Interpretable Machine Learning for Crash Severity Analysis of Food Delivery Motorcyclists

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Abstract *The COVID-19 pandemic has significantly increased the demand for online food delivery services. This surge has intensified competition among platforms and placed greater pressure on delivery riders to prioritize speed over safety. As a result, crash incidents involving food delivery motorcycles have nearly doubled compared to those used for routine commuting. While previous studies have focused on general motorcycle crashes, few have examined the specific factors influencing crash severity among delivery riders. Additionally, most existing research relies on traditional spatial models, which may fail to capture nonlinear relationships and spatial heterogeneity. Another challenge is the imbalance in severity data, with serious and fatal crashes underrepresented, limiting the reliability of standard statistical analysis.*

To address these gaps, this study applies GeoShapley, an explainable machine learning (XAI) framework that captures both spatial and non-spatial effects. GeoShapley treats geographic location as an interactive predictor, allowing for interpretable, location-specific insights. We also apply the Synthetic Minority Oversampling Technique (SMOTE) to improve class balance and reduce model bias.

The analysis uses crash data from 2,314 food delivery motorcycle incidents recorded in Taipei City in 2020. Results show that severe crashes are more likely on roads with higher speed limits, straight segments, intersections, and in suburban areas near restaurants. Male riders and signal violations are also strongly linked to higher crash severity. GeoShapley reveals that these risk factors vary significantly across locations, highlighting the importance of spatial heterogeneity in crash modeling. This study demonstrates the benefits of combining interpretable machine learning with spatial analysis and class-balancing techniques. The findings offer practical insights for developing targeted, location-specific safety interventions for food delivery motorcyclists in urban areas.

Keywords: Food delivery motorcycles, Crash severity, GeoShapley, SMOTE, GeoAI

1. Introduction

The COVID-19 pandemic triggered a global surge in online food delivery services, reshaping urban mobility and intensifying the demand for motorcycle-based deliveries (Raj et al., 2020). In Asia, where motorcycles are the dominant transport mode due to dense urban fabrics and narrow road networks, this transformation has been particularly pronounced. For example, Uber Eats' revenue in Taipei City alone reached NT$1.2 billion in the second quarter of 2020, while the number of food delivery workers nationwide exceeded 88,000 in the same year (Elliott & Yang., 2021). This rapid expansion has provided employment opportunities but has also heightened traffic safety concerns, especially for delivery riders navigating congested roadways under strict time constraints.

With the rise of gig-economy platforms, delivery riders are increasingly pressured to prioritize speed and efficiency, often at the expense of safety (Putra et al., 2023). Hazardous practices such as speeding, weaving through traffic, red-light running, and mobile phone use while riding have become commonplace. These risky behaviors have contributed to an increase in delivery-related motorcycle crashes. For instance, Moon et al. (2022) found that rising use of delivery services corresponded with higher motorcycle dispatch crash incidence and severity in their study region. In Korea, Chung et al. (2014) report that motorcycles account for about 5% of all traffic crashes but contribute to roughly 12% of road traffic fatalities, reflecting the relatively high risk borne by motorcyclists compared to other vehicles. Retrospective cohort studies of delivery motorcycles likewise observe that the number of crash incidents has grown over time, although rates of severe injuries remain variable. These statistics highlight an urgent need to better understand the determinants of crash severity in this specific occupational group.

Although prior studies have examined general motorcycle crash severity, research focusing specifically on food delivery riders remains scarce (Putra et al., 2023). Most existing studies emphasize behavioral risks, such as speeding and red-light running, while giving limited attention to environmental and spatial determinants such as road geometry, land use, and proximity to delivery hotspots (Chung et al. 2014). Moreover, conventional crash severity models (e.g., ordered probit, multinomial logit) assume global relationships and often overlook spatial heterogeneity. As a result, their predictive accuracy and policy relevance may be limited, particularly in complex urban environments like Taipei, where risk factors vary considerably between districts.

At the same time, the emergence of machine learning (ML) and Explainable Artificial Intelligence (XAI) offers new opportunities for crash analysis. ML algorithms can model nonlinearities and high-dimensional interactions, but their “black-box” nature limits interpretability for practitioners and policymakers (Li, 2024). To bridge this gap, interpretable AI methods such as SHAP (Shapley Additive Explanations) have gained traction, providing transparent, game-theoretic attributions of variable importance. However, standard SHAP methods assume homogeneity across space, thereby failing to capture localized variations critical for urban safety interventions. Recently, GeoShapley has been introduced as an innovative extension that explicitly integrates spatial coordinates into the XAI framework, enabling location-specific explanations of traffic safety (Wang et al., 2025). This makes it particularly well-suited for analyzing delivery motorcycle crashes, which are shaped by both rider behaviors and spatially heterogeneous urban features.

This study applies GeoShapley to investigate the factors influencing crash severity among food delivery motorcyclists in Taipei. By incorporating both spatial and non-spatial predictors and addressing class imbalance through Synthetic Minority Oversampling Technique (SMOTE), the study advances the methodological frontier in traffic safety research. Beyond improving predictive accuracy, the approach provides interpretable, spatially explicit insights that can guide targeted safety interventions for high-risk locations and rider groups.

2. Literature Review

2.1. Food Delivery Motorcycle Safety

Food delivery riders face unique risks compared to regular motorcyclists, largely due to occupational pressures and time-sensitive workloads. Observational studies reveal that more than 90% of riders frequently exceed speed limits, run red lights, or engage in distracted riding (Wang et al., 2021). These behaviors directly contribute to higher crash involvement and greater injury severity. International evidence confirms the strong association between speeding and severe crashes, with increased speed limits linked to significant rises in motorcycle fatalities (Malyshkina & Mannering, 2008). Similarly, red-light running (RLR) is disproportionately prevalent among delivery riders. Studies in China and Taiwan show that delivery riders’ RLR rates are 15–20% higher than those of ordinary riders, often driven by strict delivery deadlines and competitive platform algorithms.

Beyond behavior, roadway and environmental factors also play a role. Hazardous locations include straight segments, signalized intersections, and single-lane roads, where motorcyclists are more vulnerable to collisions (Chang et al., 2016; Haque & Chin, 2010). Poor visibility, wet pavement, and unfavorable geometry (e.g., curved segments with slopes) further exacerbate crash severity risks. Additionally, Points of Interest (POIs) such as restaurants, convenience stores, and residential areas act as activity hotspots for delivery riders, increasing exposure and potential for crashes (Qin et al., 2021; Lin et al., 2022). Despite these findings, research has rarely integrated behavioral, roadway, and spatial factors into a unified, interpretable framework for analyzing delivery-related crash severity.

2.2. Spatial Modelling Approaches in Crash Severity

Crash severity has traditionally been modeled using discrete outcome frameworks such as multinomial logit, ordered probit, and mixed logit models (Savolainen & Mannering, 2007; Ye & Lord, 2014). These methods provide structured interpretations but face limitations when dealing with unobserved heterogeneity and spatial dependencies. Recognizing the importance of spatial correlation in crash data, researchers have advanced spatially explicit models, such as spatial ordered probit and Geographically Weighted Ordinal Regression (GWOR). These models capture spatial dependence and allow local coefficients to vary, thus providing richer insights into how crash determinants differ across locations (Liu et al., 2019; Zeng et al., 2019). Nonetheless, geographically weighted models are often constrained to linear relationships and may become unstable in areas with sparse data. More importantly, they lack the capacity to capture complex nonlinear interactions that characterize real-world crash phenomena.

Machine learning (ML) methods such as random forests, gradient boosting, and neural networks have demonstrated superior predictive accuracy in traffic safety research, especially when integrating high-dimensional data that combines driver, roadway, environmental, and spatial attributes (Abdel-Aty et al., 2013; Yu et al., 2020). However, their predictive strength is counterbalanced by limited transparency, making it difficult to translate findings into policy recommendations. This has led to increasing interest in Explainable AI (XAI) frameworks. Among them, SHAP has emerged as a leading method, leveraging cooperative game theory to fairly attribute the contribution of each predictor to model outputs (Lundberg & Lee, 2017). SHAP has been successfully applied in transportation studies to analyze crash severity (Sun et al., 2022), and congestion dynamics (Liu et al., 2023). Despite its advantages, conventional SHAP does not incorporate spatial heterogeneity, potentially masking localized risks in urban crash analysis.

GeoShapley extends the SHAP framework by integrating spatial structure directly into the explanatory process. By treating geographic coordinates as interactive predictors, GeoShapley decomposes predictions into contributions from non-spatial features, spatial context, and their interactions (Li, 2024). This enables location-specific interpretations of feature importance, overcoming the limitations of both global statistical models and non-spatial XAI. Early applications of GeoShapley have demonstrated its ability to reveal spatially varying influences of built environment features, traffic conditions, and land use patterns on crash outcomes (Chen et al., 2025; Putra et al., 2024). For food delivery motorcyclists, whose crash risks are shaped by both behavioral pressures and heterogeneous urban environments, GeoShapley offers a particularly promising tool. It not only improves the interpretability of ML models but also provides actionable, spatially targeted insights that can inform evidence-based interventions.

3. Methodology

3.1 Data Description

Taipei City was selected as the study site because it is one of the few urban areas that provides separate crash records for delivery and non-delivery motorcycles, and these records are publicly accessible. This makes Taipei an ideal setting for investigating the unique safety challenges of delivery riders. According to official statistics from the Taipei Department of Transportation, a total of 2,314 food delivery motorcycle crashes were reported in 2020.

The crash dataset contains both spatial information (latitude and longitude of crash sites) and a range of non-spatial attributes. These include crash ID codes, reported causal factors, collision type, severity levels, numbers of fatalities and injuries, roadway conditions (e.g., pavement status, surface slipperiness), environmental conditions (e.g., weather, lighting), as well as the date, vehicle types, and driving maneuvers involved. To keep the analysis focused and feasible, irrelevant variables were excluded after initial data processing.

To account for the influence of the built environment, we incorporated point-of-interest (POI) data extracted from OpenStreetMap. These POIs included supermarkets, shopping malls, schools, universities, hotels, and hospitals within a 500-meter radius of each crash site. Because restaurants are central to food delivery activities, we also compiled a dedicated dataset of restaurant partners affiliated with major delivery platforms. This information was gathered using the Python library Selenium, which allowed efficient web scraping of platform websites to identify delivery-related establishments in a short timeframe (see Raghavendra [34] for further details on Selenium-based data collection).

Table 1 presents the descriptive statistics and expected associations of the selected variables, which were chosen based on their relevance in previous motorcycle crash research (1,16,26). The dataset shows that the average delivery rider age was 33 years, with the vast majority being male. Traffic violations were common: 62.3% of riders had committed signal violations, while nearly 95% of crashes involved another vehicle, highlighting the high interaction risk between motorcycles and other traffic participants. By contrast, crashes linked to driving under the influence (DUI) were rare in this dataset, differing from earlier studies such as Chung et al. (1), which reported higher DUI involvement.

Table 1: Data description and descriptive statistics

Category	**Variables**	**Expected Relationship**	**Mean**	**Std Dev**	**Description**
Dependent Variable	Crash Severity	n/a	1.8261	0.3842	(1) No injury (17.6%) (2) Injury (82.2%) (3) Fatal crash (0.2%)
Driver related	Age	-	33.294	10.195	Driver age
	Gender	-	0.114	0.317	(0) Male; (1) Female
Road Characteristic	Speed limit	+	45.559	6.967	The road speed limit on crash site
	Straight lane	+	0.687	0.463	(0) Curved Road; (1) Straight Road
	Intersection	+	0.628	0.483	(0) Non-intersection; (1) Intersection
	Elevation	-	0.001	0.036	(0) non-elevated road; (1) elevated road
Environmental Condition	Weather	+	0.373	0.483	(0) Clear; (1) Raining
	Slippery road	+	0.198	0.399	(0) Not slippery; (1) wet or muddy road
Traffic Violation	Traffic Signal Violation	+	0.623	0.151	(1) if ignoring traffic signal violation; (0) otherwise
	DUI	+	0.0006	0.025	(1) DUI crash; (0) otherwise
	Lane change	+	0.055	0.228	(1) if conducting lane change; (0) otherwise

	Deacceleration	+	0.0188	0.136	(1) if conducting immediate brake; (0) otherwise
	Using a Phone while driving	+	0.248	0.439	(1) if using a phone; (0) otherwise
Type of crash	Crash with pedestrian	-	0.031	0.175	(1) if the crash involved a pedestrian; (0) otherwise
	Crash with vehicle	+	0.944	0.229	(1) if the crash involved the vehicle; (0) otherwise
	Self-crash	-	0.016	0.126	(1) if the crash involved properties; (0) otherwise
Point-of-interest (POI)	Supermarket	+	2.197	1.767	Count of POI around 500 buffers from crash point
	School	+	2.010	1.345	
	Shopping mall	+	0.365	1.049	
	Hotel	+	3.626	8.674	
	Hospital	-	0.403	0.772	
	Bus stop	+	1.688	2.111	
	Restaurant	+	15.199	2.756	

3.2. Methods

3.2.1. Resampling methods

One of the major challenges in crash severity analysis is the imbalance of class distributions. In most datasets, crashes that result in fatalities or severe injuries are much less common than property-damage-only or slight injury crashes. This imbalance makes it difficult for standard classifiers to correctly recognize the minority classes. Models often become biased toward predicting the majority class, leading to misleading accuracy results but poor performance on the outcomes that matter most for road safety.

To address this, we applied the Synthetic Minority Over-Sampling Technique (SMOTE), which is one of the most widely used approaches for rebalancing imbalanced datasets Kuo et al., 2024; Mathew et al., 2018). Unlike simple random oversampling, which merely duplicates existing cases, SMOTE generates artificial but realistic samples for the minority class by interpolating between existing observations. This helps expand the dataset without simply repeating records, thereby reducing the risk of model overfitting. As illustrated in Figure 1, SMOTE works by first identifying the k nearest neighbors for a selected minority sample in the feature space. Then, one of these neighbors is randomly chosen, and the algorithm calculates the Euclidean distance between the two points:

$$D(x, x_k) = \sqrt{(x - x_k)^2} \tag{1}$$

A new synthetic sample is then created at a random location along the line segment between the original sample x and its neighbor x_k:

$$x_{new} = x + rand(0, 1) * (x - x_k) \tag{2}$$

This process generates a more diverse set of minority-class examples, ensuring that the classifier is exposed to a broader distribution of possible cases. In the context of our study, SMOTE was crucial to balance the dataset, where fatal crashes were extremely rare compared to minor injury cases. By creating synthetic severe-crash records, we improved the ability of the machine learning model to detect patterns associated with high-severity outcomes.

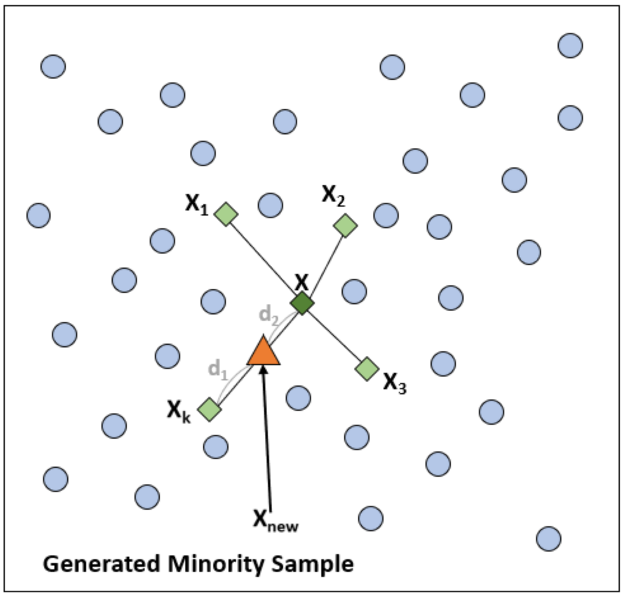


Figure 1. SMOTE algorithm schematic (Kuo et al., 2024).

3.2.2. GeoShapley

While predictive accuracy is important, understanding why certain crashes are more severe is equally critical for designing interventions. Traditional crash severity models, such as ordered probit or logit, provide some interpretability but often assume that the effects of predictors are constant across space. Machine learning models, such as XGBoost or random forests, capture complex nonlinear relationships but are often criticized as "black boxes."

To balance predictive strength with interpretability, we employed Shapley Additive Explanations (SHAP) (Lundberg & Lee, 2017). SHAP is a game-theoretic method that distributes the contribution of each input feature fairly across the model's predictions. Each feature is treated like a "player" in a cooperative game, and its SHAP value indicates how much it contributes—positively or negatively—to a specific prediction. This allows us to interpret model outputs at two levels: First, local interpretation regarding why a specific crash was predicted to be severe. Second, global interpretation illustrating which features matter most across all crashes. Mathematically, the SHAP value for feature k is defined as:

$$\phi_k = \sum_{s \subseteq N(k)} \frac{s!\,(p-s-1)!}{p!}\left[f(S \cup (k)) - f(S)\right] \tag{3}$$

This ensures that each feature's contribution is fairly attributed by averaging its impact across all possible feature orderings.

However, standard SHAP methods assume that feature effects are spatially uniform. In reality, the impact of risk factors such as road geometry, traffic violations, or surrounding land use often varies across different parts of a city. To capture this, we applied GeoShapley, a recent extension of SHAP that incorporates spatial information directly into the explanation process (Li, 2024). GeoShapley decomposes the model's prediction into four components:

$$\hat{y} = \phi_0 + \phi_{GEO} + \sum_{k=1}^{p} \phi_k + \sum_{k=1}^{p} \phi_{(GEO,k)} \tag{4}$$

Where, ϕ_0 represent the overall model baseline (global intercept). ϕ_{GEO} represent contribution of geographic location itself. ϕ_k is the effect of each non-spatial feature. Then $\phi_{(GEO,k)}$ is the spatial interaction, showing how the influence of a feature varies across locations.

The spatial term ϕ_{GEO} works like a spatial intercept, while $\phi_{(GEO,k)}$ allows each feature's importance to change geographically. For example, a traffic signal violation might have a stronger effect on crash severity in suburban areas than in dense downtown districts. The contribution of spatial features can be formally expressed as:

$$\phi_{GEO} = \sum_{S \subseteq N \backslash (GEO)} \frac{S!\,(p-s-g)!}{(p-g+1)!} [f(S \cup (GEO)) - f(S)] \quad (5)$$

where g is the number of spatial dimensions (e.g., $g = 2$ for latitude and longitude). Finally, to make GeoShapley outputs comparable to regression models, we aligned them with spatially varying coefficients (SVCs):

$$\beta_{i0} = \phi_0 + \phi_{GEO} \quad (6)$$

$$\beta_{ik} = \frac{\phi_k + \phi_{(GEO,k)}}{X_k - E(X_k)} \quad (7)$$

This transformation allowed us to interpret results in a familiar regression-like framework while retaining the fine-grained interpretability of Shapley values. Empirical applications in other domains such as housing prices (Li et al., 2024) and environmental health risks (Foroutan et al., 2025) demonstrate that GeoShapley effectively uncovers spatial heterogeneity in predictor importance. In this study, applying GeoShapley to delivery motorcycle crashes allowed us to identify not only which factors matter for severity, but also where they matter most, offering a powerful tool for designing targeted and location-specific safety interventions.

4. Results and Discussion

4.1. Model Comparison

To evaluate predictive performance and identify location-sensitive factors influencing delivery motorcycle crash severity, we compared the results of a traditional Ordered Probit model with the GeoShapley framework (Table 2). The GeoShapley model achieved substantially better performance, with a higher pseudo R^2 (0.76 and 0.543 respectively), improved log-likelihood (−116.371 and −1022.484 respectively), and a much lower AIC (268.744 and 2084.972 respectively). These results demonstrate that incorporating nonlinear relationships, interactions, and spatial heterogeneity through GeoShapley significantly enhances both predictive accuracy and interpretability compared to conventional econometric approaches.

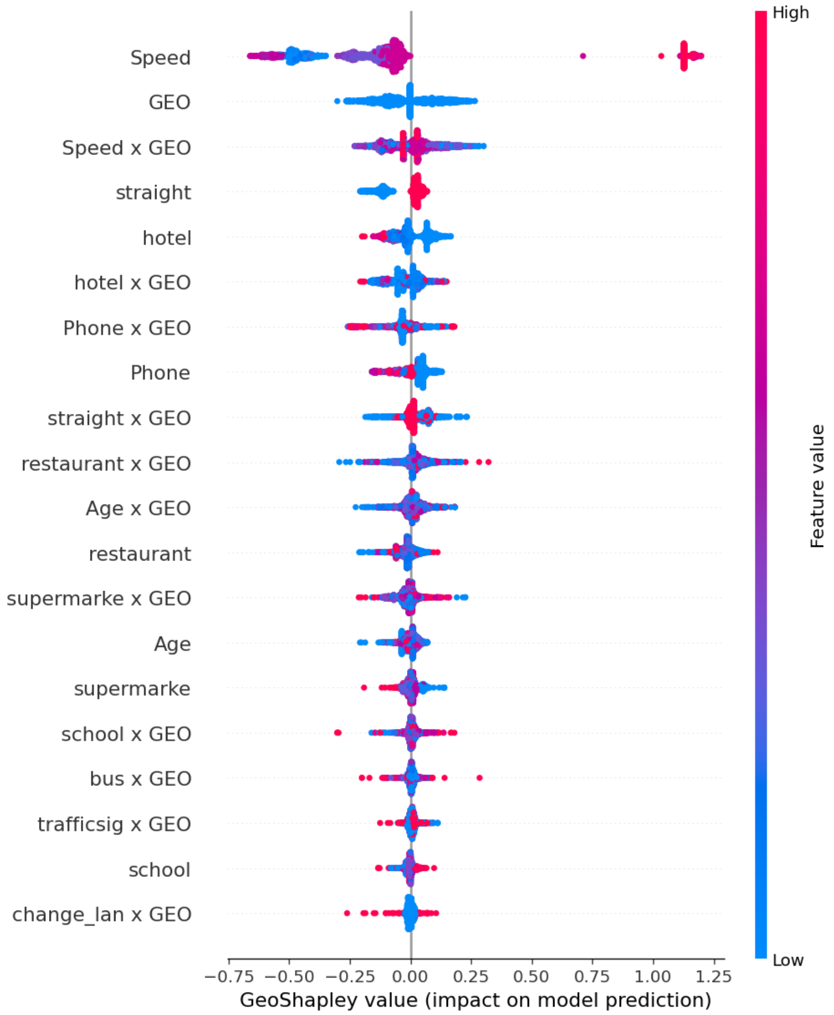


Figure 2. Feature contribution ranking and distribution of GeoShapley values in delivery motorcycle crash severity model. Note: GEO = location.

The GeoShapley summary plot (Figure 2) highlights the ranking and distribution of feature contributions across the study area. Among the most influential predictors were speed, road geometry (straight segments), hotel density, and phone use while riding. Notably, the spatial term (GEO) itself made a substantial contribution, confirming that underlying location effects strongly shape crash severity patterns. The plot also illustrates the geographic interactions (e.g., Speed × GEO, Hotel × GEO, Restaurant × GEO), showing how the influence of key variables differs across locations. For instance, speeding consistently increased severity risk, but its impact was more pronounced in certain districts, reflecting the spatial heterogeneity of traffic environments.

Comparing Ordered Probit and GeoShapley results reveals both consistencies and refinements. In both models, speeding, intersections, traffic signal violations, and phone use were significant factors associated with higher crash severity. However, GeoShapley provided additional insights by capturing location-specific variations. For example, while the Ordered Probit model suggested a positive relationship between school proximity and severity, GeoShapley showed that this effect varied substantially across the city, with stronger impacts near busy arterials. Similarly, features such as restaurants and supermarkets, which appeared weak or insignificant in the global model, were found to exert localized influences once spatial interactions were considered.

Table 2: Model Outcomes for Delivery Motorcycle Crash Severity

Variables	**Ordered Probit Model**	**GeoShapley SVC**				
	Value	**Mean**	**Min**	**Median**	**Max**	**Rank**
Speeding	0.11782*	-0.00258	-0.02447	-0.00155	0.02421	1
Straight Lane	1.03739*	-0.01321	-0.39311	0.00773	0.16294	2
Hotel	-0.01724*	0.00823	-0.20500	0.00161	0.30402	3
Using Phone	-0.30096*	-0.00273	-0.32102	0.00248	0.27683	4
Restaurant	0.00003	-0.00050	-0.41717	-0.00001	0.13273	5
Driver Age	-0.01943*	0.00024	-0.02409	0.00012	0.01154	6
Supermarket	-0.00856	0.00099	-0.14244	0.00121	0.36596	7
School	0.09638*	-0.00081	-0.24672	0.00029	0.12677	8
Bus Stop	-0.03694*	0.00069	-0.04149	0.00057	0.05322	9
Intersection	0.43033*	-0.00007	-0.09022	0.00028	0.03217	10
Crash with Vehicle	1.30317*	-0.00081	-0.31746	0.0011	0.01239	11
Traffic Sig Violation	-0.53631*	0.0046	-0.08744	0.00152	0.14792	12
Lane Change	-0.04077	-0.00023	-0.21046	0.00206	0.03609	13
Shopping Mall	-0.05407	-0.00152	-0.02699	-0.00116	0.08381	14
Hospital	0.15132*	-0.00065	-0.05097	-0.00077	0.07961	15
Driver Gender	-0.34361*	0.00055	-0.10904	-0.00028	0.13703	16
Crash with Ped.	1.59962	0.00021	-0.03830	-0.00057	0.08059	17
PDO | Injury	6.03955					

Injury | Fatal	8.54657	
Model Performance		
R-square	0.543	0.76
Log Likelihood	-1022.484	-116.371
AIC	2084.972	268.744

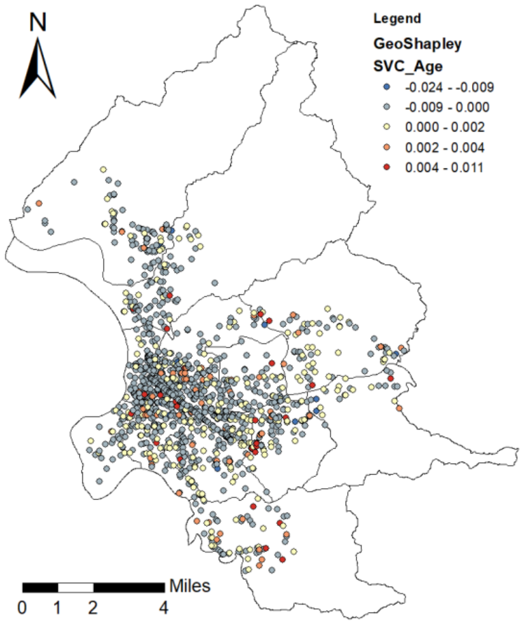
* Significant Variable P-value < 0.05

4.2. Discussions

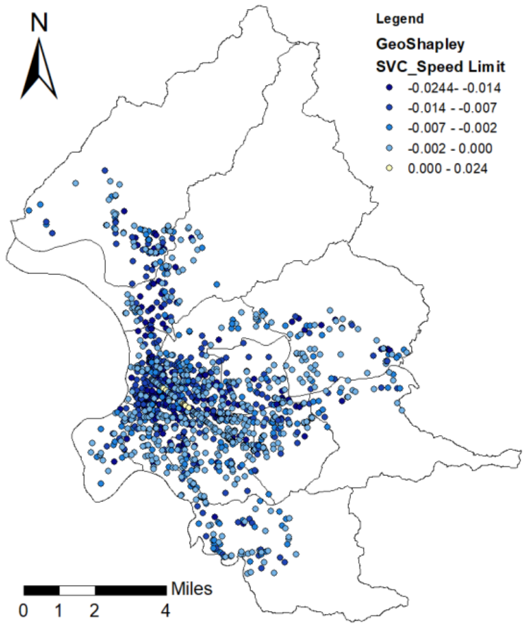
The GeoShapley analysis highlights the spatial heterogeneity of factors contributing to delivery motorcycle crash severity in Taipei City. Figure 3 illustrates how driver characteristics, road design, traffic violations, and environmental features exert varying levels of influence across the study area, underscoring the importance of location-sensitive safety strategies.

Age shows a generally negative association with crash severity, indicating that younger delivery riders are more likely to experience severe crashes (Figure 3a). This pattern is strongest in central Taipei, where traffic density and delivery demand are highest. In other words, younger drivers showing higher risk in certain clusters, particularly in central districts with dense traffic activity (Figure 3a). This finding is consistent with previous research showing that younger delivery riders are more likely to engage in risky behaviors such as speeding, weaving through traffic, and using mobile phones while riding (Wang et al., 2021). By contrast, older riders displayed relatively lower severity risk, which may reflect more cautious riding habits and greater risk awareness. Similar results have been reported in broader motorcycle crash studies, where younger drivers exhibited disproportionately higher injury and fatality rates compared to older cohorts (Shaheed & Gkritza, 2014).

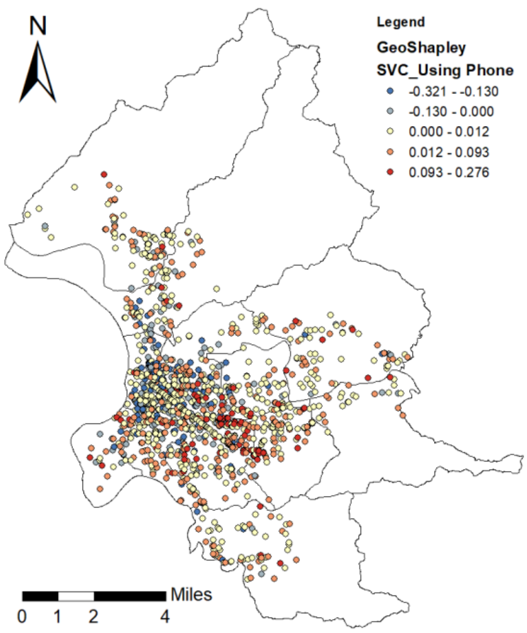
The impact of road speed limit was one of the most consistent predictors across the city (Figure 3b). Areas with higher speed limits—particularly suburban zones—were strongly associated with more severe crashes. This aligns with findings from Zheng et al. (2020), who demonstrated that higher posted speed limits significantly increased crash severity for motorcyclists, especially those making frequent stops and reentries into fast-moving traffic, as is common for delivery riders. Straight road segments further amplified this risk by encouraging speeding and reducing opportunities for natural deceleration. Together, these results confirm that high-speed environments pose heightened dangers for delivery riders, echoing earlier studies linking speed and linear road geometry with elevated motorcycle fatality rates (Chang et al., 2016).



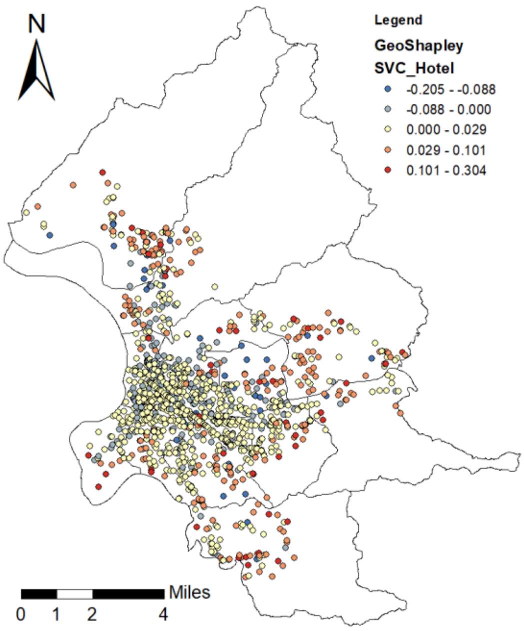
(a) Driver Related



(b) Road Characteristic



(c) Traffic Violation



(d) Point of Interest

Figure 3. Related Factor of Delivery Motorcycle Crash Severity

Traffic violations. The influence of phone use while riding varies considerably across Taipei, but it displays a generally positive association with crash severity (Figure 3c). The strongest effects are concentrated in the central area and southern districts, which are characterized by dense commercial zones and high volumes of delivery demand. In these areas, constant communication with customers or platforms likely increases distracted riding and reduces situational awareness. This aligns with Zhang et al. (2020), who found that delivery riders using phones demonstrated poorer hazard detection and higher crash likelihood. Our findings suggest that distracted riding is not a uniform problem but is particularly acute in high-demand corridors.

As the point of interest (POI), hotel density shows a mixed but overall positive association with crash severity (Figure 3d). The effect is strongest in the sub urban area, where hotel activity generates complex traffic flows involving taxis, ride-hailing vehicles, tourists, and pedestrians. Delivery riders entering these environments are exposed to multiple conflicts, heightening the severity of crashes. This extends prior research that emphasized restaurants as the primary POI risk factor (Qin et al., 2021; Lin et al., 2022). Our results highlight that other service-related POIs, particularly hotels, also play a significant role in shaping delivery crash risks, likely due to the irregular traffic patterns they generate.

5. Conclusions

This study applied an interpretable spatial machine learning framework, GeoShapley, to analyze the factors influencing the severity of food delivery motorcycle crashes in Taipei City. By integrating crash data with driver characteristics, roadway features, traffic violations, and points of interest, the model not only achieved stronger predictive performance than the traditional Ordered Probit model but also revealed location-specific variations in risk factors.

The findings indicate that several variables consistently elevate crash severity: younger riders, higher speed limits, straight road segments, phone use while riding, and service-related POIs such as hotels. Importantly, GeoShapley uncovered that the strength of these associations varies spatially: younger riders are most at risk in central districts, higher speed limits show the strongest effect in suburban arterials, phone use has the greatest impact in western and southern commercial zones, and hotel density exerts influence in central business hubs. These results emphasize that delivery-related crash risks are shaped not only by rider behaviors and road environments but also by the spatial context of urban mobility.

From a policy perspective, the study underscores the need for location-sensitive interventions rather than uniform city-wide measures. Speed management policies, such as stricter enforcement and traffic calming, should be targeted at suburban arterials where the severity risk from speeding is highest. Distracted riding prevention campaigns and enforcement should focus on commercial zones with high delivery demand, where riders are most likely to use phones while riding. Training programs tailored to younger gig-economy riders could address the disproportionate risks faced by this group, improving their hazard perception and encouraging safer practices. Moreover, traffic management and infrastructure design around hotels and restaurants should be reconsidered, as these POIs generate complex flows of vehicles and pedestrians that heighten crash severity. Finally, stronger monitoring and signal compliance measures at intersections remain critical, given the significant role of violations in exacerbating delivery rider crash risks.

While the study provides important insights, several limitations should be acknowledged. First, the analysis used crash data from a single year (2020), limiting its ability to capture long-term temporal trends or policy changes. Second, although GeoShapley accounts for spatial heterogeneity, the results depend heavily on the resolution and quality of available data; unobserved factors such as enforcement intensity, real-time traffic flow, or riders' working conditions could not be included. Third, the use of SMOTE to address class imbalance improves model robustness but may not perfectly replicate the complexity of rare fatal crashes. Finally, because the study was conducted in Taipei City, the findings may not be directly generalizable to other urban contexts with different traffic environments or regulatory frameworks.

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