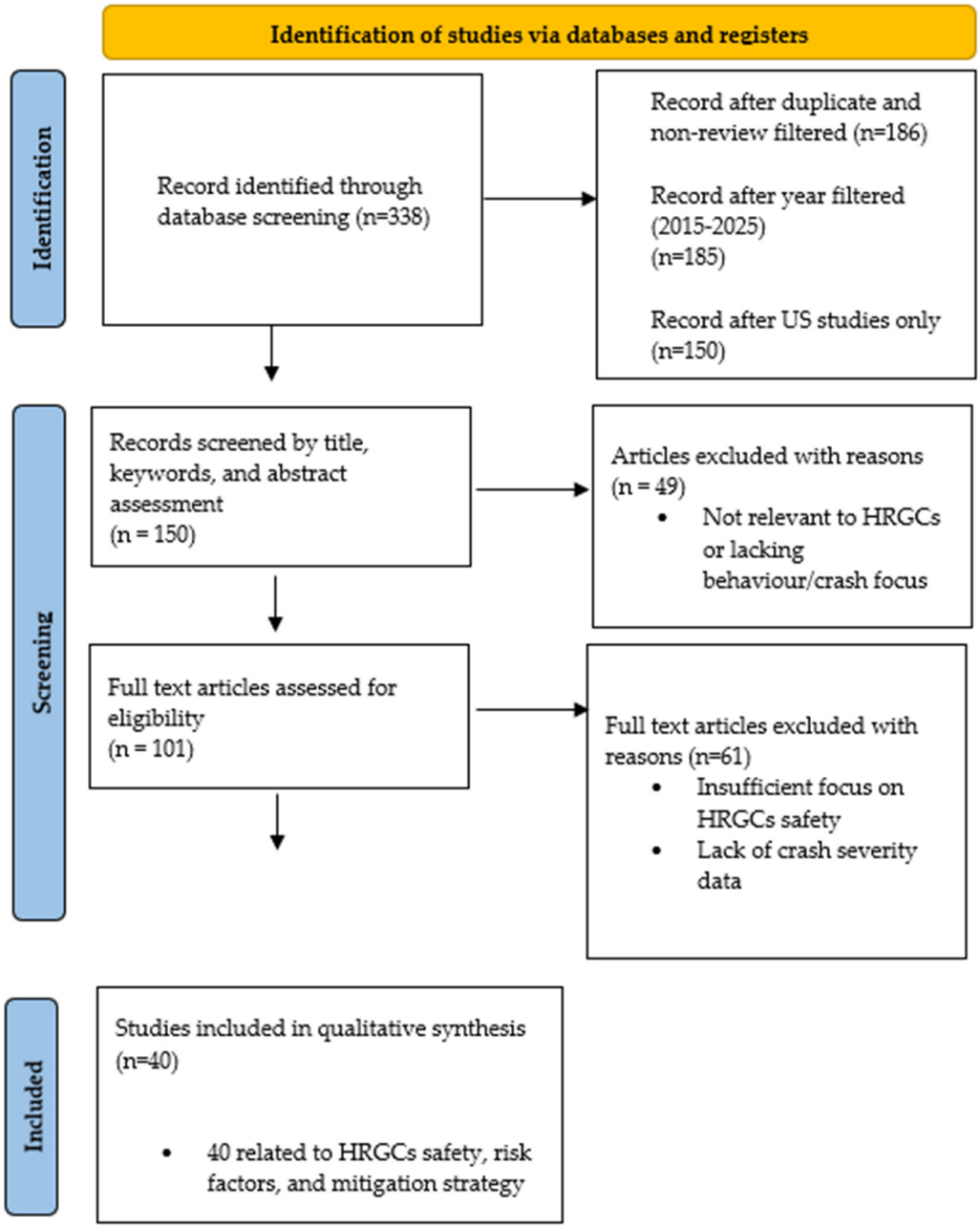


Figure 2. PRISMA Flow Diagram: Systematic Review HRGCs Literature (2015–2025).

The selected studies were grouped into four main categories to organize the review and highlight the key research areas, as shown in Table 2.

Table 2. Thematic Classification of Studies on Highway–Rail Grade Crossing Safety (HRGCs).

Classification	Description
Risky User Behavior Patterns at Highway–Rail Crossings	Studies focusing on driver, pedestrian, and cyclist behaviors that increase crash risk including signal violations, misjudgment of train approach and unsafe decision making
Crash Severity Analysis and Contributing Factors	Research examining factors that influence the severity of crashes at crossings including impact conditions vehicle characteristics and user demographics
Spatial and Environmental Influences on Crossing Safety	Studies addressing how location, land use, infrastructure design, weather conditions, and visibility affect safety risks and user behavior at crossings?
Predictive Modeling and Risk Assessment Approaches	Research focusing on methods for forecasting crash risks identifying high risk crossings and developing tools to predict dangerous situations

Information was extracted from each study using a standardized format. Key details included publication year, study location, methods used, sample size, user type, crash outcomes, environmental context, and modeling approaches. This helped in identifying common findings and research gaps. The review showed how risky behaviors such as ignoring signals or misjudging train speed contribute to crash outcomes. It also highlighted how environmental conditions and crossing design affect safety. Finally, the review examined how current models predict crash risks and where further improvements are needed. A detailed summary of the article selection process, including inclusion and exclusion criteria, is presented in Figure 2 (PRISMA Flow Diagram).

Data extraction followed a structured process. Two reviewers extracted information from each study independently. They used a standardized form that included fields for study location, sample size, user type, crash outcomes, behavior categories, environmental conditions, and statistical methods. The reviewers meet weekly to compare extracted data. Disagreements about data interpretation occurred in eight studies. These were resolved by reviewing the original articles together and reaching consensus.

When information was unclear, we attempted to contact study authors. We sent emails to authors of six studies requesting clarification about crash severity classifications and sample sizes. Three authors responded and provided the needed information. For the remaining three studies, we used the information available in the published reports. No automation tools were used for data extraction. All extraction was done manually to ensure accuracy and proper interpretation of study-specific contexts.

To validate the findings from the literature, an empirical analysis was carried out using crash data from two U.S. states: New Jersey, and Texas. These states were selected to reflect different levels of crash frequency and risk. Texas had higher numbers of crashes, while New Jersey represented lower crash record. This allowed for comparison across different regions and conditions. These two states included in the analysis were selected based on different geography and crash record. This selection supports an examination of specific behavioral patterns and crash trends.

Crash data from 2013 to 2022 were collected from the Federal Railroad Administration (FRA) *(Highway-Rail Grade Crossing Accident Data (Form 57), 2024)*. This database provided detailed information about crash severity, user actions, vehicle types, and environmental conditions. Additional data were obtained from the National Highway Traffic Safety Administration (NHTSA) to calculate vehicle miles travel (VMT), which were used to determine accident rates.

The empirical analysis was conducted in two stages. In the first stage, descriptive analysis was used to examine the distribution of highway user actions and crash outcomes. Comparisons across states helped identify patterns in risky behavior and crash severity. In the second stage, a statistical model was applied to assess the relationship between user behavior and crash severity. A multinomial logistic regression model was used, with crash severity as the outcome variable. The model included predictor variables such as highway user actions, user age, gender, temperature, train speed, and year of the crash. Multinomial logistic regression framework directly addresses gaps identified in the literature review, particularly the absence of quantified behavior-severity relationships across different geographic contexts. The results were reported using odds ratios to estimate the influence of each factor on the likelihood of injury or fatality relative to property damage only. The model demonstrated statistical significance and reliability. This combined methodology clearly explains the influence of human behavior and environmental conditions on HRGC safety.

Two reviewers independently assessed the quality of each included study using a structured approach across four types of bias: selection bias (use of representative crash

data), measurement bias (use of validated measures for crash severity and behavior), confounding (control for factors like traffic volume, weather, and crossing features), and reporting bias (whether all outcomes listed in the methods were reported). Each study was rated as low risk, some concerns, or high risk for each domain. Low risk studies met all four criteria with full confounding control. Disagreements in 12 cases were resolved through discussion, with a third reviewer consulted for three unresolved cases. Studies rated as high risk in two or more domains (five in total) were marked for sensitivity analysis. Most studies raised some concerns about confounding, particularly for factors like driver familiarity or time of day. Despite this, excluding high-risk studies did not change the main findings about risky behaviors at crossings.

Multinomial Model

We used multinomial logistic regression to analyze the relationship between crash severity and predictor variables. This method allows simultaneous comparison of multiple severity outcomes and has been widely applied in highway–rail crossing safety research.

Considering $X = (X_1, X_2, \ldots, X_k)$ as the set of contributors and J = 0, 1, and 2 representing crash severity levels of "no injury," "non-fatal injury," and "fatal injury," respectively, the proposed MLR model is given by Equation (1):

$$P\,(Y = j|X) = \begin{cases} \frac{1}{1+\sum_{m=1}^{2} exp\left(\beta_{m0}+\sum_{i=1}^{k}\beta_{mi}X_i\right)}\,, & if\ \ j = 0 \\ \frac{exp\left(\beta_{j0}+\sum_{i=1}^{k}\beta_{ji}X_i\right)}{1+\sum_{m=1}^{2} exp\left(\beta_{m0}+\sum_{i=1}^{k}\beta_{mi}X_i\right)}\,, & if\ \ j = 1,\ 2 \end{cases} \quad (1)$$

- Y: is the outcome variable representing crash severity,
- X: is the vector of predictors (e.g., user actions, train speed, age, temperature),
- β_{j0}: is the intercept for outcome j,
- β_{ji}: is the coefficient for predictor X_i when the outcome is j,
- $P(Y = j|X)$: is the predicted probability of crash severity level j given values of X.

Note that Equation (1) assumes $j = 0$ as the reference category.

Odds Ratios: For any severity level j compared to the base level (no injury), the log-odds of outcome j is given by

$$\log\left(\frac{P(Y_i = j)}{P(Y_i = 0)}\right) = \beta_{j0} + \sum_{i=1}^{K}\beta_{j0}\ X_i$$

If one unit is added to a specific predictor X_p, the change in log-odds for outcome j is:

$$\Delta\log\left(\frac{P(Y_i = j)}{P(Y_i = 0)}\right) = \ \beta_{jp}\,, \qquad p\ \in \{1, \ldots,\ K\}$$

The odds ratio for this change is:

$$OR_{jp} = \exp(\beta_{jp})$$

This value shows how the odds of outcome j change relative to the reference category when predictor X_p increases by one unit. An odds ratio greater than 1 indicates increased risk, while a value less than 1 indicates decreased risk.

Data preparation required several steps before analysis. Studies used different severity classification systems. Some used three levels while others used five or more categories. We standardized these into three levels: no injury, non-fatal injury, and fatal injury. Crashes originally classified as minor injury and major injury were combined into the non-fatal

injury category. This approach-maintained consistency across all studies and allowed for direct comparison.

Missing data requires attention in empirical analysis. Temperature data were missing for 8% of crash records. We implemented these values using monthly average temperatures for each state. Train speed was missing in 3% of records. These records were excluded from the speed-related analysis but retained for other variables. User action data were missing out of 47 records out of the total sample. These records were excluded entirely because user action was a primary variable of interest. Age and gender data were complete in both state datasets. No imputation was needed for these variables.

3. Findings

HRGCs are points where roadways intersect railway tracks at the same grade level, creating high-risk environments for potential collisions between trains and road users [13]. These locations pose significant safety concerns due to the severe consequences as both trains and vehicles pass the same conflict point, often leading to fatalities and major property damage [14]. HRGCs are complex because they involve various transportation modes, each with distinct operational characteristics, creating challenges for safe management, particularly when high speed trains are involved [15]. Study indicates that despite substantial safety investments over the past decades, these crossings continue to be major contributors to rail-related casualties in transportation networks [16,17].

Safety measures at HRGCs have evolved over time from basic passive warning systems [18], such as crossbucks and signage, to more sophisticated active warning devices such as flashing lights, bells, and automatic gates [19]. However, these improvements have shown limited gains to control crashes, as the t rate remains high despite ongoing safety investments [20]. The challenge is further complicated by the need to balance safety improvements with economic considerations, as transportation authorities must prioritize limited resources among thousands of crossings nationwide [21]. Studies demonstrate that the integration of warning systems with broader traffic management infrastructure, particularly the interconnection of highway signals with rail-grade crossing warnings, represents a critical factor in enhancing overall safety outcomes [22].

Despite advancements in safety technology, research failed to justify the cause of severer HRGCs crashes [19,20]. Decisions regarding resource allocation are also not analyzed in the literature for their impact on safety outcomes at various crossings [21]. In addition, the effectiveness of integrated warning systems has not been compared to standalone crossings [22].

3.1. Risky User Behavior at Highway–Rail Grade Crossings

Driver behavior emerges as a central factor in crossing safety [23], with research highlighting various risky actions that increase crash probability [24]. At HRGC crossing, the most dominant risky behavior is moving around lowered gates [25], as it ignores all the active warnings. Such behaviors are often more common when drivers are familiar with crossings and train schedules. Studies show that drivers often misjudge train speeds and distances due to an optical illusion, where large objects moving quickly appear to travel slower [26].

Environmental conditions play an imperative role in user behavior and decision-making process at HRGCs. Poor weather, such as fog, rain, and snow, greatly increases crash risks by reducing visibility and deteriorating road surfaces Studies reveal that fatal crashes during daylight hours are less severe compared to those occurring in harsh weather conditions. Additionally, vehicle characteristics and crossing conditions also contribute to increased risk levels [26].

Pedestrian and cyclist behaviors present additional safety challenges at HRGCs. Studies focusing on bicycle safety reveal that approach angle represents the most significant determinant of crash likelihood, with a critical threshold identified at 30 degrees [27]. Cyclists approaching tracks at angles less than this threshold face dramatically increased risks due to wheel-rail flangeway interactions. Study revealed that group dynamics, gender differences, and environmental conditions such as wet roadway surfaces contribute to elevated crash probabilities for vulnerable road users [27]. The analysis of empirical video data from heavily traveled crossings demonstrates that demographic factors, riding behaviors, and environmental characteristics significantly influence single-bicycle crash rates [27].

Three critical gaps exist in behavioral research. First, studies describe risky behaviors but do not measure how specific actions affect crash severity in different places. While research documents gate violations and signal non-compliance [23–25], it does not quantify the relative risk of each violation type. Second, most studies examine behaviors without considering geographic or environmental contexts that may change risk levels [26]. Third, the literature does not explain why identical behaviors produce different outcomes across locations. Studies show environmental conditions influence severity [26] but they do not identify which local factors cause the same violation to result in varying fatality rates.

3.2. Crash Severity Analysis and Contributing Factors

Vehicle characteristics and occupancy patterns significantly influence crash severity outcomes at HRGCs. Research shows that truck-trailer crashes have a higher likelihood of driver fatalities compared to passenger car incidents, especially at crossings in regions like Texas [20]. Such analysis reveals that larger vehicles facing extended exposure times due to slower crossing speeds [28], while smaller vehicles encounter risks from reduced maneuverability and reaction time. Some studies also examine the impact of occupancy levels, showing that crashes involving multiple occupants result in higher injury and fatality rates compared to single-occupant crashes, suggesting that crash severity assessments should consider exposure levels rather than focusing solely on vehicle-based metrics [29].

Driver demographics and behavioral characteristics emerge as critical determinants of crash severity. Driver age affects crash severity, with younger drivers taking more risks and older drivers being more cautious but slower to react [30]. In addition to age, gender differences affect risk assessment and compliance, showing varying responses to warning systems due to differences in driver attitudes [30]. Besides that, impairment from alcohol significantly increases the risk level when crossing HRGCs [26]. Lastly, driver fatigue and prevailing traffic conditions are also contributing factors in fatal truck-related crashes at HRGCs [31].

Temporal and spatial patterns reveal systematic variations in crash severity across different contexts. In most cases, severe accidents are recorded during low-visibility hours and at rural crossings, where differences in warning systems and emergency response contribute to higher severity [32]. This analysis reveals a compound effect of both environment and infrastructure, highlighting that failure of traditional single factor model.

Severity research shows three major limitations. First, studies examine vehicle types, demographics, and temporal patterns separately without analyzing how these factors interact [28–30]. No research tests whether age effects differ by vehicle type or whether gender patterns vary across urban versus rural settings. Second, the literature does not explain geographic differences in severity outcomes. Studies note that Texas shows higher truck-related fatalities [20] and rural areas show different patterns [32], but do not identify what local factors cause these variations. Third, research lacks quantified comparisons of severity risk across different violation types within the same geographic context.

3.3. Predictive Modeling and Risk Assessment Approaches

Current risk prediction methodologies for HRGCs rely primarily on historical accident data combined with infrastructure and traffic characteristics. The FRA accident prediction model represents the standard approach, incorporating factors such as average daily traffic volume, train frequency, maximum train speed, and existing warning devices [14]. However, research demonstrates significant limitations in these traditional approaches, particularly regarding data quality and completeness issues that directly impact prediction accuracy [33]. Studies comparing predictions using original database inputs versus field-validated data show statistically significant differences in model outputs, emphasizing the critical importance of accurate inventory information [33].

Machine learning approaches have emerged as promising alternatives to traditional statistical methods for crossing risk assessment. Gradient boosting models demonstrate superior prediction accuracy compared with conventional linear models and decision trees, while providing enhanced capability to identify nonlinear relationships among contributing factors [34]. These advanced techniques offer improved handling of complex interactions between traffic exposure factors, infrastructure characteristics, and environmental conditions. However, the "black box" nature of many machine learning models presents challenges for practical implementation, as transportation professionals require interpretable results to guide decision-making processes [34].

Competing risks methodologies represent an innovative approach to simultaneously analyzing crash frequency and severity outcomes. These survival analysis techniques accommodate the competing nature of multiple severity levels while providing integrated assessment capabilities that traditional separate models cannot achieve [35]. The approach enables direct hazard ranking considering both frequency and severity likelihood, offering interpretative effects from both directional and magnitude perspectives. Long-term cumulative effect analysis through cumulative incidence functions provides insights into temporal risk evolution that conventional models fail to capture [35].

Predictive modeling faces four fundamental limitations. First, existing models predict crash frequency but cannot forecast which specific risky behaviors will occur at crossings [17]. This limitation restricts practical utility for targeted interventions. Second, while machine learning shows better accuracy [17], the interpretability problem prevents transportation professionals from understanding causal relationships needed to design effective countermeasures [17]. Third, no models account for geographic variation in crash outcomes. Studies develop models using data from single states or regions without testing whether predictions hold across different contexts. Fourth, competing risks methods show promise [35] but have not been validated using multi-state datasets or tested for geographic transferability.

3.4. Emerging Technologies and Future Research Directions

Advanced sensor technologies and Internet of Things applications present significant opportunities for enhancing crossing safety through improved monitoring and real-time risk assessment. Research identifies multiple sensor technologies applicable to railway operations, including wireless sensor networks, long-term evolution technology, and fifth-generation cellular communications [36]. These technologies enable comprehensive data collection regarding traffic flows, environmental conditions, and infrastructure performance that can support more sophisticated risk prediction models. The integration of video surveillance, digital detection systems, and artificial intelligence methods offers potential for automated threat detection and response capabilities [37].

Autonomous vehicle technologies introduce both opportunities and challenges for crossing safety management [38]. The development of connected and autonomous vehicles

provides possibilities for direct communication between vehicles and crossing warning systems, potentially enabling coordinated responses to approaching trains [37]. However, research indicates that external human–machine interfaces on automated vehicles may inadvertently influence pedestrian behavior, potentially creating false security perceptions that encourage unsafe crossing decisions. The transition period during autonomous vehicle deployment will require careful consideration of mixed traffic conditions and varying levels of vehicle automation [37].

Digital twin technologies and simulation-based approaches represent emerging methodologies for crossing safety analysis and intervention design. These approaches enable virtual testing of safety improvements and operational modifications before physical implementation, potentially reducing costs and implementation risks [39]. The integration of real-time data feeds with simulation models supports dynamic optimization of traffic signal timing and coordination with train operations [40]. Genetic algorithm optimization approaches demonstrate potential for improving both safety and efficiency outcomes in corridor-level applications involving multiple crossings [41]. Future research directions should focus on developing comprehensive frameworks that integrate multiple data sources, account for user behavior variability, and provide interpretable results for practical implementation by transportation professionals.

Technology research lacks practical validation. First, while studies describe sensor technologies and IoT application [36,37], no research tests these systems in real-world crossing environments or measures their effectiveness in preventing crashes. Second, the literature discusses autonomous vehicle potential [39,40] but does not examine how mixed traffic (automated and human-driven vehicles) affects crossing safety during the transition period. Third, studies propose digital twin and simulation approaches [39,40] but provide no empirical validation showing these methods produce better safety outcomes than traditional engineering approaches. Fourth, no research addresses implementation barriers such as costs, maintenance requirements, or integration with existing infrastructure.

3.5. Thematic Classification of Literature by Research Focus Areas

Table 3 categorizes the reviewed studies into six thematic areas related to HRGC safety, revealing research priorities and identifying underexplored topics. This classification facilitates the identification of studies addressing specific aspects of crossing safety and clarifies the relationships between various contributing factors.

Table 3. Thematic Classification of Literature by Research Focus Areas.

Authors	Safety Challenges & Infrastructure Design	Risky User Behavior Analysis	Crash Severity & Contributing Factors	Spatial & Environmental Influences	Predictive Modeling & Risk Assessment	Data Quality & Emerging Technologies
Keramati et al. [1]	✓		✓		✓	
Kutela et al. [2]		✓				
Haleem & Gan [3]			✓	✓		
Witte & Donohue [4]		✓				
Chatterjee et al. [5]	✓					✓
Banerjee et al. [6]			✓	✓		
Hsu & Jones [7]	✓					✓
Abioye et al. [8]					✓	✓
Liu et al. [9]		✓				
Mathew et al. [10]	✓					
Khattak et al. [11]		✓				
Raub [12]			✓			
Soltaninejad et al. [13]					✓	
Pasha et al. [14]					✓	
Rai et al. [15]	✓					

Table 3. *Cont.*

Authors	Safety Challenges & Infrastructure Design	Risky User Behavior Analysis	Crash Severity & Contributing Factors	Spatial & Environmental Influences	Predictive Modeling & Risk Assessment	Data Quality & Emerging Technologies
Bridgelall & Tolliver [16]					✓	✓
Zhang et al. [17]	✓					✓
Soltaninejad et al. [18]			✓		✓	
Mok & Savage [19]	✓					
Haces-Garcia et al. [20]	✓					✓
Kavoosi et al. [21]	✓				✓	
Lin et al. [22]	✓					✓
Khattak et al. [23]		✓				
Khattak [24]		✓				
Khattak & McKnight [25]		✓				
Das et al. [26]			✓	✓		
Ling et al. [27]	✓	✓				
Hao & Daniel [28]			✓			
Kutela et al. [29]			✓			
Ouimet et al. [30]		✓				
Khan & Khattak [31]			✓	✓		
Singh et al. [32]			✓			
Farooq & Khattak [33]						✓
Lu et al. [34]					✓	✓
Keramati et al. [35]			✓		✓	
Singh et al. [36]	✓					✓
Singh et al. [37]	✓					✓
Ahmed et al. [38]						✓
Abdelkader et al. [39]						✓
Chen & Rilett [40]	✓				✓	✓

Based on this classification, a synthesis diagram is developed to represent key risk factors identified in the reviewed studies. Figure 3 illustrates the main contributors to HRGC crashes and their relationships with safety outcomes.

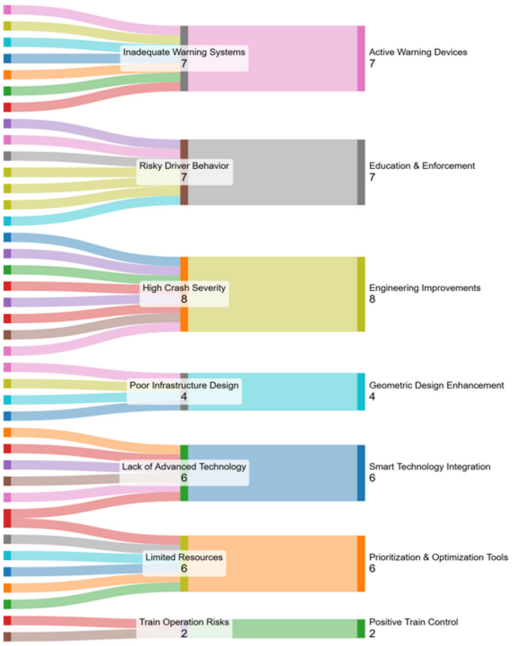


Figure 3. Synthesis of risk factors and mitigation strategies in HRGC safety research (2015–2025). Sources: Keramati et al. (2021); Kutela et al. (2022); Haleem and Gan (2015); Witte and Donohue (2000); Chatterjee et al. (2025); Banerjee et al. (2025); Hsu and Jones (2017); Abioye et al. (2020); Liu et al. (2016); Mathew et al. (2021); Khattak et al. (2021); Raub (2009); Soltaninejad et al. (2024); Pasha

et al. (2020); Rai et al. (2024); Bridgelall and Tolliver (2021); Zhang et al. (2018); Soltaninejad et al. (2025); Mok and Savage (2005); Haces-Garcia et al. (2021); Kavoosi et al. (2020); Lin et al. (2025); Khattak et al. (2024); Khattak (2009); Khattak and McKnight (2008); Das et al. (2022); Ling et al. (2017); Hao and Daniel (2014); Kutela et al. (2023); Ouimet et al. (2008); Khan and Khattak (2018); Singh et al. (2021a); Farooq and Khattak (2023); Lu et al. (2020); Keramati et al. (2020); Singh et al. (2022); Singh et al. (2021b); Ahmed et al. (2025); Abdelkader et al. (2021); Chen and Rilett (2018) [1–40].

Figure 3 synthesizes 40 studies on HRGC safety using a Sankey diagram that illustrates the connections between research sources, identified risk factors, and proposed mitigation strategies. Among seven main risk categories, high crash severity (8 studies) and inadequate warning systems (7 studies) received the most research attention, collectively representing 37.5% of the reviewed literature.

The literature review identified three critical gaps: lack of quantified behavior-severity relationships, absence of geographic comparisons, and failure to explain regional outcome variations.

3.6. Empirical Evidence on Highway User Actions and Crash Severity Patterns

Empirical study explores the relationship between highway user actions and crash severity using Federal Railroad Administration (FRA) database. The analysis focuses on two states, New Jersey and Texas, to identify geographic differences in crash frequency, risk environments, and user behavior. A detailed summary of dataset and key attribute is shown in Table 4. Texas reported a higher accident rate compared to New Jersey shown in Table 5. Furthermore, highway user actions (HUA) were categorized into eight distinct types, as outlined in Table 6.

Table 4. Highway User Actions and Crash Outcomes by State (2013–2022).

State	Attribute of Highway User Action	No. Collision	Mean (VMT)	Accident Rate	Fatal Injury	Non-Fatal Injury
New Jersey	Went around the gates	47	75,042.70	626.31	21	24
	Stopped and then proceeded	24		319.82	0	3
	Did not stop	129		1719.02	2	42
	Stopped on crossing	82		1092.71	6	49
	Other	24		319.82	1	16
	Went around/thru temporary barricade	0		0	3	5
	Went through the gate	10		133.26	7	0
	Suicide attempt	7		93.28	7	4
Texas	Went around the gates	417	329,741.80	1264.63	64	204
	Stopped and then proceeded	135		409.41	11	40
	Did not stop	659		1998.53	63	348
	Stopped on crossing	451		1367.74	20	123
	Other	555		1683.14	31	146
	Went around/thru temporary barricade	5		15.16	1	0
	Went through the gate	147		445.8	8	64
	Suicide attempt	23		69.75	18	5

Table 5. Descriptive Analysis of Accident Rate.

Year	Accident Rate	
	New Jersey	Texas
Mean	446.15	889.22
Std	74.24	116.02
Max	550.11	1188.93
Min	324.28	732.97

Table 6. Highway User Actions at HRGCs.

Highway User Actions	
1	Went around the gates
2	Stopped and then proceeded
3	Did not stop
4	Stopped on crossing
5	Other
6	Went around/thru temporary barricade
7	Went through the gate
8	Suicide attempt

The study compared crash severity and user actions in Texas and New Jersey in Table 7. Texas had more crashes and injuries, likely due to higher (VMT). In New Jersey, most fatal and non-fatal injuries were linked to three actions: going around the gates, not stopping, and stopping on the crossing. These three actions caused 77.8% of injuries in New Jersey and 72.1% in Texas. This suggests that in states with lower traffic, a small number of risky behaviors lead to most injuries. The same actions may have different impacts depending on traffic levels and location.

Table 7. Crash Severity for User Actions 1, 3, and 4 (2013–2022).

States	Fatal Injury for Actions 1–8	Non-Fatal Injury for Actions 1–8	Fatal Injury for Actions 1, 3, & 4	Non-Fatal Injury for Actions 1, 3, & 4	Proportion of Fatal and Non-Fatal Injuries Account for by Actions 1, 3, & 4
New Jersey	42	143	29	115	77.8
Texas	216	924	147	675	72.1

Table 8 shows the model fitting results for multinomial logistic regression. It includes values for −2 log likelihood, chi-square, degrees of freedom, and significance levels. The analysis was done separately for New Jersey and Texas. The predictors were temperature, train speed, user age, year, gender, and highway user actions. These values show which factors are important in explaining crash severity in each state. These variables were selected based on established prior research: temperature affects vis-ability and road conditions; year captures temporal safety trends; train speed relates to impact severity; and user age and gender reflect demographic.

Table 8. Multinomial Logistic Regression Model Fitting Statistics by State.

State	Model Fitting Criteria	Intercept	Temp	Train Speed	User Age	Year	Gender	Highway User Action
New Jersey	-2LLRM	3131.63	3136.55	3330.84	3158.89	3140.89	3155.96	3269.07
	Chi-Square		4.92	199.21	27.26	9.26	24.33	137.44
	df		2	2	2	2	2	10
	Sig		0.086	<0.001	<0.001	<0.001	<0.001	<0.001
			Sig	Sig	Sig	Sig	Sig	Sig
Texas	-2LLRM	3077.28	3090.12	3290.85	3098.71	3083.25	3107.63	3214.54
	Chi-Square		12.84	213.57	21.44	5.97	30.36	137.26
	df		2	2	2	2	2	10
	Sig		<0.001	<0.001	<0.001	0.051	<0.001	<0.001
			Sig	Sig	Sig	sig	Sig	Sig

This study also compared the influence of different factors on crash severity in Texas and New Jersey using model fitting results. The detailed results shown in Table 9. In both states, highway user action, train speed, and gender were the strongest predictors of crash severity. These variables were statistically significant with very low *p*-values (Sig < 0.001). In New Jersey, user actions explained much of the variation, with a chi-square value of 137.44. Texas showed a similar result, with a chi-square of 137.26 for user actions. Temperature, user age, and year were also significant in both states, though their influence was smaller. Overall, user behavior and train-related factors had the greatest impact on crash outcomes in both states.

Table 9. Odds Ratios for Fatal Injury by HUA.

Severity		NJ		TX	
		B	**Exp(B)**	**B**	**Exp(B)**
1	Intercept	−0.858		−1.671	
	Temp	0.005	1.005	0.011	1.011
	T speed	0.023	1.024	0.027	1.027
	User age	0.003	1.003	0.004	1.004
	Year	−0.052	0.95	−0.042	0.959
	[G = F]	0.614	1.849	0.697	2.008
	[G = M]				
	[HUA = 1]	0.201	1.222	0.092	1.096
	[HUA = 2]	−0.755	0.47	−0.713	0.49
	[HUA = 3]	0.096	1.101	0.102	1.107
	[HUA = 4]	−0.863	0.422	−1.1	0.333
	[HUA = 5]	−1.041	0.353	−1.088	
	[HUA = 7]				
2	Intercept	−7.509		−7.03	
	Temp	0.008	1.008	0.007	1.007
	T speed	0.063	1.066	0.065	1.067
	User age	0.03	1.03	0.027	1.027
	Year	0.044	1.045	0.007	1.007
	[G = F]	0.381	1.464	0.597	1.817
	[G = M]				
	[HUA = 1]	1.502	4.49	1.304	3.686
	[HUA = 2]	0.301	1.352	0.527	1.695
	[HUA = 3]	0.651	1.917	0.992	2.697
	[HUA = 4]	−0.402	0.669	−0.257	0.773
	[HUA = 5]	−0.166	0.847	0.072	1.074
	[HUA = 7]				

The study found clear differences in fatal injury risks. For the same user action, the odds of a fatal injury "2" were 0.81 times higher in New Jersey despite lower VMT. This means the risk associated with the same behavior was much greater in New Jersey. Local factors like road design, train speed, or enforcement may influence these outcomes. These state-level differences are important for targeting safety improvements. Gender patterns also emerged from data analysis. Female drivers consistently face higher injury risk across in both New Jersey and Texas. The elevated injury risk for female drivers represents an underdeveloped area requiring further investigation. Recent research suggests that young women face approximately 20% higher risk of dying in car crashes compared to men in matched scenarios, potentially due to vehicle safety systems designed primarily around male occupant characteristics, though the mechanisms remain incompletely understood and warrant expanded research strategies to ensure equitable crash protection across all demographics [41].

The integration of literature findings with empirical evidence shows both agreements and gaps in current understanding. While research has discussed many factors that influence crash severity, the statistical analysis demonstrates that behavioral factors have the strongest relationship with crash outcomes. This suggests that safety efforts should focus primarily on changing driver behavior while also addressing the local factors that create geographic variation in risk levels.

The empirical validation of literature-identified risk factors provides a solid foundation for developing evidence-based safety policies and targeted interventions at HRGCs. The specific risk numbers can help transportation agencies prioritize their safety investments and develop more effective warning systems and enforcement programs.

4. Result and Discussion

This systematic literature review examined risky user behavior at HRGCs through analysis of 40 studies published between 2015 and 2025, supported by empirical data from six U.S. states covering 2013 to 2022. The research addressed two questions about driver behavior's role in crash severity and ways to improve predictive models for risky actions.

4.1. Assessment of Study Heterogeneity

The included studies varied in several ways. The biggest differences were geographically. Studies from Texas reported higher crash frequencies than those from other states. In New Jersey, the impact of violations on severity followed a different pattern. For example, going around gates showed different odds ratios depending on the state. This suggests that local conditions affect outcomes beyond just the behavior. Study design also influenced findings. Most studies used observational crash data from state or federal sources. Five studies used to drive simulators. These gave more detail about driver decisions but showed different effect sizes. Simulator studies reported lower severity, likely because they cannot replicate real crashes.

Time period made a difference too. Studies from 2015 to 2019 showed higher crash severity than those from 2020 to 2025. This may reflect real safety improvements. Newer cars are safer. Some crossings got better warning systems. Changes in population may have affected traffic at crossings. These time-based changes made it hard to compare results across all studies. Because of these differences, a meta-analysis was not possible. Studies used different outcomes and measurement scales. We used narrative synthesis instead. This allowed us to describe trends and compare findings. We focused on patterns that appeared across multiple studies, despite their differences.

4.2. Sensitivity Analysis

We performed three tests to validate our conclusion. The first test excluded five studies that had high risk bias ratings. These studies had problems with confounding control or using small samples from single crossings. Removing them did not change the main findings. Gate violations still showed the strongest association with fatal outcomes. The odds ranged from 3.2 to 4.8 across the remaining studies. This range was like the full sample results.

The second test excluded all simulation studies. We wanted to confirm that real-world crash data supported the same patterns. The analysis used only the 35 observational studies with actual crash records. The findings held. Driver behaviors remained the strongest predictors of crash severity. Geographic variation persisted in real-world data. Female drivers still faced higher injury odds in multiple studies. The simulation studies had not been drawing overall conclusions.

The third test used only recent studies from 2020 to 2025. This addressed concerns about temporal changes in safety conditions. Fifteen studies came from this period. Recent studies confirmed geographic differences in outcomes. They also showed that despite newer safety technology, risky behaviors still led to severe crashes. The effect sizes were slightly smaller in recent studies, suggesting some improvement. However, the patterns and relationships remained consistent.

All three sensitivity analyses supported the main conclusions. Risky driver behaviors increase crash severity. The same behaviors produce different outcomes in different states. Current models cannot explain this geographic variation. These findings were robust across different subsets of studies and time periods.

4.3. Confidence in Study Finding

We rated the confidence level for key findings. This reflects how confident we are that the results are close to the true effect. We considered study design, consistency, and sample size. For going around gates, the evidence had moderate strength. Eight studies showed this behavior increased fatal crash risk. Results were consistent, but all used observational data, so we downgraded to one level. For geographic variation, the evidence was limited. Only two states were directly compared. Other studies focused on single states. We downgraded for indirectness and imprecision. For gender and injury risk, we had moderate confidence. Several studies showed higher injury odds for females, though some had small sample sizes. For age and train speed, the evidence was strong. These findings were consistent and matched prior research.

4.4. Driver Behavior and Crash Severity

The first research question examined the contribution of driver behavior to crash severity at HRGCs. The findings show that risky drivers' actions are the primary cause of serious crashes. These dangerous behaviors include ignoring warning signals, driving around closed gates, and stopping vehicles on railroad tracks. The empirical analysis provides specific numbers for these risks. Going around gates increases the odds of fatal injury by 3.5 to 4.5 times in Texas and New Jersey.

However, the study found important differences between states. The same risky behavior leads to different outcomes depending on location. This difference has not been explained in existing research. The geographic variation suggests that local factors such as road design, enforcement practices, train speeds, and environmental conditions influence risk levels. Geographic differences in outcomes likely stem from interaction effects between violation types and local conditions. New Jersey's higher fatality odds despite lower traffic volumes suggest that crossing design characteristics, enforcement patterns, train acceleration pro-files, and sight distance limitations modify crash severity independent of violation frequency. Most studies examine behavior patterns and severity outcomes separately but do not address how these outcomes vary across locations.

Female drivers consistently face higher injury risk in both New Jersey and Texas. The odds range from 1.34 to 1.46 for non-fatal injuries and from 1.464 (NJ) to 1.817 (TX) for fatal injuries. This pattern holds across different states and severity levels. The literature acknowledges gender differences in risk assessment and compliance behavior but does not explain why female drivers face higher injury risk even when engaging in the same violations as male drivers. Age shows a smaller effect. Each additional year of driver age slightly increases injury odds, though this effect is much smaller than the impacts of risky behaviors or gender.

4.5. Predictive Model Limitations

The second research question focused on improving predictive models using available data on location, environment, and road features. Current models have serious problems that limit their usefulness. Most traditional prediction methods rely on historical crash data that contains errors and missing information. Studies comparing original database inputs versus field-validated data show statistically significant differences in model outputs. This poor data quality directly reduces the accuracy of risk predictions.

Existing models face a fundamental limitation. They predict when crashes might happen but cannot forecast which specific risky behaviors drivers are likely to engage in at locations. Models use factors like traffic volume, train frequency, and warning device type but do not incorporate behavioral or demographic patterns that this study found to be strong predictors of severity. No models account for the geographic variation in outcomes that this study documented.

4.6. Environmental and Infrastructure Factors

The analysis revealed that multiple factors work together to influence crash risks. Environmental conditions play a major role in crash likelihood and severity. Poor weather conditions like fog, rain, and snow reduce visibility and make road surfaces dangerous. Crashes that occur during early morning or evening hours, when lighting is poor, tend to be more severe than those happening during clear daylight conditions. The literature documents these patterns but does not examine how environmental factors interact with violation types or geographic contexts to modify severity outcomes.

Physical features of crossings create important differences in safety outcomes. Urban crossings face challenges from heavy pedestrian traffic and complex road patterns that can confuse drivers. Rural crossings often lack active warning systems but may benefit from better sight lines that allow drivers to see approaching trains. Design elements like crossing angles, track layout, and sight distances directly affect collision risk. For cyclists, approach angles below 30 degrees dramatically increase crash risk because bicycle wheels can get caught in rail gaps.

Literature documents these factors separately but does not examine how they interact. Studies show that behavior, environment, vehicle type, and infrastructure design all affect crash outcomes, yet no research tests whether these effects are additive or multiplicative. For instance, does bad weather increase risk equally for all violation types, or do certain violations become particularly dangerous under specific environmental conditions? Does crossing design modify the severity risk associated with gate violations? The empirical analysis in this study suggests that such interactions exist, given the large geographic differences in outcomes, but the literature provides no framework for understanding or predicting these interaction effects.

4.7. Integration of Literature and Empirical Findings

The major gap is geographic variation. Literature treats crossing safety as a general problem with universal solutions. Studies develop models and test interventions without examining whether results transfer across different contexts. The empirical findings show this assumption is wrong.

The empirical validation of literature-identified risk factors provides a foundation for developing evidence-based safety policies shown in Table 10. However, it also reveals that current research cannot explain why safety interventions work in some places but not others. The specific risk numbers can help transportation agencies prioritize their safety investments, but without understanding geographic modifiers, agencies cannot predict whether interventions will be effective in their specific contexts. In addition, the litera-

ture's failure to account for geographic variation stems from meth-od-logical tendencies: single-state studies lack comparative scope, while national studies ag-gregale data and mask regional differences. Few researchers test cross-state transferability and examine local factors such as enforcement intensity, crossing design, traffic volumes, and train speeds modify behavior-severity relationships, leaving practitioners uncertain whether interventions proven effective in one region will work in their specific context.

Table 10. Summary of Key Findings: Literature vs. Empirical Evidence.

Finding Category	Literature Findings	Empirical Validation	Gap Identified
Risky Behavior Impact	Gate violations, signal non-compliance, and stopping on tracks identified as dangerous	Gate violations increase fatal injury odds: NJ (OR = 4.49), TX (OR = 3.69)	Literature does not quantify relative risk of specific violations or provide state-specific comparisons
Geographic Variation	Not addressed in existing studies	Same violation (going around gates) produces different fatal injury risks: NJ shows 0.81 times higher odds despite lower VMT compared to TX	Literature treats crossing safety as universal problem; does not examine location-specific modifiers that cause identical behaviors to produce varying outcomes
Gender Effects	Gender differences noted in risk assessment and compliance	Female drivers had consistently higher fatal injury odds: NJ (OR = 1.464), TX (OR = 1.817) across both states	Literature does not explain why females face higher injury risk for same violations across different geographic contexts
Age Effects	Age-related patterns mentioned	Age shows small but consistent effect; each additional year slightly increases injury odds in both states	Literature describes age patterns but lacks quantification and state-level comparison
Environmental Conditions	Poor weather and lighting increase crash risk	Temperature and environmental factors showed statistical significance in both NJ and TX models	Literature does not examine how environment interacts with violation types or varies by geographic region
Vehicle Characteristics	Larger vehicles face extended exposure; higher fatality rates	Not assessed in current two-state analysis	Literature does not test whether effects vary by crossing design or between states like NJ and TX
Predictive Models	Traditional models use traffic volume, train frequency, warning devices; ML models show better accuracy	Multinomial logistic regression revealed highway user action, train speed, and gender as strongest predictors in both states (Chi-square: NJ = 137.44, TX = 137.26)	Models lack behavioral/demographic variables and cannot account for the documented geographic variation between states
Data Quality Issues	Errors and missing data compromise predictions	FRA database used for NJ and TX (2013–2022) provides comprehensive crash records but may contain inherent quality limitations	Literature does not quantify state-specific data quality variations or their impact on prediction accuracy differences

Practitioners should prioritize gate violation countermeasures at high-risk crossings, recognizing that effectiveness varies by location. New Jersey agencies should emphasize enforcement and driver education given higher fatality odds, while Texas interventions should address volume-related exposure through infrastructure improvements. Gen-der-specific messaging may reduce female driver injury risk observed across both con-texts.

5. Conclusions

This systematic review revealed "going around the gate" as a significant behavior noted in HRGCs crashes. Risk of fatal injury is 4.49 times higher in New Jersey and

3.69 times higher in Texas for this behavior. However, the same action leads to different outcomes depending on location. New Jersey has lower VMT but higher fatal injury odds, which shows that local factors affect crash severity. Current safety strategies often use the same solutions across all locations. This study challenges that practice. It shows that regional differences in road design, enforcement, train speed, and traffic patterns influence how risky behavior affects outcomes. Using the same safety measures everywhere may not be effective. The study makes three key points. It provides state-specific risk data. It shows that geography changes how risky actions impact crashes. It calls for better prediction models that include both behavior and local conditions. This study has limitations. The review relied on published peer-reviewed articles, which may exclude relevant gray literature from transportation agencies. The empirical validation used data from only two states, limiting generalizability to other geographic contexts. Future research should include more states and non-academic sources to strengthen findings.

6. Future Research

Research in the next one to three years should focus on two main areas. First, researchers need to build prediction models that can forecast specific dangerous behaviors rather than just predicting when crashes might happen. Current models tell us a crossing is risky but cannot tell us which drivers are likely to go around gates or stop on tracks. Second, studies should compare multiple states to identify what location factors cause the same risky behavior to produce different outcomes. Understanding these differences is crucial for developing targeted safety measures.

Medium-term research over the next three to five years should move toward real-time prediction and testing. Connected vehicle technology offers new ways to track driver's behavior as happens at crossings. Researchers should use this data to build systems that can warn drivers or alert authorities when dangerous actions are likely. Additionally, studies need to test actual safety interventions using controlled experiments. Most current research describes what happens but does not test what works. We need proof that specific safety measures change driver behavior and reduce crashes.

Long-term research over the next 5 years and beyond should create complete prediction systems. These systems should combine real-time data about weather, traffic, and train movements with information about driver patterns and crossing characteristics. The goal is to predict both when crashes are likely and what specific dangerous behaviors might occur. This requires new methods that can handle large amounts of data while still providing results that transportation agencies can understand and use.

Future studies must also address current limitations. This research used crash data that only shows what happened after dangerous situations occurred. New studies should observe driver behavior at crossings using video analysis or driving simulators to understand decision-making before crashes happen. Researchers should also examine how factors like time pressure, familiarity with crossings, and perception of train distance influence driver choices. Success in improving crossing safety will require cooperation between researchers, transportation agencies, and technology companies to turn research findings into practical solutions that reduce both the number and severity of crashes at these dangerous locations.

Author Contributions: Conceptualization, I.B.; methodology, I.B.; formal analysis, I.B. and A.A.; writing—original draft preparation, I.B.; writing—review and editing, A.A. and P.L.; supervision, P.L. All authors have read and agreed to the published version of the manuscript.

Funding: The authors received no financial support for this research.

Data Availability Statement: The data used in this study is publicly available from the Federal Railroad Administration (FRA) database online.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Keramati, A.; Lu, P.; Ren, Y.; Tolliver, D.; Ai, C. Investigating the effectiveness of safety countermeasures at highway-rail at-grade crossings using a competing risk model. *J. Saf. Res.* **2021**, *78*, 251–261. [CrossRef]
2. Kutela, B.; Kidando, E.; Kitali, A.E.; Mwende, S.; Langa, N.; Novat, N. Exploring pre-crash gate violations behaviors of drivers at highway-rail grade crossings using a mixed multinomial logit model. *Int. J. Inj. Contr. Saf. Promot.* **2022**, *29*, 226–238. [CrossRef]
3. Haleem, K.; Gan, A. Contributing factors of crash injury severity at public highway-railroad grade crossings in the U.S. *J. Saf. Res.* **2015**, *53*, 23–29. [CrossRef]
4. Witte, K.; Donohue, W.A. Preventing vehicle crashes with trains at grade crossings: The risk seeker challenge. *Accid. Anal. Prev.* **2000**, *32*, 127–139. [CrossRef] [PubMed]
5. Chatterjee, K.; Li, J.Q.; Ansari, F.; Munna, M.R.; Parajulee, K.; Schwennesen, J. Hybrid LSTM-Transformer Models for Profiling Highway-Railway Grade Crossings. *arXiv* **2025**, arXiv:2508.00039. [CrossRef]
6. Banerjee, A.; Justice, D.; Noronha, A.; Cissell, T.; Southard, L.; Crump, S.; Khan, T.; Raoniar, R.; Haleem, K. Investigating Crash Contributing Factors at Public Highway-Railroad Grade Crossings in Kentucky. In Proceedings of the International Conference on Transportation and Development, Glendale, AZ, USA, 8–11 June 2025; American Society of Civil Engineers: Glendale, AZ, USA, 2025; pp. 94–107. [CrossRef]
7. Hsu, C.-J.; Jones, E.G. Sensitivity analyses of stopping distance for connected vehicles at active highway-rail grade crossings. *Accid. Anal. Prev.* **2017**, *99*, 210–217. [CrossRef] [PubMed]
8. Abioye, O.F.; Dulebenets, M.A.; Pasha, J.; Kavoosi, M.; Moses, R.; Sobanjo, J.; Ozguven, E.E. Accident and hazard prediction models for highway–rail grade crossings: A state-of-the-practice review for the USA. *Railw. Eng. Sci.* **2020**, *28*, 251–274. [CrossRef]
9. Liu, J.; Bartnik, B.; Richards, S.H.; Khattak, A.J. Driver behavior at highway–rail grade crossings with passive traffic controls: A driving simulator study. *J. Transp. Saf. Secur.* **2016**, *8* (Suppl. S1), 37–55. [CrossRef]
10. Mathew, J.; Benekohal, R.F.; Berndt, M.; Beckett, J.; McKerrow, J. Multi-criteria prioritization of highway-rail grade crossings for improvements: A case study. *Urban Plan. Transp. Res.* **2021**, *9*, 479–518. [CrossRef]
11. Khattak, A.J.; Ahmad, N.; Wali, B.; Dumbaugh, E. A taxonomy of driving errors and violations: Evidence from the naturalistic driving study. *Accid. Anal. Prev.* **2021**, *151*, 105873. [CrossRef]
12. Raub, R.A. Examination of Highway–Rail Grade Crossing Collisions Nationally from 1998 to 2007. *Transp. Res. Rec. J. Transp. Res. Board* **2009**, *2122*, 63–71. [CrossRef]
13. Soltaninejad, M.; Salum, J.; Kodi, J.; Alluri, P.; Lin, P.-S.; Wang, Z. Modeling Highway-Rail Grade Crossing (HRGC) Crash Frequency. *Res. Sq.* **2024**. *preprint*. [CrossRef]
14. Pasha, J.; Dulebenets, M.A.; Abioye, O.F.; Kavoosi, M.; Moses, R.; Sobanjo, J.; Ozguven, E.E. A Comprehensive Assessment of the Existing Accident and Hazard Prediction Models for the Highway-Rail Grade Crossings in the State of Florida. *Sustainability* **2020**, *12*, 4291. [CrossRef]
15. Rai, D.; Li, J.Q.; Yang, X.; Chatterjee, K. Safety Analysis of the Britton Highway Railroad Grade Crossing. In Proceedings of the International Conference on Transportation and Development, Glendale, AZ, USA, 15–18 June 2024; American Society of Civil Engineers: Atlanta, GA, USA, 2024; pp. 658–669. [CrossRef]
16. Bridgelall, R.; Tolliver, D.D. Railroad accident analysis using extreme gradient boosting. *Accid. Anal. Prev.* **2021**, *156*, 106126. [CrossRef] [PubMed]
17. Zhang, Z.; Liu, X.; Holt, K. Positive Train Control (PTC) for railway safety in the United States: Policy developments and critical issues. *Util. Policy* **2018**, *51*, 33–40. [CrossRef]
18. Soltaninejad, M.; Salum, J.; Kinero, A.; Alluri, P. Modeling highway-rail grade crossing (HRGC) crash severity using statistical and machine learning methods. *Int. J. Inj. Contr. Saf. Promot.* **2025**, 1–25. [CrossRef] [PubMed]
19. Mok, S.C.; Savage, I. Why Has Safety Improved at Rail-Highway Grade Crossings? *Risk Anal.* **2005**, *25*, 867–881. [CrossRef]
20. Haces-Garcia, J.; Haces-Garcia, A.; Haces-Garcia, F.; Haces-Fernandez, F. Advanced Warning System to Improve Safety at Train Grade Crossings. *Sustainability* **2021**, *13*, 11779. [CrossRef]
21. Kavoosi, M.; Dulebenets, M.A.; Pasha, J.; Abioye, O.F.; Moses, R.; Sobanjo, J.; Ozguven, E.E. Development of Algorithms for Effective Resource Allocation among Highway–Rail Grade Crossings: A Case Study for the State of Florida. *Energies* **2020**, *13*, 1419. [CrossRef]
22. Lin, P.-S.; Wang, Z.; Alluri, P.; Kolla, R.; Białkowska-Jelińska, E.; Soltaninejad, M. Assessment of Strategies and Technologies for Improving Highway-Rail Grade Crossings Safety. In Proceedings of the International Conference on Transportation and Development, Glendale, AZ, USA, 8–11 June 2025; American Society of Civil Engineers: Glendale, AZ, USA, 2025; pp. 207–219. [CrossRef]
23. Khattak, A.J.; Farooq, M.U.; Farhan, A. Motor Vehicle Drivers' Knowledge of Safely Traversing Highway-Rail Grade Crossings. *Transp. Res. Rec. J. Transp. Res. Board* **2024**, *2678*, 604–621. [CrossRef]

24. Khattak, A.J. Comparison of Driver Behavior at Highway–Railroad Crossings in Two Cities. *Transp. Res. Rec. J. Transp. Res. Board* **2009**, *2122*, 72–77. [CrossRef]
25. Khattak, A.J.; McKnight, G.A. Gate Rushing at Highway–Railroad Grade Crossings: Drivers' Response to Centerline Barrier. *Transp. Res. Rec. J. Transp. Res. Board* **2008**, *2056*, 104–109. [CrossRef]
26. Das, S.; Kong, X.; Lavrenz, S.M.; Wu, L.; Jalayer, M. Fatal crashes at highway rail grade crossings: A U.S. based study. *Int. J. Transp. Sci. Technol.* **2022**, *11*, 107–117. [CrossRef]
27. Ling, Z.; Cherry, C.R.; Dhakal, N. Factors influencing single-bicycle crashes at skewed railroad grade crossings. *J. Transp. Health* **2017**, *7*, 54–63. [CrossRef]
28. Hao, W.; Daniel, J. Motor vehicle driver injury severity study under various traffic control at highway-rail grade crossings in the United States. *J. Saf. Res.* **2014**, *51*, 41–48. [CrossRef]
29. Kutela, B.; Kitali, A.E.; Kidando, E.; Mbuya, C.; Langa, N. Exploring the need to model severity of single- and multi-occupant vehicles crashes separately: A case of crashes at highway-rail grade crossings. *Int. J. Transp. Sci. Technol.* **2023**, *12*, 996–1005. [CrossRef]
30. Ouimet, M.C.; Morton, B.G.S.; Noelcke, E.A.; Williams, A.F.; Leaf, W.A.; Preusser, D.F.; Hartos, J.L. Perceived Risk and Other Predictors and Correlates of Teenagers' Safety Belt Use During the First Year of Licensure. *Traffic Inj. Prev.* **2008**, *9*, 1–10. [CrossRef]
31. Khan, W.A.; Khattak, A.J. Injury Severity of Truck Drivers in Crashes at Highway-Rail Grade Crossings in the United States. *Transp. Res. Rec. J. Transp. Res. Board* **2018**, *2672*, 38–47. [CrossRef]
32. Singh, P.; Pasha, J.; Khorram-Manesh, A.; Goniewicz, K.; Roshani, A.; Dulebenets, M.A. A Holistic Analysis of Train-Vehicle Accidents at Highway-Rail Grade Crossings in Florida. *Sustainability* **2021**, *13*, 8842. [CrossRef]
33. Farooq, M.U.; Khattak, A.J. Investigating Highway–Rail Grade Crossing Inventory Data Quality's Role in Crash Model Estimation and Crash Prediction. *Appl. Sci.* **2023**, *13*, 11537. [CrossRef]
34. Lu, P.; Zheng, Z.; Ren, Y.; Zhou, X.; Keramati, A.; Tolliver, D.; Huang, Y. A Gradient Boosting Crash Prediction Approach for Highway-Rail Grade Crossing Crash Analysis. *J. Adv. Transp.* **2020**, *2020*, 6751728. [CrossRef]
35. Keramati, A.; Lu, P.; Zhou, X.; Tolliver, D. A Simultaneous Safety Analysis of Crash Frequency and Severity for Highway-Rail Grade Crossings: The Competing Risks Method. *J. Adv. Transp.* **2020**, *2020*, 8878911. [CrossRef]
36. Singh, P.; Elmi, Z.; Krishna Meriga, V.; Pasha, J.; Dulebenets, M.A. Internet of Things for sustainable railway transportation: Past, present, and future. *Clean. Logist. Supply Chain* **2022**, *4*, 100065. [CrossRef]
37. Singh, P.; Dulebenets, M.A.; Pasha, J.; Gonzalez, E.D.R.S.; Lau, Y.-Y.; Kampmann, R. Deployment of Autonomous Trains in Rail Transportation: Current Trends and Existing Challenges. *IEEE Access* **2021**, *9*, 91427–91461. [CrossRef]
38. Ahmed, T.; Ali, A.; Huang, Y.; Lu, P. Evaluating the Impact of Human-Driven and Autonomous Vehicles in Adverse Weather Conditions Using a Verkehr in Städten—SIMulationsmodell (VISSIM) and Surrogate Safety Assessment Model (SSAM). *Electronics* **2025**, *14*, 2046. [CrossRef]
39. Abdelkader, G.; Elgazzar, K.; Khamis, A. Connected Vehicles: Technology Review, State of the Art, Challenges and Opportunities. *Sensors* **2021**, *21*, 7712. [CrossRef]
40. Chen, Y.; Rilett, L.R. Signal Timing Optimization for Corridors with Multiple Highway-Rail Grade Crossings Using Genetic Algorithm. *J. Adv. Transp.* **2018**, *2018*, 9610430. [CrossRef]
41. Abrams, M.Z.; Bass, C.R. Female vs. male relative fatality risk in fatal motor vehicle crashes in the US, 1975–2020. *PLoS ONE* **2024**, *19*, e0297211. [CrossRef] [PubMed]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.