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Truck-involved crash severity in Thailand: a multilevel perspective on driver behavior and contextual influences

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Truck-involved crashes in Thailand frequently lead to severe consequences due to the vehicles' large size, heavy loads, and high-speed operations. Despite growing concerns, most previous studies have used single-level models that overlook the hierarchical structure of crash data and fail to account for spatial and contextual variations across regions. This study applies a Multilevel Ordered Logit Model to examine factors influencing truck crash severity by integrating individual-level variables (e.g., driver behavior, vehicle condition, environmental factors) with province-level contextual factors (e.g., population size, AADT, Highway length). The model captures both direct effects and cross-level interactions to assess how regional characteristics shape the relationship between individual risk factors and crash severity. The results reveal substantial provincial variation and demonstrate that contextual factors significantly moderate the impact of driver behavior on crash outcomes. These findings emphasize the importance of adopting multilevel analytical frameworks in road safety research, especially in developing countries. The study contributes to a more comprehensive understanding of truck-related crash mechanisms and provides practical insights for designing targeted, context-sensitive safety policies that align with the unique characteristics of each province.

KEYWORDS

multilevel modeling, truck crashes, injury severity, cross-level interactions, spatial analysis

1 Introduction

Road traffic crashes remain one of the most pressing safety challenges in Thailand, particularly those involving trucks, which tend to be more severe and result in substantial loss of life and property. According to the World Health Organization (World Health Organization, 2023), Thailand reports a road traffic fatality rate of 25.4 deaths per 100,000 population, among the highest in Southeast Asia. Truck-related crashes play a significant role in this statistic due to the inherent characteristics of

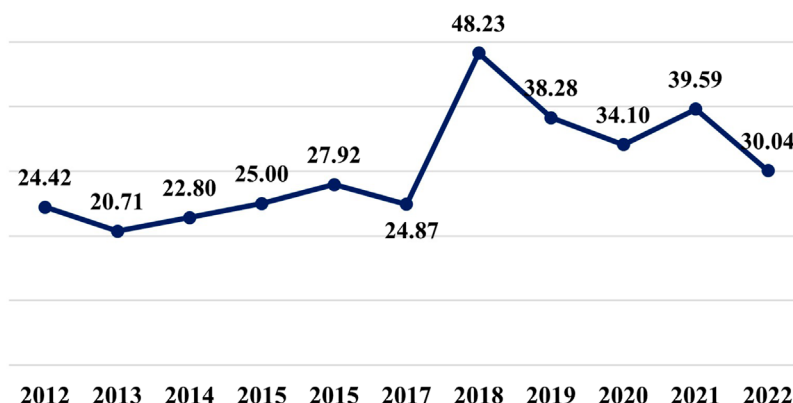


FIGURE 1
Annual truck crash rate per 10,000 registered trucks in Thailand (2012–2022).

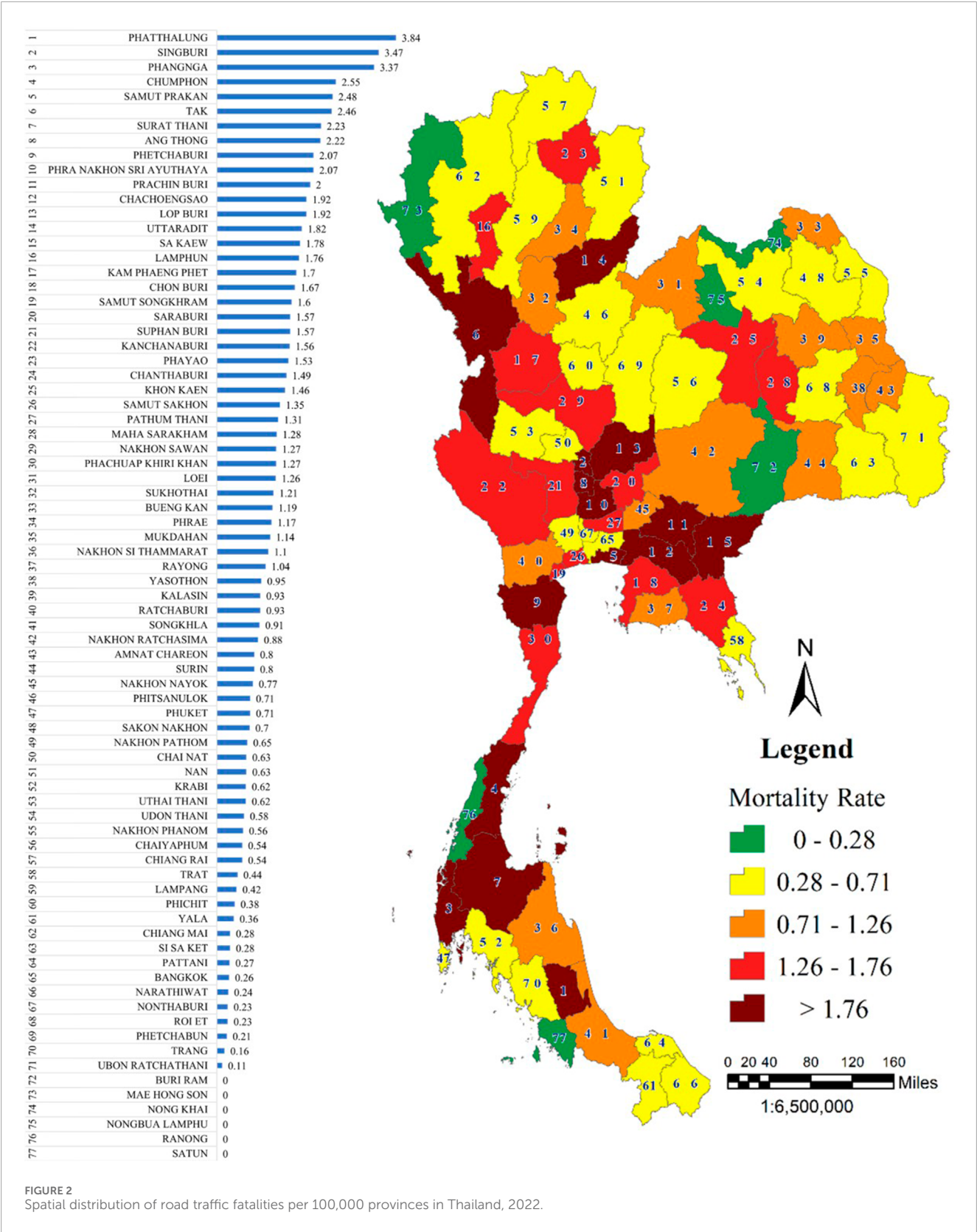
large commercial vehicles such as their size, weight, and high-speed operation over long distances. Data from the Department of Land Transport indicate that, as of 2024, the number of registered trucks in Thailand exceeded 1.24 million units, marking a 6.70% increase from the previous year (Department of Land, 2024). As shown in Figure 1, the number of truck crashes per 10,000 registered vehicles fluctuated notably between 2012 and 2022, peaking at 48.23 incidents per 10,000 trucks in 2018, before declining to 30.04 in 2022 (Thailand Road Safety Collaboration, 2023). This variability underscores the unpredictability of road freight safety trends and highlights the urgent need to investigate the underlying factors contributing to crash injury severity. Of particular interest are driver behavior characteristics, in conjunction with provincial-level contextual factors, which may exert hidden but critical influences on crash outcomes.

Beyond temporal fluctuations, spatial disparities are also evident. Figure 2 illustrates the provincial-level fatality rates per 100,000 population across Thailand, revealing substantial spatial disparities in road traffic risk. To effectively illustrate these variations, the fatality rates are categorized into distinct ranges using percentile divisions. This methodological approach not only highlights absolute differences but also clarifies each province's relative position within the national spectrum of risk. Provinces with high fatality rates (exceeding 1.76 deaths per 100,000 population) tend to cluster in specific regions, while others report zero fatalities. These variations may reflect differences in geographic conditions, data reporting systems, law enforcement rigor, or road user behavior across regions. Such disparities underscore the uneven distribution of road safety risks nationwide and highlight the necessity of integrating spatial-level factors with individual-level driving behaviors. A more systematic, multilevel approach is therefore essential to uncover the underlying mechanisms shaping the severity of traffic crashes.

Previous research has identified a wide range of risk factors associated with the severity of traffic crashes, including driver behavior, age, gender, fatigue, speed at the time of the crash, physical road characteristics, and environmental conditions (Se et al., 2024; Tahmidul Haq et al., 2021; Laphrom et al.,

2024). However, most of these studies have relied on single-level statistical models that assume the independence of observational units, without accounting for the hierarchical structure of real-world crash data. For instance, individual drivers are embedded within distinct provincial contexts that differ in terms of social, economic, and physical characteristics. Such analytical limitations may lead to incomplete interpretations, as they fail to capture contextual influences or spatial heterogeneity across provinces. Structural-level factors such as population size (Niemenen et al., 2002; Cespedes et al., 2024), average annual daily traffic (AADT) (Geedipally et al., 2010; Gatarić et al., 2023), and road network density (Bureau of Highway Safety, 2022a), may play a critical role in shaping both driving behavior and crash outcomes. In this regard, multilevel modeling has been proposed as a more effective analytical framework for disentangling the effects of individual-level and contextual-level variables. It enables the estimation of between-group variability and the exploration of cross-level interactions.

In transportation safety research, only a limited number of studies have explicitly adopted multilevel approaches. Chen et al. (2015) employed a hierarchical Bayesian model to investigate truck driver injury severity and demonstrated that failure to account for nested crash data structures led to biased estimates of behavioral risk factors. Chen et al. (2016) extended this line of work by applying a hierarchical ordered logit model to rural crashes, showing that the inclusion of crash-level random effects and cross-level moderators substantially improved explanatory accuracy. These studies provide strong evidence that multilevel frameworks are superior to single-level approaches in analyzing crash severity, as they quantify higher-level variance and capture contextual moderation effects that would otherwise remain hidden. By contrast, other advanced modelling contributions such as Islam et al. (2022), Hosseinpour and Haleem (2021), Alrejail et al. (2021), Casado-Sanz et al. (2020) focus on unobserved heterogeneity through mixed logit, random-parameters, correlated random-parameters, or latent-cluster frameworks. While valuable, these approaches primarily capture individual-level variation and do not explicitly estimate higher-level variance or cross-level interactions. Building on these



empirical insights, it is important to articulate the theoretical mechanisms through which provincial-level contexts may influence severity.

Theoretically, provincial-level conditions such as population density, traffic volumes, and highway length may influence injury severity through several mechanisms. Higher traffic volumes

can intensify time pressure and overtaking maneuvers; greater population density may alter enforcement visibility and emergency response times; and longer highway networks can heighten fatigue risks for truck drivers. These pathways highlight why contextual conditions are essential moderators of individual-level crash determinants.

In addition, behavioural theories provide further insight into why contextual effects matter. According to Risk Homeostasis Theory (Wilde, 1982), drivers adjust their perceived level of acceptable risk in response to environmental cues. This implies that the same risky behavior may result in different severity outcomes depending on provincial-level conditions, reinforcing the importance of modeling cross-level interactions.

For these reasons, this study adopts a multilevel ordered logit model. While mixed logit frameworks account for unobserved individual heterogeneity and generalized ordered logit models relax the proportional odds assumption, neither directly estimates between-province variance nor tests for cross-level moderation. Given our research objective to examine how provincial-level factors interact with individual-level risks in truck crashes the multilevel ordered logit model provides the most conceptually and methodologically appropriate framework.

To date, no known studies in Thailand have systematically applied multilevel models to investigate truck crash severity by integrating individual-level driver behavior with province-level contextual factors. In particular, there is a lack of research linking risky driving behavior to structural characteristics such as population size, AADT, or road infrastructure, nor has there been adequate examination of how these contextual variables moderate the relationship between driving behavior and crash severity. This research gap is of both theoretical and policy significance, as it limits our ability to develop localized, evidence-based road safety interventions tailored to regional conditions. Recognizing these limitations, the present study seeks to fill this gap.

To address this gap, the present study aims to examine the factors influencing the severity of truck-involved crashes in Thailand using a Multilevel Ordered Logit Model. This method is well-suited for analyzing hierarchically structured data where individuals are nested within provinces. The model incorporates individual-level factors such as driver behavior, vehicle conditions, environmental settings, and collision characteristics, alongside province-level factors such as population size, AADT, and total highway length. The study also investigates provincial differences in crash severity and assesses whether province-level characteristics moderate the effects of individual-level risk factors.

This research is grounded in a conceptual framework that acknowledges the hierarchical nature of crash data a perspective that has not yet been applied to truck-related crashes in Thailand. By integrating micro-level behavioral data with macro-level spatial contexts, the study highlights the complex interconnections between risky behaviors and structural environments. Moreover, the inclusion of cross-level interaction analysis offers new insights into how the same behavior may have differing impacts across regions, underscoring the importance of flexible and context-sensitive road safety strategies. The findings are expected to contribute empirical evidence to support the development of region-specific traffic safety policies that are responsive to local realities.

2 Conceptual foundations and related studies

2.1 Individual-level impact on the severity of truck injuries

The severity of injuries resulting from truck-related crashes is not a random occurrence, nor can it be attributed to a single factor. Instead, it results from the complex interplay of various individual-level determinants, including driver behavior, vehicle technical conditions, environmental contexts, and the specific nature of the collision. A systematic investigation that clearly distinguishes the roles of these factor groups allows for a more profound understanding of the mechanisms underlying injury severity. Such insights are essential for designing targeted and effective policy interventions that correspond to the behavioral risk profiles of specific groups.

Based on empirical evidence and an extensive literature review, individual-level determinants of injury severity can be categorized as follows:

Environmental Factors, Environmental conditions at the time of the crash play a critical role in determining injury severity. Crashes occurring during weekends, nighttime hours (Behnood and Al-Bdairi, 2020; Habib et al., 2025; Champahom et al., 2023; Wang et al., 2019), or in poorly lit areas often reflect temporal and spatial contexts where changes in driver behavior and roadway conditions are more pronounced (Uddin and Huynh, 2018; Wei et al., 2022; Hao et al., 2016; Habib et al., 2025; Azimi et al., 2022; Uddin and Huynh, 2020). Furthermore, road surface conditions such as dry versus wet pavement may influence vehicle traction and visibility, thereby affecting crash outcomes (Habib et al., 2024; Yu et al., 2022; Chen et al., 2015; Champahom et al., 2023; Chen and Chen, 2011).

Roadway Characteristics, Roadway characteristics represent critical physical factors that should be incorporated into analyses of crash severity. In particular, roads without a median, straight road segments, two-way traffic roads, and areas with direct access to private or commercial premises such as U-turn locations, pedestrian crossings with central refuges, or grade-separated intersections often involve complex traffic patterns. These conditions can encourage risky driving behaviors, such as abrupt lane changes or sudden cut-ins, reflecting both the intricacy of traffic flow and deficiencies in road space management. Such features may be linked to different patterns of driver behavior and crash occurrence (Azimi et al., 2022; Alrejja et al., 2021; Champahom et al., 2023).

Vehicle Characteristics, the technical condition of trucks such as defective brakes, malfunctioning steering systems, or worn tires can significantly influence both the occurrence and severity of crashes. These mechanical deficiencies represent the operational readiness of the vehicle and its actual condition during use. They serve as key indicators of roadworthiness and may play a crucial role in shaping crash outcomes.

Driving Risk Behaviors, Risky driving behavior is a critical individual-level factor that contributes both to the likelihood of crash occurrence and the severity of its outcomes. Common behaviors examined in the literature include abrupt cut-ins, driving under the influence of alcohol, and violations of traffic regulations (Chen et al., 2015; Behnood and Al-Bdairi, 2020; Champahom et al.,

2023). Additional behaviors such as overloading beyond legal limits (Wang et al., 2019; Wang et al., 2021; Chen et al., 2020), excessive speeding (Chen et al., 2015; Wang et al., 2021), and impaired driver condition such as drowsiness, fatigue, or lack of attention have also been found to significantly affect drivers' decision-making and their ability to respond to sudden hazards (Behnood and Al-Bdairi, 2020).

Collision Types, the type of collision plays an important role in determining the severity of injuries sustained in truck crashes. Common patterns such as rear-end collisions or crashes involving parked vehicles frequently occur in truck-related incidents and are often included in severity analyses. These characteristics provide insight into the magnitude of impact forces, pre-crash movement patterns, and the specific locations of impact, all of which may influence the extent of injury and damage in different scenarios (Behnood and Al-Bdairi, 2020; Behnood and Mannering, 2019; Uddin and Huynh, 2020).

A deep understanding of each group of individual-level factors is therefore crucial not only for explaining why certain crashes result in more severe outcomes than others, but also for identifying the root causes of risk with greater specificity. These causes may stem from driver behavior, inadequate vehicle maintenance, or poor management of critical environmental conditions at the time of the crash. Analysis at this level serves as a foundation for designing effective prevention strategies that can substantially reduce the negative impacts of truck-related crashes.

However, while individual-level factors play a significant role in determining crash severity, the behaviors and outcomes observed are also shaped by the broader spatial context in which they occur. These contextual conditions lie beyond an individual's control, yet they may significantly influence crash severity. Therefore, the next section turns to provincial-level factors as contextual elements that may frame, amplify, or moderate the severity of truck-related crashes across different regions.

2.2 Provincial-level impact on the severity of truck injuries

Although individual-level factors such as driving behavior and vehicle condition play a crucial role in explaining the severity of road traffic crashes, provincial-level contextual factors also serve as essential structural components that should not be overlooked. Spatial environments exert subtle but significant influences on driver behavior and the conditions under which crashes occur. Factors such as population density, Average Annual Daily Traffic, and the extent of the Highway Lengths as highlighted in previous studies (Jafari Anarkooli and Hadji Hosseinlou, 2016; Shinstine et al., 2016; Hosseinpour and Haleem, 2021; Islam et al., 2022; Hao et al., 2016; Habib et al., 2025; Casado-Sanz et al., 2020), reflect systemic risk levels, traffic complexity, and the region's capacity to manage road safety. These elements can either mitigate or amplify the consequences of individual risk behaviors. Studying provincial-level factors is therefore critical not only for understanding the broader context in which road users operate, but also for uncovering the spatial mechanisms underlying crash severity. Such insights are essential for designing safety interventions that are responsive to the specific characteristics of each region.

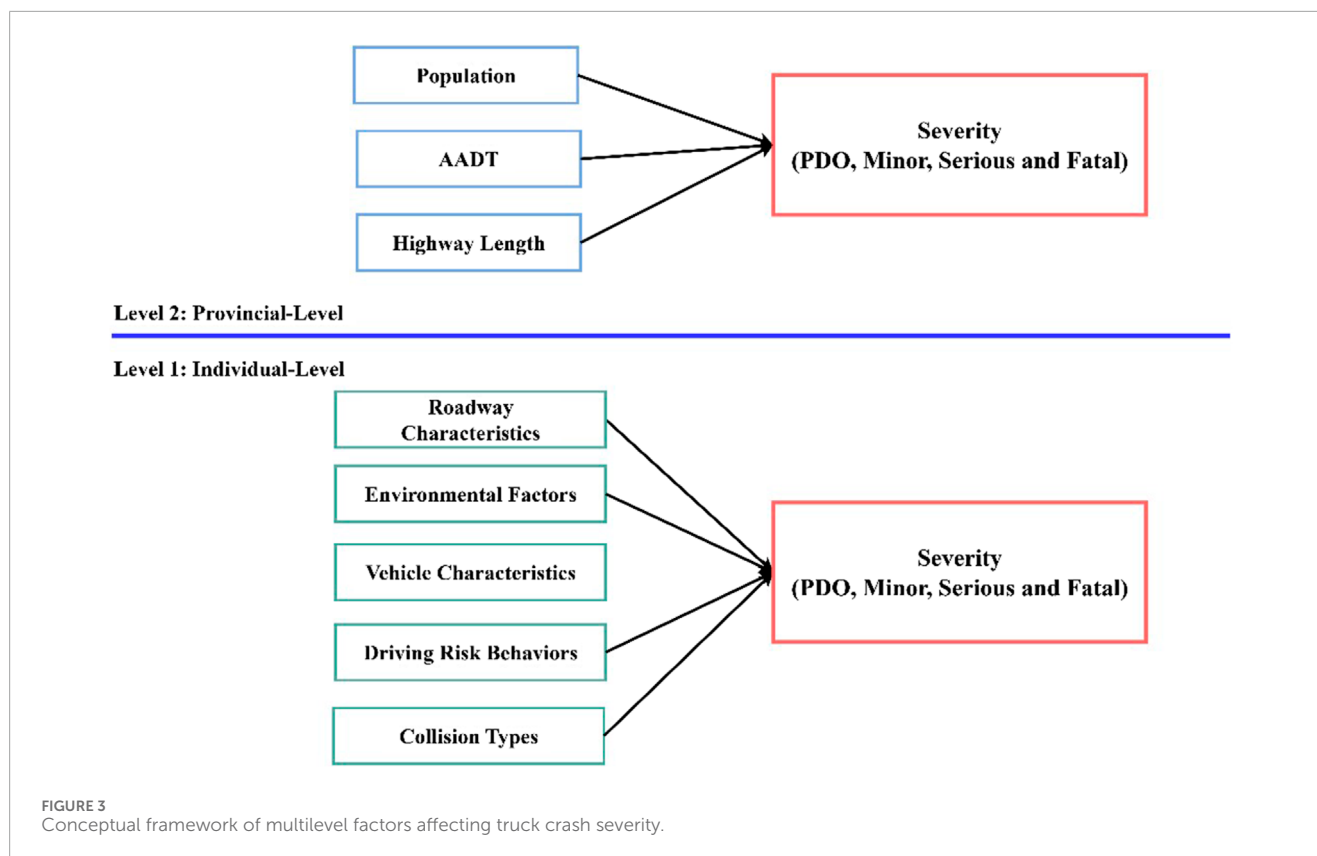
Figure 3 illustrates the conceptual framework employed in this study, which distinguishes between individual-level and provincial-level factors affecting the severity of truck-involved crashes. The individual-level domain encompasses roadway characteristics, environmental conditions, vehicle attributes, driving risk behaviors, and collision types all of which directly influence the outcome of crash severity. Meanwhile, the provincial-level context defined by factors such as population, AADT, and highway length represents broader structural conditions that may exert contextual effects or moderate individual-level influences. This two-level structure underpins the multilevel modeling approach adopted in the analysis and reflects the hierarchical nature of crash data.

3 Methodology

3.1 Data description

This study utilized data on truck-involved crashes that occurred on major highways in Thailand in 2022. The data were obtained from the Highways Accident Information Management System (HAIMS) (HAIMS, 2022), maintained by the Department of Highways. A total of 4,462 crash cases were included in the analysis, selected based on the completeness of relevant variables, with missing cases excluded using listwise deletion. Data from a single year were used because this period provided the most comprehensive and internally consistent coverage across provinces, thereby ensuring uniform reporting standards and variable definitions. Such consistency is essential for multilevel modeling, which requires comparable data structures across all provinces. Moreover, because these cases were distributed across 77 provinces, the dataset provided not only a large number of Level-1 observations but also a sufficient number of Level-2 units for robust estimation. Previous methodological guidelines indicate that reliable estimation of cross-level interactions requires at least 30–50 groups at Level-2 with adequate within-group cases (Hox and Maas, 2004; Snijders and Bosker, 2011). Accordingly, the present dataset exceeds these recommended thresholds, ensuring adequate statistical power for detecting cross-level moderation effects. The dependent variable (Y) in this study is crash severity, classified into four ordinal levels: (1) Property Damage Only (PDO), denoting crashes with material damage but no injuries; (2) Minor Injury, involving non-hospitalized injuries; (3) Serious Injury, requiring hospitalization; and (4) Fatality, referring to crashes with at least one fatality. This classification reflects a logically ordered progression of crash severity, recorded according to official Department of Highways standards, consistent with police definitions, and cross-validated with hospital data for serious and fatal cases.

The individual-level variables, as shown in Table 1 and detailed in the Appendix Table A1, were also derived from the HAIMS database to ensure consistency in data structure and technical compatibility for multilevel modeling. These variables encompass a range of factors, including environmental conditions at the time of the crash (e.g., lighting and road surface), roadway characteristics (e.g., median type and road alignment), vehicle conditions, risky driving behaviors (e.g., speeding, driving under the influence, impaired driving), and collision types. The frequency



and percentage distributions of these variables across severity levels provide preliminary insights into how different factors may contribute to increased crash severity.

In addition to individual-level characteristics, provincial-level contextual factors were incorporated as Level-2 predictors to account for regional variation in crash severity. Table 2 summarizes the provincial-level variables used as Level-2 contextual predictors in the multilevel analysis. These include total population (National Statistical Office of Thailand, 2022), annual average daily traffic (AADT) (Bureau of Highway Safety, 2022b), and total Highway Length (Bureau of Highway Safety, 2022a) under the jurisdiction of the Department of Highways. The mean values indicate that, across all provinces, the average population was approximately 14.44 million people, the average daily traffic volume was about 945,850 vehicles, and the average Highway Length was 745.39 km per province. These variables provide important contextual information for capturing inter-provincial variation in crash severity.

3.2 Multilevel ordinal logit model

Multilevel analysis is a statistical technique used to investigate relationships among variables that are structured at more than one level or exhibit a hierarchical (nested) data structure, such as individual-level data nested within group-level contexts (Kanjawasee, 2011; Singer, 1998). In this study, a Multilevel Ordered Logit Model is employed an extension of ordinal logistic regression that accounts for group-level clustering to analyze the

severity of truck-involved crashes, an outcome categorized into ordered levels: (1) Property Damage Only, (2) Minor Injury, (3) Serious Injury, and (4) Fatality. The analysis is based on individual-level crash records nested within provincial-level contexts. These provincial contexts may exert influences on individual behavior and crash outcomes and ignoring such influences may lead to biased estimates. By applying a multilevel modeling framework, the study is able to disentangle and estimate the distinct effects of variables operating at both individual and provincial levels, thereby enhancing both the explanatory power and predictive accuracy of the model.

Parameter estimation for the Multilevel Ordered Logit Model was conducted using Maximum Likelihood Estimation (ML) implemented via Mplus version 7. To evaluate model fit, several key indices were employed: Akaike Information Criterion (AIC) (Akaike, 1998), Bayesian Information Criterion (BIC) (Gideon, 1978), and the Likelihood Ratio Test (LRT) for comparing nested models. Models with lower AIC and BIC values are considered to have better fit, while the LRT is used to assess whether a more complex model provides a significant improvement in explaining data variability over a simpler nested model.

3.3 Model development

To comprehensively capture both direct effects and cross-level contextual influences, this study adopts a stepwise modeling strategy comprising four hierarchical models, progressing from a basic to a more complex structure. This modeling approach aligns with prior empirical studies such as Chen et al. (2015),

TABLE 1 Descriptive statistics of individual-level variables.

Variables	Category	Severity injury				
		PDO	Minor	Serious	Fatal	Total
Environmental Factors	Crash Day Type					
	WeekDay	1837 (41.17%)	969 (21.72%)	215 (4.82%)	377 (8.45%)	3,398 (76.15%)
	Weekend	517 (11.59%)	330 (7.40%)	78 (1.75%)	139 (3.12%)	1,064 (23.85%)
	Crash Time Period					
	Day	1,445 (32.38%)	733 (16.43%)	152 (3.41%)	258 (5.78%)	2,588 (58.00%)
	Night	909 (20.37%)	566 (12.68%)	141 (3.16%)	258 (5.78%)	1874 (42.00%)
	Lighting Condition					
	Dark_Lit	739 (16.56%)	447 (10.02%)	103 (2.31%)	189 (4.24%)	1,478 (33.12%)
	Dark_NoLit	1,615 (36.19%)	852 (19.09%)	190 (4.26%)	327 (7.33%)	2,984 (66.88%)
	Road Surface Condition					
	Dry	2025 (45.38%)	1,133 (25.39%)	265 (5.94%)	473 (10.60%)	3,896 (87.32%)
	Wet	329 (7.37%)	166 (3.72%)	28 (0.63%)	43 (0.96%)	566 (12.68%)
Roadway Characteristics	Median					
	Med_No	238 (5.33%)	189 (4.24%)	48 (1.08%)	113 (2.53%)	588 (13.18%)
	Med_Yes	2,116 (47.42%)	1,110 (24.88%)	245 (5.49%)	403 (9.03%)	3,874 (86.82%)
	Road Alignment					
	Curve	383 (8.58%)	220 (4.93%)	35 (0.78%)	65 (1.46%)	703 (15.76%)
	Straight	1971 (44.17%)	1,079 (24.18%)	258 (5.78%)	451 (10.11%)	3,759 (84.24%)
	Road Connection					
	NoCon	2,334 (52.31%)	1,285 (28.80%)	287 (6.43%)	502 (11.25%)	4,408 (98.79%)
	Con	20 (0.45%)	14 (0.31%)	6 (0.13%)	14 (0.31%)	54 (1.21%)
	Specific Locations					
	Others	2,166 (48.54%)	3,188 (71.45%)	4,171 (93.48%)	3,954 (88.62%)	93 (2.08%)
	U-turn	21 (0.47%)	8 (0.18%)	1 (0.02%)	4 (0.09%)	34 (0.76%)
	CROSS_MED	2,275 (50.99%)	1,266 (28.37%)	290 (6.50%)	504 (11.29%)	4,335 (97.16%)
	Traffic Direction					
	Oneway	24 (0.54%)	9 (0.20%)	1 (0.02%)	4 (0.09%)	38 (0.85%)
	TwoWay	2,330 (52.22%)	1,290 (28.91%)	292 (6.54%)	512 (11.47%)	4,424 (99.15%)
Vehicle Characteristics						
	Other	4,309 (96.57%)	4,401 (98.63%)	4,456 (99.87%)	4,445 (99.62%)	4,225 (94.69%)
	Damage_V	153 (3.43%)	61 (1.37%)	6 (0.13%)	17 (0.38%)	237 (5.31%)

(Continued on the following page)

TABLE 1 (Continued) Descriptive statistics of individual-level variables.

Variables	Category	Severity injury				
		PDO	Minor	Serious	Fatal	Total
Driving Risk Behaviors						
	Others	2,598 (58.22%)	3,420 (76.64%)	4,221 (94.61%)	4,022 (90.14%)	875 (19.61%)
	OverLoad	42 (0.94%)	15 (0.34%)	0 (0.00%)	3 (0.07%)	60 (1.34%)
	OverSpeed	1,555 (34.85%)	874 (19.59%)	194 (4.35%)	341 (7.64%)	2,964 (66.43%)
	CUT_IN	155 (3.47%)	101 (2.26%)	31 (0.69%)	52 (1.17%)	339 (7.60%)
	IMP_DRV	78 (1.75%)	23 (0.52%)	6 (0.13%)	13 (0.29%)	120 (2.69%)
	TF_VIOL	27 (0.61%)	24 (0.54%)	8 (0.18%)	26 (0.58%)	85 (1.90%)
	Drunk	7 (0.16%)	5 (0.11%)	2 (0.04%)	5 (0.11%)	19 (0.43%)
Collision Type						
	Other	3,604 (80.77%)	4,070 (91.22%)	4,369 (97.91%)	4,354 (97.58%)	3,011 (67.48%)
	REAREND	771 (17.28%)	353 (7.91%)	78 (1.75%)	88 (1.97%)	1,290 (28.91%)
	HITPCAR	87 (1.95%)	39 (0.87%)	15 (0.34%)	20 (0.45%)	161 (3.61%)

TABLE 2 Descriptive statistics of provincial-level variables.

Variables	Mean	Unit
Population	1444035.27	Persons
Annual Average Daily Traffic (AADT)	945850.30	Vehicles per day
Highway Length	745.39	Kilometers (km)

who employed a hierarchical Bayesian multinomial logit model to examine truck driver injury severity in rural crashes, explicitly incorporating cross-level interaction effects. Similarly, [Chen et al. \(2016\)](#) utilized a hierarchical ordered logit model that integrated crash-level random effects to account for within-crash correlations and between-crash heterogeneity, emphasizing the importance of acknowledging the nested structure commonly found in traffic safety data.

Following these methodological precedents, the present study begins with Model 1, the Null Model, which excludes explanatory variables and instead focuses solely on estimating the proportion of variance in crash severity attributable to provincial-level differences. This is assessed using the Intraclass Correlation Coefficient (ICC), where a value exceeding 0.05 ([Heck and Thomas, 2009](#)). Indicates substantial between-group variance and thus supports the use of multilevel modeling. The Null Model serves as a baseline for evaluating the added explanatory power of more advanced models in subsequent stages.

Model 2 extends the analysis by incorporating both individual-level (Level 1) and provincial-level (Level 2) explanatory variables

as fixed effects to examine the direct impact of various factors on crash severity. This model assumes that the effects of all predictors are constant across provinces, thereby disallowing any variation in the strength of associations by contextual settings (i.e., no random slopes). Such an approach is appropriate for identifying direct effects of environmental, infrastructural, and behavioral factors on the severity outcomes, under the assumption of uniform influence across all provinces.

However, the assumption of constant effects across provinces in Model 2 may not fully capture the spatial heterogeneity present in real-world settings. To address this limitation, Model 3 introduces additional complexity by allowing random slopes for selected behavioral and vehicle-related predictors. As noted by [Grilli and Rampichini \(2015\)](#), relaxing the assumption of constant effects is often necessary when contextual differences are expected to influence the relationship between predictors and outcomes. In line with this reasoning, the predictors in our study were chosen because their impacts on crash severity are plausibly shaped by provincial differences such as enforcement rigor, inspection practices, infrastructure conditions, and traffic environments. Recent evidence from Thailand supports this approach: [Champahom et al. \(2021\)](#) showed that risky driving behaviors, including abrupt lane changes and rear-end crashes, vary significantly across provinces, indicating context-dependent effects. Similarly, [Salgado et al. \(2022\)](#) found that mechanical failure risks differed across cities depending on inspection and maintenance systems, while [Ben Laoula et al. \(2023\)](#) documented that traffic violations such as speeding and license-related offenses were more prevalent in certain districts. By specifying random slopes for these predictors, Model 3 accounts for realistic cross-provincial variability

TABLE 3 Multilevel ordinal logit analysis results of truck crashes.

Variables		Model 1		Model 2				Model 3				Model 4				
Category		Est.	Est.	Est.	OR	SE	CI 95%	Est.	OR	SE	CI 95%	Est.	OR	SE	CI 95%	
Provincial-level factors																
	POP	-		0.121	-	0.135	(0.866–1.470)	0.281**	-	0.11	(1.068–1.643)	0.153	-	0.127	(0.909–1.495)	
	AADT	-		-0.229**	-	0.098	(0.656–0.964)	-0.190*	-	0.103	(0.676–1.012)	-0.297**	-	0.1	(0.611–0.904)	
	HW	-		0.16*	-	0.097	(0.970–1.419)	-0.037	-	0.095	(0.800–1.161)	0.194**	-	0.097	(1.004–1.468)	
Individual-level Factors																
Environmental Factors	Crash Day Type															
	WeekDay (Ref)															
	Weekend	-		0.215**	1.24	0.068	(1.085–1.417)	0.212**	1.236	0.069	(1.080–1.415)	0.207**	1.23	0.069	(1.074–1.408)	
	Crash Time Period															
	Day (Ref)															
	Night	-		0.309***	1.362	0.065	(1.199–1.547)	0.311***	1.365	0.066	(1.199–1.553)	0.321***	1.378	0.066	(1.211–1.569)	
	Lighting Condition															
	Dark_Lit (Ref)															
	Dark_NoLit	-		0.162	1.176	0.111	(0.946–1.462)	0.17	1.185	0.112	(0.952–1.476)	0.186	1.205	0.113	(0.965–1.503)	
	Road Surface Condition															
Roadway Characteristics	Dry (Ref)															
	Wet	-		-0.272**	0.762	0.092	(0.636–0.912)	-0.301**	0.74	0.093	(0.617–0.888)	-0.301**	0.74	0.094	(0.616–0.890)	
	Median															
	Med_Yes (Ref)															
	Med_No	-		0.440***	1.553	0.099	(1.279–1.885)	0.477***	1.611	0.102	(1.319–1.968)	0.482***	1.62	0.106	(1.316–1.993)	
	Road Alignment															
	Curve (Ref)															

(Continued on the following page)

TABLE 3 (Continued) Multilevel ordinal logit analysis results of truck crashes.

Variables		Model 1			Model 2			Model 3			Model 4		
Category		Est.	Est.		Est.	OR	SE	CI 95%	Est.	OR	SE	CI 95%	
Straight		-	0.334***		1.396	0.089	0.089	(1.173–1.663)	0.322***	1.379	0.09	(1.157–1.646)	0.269** (1.095–1.564)
Road Connection													
NoCon (Ref)													
Con		-	0.525**		1.691	0.267	0.267	(1.002–2.853)	0.431	1.539	0.28	(0.889–2.664)	0.422 (0.876–2.656)
Specific Locations													
Others (Ref)													
U-turn			0.467**		1.595	0.221	0.221	(1.034–2.460)	0.461**	1.585	0.228	(1.014–2.479)	0.522** (1.082–2.625)
CROSS_MED		-	0.503		1.653	0.419	0.419	(0.727–3.759)	0.455	1.577	0.425	(0.685–3.626)	0.534 (0.739–3.939)
Traffic Direction													
Oneway (Ref)													
TwoWay		-	0.162		1.176	0.345	0.345	(0.598–2.312)	0.335	1.398	0.364	(0.685–2.853)	0.183 (0.604–2.389)
Vehicle Characteristics													
Other (Ref)													
Damage_V			−0.403**		0.668	0.159	0.159	(0.489–0.913)	-	-	-	-	-
Driving Risk Behaviors													
Others (Ref)													
OverLoad		-	−0.763**		0.466	0.296	0.296	(0.261–0.833)	-	-	-	-	-
Speed			0.199**		1.22	0.088	0.088	(1.027–1.450)	0.114	1.121	0.1	(0.921–1.363)	0.177* (0.997–1.429)
CUT_IN		-	0.444**		1.559	0.134	0.134	(1.199–2.027)	-	-	-	-	-

(Continued on the following page)

TABLE 3 (Continued) Multilevel ordinal logit analysis results of truck crashes.

Variables	Model 1			Model 2			Model 3			Model 4				
	Category	Est.	Est.	OR	SE	CI 95%	Est.	OR	SE	CI 95%	Est.	OR	SE	CI 95%
Collision Type	IMP_DRV	-	-0.471**	0.624	0.213	(0.411–0.948)	-0.557**	0.573	0.215	(0.376–0.873)	-0.482**	0.617	0.217	(0.404–0.945)
	TF_VIOL	-	1.172***	3.228	0.221	(2.094–4.979)	-	-	-	-	-	-	-	-
	Drunk			2.475	0.443	(1.038–5.896)	0.804**	2.234	0.443	(0.938–5.324)	0.796*	2.216	0.447	(0.923–5.323)
Collision Type														
Collision Type	Other (Ref)													
	REAREND	-	-0.270***	0.763	0.082	(0.650–0.896)	-	-	-	-	-	-	-	-
	HITPCAR	-	-0.145	0.865	0.183	(0.604–1.238)	-0.178	0.837	0.18	(0.588–1.191)	-0.193	0.824	0.212	(0.544–1.249)

Est. = estimates; OR, odds ratio; SE, standard error; *p-value <0.1; **p-value <0.05; ***p-value <0.01.

and better reflects how contextual characteristics can moderate the effects of individual-level risk factors.

Finally, Model 4, the most comprehensive and complex model in this study, incorporates cross-level interactions to examine whether provincial-level characteristics such as population size, average annual daily traffic (AADT), and total highway length under the Department of Highways moderate the relationships between individual-level behaviors and crash severity. This modeling approach allows for a nuanced understanding of how macro-level contextual factors can amplify or mitigate the effects of micro-level behaviors. A similar four-stage hierarchical modeling framework was adopted in a previous study by [Chen and Jou \(2019\)](#), which analyzed traffic crash risks in relation to public transportation systems in metropolitan Taiwan. Their use of nested structures and interaction effects highlights the importance of capturing contextual variability in transportation safety research.

Such an analysis provides significant policy-relevant insights, particularly for the development of area-based road safety interventions. By identifying where and how context modifies risk patterns, Model 4 supports the design of more targeted, efficient, and contextually appropriate safety measures that align with the geographic and infrastructural diversity of Thailand.

4 Results

4.1 Multilevel model estimation results

All four models converged successfully with stable log-likelihood values after a reasonable number of iterations. Parameter estimates were within admissible ranges, and standard errors were of acceptable magnitude, confirming the stability and robustness of the estimation process. No convergence failures or estimation problems were detected. Although the primary aim of this model development was not to select the model with the best statistical fit, the stepwise progression from Model 1 to Model 4 reflects a logical advancement in the analysis and reveals contextual mechanisms that are not identifiable in the initial baseline models. The inclusion of provincial-level variables and the examination of cross-level interactions play a crucial role in explaining complex phenomena, particularly in the context of highway crashes, which are influenced by both individual-level factors and broader spatial structures. The estimation results for all models are summarized in [Tables 3–5](#).

4.1.1 Null Model

The analysis began with Model 1 (Null Model), which included no explanatory variables at either the individual or provincial levels. This baseline model aimed to assess whether there were significant differences in crash severity across provinces. The results indicated that the intraclass correlation coefficient (ICC) was 0.051, which is considered relatively substantial and statistically significant. This suggests that approximately 5.1% of the total variance in crash severity can be attributed to differences between provinces. Therefore, it is appropriate to apply a multilevel modeling approach instead of a single-level model, which would be inadequate for capturing the contextual effects at the provincial level.

TABLE 4 Random effects and cross-level interactions from multilevel ordered logit models (Models 1–4).

Variables	Model 1	Model 2				Model 3				Model 4			
	Est.	Est.	OR	SE	CI 95%	Est.	OR	SE	CI 95%	Est.	OR	SE	CI 95%
Random Effect													
DAMAGE_V	-	-	-	-	-	0.09	1.094	0.076	(0.943–1.270)	0.074	1.077	0.063	(0.952–1.218)
CUT_IN	-	-	-	-	-	0.375**	1.455	0.163	(1.057–2.003)	0.273	1.314	0.195	(0.897–1.926)
TF_VIOL	-	-	-	-	-	0.55	1.733	0.545	(0.596–5.044)	0.297	1.346	0.271	(0.791–2.289)
OVERLOAD	-	-	-	-	-	1.043*	2.838	0.55	(0.966–8.339)	0.843	2.323	0.579	(0.747–7.227)
REAREND	-	-	-	-	-	0.124	1.132	0.082	(0.964–1.329)	0.199	1.220	0.159	(0.893–1.666)
Cross-Interaction													
DAMAGE_V × POP	-	-	-	-	-	-	-	-	-	-0.09	0.914	0.331	(0.478–1.749)
DAMAGE_V × AADT	-	-	-	-	-	-	-	-	-	0.076	1.079	0.291	(0.610–1.909)
DAMAGE_V × HW	-	-	-	-	-	-	-	-	-	0.217	1.242	0.221	(0.806–1.916)
CUT_IN × POP	-	-	-	-	-	-	-	-	-	-0.695**	0.499	0.33	(0.261–0.953)
CUT_IN × AADT	-	-	-	-	-	-	-	-	-	0.167	1.182	0.277	(0.687–2.034)
CUT_IN × HW	-	-	-	-	-	-	-	-	-	0.599**	1.820	0.255	(1.104–3.001)
TF_VIOL × POP	-	-	-	-	-	-	-	-	-	-1.288	0.276	0.807	(0.057–1.341)
TF_VIOL × AADT	-	-	-	-	-	-	-	-	-	0.131	1.140	0.399	(0.522–2.492)
TF_VIOL × HW	-	-	-	-	-	-	-	-	-	0.334	1.397	0.34	(0.717–2.719)
OVERLOAD × POP	-	-	-	-	-	-	-	-	-	2.199***	9.016	0.308	(4.930–16.489)
OVERLOAD × AADT	-	-	-	-	-	-	-	-	-	-0.797	0.451	0.572	(0.147–1.383)
OVERLOAD × HW	-	-	-	-	-	-	-	-	-	-0.396	0.673	0.394	(0.311–1.457)
REAREND × POP	-	-	-	-	-	-	-	-	-	0.401	1.493	0.304	(0.823–2.710)
REAREND × AADT	-	-	-	-	-	-	-	-	-	-0.734**	0.480	0.267	(0.284–0.810)
REAREND × HW	-	-	-	-	-	-	-	-	-	-0.018	0.982	0.248	(0.604–1.597)

(Continued on the following page)

TABLE 4 (Continued) Random effects and cross-level interactions from multilevel ordered logit models (Models 1–4).

	Model 1	Model 2				Model 3				Model 4			
	Est	Est	OR	SE	CI 95%	Est	OR	SE	CI 95%	Est	OR	SE	CI 95%
Thresholds													
PDO	0.110***	0.834	-	1.191	-	2.261**	-	0.865	-	-0.097*	-	0.057	-
Minor	1.508***	2.332**	-	1.192	-	3.780***	-	0.87	-	1.426***	-	0.061	-
Serious	2.034***	2.888**	-	1.193	-	4.343***	-	0.873	-	1.991***	-	0.066	-

Est. = estimates; OR, odds ratio; SE, standard error; *p-value <0.1; **p-value <0.05; ***p-value <0.01.

TABLE 5 Model fit statistics for multilevel ordered logit models (models 1–4).

Model fit	Model 1	Model 2	Model 3	Model 4
AIC	10044.676	9743.178	9736.899	9732.572
BIC	10063.886	9909.665	9935.403	10027.127
LL	-5019.338	-4845.589	-4837.449	-4820.286
-2LL	10038.676	9691.178	9674.898	9640.572
Likelihood Ratio Test (LRT)	-	0.000	0.006	0.003
Number of parameters	3	26	31	46

4.1.2 Individual-level predictors

In Model 2, individual-level (Level-1) variables were introduced, encompassing road characteristics, environmental conditions, vehicle condition, driving behaviors, and collision types. The aim was to identify preliminary risk factors associated with crash severity. The results revealed that several factors were significantly correlated with the severity of crashes.

Notably, certain physical characteristics of roads showed strong associations. Roads without a central median increased the likelihood of severe outcomes by approximately 55.30%–62%, while straight road segments were associated with a 30.90%–39.60% higher risk. U-turn zones also exhibited a heightened probability of severe crashes.

Regarding environmental conditions, crashes occurring at night and on weekends tended to be more severe, particularly those at night, which increased the risk by around 36.20%–37.80%. Interestingly, wet road surfaces were associated with a reduction in crash severity by about 23.80%–26.00%, possibly reflecting more cautious driving behavior in adverse road conditions.

As for vehicle-related factors, trucks with mechanical defects were associated with a 33.20% reduction in severity, which might be due to more careful driving when vehicle issues are known. In terms of driver behavior, driving under the influence of alcohol was the most critical risk factor, increasing the likelihood of severe crashes by 121.60%–147.50%. Conversely, drivers with impaired performance due to fatigue or drowsiness showed a decrease in severity, potentially because of increased caution while driving in such conditions. Speeding was associated with increased severity only in specific areas.

Finally, regarding collision types, rear-end crashes were associated with a reduction in severity by about 23.70%, likely due to their occurrence at lower speeds. Collisions involving parked vehicles showed a slight decrease in severity but were not statistically significant.

These findings indicate that crash severity results from specific risk behaviors and localized environmental conditions, forming a solid foundation for advancing to higher-level models.

4.1.3 Provincial-level predictors

In Model 3, provincial-level (Level-2) variables were incorporated, including population size, average annual daily traffic (AADT), and total highway length in each province, to examine whether spatial context contributes to crash severity. The results indicated that AADT had a statistically significant negative coefficient, suggesting that provinces with higher traffic volumes tend to experience less severe crashes. This may reflect the effects of slower traffic speeds or improved road infrastructure in high-volume areas.

Additionally, the total highway length in a province was also negatively associated with crash severity, implying that greater road coverage may contribute to better traffic dispersion or access to safer routes. However, provincial population size did not show a significant association at this stage, although its influence becomes more apparent in Model 4 when cross-level interactions are considered.

The inclusion of Level-2 variables also led to a reduction in the residual variance of certain driving behaviors, indicating that crash severity is not solely the result of individual-level risk factors.

Instead, it is also shaped by the structural characteristics of the province in which the driver operates.

4.1.4 Cross-level interactions

Finally, Model 4 introduced an additional layer of complexity by incorporating cross-level interactions between individual-level factors and provincial-level contextual variables. This step aimed to examine whether the effects of certain risk behaviors vary depending on the spatial characteristics of the province where the crash occurred.

The results indicate that the influence of risky driving behaviors among truck drivers is significantly moderated by contextual characteristics at the provincial level. Notably, abrupt cut-in behavior was associated with lower crash severity in provinces with higher population density, likely due to reduced average speeds and more defensive driving in congested urban environments. In contrast, the same behavior was linked to increased severity in provinces with greater Highway Length, which typically reflects rural areas where higher travel speeds and limited safety infrastructure heighten the consequences of such maneuvers.

For overloading behavior, a significant positive interaction with population density was observed, suggesting that crashes involving overloaded trucks tend to be more severe in densely populated areas. This may stem from a higher likelihood of collisions involving vulnerable road users such as pedestrians and motorcyclists. In contrast, rear-end collisions demonstrated a negative interaction with average annual daily traffic (AADT). In provinces with high AADT often urbanized areas with frequent congestion slower speeds likely mitigate the severity of such crashes due to reduced kinetic energy upon impact.

Taken together, these findings underscore that the relationship between truck driver behavior and crash severity is not homogeneous across space. Instead, it is shaped by interactions with regional-level characteristics, emphasizing the importance of incorporating contextual variables into models assessing crash risk.

4.1.5 Model fit evaluation and methodological implications

Beyond parameter estimation, model fit indices such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the -2 Log-Likelihood ($-2LL$) offer valuable insights into the explanatory performance of the models developed. From Model 1 to Model 4, both AIC and $-2LL$ consistently declined (e.g., from 10,044.676 to 10,038.676 in Model 1 to 9,733.306 and 9,640.572 in Model 4), suggesting improvements in model fit and a reduction in residual deviance as model complexity increased.

In addition, Likelihood Ratio Tests (LRT) used to compare nested models indicated that incorporating random slopes and cross-level interactions (from Model 2 to 3 and from Model 3–4) significantly enhanced the ability to account for variance in the outcome variable. This reflects the contribution of hierarchical model structures to capturing latent heterogeneity across provinces.

On the other hand, BIC values showed a slight increase in later models, particularly in Model 4 (10,027.860), despite improvements in log-likelihood. This occurs because BIC applies a stronger penalty for model complexity, which is sensitive to both the number of parameters and the sample size. Accordingly, while AIC and $-2LL$ consistently indicated improved explanatory

performance as complexity increased, BIC values reflected a more conservative stance that prioritizes parsimony and the avoidance of overfitting (Burnham and Anderson, 2004; Raftery, 1995). This divergence illustrates the expected trade-off between favoring richer explanatory structures versus maintaining model simplicity.

In this study, the primary objective was not to identify a single “best” model based solely on statistical fit, but rather to uncover how individual-level driver behaviors interact with provincial-level contextual factors. From this perspective, the added complexity of Models 3 and 4 is substantively justified, as these specifications revealed cross-level interactions and contextual heterogeneity that would not be visible in simpler structures. Thus, fit indices must be interpreted alongside the study’s analytical goals: although BIC favors parsimony, the richer models offer greater theoretical insight and policy relevance. From a methodological perspective, changes in fit indices should therefore be viewed in conjunction with the research objectives. The progression from basic to more contextually nuanced models was aimed not only at improving statistical fit but also at identifying underlying behavioral and contextual mechanisms driving crash severity.

For instance, results from Models 3 and 4 highlighted that the effects of certain driver behaviors (e.g., straight-path driving, traffic violations) can vary by province. Moreover, provincial-level attributes such as population size and AADT appear to influence the strength of individual-level risk factors interactions that were not evident in the more basic models. These findings illustrate the methodological value of incorporating both random effects and cross-level interactions. While some fit indices may favor simpler structures, richer models enable more nuanced interpretations of behavioral dynamics and contextual influences, offering deeper insight into the mechanisms driving crash severity.

5 Discussion

5.1 Interpretation and contextual insights

The results of the multilevel model indicate that the severity of truck-involved crashes is not solely the result of driver behavior but is also significantly influenced by the contextual characteristics of the crash location. This finding highlights the importance of analytical approaches capable of handling nested data structures, where observations are organized at multiple levels. The statistically significant intraclass correlation coefficient ($ICC = 0.051$) supports the fundamental assumption that crash severity is not uniformly distributed across provinces in Thailand, thereby reinforcing the hypothesis of spatial heterogeneity in road safety research.

At the individual level, roadway design features emerged as critical determinants of crash severity. Roads lacking median barriers consistently exhibited higher risks of severe outcomes, consistent with Russo and Savolainen (2018), who showed that median-crossover crashes are among the most hazardous events and that the installation of barriers substantially reduces severity. In Thailand, Se et al. (2024) further demonstrated that roadway geometry, alignment, and median openings significantly shape truck crash outcomes, with effects varying over time. Similarly, Ahmed et al. (2018) found that heavy truck crashes on state and interstate highways in the United States were two to four times

more likely to be severe than those on local roads, highlighting the role of road classification and geometry. Evidence from other developing countries also corroborates these patterns: [Rahimi et al. \(2020\)](#) reported in Iran that roadway alignment, curvature, and classification strongly influenced the likelihood of severe truck crashes, while [Tian et al. \(2024\)](#) found in China that alignment, visibility, and section type were critical determinants of heavy truck crash severity. Taken together, these studies reinforce the robustness of our findings by showing that straight segments, U-turn points, and the absence of median barriers consistently exacerbate truck crash severity not only in Thailand but also across diverse developing contexts. The influence of proximity to access points of public or commercial areas was evident only in preliminary models and diminished after controlling for provincial-level variables. This suggests that increased risk is more attributable to broader contextual factors such as urban density, land-use patterns, and the complexity of the road network, rather than the mere presence of access points.

Environmental and temporal factors also played a significant role. Nighttime crashes showed higher severity, likely due to reduced visibility, fatigue, and higher speeds in low-traffic periods, while weekend crashes were more severe ([Anderson and Hernandez, 2017](#)), reflecting altered freight travel patterns and delivery pressures. Comparable evidence has been reported in other developing countries. For instance, [Bhuiyan et al. \(2022\)](#), analyzing crash severity in Bangladesh, identified environmental conditions such as the day and time of crash as significant determinants of injury outcomes. Similarly, [Junaid et al. \(2025\)](#) found in Pakistan that involvement of heavy vehicles, rainy weather, and the presence of only painted medians significantly increased the likelihood of severe injuries among vulnerable road users. This convergence of findings indicates that temporal and environmental risk factors are not unique to Thailand but represent broader patterns across developing contexts where enforcement gaps and fatigue accumulation further exacerbate crash severity.

Regarding driver behavior, driving under the influence of alcohol emerged as a primary risk factor, consistently doubling the likelihood of severe crashes across all models. This underscores the critical need for stringent law enforcement and targeted interventions, especially among commercial drivers. Similar findings have been reported in developing countries, where weak enforcement of drink-driving regulations has been linked to heightened severity in heavy-vehicle crashes ([Rahimi et al., 2020](#)). Conversely, conditions indicative of impaired driver capacity such as drowsiness, fatigue, or distraction were associated with reduced crash severity, possibly reflecting more cautious driving behavior when drivers are aware of their limitations, although such effects remain inconsistent across real-world settings. Speeding violations were also linked to increased severity in certain models, indicating potential interactions between speed and regional contextual factors. This highlights that increased speed not only raises the probability of crash occurrence but also directly exacerbates injury severity for drivers and other road users involved in truck-related incidents ([Chen and Chen, 2011](#); [Ahmed et al., 2018](#)). Collision types also influenced severity outcomes. Rear-end collisions generally resulted in lower severity compared to other types, although this effect was not statistically significant after adjusting for provincial factors. Random slope analyses indicated that the effect

of rear-end collisions was consistent across provinces. Collisions involving stationary vehicles showed a trend toward reduced severity but lacked statistical significance.

Some findings appeared counterintuitive. Notably, crash severity was found to decrease in wet road conditions and when vehicles had mechanical defects. While unexpected, such outcomes can be understood through risk compensation theory ([Wilde, 1982](#)), which posits that drivers consciously or subconsciously adjust their behavior when they perceive higher risks. For instance, in the presence of wet road surfaces or mechanical defects, drivers may reduce speed or adopt more cautious driving styles, thereby lowering the likelihood of severe outcomes ([Chen and Chen, 2011](#)). Importantly, these results should not be interpreted as suggesting that adverse conditions are protective factors; rather, they reflect temporary behavioral adaptations that may buffer severity in specific contexts. To avoid misinterpretation, this study acknowledges the limitation that such compensatory behaviors may not consistently occur in real-world settings, and future research should incorporate behavioral or telematics data to validate these mechanisms. Accordingly, safety policies should integrate direct risk mitigation with strategies that enhance drivers' risk perception and self-regulation.

Meanwhile, the analysis at the provincial level reveals that structural characteristics of geographical areas significantly influence the severity of truck-involved crashes. Key contextual factors such as population size, average annual daily traffic (AADT), and the total length of highways under the responsibility of the Department of Highways exert varying effects on crash outcomes. Provinces with higher population density tend to experience more severe crashes, likely due to the increased complexity of traffic environments and heightened risk of conflicts between various types of road users ([Cespedes et al., 2024](#)). In contrast, provinces with higher AADT levels typically report crashes of lower severity. This inverse relationship may be attributed to the fact that in areas with high traffic volumes, average driving speeds tend to be lower, thereby reducing the likelihood of severe crashes. This finding aligns with prior studies [Golob Thomas and Recker Wilfred \(2003\)](#), [Golob et al. \(2004\)](#), which have noted that crash severity tends to be negatively associated with overall traffic volume. Comparable evidence has also been reported in other developing contexts. [Zhang et al. \(2013\)](#), analyzing over 7,000 crashes annually in Guangdong Province, China, found that roadway and environmental conditions were significant predictors of accident severity, and highlighted that traffic exposure and insufficient enforcement aggravated fatality risks. Their results reinforce that AADT, and related exposure measures are structural determinants of crash severity across rapidly developing economies. On the other hand, provinces with longer highway networks under government jurisdiction tend to experience more severe crashes. This may be because such roads are often located in rural or interurban areas where average vehicle speeds are higher, and enforcement of traffic regulations as well as the availability of safety infrastructure are limited. As a result, crashes in these settings are more likely to lead to serious injuries or fatalities.

Further insight is gained through the analysis of cross-level interaction results provide critical insights into how the severity of truck-involved crashes is shaped by the interplay between individual driving behavior and regional contextual factors. As illustrated in

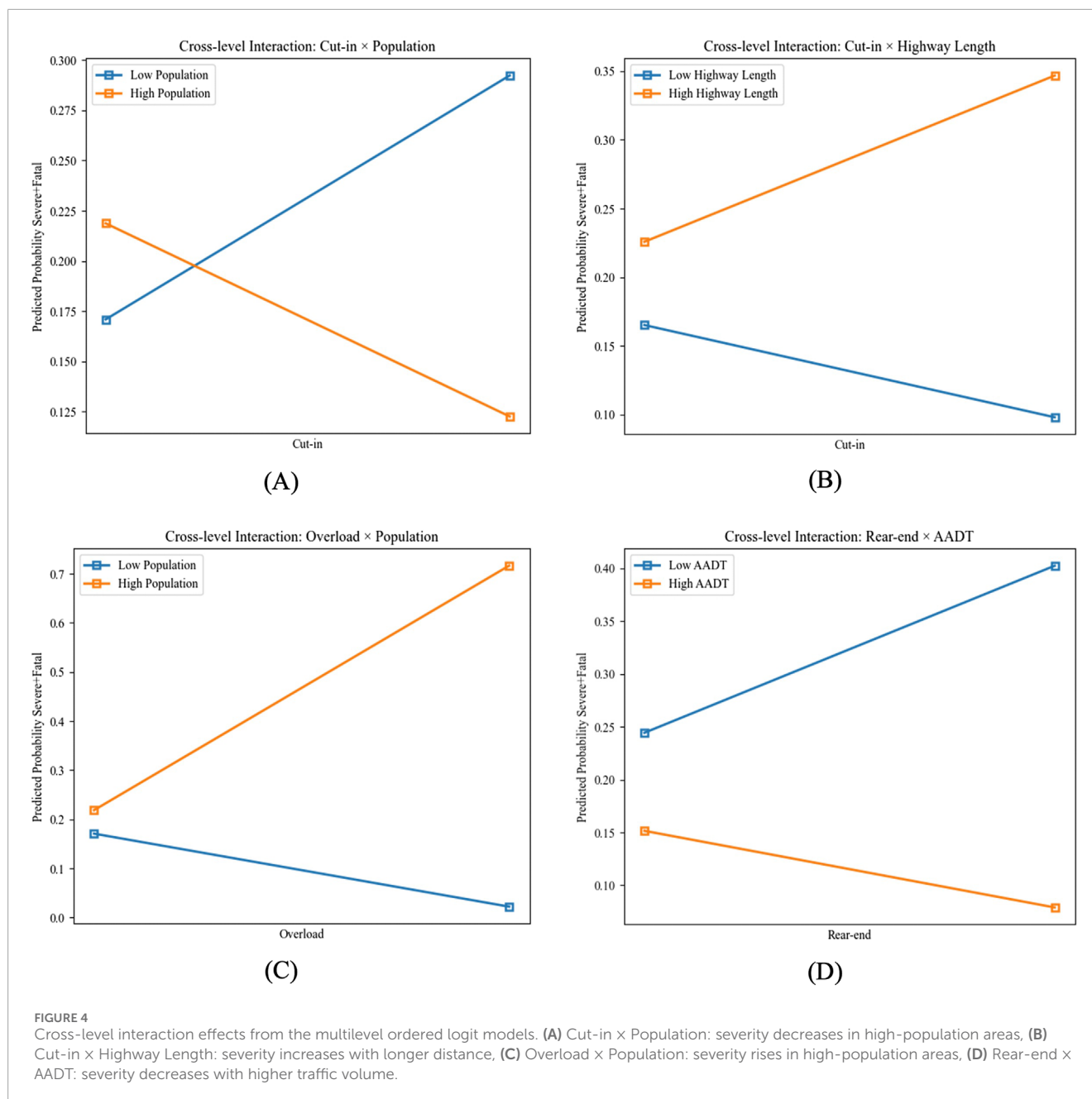


Figure 4A, cut-in maneuvers were more consequential in provinces with lower population density, where higher operating speeds and weaker safety infrastructure exacerbate the risks of abrupt lane changes. Conversely, Figure 4B shows that cut-in severity was heightened in provinces dominated by long-distance highways, underscoring the role of traffic speed and road type in amplifying crash outcomes. These spatial dynamics magnify the consequences of risk-taking behaviors in rural contexts where crash energy is amplified, and protective infrastructure is often lacking.

The vehicle-related interactions also confirm the influence of contextual moderators. Figure 4C demonstrates that overloading leads to disproportionately severe crashes in densely populated provinces, highlighting the risks of heavy trucks operating in constrained urban environments with limited maneuvering space.

Meanwhile, Figure 4D shows that rear-end collisions appear to be less harmful in high-AADT areas, suggesting that traffic congestion and reduced operating speeds can buffer the severity of impacts. Taken together, these findings emphasize the dual influence of socio-demographic and infrastructural conditions on the relationship between driver behavior and crash severity.

Collectively, these findings underscore the importance of designing context-sensitive road safety interventions for heavy vehicles. One-size-fits-all policies may fail to account for how local traffic environments interact with driver behaviors. Policymakers should therefore account for provincial heterogeneity considering variations in highway extent, traffic exposure, and population density when developing targeted strategies. By tailoring safety measures to reflect both behavioral and contextual dynamics, greater

effectiveness and efficiency in reducing severe outcomes can be achieved, such as stricter enforcement of lane-change violations in rural provinces, enhanced monitoring of truck overloading in urban areas, and targeted interventions to mitigate rear-end crashes in low-AADT settings.

5.2 Policy implications

Based on the empirical analysis, this study proposes targeted policy recommendations aligned with key risk factors in truck-related crashes. These recommendations are organized by four major domains: environmental factors, roadway characteristics, driving risk behaviors, and collision types, each of which significantly influences crash severity and requires context-specific policy responses.

Environmental Factors, including crash day type, crash time period, lighting conditions, and road surface conditions, are critical determinants of crash severity involving trucks. Wet road surfaces, although associated with a lower severity level, may still correspond with an increased frequency of crashes during adverse weather conditions. This finding likely reflects behavioral adaptation, whereby truck drivers reduce their speed or drive more cautiously. Nonetheless, adverse weather can still elevate crash risk. Therefore, policy recommendations include the development of real-time weather alert systems, adaptive speed limit signage responsive to weather changes, and infrastructure investments in high-friction pavement and effective drainage systems to prevent skidding and loss of control under wet conditions. With regard to lighting, enhancing nighttime illumination and visibility through signage especially at conflict-prone locations such as intersections and U-turn areas can significantly improve safety. Additionally, time-specific crash patterns, such as incidents during nighttime or holidays, should inform targeted enforcement schedules and possible restrictions on truck operations during high-risk periods.

Roadway Characteristics, including median presence, road alignment, intersection design, and traffic direction, strongly influence crash severity in truck-related incidents. Roads lacking central medians are significantly associated with higher severity due to the increased risk of head-on collisions involving heavy trucks. Consequently, these locations should be prioritized for median installation, particularly along truck-dense corridors. Moreover, long straight segments, often perceived as safe, can encourage speeding and driver inattention in truck operators. Accordingly, infrastructure countermeasures such as rumble strips, dynamic speed displays, and variable speed limits should be implemented. Special attention is also needed for geometric design at critical points like U-turns or merging zones. Design standards must accommodate the turning radius and braking characteristics of large trucks while ensuring sufficient sight distance to reduce crash risk with smaller vehicles.

Vehicle Defects Interestingly, vehicle defects are associated with lower crash severity, possibly due to more cautious driving when mechanical issues are present. While this may reflect behavioral compensation, it does not diminish the need for proactive policies. Regular vehicle inspections, preventive maintenance certifications, and in-vehicle diagnostic systems are essential to ensure mechanical safety and reduce crash risk.

Driving Risk Behaviors among truck drivers most notably alcohol-impaired driving and overloading emerge as key contributors to crash severity. Alcohol use behind the wheel significantly increases the likelihood of fatal outcomes, more than doubling the risk. Effective countermeasures include mandatory installation of in-cab alcohol ignition interlocks for repeat offenders and stricter legal penalties. Overloading also exhibits context-dependent effects, particularly exacerbating severity in high-population provinces. This highlights the need for localized enforcement strategies, such as mobile weigh-in-motion (WIM) technology, expanded random inspections in urban freight corridors, and differentiated fines based on area-specific risk. These approaches ensure more efficient enforcement aligned with local risk patterns.

Collision Type plays a defining role in injury outcomes among truck crashes. Specifically, rear-end collisions are associated with comparatively lower severity, potentially due to reduced impact force or lower speeds in congested conditions. However, given the high frequency of rear-end crashes in truck operations, preventive measures remain essential. Policy actions include installing forward collision warning systems, automatic emergency braking (AEB) technologies, and head-up displays (HUDs) providing real-time distance monitoring to reduce abrupt braking and improve reaction time in high-risk zones.

Cross-Level Policy Insights, Multilevel analysis reveals that the effects of risk behaviors vary according to provincial-level characteristics. In densely populated provinces, overloading significantly increases crash severity suggesting the need for intensified enforcement and urban-specific inspection protocols. Conversely, cut-in behaviors (i.e., abrupt lane changes) are more hazardous in provinces with longer highway networks and higher average speeds. These findings underscore the need for safer entry/exit designs, location-specific enforcement via surveillance technology, and hazard signage. Rear-end collisions, although less severe in provinces with higher AADT, still occur frequently and warrant continuous implementation of in-vehicle warning systems.

In summary, effective truck safety policy must be spatially adaptive, taking into account both driver behavior and the structural features of each province. This context-aware approach can more precisely address localized risk patterns and reduce the severity of crashes involving heavy vehicles.

6 Conclusion

This study provides compelling evidence that the severity of truck-involved crashes is shaped by a dynamic interplay between driver behavior and the spatial characteristics of the crash environment. By employing a multilevel modeling framework, the research reveals hidden contextual mechanisms and cross-level interactions that challenge the conventional assumption of uniform risk patterns across regions. Key findings include the elevated severity associated with overloading in densely populated provinces, the mitigating role of high traffic volumes in rear-end crashes, and the variation in crash outcomes caused by abrupt driving maneuvers depending on highway characteristics.

These results highlight the need for safety strategies that go beyond individual behavior modification. Effective road safety

interventions must be spatially adaptive incorporating regional infrastructure, enforcement capabilities, traffic density, and demographic factors. Tailoring safety measures to align with the local conditions of each province will enhance the precision and equity of policy implementation.

Ultimately, this study contributes to the broader discourse in transportation safety research by demonstrating the methodological and practical value of multilevel analysis. It calls for a paradigm shift in national safety planning: from standardized, one-size-fits-all approaches to differentiated, evidence-based strategies that reflect Thailand's spatial diversity. Such a direction is critical for sustainably reducing the burden of severe truck-related crashes and improving road safety outcomes at both individual and provincial levels.

7 Limitations and future research

Although this study provides valuable insights through the application of a multilevel framework, several considerations should be noted. The use of cross-sectional data offers a complete and consistent view of truck-involved crashes; however, such a design restricts causal inference, and the results should therefore be interpreted as associations rather than causal relationships. In this regard, potential endogeneity between AADT and crash severity cannot be fully ruled out, as reverse causality or unobserved confounding may still exist despite the inclusion of provincial-level controls. Extending future research to longitudinal or multi-year datasets would allow for a more dynamic assessment of how crash severity patterns evolve over time and under changing policy or infrastructural conditions, and would also permit more rigorous treatment of endogeneity, for example, through panel designs or instrumental variable approaches.

In addition, the HAIMS database, while official and comprehensive, may be influenced by differences in reporting practices and data accessibility across provinces. Such variation can affect comparability at the provincial level. Future studies could benefit from triangulating HAIMS records with complementary sources such as hospital injury registries, police data, or insurance claims to strengthen both representativeness and validity.

Moreover, the stepwise progression from Models 1 to 4 provided an internal form of robustness assessment, as the main findings remained consistent across increasingly complex model specifications. Building on this, future research could further extend robustness evaluations by exploring alternative modeling strategies or integrating complementary datasets to enhance the stability and generalizability of the results.

While the multilevel analysis identifies significant contextual relationships at the provincial level, it does not fully explain the underlying mechanisms through which regional characteristics influence driver behavior and crash outcomes. Further studies should incorporate qualitative methods, such as in-depth interviews, or more granular quantitative approaches, including spatial analytics or vehicle mobility data, to gain deeper insight into how structural contexts shape risky driving behaviors and crash severity.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

SN: Conceptualization, Data curation, Formal Analysis, Methodology, Writing – original draft. PW: Conceptualization, Methodology, Writing – review and editing. CB: Methodology, Validation, Writing – review and editing. AD: Data curation, Writing – original draft. TC: Validation, Writing – review and editing. VR: Software, Supervision, Writing – review and editing. SJ: Conceptualization, Supervision, Visualization, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

TABLE A1 Variable descriptions.

Variable	Category	Description
Provincial-level factors		
Population		Total population of the province
AADT		Average Annual Daily Traffic on provincial highways
Highway Length		Total length (in kilometers) of highways under the Department of Highways within the province
Individual-level factors		
Environmental factors		
Crash Day Type	Weekday	Monday to Friday
	Weekend	Saturday and Sunday
Crash Time Period	Day	06:01–18:00
	Night	18:01–06:00
Lighting Condition	Dark_Lit	Dark with street lighting
	Dark_NoLit	Dark without street lighting
Road Surface Condition	Dry	Dry road surface
	Wet	Wet or slippery road surface
Roadway Characteristics		
Median Presence	Med_Yes	Presence of central median
	Med_No	No central median
Road Alignment	Curve	Curved road segment
	Straight	Straight road segment
Road Connection	NoCon	No road connection
	Con	Presence of road connection or merging point
Specific Locations	Others	Other locations
	U-turn	U-turn area
	CROSS_MED	Median crossing area
Traffic Direction	Oneway	One-way traffic
	TwoWay	Two-way traffic
Vehicle Characteristics		
	Others	Vehicle without mechanical defects
	Damage_V	Vehicle with mechanical defects

TABLE A1 (Continued) Variable descriptions.

Variable	Category	Description
Driving Risk Behaviors	Others	Other risky driving behaviors
	OverLoad	Vehicle overloaded
	Speed	Speeding behavior
	CUT_IN	Cut-in or abrupt lane changes
	IMP_DRV	Improper driving
	TF_VIOL	Traffic violation
	Drunk	Driving under the influence of alcohol
Collision Type	Other	Other types of collisions
	REAREND	Rear-end collision
	HITPCAR	Collision with a parked vehicle on the roadside