Exploration of the tram-involved crashes' characteristics and contributing factors to fatality in tram crashes in Japan

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Abstract:

Trams have garnered worldwide attention as an alternative urban rail transit system since they offer advantages such as higher accessibility, convenience, lower construction and maintenance costs compared with subway. Nevertheless, due to the system's characteristics, particularly regarding right-of-way issues, crashes involving trams often lead to severe consequences. This study utilizes traffic crash data from across Japan, including 1,121,299 crashes that occurred from 2019 to 2022, of which 304 were tram involved. The study has two major analyses using random-parameter model with heterogeneity in means: (1) tram-involved crashes' characteristics (vs. non-tram-involved) and (2) factors affecting the probability of fatality in tram crashes. The first analysis' findings suggest that fatalities and crashes at rail crossings are more likely to be associated with tram crashes, while non-tram crashes are more likely to occur during daytime, at intersections, or on narrower lanes. Furthermore, the presence of a median between opposing directions increases the likelihood of a non-tram crash. The second analysis to identify the factors to fatality reveal how factors such as the season, lighting conditions, road conditions, crash locations, and the age and category of victims affect the characteristics of tram crashes and fatalities. Specifically, it explains the heterogeneous effects of daytime and intersections on tram crashes, as well as the heterogeneous impacts of rail crossings and densely populated areas on tram fatalities. The findings are expected to assist authorities in formulating strategies to minimize the incidence of tram crashes and related fatalities, potentially saving lives and bringing about economic benefits.

Keywords

Tram safety, Fatal crash, Random parameter model, Probit model, Heterogeneity in means

1. Introduction

1.1 Tram construction and operation

Major traffic problems such as traffic congestion, environmental pollution, occupying parking resources caused by excessive private motor vehicles have been widely seen around the world (Pervez et al., 2024), while public transportation has become an efficient alternative mode around the world because of its efficient, convenient, and environmentally friendly characteristics (Pervez et al., 2022 ; Sinha, 2003). In the post-pandemic period, public transportation has taken on a more important role (Baig et al., 2024).

Trams, trolleys, or streetcars are light rail transit vehicles driven by electricity and running on the track and they have been operating as an important mode of public transportation in many cities (Topp, 1999). Due to its high comfort, large passenger capacity, low installation cost (Kang et al., 2023), environmental protection and pollution-free exhaust emissions, it has been applied on every continent in the world (Chen, 2018; Park and Kang, 2021).

Tram systems first emerged in Europe, and after more than a century of construction and development, they now exist on all continents. By 2023, there are over 60 countries and more than 400 cities worldwide that have built and operate tram systems. As shown in **Table 1**, in the rankings of total tram route mileage and new mileage added, Asia ranks second, closely following Europe (Liang, 2020).

Table 1. Summary of Tram Route Mileage and New Mileage Added Worldwide in 2023

Continent	Mileage of tram	Percentage in all rail traffic	Added mileage of tram	Percentage in all added rail traffic
Asia	1868.72	10.35%	210.68	14.56%
Europe	14238.12	74.34%	380.69	89.66%
South America	39.90	4.39%	0.00	0.00%
Africa	225.64	47.03%	14.20	26.35%
Oceania	270.40	73.92%	0.00	-
North America	385.91	8.70%	4.10	3.42%
Total	17028.69	39.24%	609.67	29.33%

Since the 21st century, tram systems have shown rapid growth worldwide, with at least 108 cities (re)opening their first intra-city tram line during this period. Compared with other continents, Europe has led the way with 60 new opened tram lines (not including the reopening of existing lines or line extensions) (Liang, 2020). The development of trams in Asia has also shown potential, driven by Japan's highly advanced rail transit systems and China's large-scale investment in mass transit construction in recent years.

In the future, modern tram systems, as a medium-low-capacity urban rail transit mode, align with the ecological and environmental requirements of urban development. They provide green, safe, comfortable and flexible services at a lower cost. Moreover, new-generation trams may integrate advanced technologies such as autonomous driving, facial recognition, and network connectivity, representing high-tech products. Their aesthetically pleasing designs also make them well-suited to seamlessly integrate into the urban landscape, cementing their important role in cities.

1.2 Research about tram safety

Due to the operation and organization mode of trams (Currie and Reynolds, 2010; Currie and Reynolds, 2011; Marti et al., 2016) and the characteristics of right of way allocation, trams are more likely to collide with other road traffic participants, especially the vulnerable groups such as pedestrians, and the casualties of crashes are often more serious (Maempel et al., 2018; Castanier et al., 2012; Hedelin et al., 1996).

There have been many studies on tram crashes, which have analyzed the main characteristics of tram crashes: due to reasons such as speed control, road openness, and mixed traffic at intersections, tram crashes are prone to occur in complex, restricted, and mixed traffic environments (Zhou et al., 2018; Currie and Shalaby, 2007; Cheung et al., 2008; Currie and Reynolds, 2011). On shared-use lanes where tram routes overlap and intersect with urban roads, conflicts arise regarding priority between trams and other vehicles at intersections or sections, leading to an increased occurrence of conflicts. Extensive literatures indicates that in mixed traffic scenarios, the likelihood of crashes is heightened (Marti et al., 2016). Studies have shown that differences in the quality, volume, and type of trams can also impact the probability and severity of crashes (Naznin et al., 2016a).

Crashes involving trams and other urban road users, especially those more vulnerable such as pedestrians, cyclists, and motorcyclists, appear to be more complex and frequent compared to other rail transit crashes (Currie and Reynolds, 2010; Castanier et al., 2012; Naznin et al., 2018).

Furthermore, road infrastructure can also influence the occurrence of tram crashes: the absence of segregation from slower traffic, such as pedestrians and cyclists, poses a safety hazard particularly during peak traffic times (Pervez et al., 2024). There is a notable absence of dedicated protective measures for passengers navigating tram stops, with most stops only demarcated by lines (Naznin et al., 2016b). This lack of special protection measures results in pedestrians potentially entering directly into the flow of traffic route to the stop, consequently elevating the risk of conflicts with motor vehicles, this may be related to people's perceived safety (Lee et al., 2024). Additionally, an examination of crash data and photographs reveals a deficiency in signage indicating tram stops or waiting areas, leaving vulnerable road users without adequate protection (Naznin et al., 2018; Wong et al., 2007).

However, the existing research on this topic mainly based on Europe, North America, and Australia, while Asian countries' study is lacking. There are notable distinctions in the operational methods and vehicle configurations of tram systems between Asia and other continents. While the deployment of tram infrastructure in Asian nations has occurred more recently, the rapid growth and substantial scale of these systems present significant future development potential. Consequently, there is a pressing need to conduct analyses specifically focused on tram-related crashes in the Asian context.

The Japanese rail transit system exhibits unique characteristics, including high-density, efficient operations, complex network configurations, and substantial passenger volumes. As a result, the causal factors underlying crashes in this context are often more intricate. Therefore, this study elected to utilize data from Japan to investigate this important research domain.

1.3 Operation of trams in Japan

Tram in Japan have a history of more than 100 years. It was in their heyday in 1920s and spread throughout cities in Japan, with the popularity of their own cars and the interest in subways, trams began to be abolished in most cities. However, in the 1980s, the next generation of road trams (light rail transit or LRT) was introduced, and trams resumed large-scale use on the basis of the original track construction (Committee, 2013).

In Japan, there is a big difference between the way trams and other rail transit operate: railway tracks are proprietary tracks and are prohibited from being laid on roads. Tram tracks are laid on roads, divided into tracks shared with other vehicles, and new tracks (or dedicated tracks) laid specifically for road trams. Table 2 is a list of trams operating under the rail-law (Ito and Kawazoe, 2022; Cao, 2022; Zhuang et al., 2022). Examples of trams and tram stop in Japan are shown in **Figure 1**.

Table 2. List of trams operating under the rail-law in Japan

	Year of opening	Length (km)	Number of lines	Number of stations	Mixed right-of-way track	Dedicated track	Direct to the railway line
Tokyo branch	1903	12.2	1	30	Yes	Yes	No
Kochi	1904	25.3	3	76	Yes	Yes	No
Kyoto Prefecture	1910	11	2	22	Yes	Yes	No
Osaka	1911	18.3	2	40	Yes	Yes	No
Ehime-ken	1911	6.9	4	22	Yes	Yes	Yes
Kyoto Prefecture,Shiga Prefecture	1912	21.6	2	27	Yes	Yes	Yes
Okayama prefecture	1912	4.7	2	17	Yes	No	No
Hiroshima-ken	1912	19	6	57	Yes	Yes	Yes
Kagoshima Prefecture	1912	13.1	4	35	Yes	Yes	No
Hokkaido	1913	10.9	4	26	Yes	No	No
Toyama	1913	8.7	7	29	Yes	No	Yes

Nagasaki prefecture	1915	11.5	5	38	Yes	Yes	No
Hokkaido	1918	8.9	4	24	Yes	No	No
Kumamoto prefecture	1924	12.1	5	35	Yes	Yes	No
Tokyo branch	1925	5	1	10	No	Yes	No
Aichi-ken	1925	5.4	1	14	Yes	No	No
Fukui prefecture	1933	3.4	1	6	Yes	Yes	Yes
Toyama	1948	8	1	18	Yes	Yes	Yes
Tochigi prefecture	2023	14.6	1	19	Yes	Yes	No

Examples of trams and tram stop in Japan are shown in **Figure 1**.

(a) Trams track in Japan (Tosa) **(b) Tram stop in Japan (Osaka)**

Figure 1. Trams in Japan

1.4 Objectives

In summary, the characteristics of tram crashes often differ significantly from those of ordinary crashes, and the consequences tend to be more severe (such as the higher likelihood of fatality). Therefore, this study primarily investigates the unique characteristics of tram crashes (vs. non-tram crashes), and the factors influencing the fatality in tram-involved crashes (vs. non-fatal) of Japan, the country which has the most developed urban rail transit infrastructure in Asia.

The data utilized in this research were collected by the National Police Agency of Japan from 2019 to 2022, including a total of 1,121,299 crash records, among which 304 involve tram crashes. The subsequent sections will present the data description and variable selection, methods employed in this study, results and discussion, with the conclusion discussed at the end.

2. Data

2.1 Data description

The data used in this research was from National Police Agency of Japan, it includes a total of 1,121,299 traffic-related cases resulting in injuries in for the four years during 2019-2022, of which 304 cases are related to tram. Every crash is represented by a specific number. Among all recorded variables, information about natural environment such as weather, lighting, road surface conditions; road environment such as population density in the crash area, road type, road width, road alignment, lane separation method, separation method between lanes and pedestrian paths; and characteristics related to the crashes, such as the time of the crash, location of the crash, the age of participants, type of participant, and the classification of the crash.

Valid tram-involved crash data and non-tram crash data were processed, and the detailed distribution of general statistics, road factors and crash factors are shown in **Table 3, Table 4, and Table 5** respectively**.**

Table 3. Descriptive data for all crashes

Variable	Type	Tram	Percentage in tram crashes	Non-Tram	Percentage in non-tram crashes
Year	2019	97	31.91%	321,270	28.66%

	2020	69	22.70%	253,857	22.65%
	2021	76	25.00%	253,507	22.61%
	2022	62	20.39%	292,361	26.08%
Month	January	23	7.57%	92,393	8.24%
	February	28	9.21%	87,010	7.76%
	March	22	7.24%	95,362	8.51%
	April	25	8.22%	87,647	7.82%
	May	20	6.58%	82,993	7.40%
	June	32	10.53%	90,202	8.05%
	July	20	6.58%	93,202	8.31%
	August	28	9.21%	89,056	7.94%
	September	18	5.92%	90,413	8.07%
	October	20	6.58%	101,861	9.09%
	November	30	9.87%	102,174	9.11%
	December	38	12.50%	108,682	9.70%
Season	Spring (March to May)	67	22.04%	266,002	23.73%
	Summer (June to August)	80	26.32%	272,460	24.31%
	Fall (September to November)	68	22.37%	294,448	26.27%
	Winter (December to February)	89	29.28%	288,085	25.70%
Day of Week	Sunday	40	13.16%	113,983	10.17%
	Monday	39	12.83%	167,742	14.96%
	Tuesday	51	16.78%	168,917	15.07%
	Wednesday	44	14.47%	167,516	14.94%
	Thursday	52	17.11%	168,532	15.03%
	Friday	37	12.17%	185,556	16.55%
	Saturday	41	13.49%	149,053	13.30%
Time	One hour after sunrise	10	3.29%	36,181	3.23%
	Daytime	160	52.63%	719,445	64.18%
	One hour before sunset	24	7.89%	73,370	6.55%
	One hour after sunset	18	5.92%	87,935	7.84%
	Nighttime	84	27.63%	188,779	16.84%
	One hour before sunrise	8	2.63%	15,285	1.36%
Weather	Clear	208	68.42%	753,911	67.25%
	Cloudy	65	21.38%	221,493	19.76%
	Rainy	28	9.21%	134,189	11.97%
	Foggy	1	0.33%	396	0.04%
	Snowy	2	0.66%	11,006	0.98%
Area	Densely populated urban area	168	55.26%	574,594	51.26%
	Less populated suburban area	68	22.37%	334,419	29.83%
	Rural area	68	22.37%	211,982	18.91%

Table 4. Road factors of all crashes

Variable	Type	Tram	Percentage in tram crashes	Non-Tram	Percentage in non-tram crashes
Road surface	Dry	244	80.26%	943,646	84.18%
	Wet	35	11.51%	159,991	14.27%

	Frozen/ Iced	3	0.99%	9,146	0.82%
	Covered by snow	4	1.32%	6,821	0.61%
	Others	18	5.92%	1,391	0.12%
Road type	Intersection	22	7.24%	477,594	42.60%
	Near the intersection	6	1.97%	153,519	13.69%
	Segment	18	5.92%	435,149	38.82%
	Rail crossing (with a stop sign)	212	69.74%	257	0.02%
	Rail crossing (with only alarm)	10	3.29%	1	0.00%
	Rail crossing (with nothing)	34	11.18%	2	0.00%
Road width	Segment < 3.5m	90	29.61%	30,930	2.76%
	Segment 3.5m-5.5m	58	19.08%	72,022	6.42%
	Segment 5.5m-9m	92	30.26%	263,290	23.49%
	Segment 9m-13m	17	5.59%	112,843	10.07%
	Segment 13m-19.5m	16	5.26%	87,660	7.82%
	Segment >19.5m	7	2.30%	22,183	1.98%
	Intersection 5.5m-13m	6	1.97%	375,070	33.46%
	Intersection >13m	16	5.26%	102,524	9.15%
	Others	2	0.66%	54,473	4.86%
Road Alignment	Straight - flat	289	95.07%	947,659	84.54%
	Straight - uphill	7	2.30%	29,475	2.63%
	Straight - downhill	5	1.64%	43,030	3.84%
	Right curve - flat	1	0.33%	14,861	1.33%
	Right curve - uphill	0	0.00%	3,645	0.33%
	Right curve - downhill	0	0.00%	4,558	0.41%
	Left curve - flat	0	0.00%	14,731	1.31%
	Left curve - uphill	0	0.00%	3,544	0.32%
	Left curve - downhill	0	0.00%	5,019	0.45%
	Others	2	0.66%	54,471	4.86%
Crash location	Segment and near intersection	7	2.30%	566,078	50.50%
	Intersection	275	90.46%	80,147	7.15%
	Others	22	7.24%	474,770	42.35%
Median	Physically separated barrier	7	2.30%	194,769	17.37%
	Painted median: Cat eyes, stone	1	0.33%	4,969	0.44%
	Painted median: general	22	7.24%	509,204	45.42%
	No median	272	89.47%	357,580	31.90%
	Others	2	0.66%	54,473	4.86%
Lane and sidewalk separation facilities	Guardrail/ protection railing	12	3.95%	91,432	8.16%
	Curb	59	19.41%	669,273	59.70%
	Only line	35	11.51%	168,474	15.03%
	No separation	198	65.13%	191,816	17.11%

Table 5. Crash factors of all crashes

Variable	Type	Tram	Percentage in tram crashes	Non-Tram	Percentage in non-tram crashes
Injury severity	Fatal[a]	181	59.54%	9,088	0.81%

	Injury	123	40.46%	1,111,907	99.19%
Crash location	Segment and near intersection	7	2.30%	566,078	50.50%
	Intersection	275	90.46%	80,147	7.15%
	Others	22	7.24%	474,770	42.35%
Crash Classification	Pedestrian to vehicle	165	54.28%	138,330	12.34%
	Vehicle to other vehicle	110	36.18%	944,971	84.30%
	Single vehicle, including car to parked car	6	1.97%	38,694	3.45%
Age of participant A (driver of tram crash; participant A of non-tram crash)	0-24	20	6.58%	132,748	11.84%
	25-34	84	27.63%	170,945	15.25%
	35-44	80	26.32%	188,917	16.85%
	45-54	80	26.32%	222,138	19.82%
	55-64	38	12.50%	165,704	14.78%
	65-74	1	0.33%	153,630	13.70%
	75 and older	1	0.33%	86,913	7.75%
Age of participant B (victim of tram crash; participant B of non-tram crash)	0-24	29	9.54%	258,380	23.05%
	25-34	21	6.91%	167,865	14.97%
	35-44	30	9.87%	175,153	15.62%
	45-54	40	13.16%	190,179	16.97%
	55-64	33	10.86%	129,902	11.59%
	65-74	68	22.37%	112,467	10.03%
	75 and older	83	27.30%	87,049	7.77%
Type of victim	Car	38	12.50%	Unknown[b]	Unknown[b]
	Truck	82	26.97%	Unknown[b]	Unknown[b]
	Motorcycle, Electric bicycle and bicycle	19	6.25%	Unknown[b]	Unknown[b]
	Pedestrian	165	54.28%	Unknown[b]	Unknown[b]

[a]: At least one fatality occurs within 24 hours of the traffic crash.
[b]: Referring to the crash report data, it cannot differentiate the participant who is the victim of a non-tram crash.

In the statistical data on crashes in Japan from 2019-2022, tram crash and non-tram crash have a large gap in number due to the limitations of mileage, operation time, routes, etc. Tram crash account for only 0.2% of all. The severity of crashes emerges as the most concerning issue. The data indicates that fatalities account for 59.54% of tram crashes, with more than seventy times of non-tram crashes. Regarding environmental factors, the crash rate for trams is higher in winter, while the occurrence of crashes of non-tram is relatively uniform. Non-tram crashes are more likely to occur during the day and on dry road surfaces, whereas tram crashes are predominantly concentrated at rail crossings and on straight-flat road sections. The lack of median to separate different direction and the absence of barriers between motor vehicle lanes and pedestrian paths contribute to the elevated rate of tram crashes. As for human factors, more than half of tram crashes involve collisions with pedestrians, while non-tram vehicle crashes predominantly consist of collisions between vehicles. Due to the lack of comprehensive crash information, it is challenging to accurately determine the liable parties. After manually annotating the information of both parties involved in tram crashes, statistical results reveal that the ages of tram drivers range from 25 to 55 years. Additionally, victims aged 55 and older account for over 60% of those involved in these incidents.

Considering that traffic demand and supply may change during the period of COVID-19, which may cause data discontinuity and inconsistency, the author conducted separate modeling of the data. Comparative analysis of the model results revealed no significant differences, possibly due to the limited sample size. Future research on the impact of COVID-19 on the occurrence and severity of tram crashes is also a promising direction.

2.2 Variable selection for regression model

According to the results of Pearson correlation analysis, variables exhibiting similar effects on the dependent variable are selected and combined to form a new variable term. Additionally, based on the characteristics of data balancing and the commonly used variable categorization approaches in traffic crash regression modeling, the original data mentioned in Section 2.1 has been consolidated and reclassified as shown in **Table 6**.

Table 6. Processed variables

Variables[a]	Description	% in tram	% in non- tram
Crash information			
FATAL	1 = involves a fatality; 0 = involves a non-fatal injury.	59.54%	0.81%
Road and environment			
SEASON14	1 = occurs in spring or winter 0 = occurs in summer or fall	51.32%	49.43%
DAYTIME	1 = occurs in daytime 0 = otherwise	52.63%	64.18%
AREA	1 = occurs in densely populated urban area 0 = otherwise	55.26%	51.26%
DRY	1 = occurs on dry road surface 0 = otherwise	80.26%	84.18%
RCROSSING	1 = occurs at rail crossing 0 = otherwise	84.21%	0.02%
INTERSEC	1 = occurs at intersection 0 = otherwise	90.46%	7.15%
NARROW	1 = road width less than 5.5 meters 0 = otherwise	49.34%	9.18%
MEDIAN	1 = median exists to separate different directions 0 = otherwise	11.53%	68.10%
Victim classification[b] (only in tram crash)			
OLDAGE	1 = the victim is older than 65 0 = otherwise	49.67%	-
MIDDLE	1 = the victim's age between 35 to 65 0 = otherwise	33.88%	-
TRUCK	1 = another participant is truck 0 = otherwise	26.97%	-
CYCLE	1 = another participant is motorcycle, bike or e-bike 0 = otherwise	6.25%	-
PED	1 = another participant is pedestrian 0 = otherwise	54.28%	-

[a]: The processed variables have all passed collinearity test, indicating the absence of multicollinearity.
[b]: Which compared with OLDAGE and MIDDLE is young person who is under 35, compared with TRUCK, CYCLE, and PED is car.

3.Method

3.1 Stratified sampling

Imbalanced data refers to a dataset in which one or more classes have a significantly larger number of examples than others. The most prevalent class is called the majority class, while the rarest class is referred to as the minority class (Yijing et al., 2016). Imbalanced datasets often impact the accuracy and effectiveness of models, making it necessary to perform resampling techniques. Resampling is a statistical method used to draw samples from a dataset and analyze the results to estimate the properties of a population (Haixiang et al., 2017). In the data used in this study, the number of tram crash is too few to guarantee the accuracy and effectiveness of the model. Therefore, resampling technology is used to build balanced data set. One of the resampling methods is Under-sampling methods: eliminating the harms of skewed distribution by discarding the intrinsic samples in the majority class. The simplest yet most effective method is Random Under-Sampling (RUS), which involved the random elimination of majority class examples (Tahir et al., 2009). Other under-sampling methods are developed on this basis.

In this study, the overall sample size is large, and the internal complexity is greater, with significant individual differences. Simple random sampling is no longer suitable. Therefore, stratified sampling is chosen to reduce sampling error and improve sampling accuracy (Sandelowski, 2000).

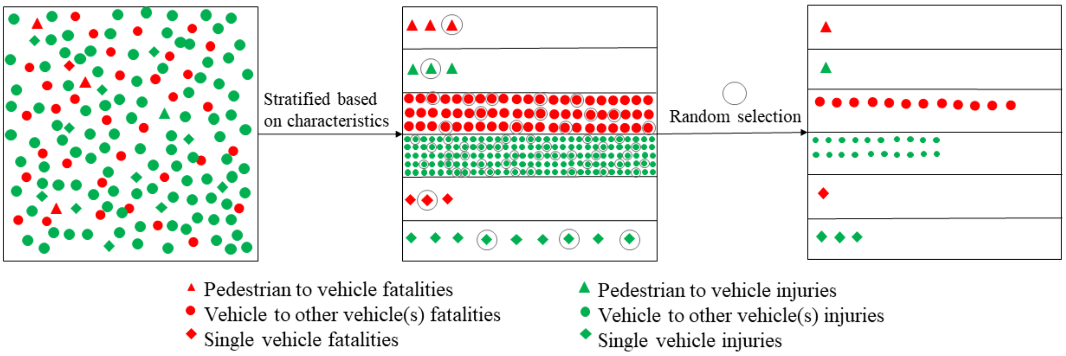

Figure 2. Steps of stratified sampling

When selecting criteria for classification, the data is divided into six groups based on the features of injury severity (fatal and injury) and crash classification (pedestrian to vehicle, vehicle to other vehicle and single vehicle), with each group forming a subsample. As shown in **Figure 2,** simple random sampling is independently conducted within each stratum according to the proportion of sample sizes between subsets. The final samples from the six groups are mixed for analysis about the characteristics of tram crash.

Previous studies have found that it is unnecessary to precisely balance the number of majority and minority classes; different sampling ratios can be determined based on the type of data and research objectives (Zhong et al., 2013). A stratified random sampling method was adopted with a sampling ratio of 0.0027, resulting in a resampled ratio of tram crashes to non-tram crashes of 1:10.

3.2 Chi-square Test of Independence

Due to the categorical nature of the data in this study, we employed the chi-square test of independence to analyze the association between the sampled data and the population, as well as the independence between tram and non-tram crashes (Sandelowski, 2000). This method is specifically designed to assess whether two categorical variables are independent, and it is particularly effective with larger sample sizes.

The basic formula for the chi-square test as **Equation 1**:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

Where, O_i represents the observed frequency and, E_i represents the expected frequency. The expected frequency is typically calculated based on the marginal totals of the sample, under the assumption that the categorical variables are independent.

3.3 Random Parameter Probit Model with Heterogeneity in Means

3.3.1 Fixed probit model

Probit model was commonly used in analyzing contributing factors to crash occurrence. These models are types of regression analysis that are particularly suited for binary outcome variables, such as whether a fatal crash occurred or not.

In the context of crash analysis, these models help in estimating the probability of a crash happening based on a set of independent variables (Fountas and Anastasopoulos, 2017), such as weather conditions, road conditions, driver behavior, etc. By using these models, researchers can identify the factors that significantly influence the likelihood of crashes and quantify their impact. The probit model assumes that the errors follow a normal distribution (Chang et al., 2019).

In this study, the dependent variable (i.e., whether a crash involves fatality or whether a crash involved tram) is binary. The binary fixed Probit model was used (Zhou and Bridges, 2019) assuming the disturbance term ε to be normally distributed. Thus, it can be mathematically expressed as **Equation 2**.

The variable i typically represents individual observations or cases within the dataset.:

$$Y_i^* = \beta X_i + \varepsilon_i \qquad Y_i = 1 \text{ if } Y_i^* > 0, \text{and 0 otherwise} \tag{2}$$

where Y_i^* represents the latent variable capturing unobserved utility. X_i is the vector of explanatory variables. (e.g., pedestrian, vehicle, road, and environment characteristics), β is the estimable parameters.

3.3.2 Random parameter probit model

To address the individual heterogeneity and the Independence of Irrelevant Alternatives (IIA) assumption limitations (Yu and Long, 2022) that the Fixed Parameter Probit model fails to consider (Bansal et al., 2018), a Random Parameter Probit model was established (Fountas et al., 2018; Yu et al., 2020). In the Fixed Parameter Probit model, the parameters β are fixed values, whereas in the Random Parameter Probit model, the parameters are not fixed but follow a certain distribution, the common ones are normal distribution, uniform distribution, triangular distribution, etc (Greene and Hensher, 2007), and the expression of parameter β is shown in the **Equation 3.**

$$\beta = \bar{\beta} + \sigma\eta_i \tag{3}$$

where $\bar{\beta}$ represents the mean values of the parameters. σ is the standard deviation of the random parameters. η_i is the individual-specific random parameter assumed to follow a standard normal distribution. In the research, the impact of crashes at intersections and during the daytime on whether the crash involved tram shows random effects and both obey normal distribution. The effects of crashes at rail crossing and densely populated areas on tram deaths show random effects and follow exponential distribution and Weibull distributions, respectively.

3.3.3 Random parameter with heterogeneity

However, the commonly used discrete choice models often rely on the assumption of data homogeneity. Analyzing the determinants of crashes from the perspective of the entire sample may to some extent obscure the direct causes of crashes (Pervez ey al., 2022), and fails to capture the inherent heterogeneity within the data (Cai and Wei, 2023). In order to better fit the real-world situation, random parameter models considering heterogeneity have been proposed as a viable alternative (Pervez et al., 2021; Huo et al., 2021). This approach provides a new perspective for the accurate identification of the factors influencing crash occurrence.

According to existing research (Greene et al., 2006; Seraneeprakarn et al., 2017), the random parameters with heterogeneity in means and variance is defined as **Equation 4**:

$$\beta_j = \beta + \delta_j Z_j + \sigma_j \exp(\omega_j W_j) \cdot \upsilon_j \tag{4}$$

where β denotes the mean estimated parameters across all the observations; Z_j is a vector of attributes that captures heterogeneity in means for injury severity level j and δ_j is a corresponding vector of estimable parameters ω_j; $\upsilon_j$is a disturbance term.

In Z_j and W_j, the attributes (e.g., drivers, vehicles, roadway, and environmental characteristics) of heterogeneity are contained. If no variables are found to be significant in W_j, the model is only heterogeneity in means (Seraneeprakarn et al., 2017). In a mixed Probit model that does not account for any heterogeneity in means and variances, the unobserved heterogeneity is not characterized in the vector of Z_j and W_j

3.3.4 Goodness of fit

Maximum likelihood approach with Halton draws (Li and Liu, 2020) is used to estimate the random parameters and is shown as **Equation 5:**

$$L(\beta, \sigma^2 | Y, X) = \prod_{i=1}^{n} \int_{-\infty}^{\infty} [\Phi(X_i\beta + \sigma\eta_i)]^{Y_i} [1 - \Phi(X_i\beta + \sigma\eta_i)]^{1-Y_i} f(\eta_i) d\eta_i \tag{5}$$

where $L(\beta, \sigma^2 | Y, X)$ represents the log-likelihood function in the Binary Probit Model for parameter estimation. β is the parameter vector to be estimated, capturing the effects of explanatory variables, σ^2 is the variance of the random parameters, Y is the vector of binary outcome variables (whether it belongs to fatal crash), X is the matrix of explanatory variables, η_i represents the individual-specific random parameter following a certain distribution, $f(\eta_i)$ represents the density function of the random parameter, $\Phi(\cdot)$ represents the standard normal cumulative distribution function. Y_i is the binary outcome for individual i.

As shown in **Equation 6**, to compare the goodness of fit among the Probit model, Random Parameter probit model and Random Parameter Probit Model with mean heterogeneity, the Akaike's Information Criterion (AIC) is selected to calculated (Gu et al., 2013) by **Equation 6:**

$$AIC = 2k - 2\ln(L) \quad (6)$$

where k is the number of variables, N denotes the number of observations, and L represents the likelihood value of the model. The model with both smaller AIC values suggest statistical superior.

The study employed the NLOGIT 5 software to conduct the simulation analysis. To ensure the accuracy and reliability of the model estimates, the maximum likelihood approach is employed to estimate the coefficients of the random parameters logit model with 1000 Halton draws, resulting in stable parameter estimates (Bhat, 2001; Train, 2009).

4. Results

4.1 Chi-square test Results

According to the sampling method mentioned in section 3.1, the number of samples of different groups in all non-tram is taken proportionally as shown in **Table 7**:

Table 7. Result of stratified sampling

Group	Characteristics		Number
	Injury severity	Crash Classification	
1	Fatal	Pedestrian to vehicle	9
2	Fatal	Vehicle to other vehicle(s)	364
3	Fatal	Single vehicle	9
4	Injury	Pedestrian to vehicle	7
5	Injury	Vehicle to other vehicle(s)	2,553
6	Injury	Single vehicle	98
Total			3,040

From **Table 8**, Pearson test results for samples and all non-tram crash showed that the hypothesis of correlation between the two sets of data cannot be rejected at the corresponding degrees of freedom. This finding validates the reliability of the sampling results, indicating that the balanced data can be utilized for further investigation into the primary distinctions between tram and non-tram crashes.

Regarding the chi-square results between tram and non-tram crashes, it is revealed that the variable distributions of the two crash types are independent of one another, with the most significant difference observed in injury severity. This underscores the necessity to explore the causes of fatal tram crashes.

Table 8. Test of independence with Pearson Chi-square

Variable	Degree of freedom	Chi-square value for sample and all non-tram	Chi-square value for tram and non-tram
Injury severity	1	0.226	12,786.481***
Year	3	1.887	5.652
Month	11	10.308	12.438
Season	3	4.729	4.143
Time	5	2.246	33.193***
Weather	4	3.951	10.126**
Area	2	2.240	8.549**
Road surface	4	1.904	817.552***
Road shape	6	0.618	505,278.837***
Lane width	8	6.718	988.280***
Road Alignment	9	6.630	29.781***
Crash location	2	0.234	3,725.331***
Median	4	4.328	464.147***

Lane and sidewalk separation facilities	3	1.620	501.028***
Crash Classification	2	0.026	518.134***
Day of week	7	2.847	8.631

***, **, * represent statistically significant at 1%, 5%, 10% levels, respectively.

4.2 Estimation results

In the process of model estimation of tram crash characteristics, whether a crash included tram or not is selected as the dependent variable, independent variables which are not statistically significant at the 0.1 level of significance were removed. The Log-likelihood at coverage of Random Parameter model with Heterogeneity in Means is -225.110, McFaddenR^2 of the model is 0.779, AIC of the model is 472.219.

Table 9. Models for tram crash occurrence (vs. non-tram)

Variables	Fixed Probit		Random Parameter Probit		Random Parameter with Heterogeneity in Means	
	Coefficient	Prob.|z|>Z*	Coefficient	Prob.|z|>Z*	Coefficient	Prob.|z|>Z*
Constant	-1.698***	<0.001	-1.685***	<0.001	-1.590***	<0.001
Road and environment						
FATAL	0.979***	0.002	1.006***	0.003	1.215***	0.002
NARROW	-0.609***	0.001	-0.635***	0.003	-0.745***	0.003
RCROSSING	4.527***	<0.001	4.672***	<0.001	5.586***	<0.001
MEDIAN	-0.498***	<0.001	-0.520***	<0.001	-0.664***	<0.001
INTERSEC (Means)	-0.092	0.468	-0.176	0.207	-2.786***	<0.001
INTERSEC (S.D.)			0.287***	0.003	1.473***	<0.001
DAYTIME (Means)	-0.099	0.411	-0.179	0.189	-1.156**	0.018
DAYTIME (S.D.)	-		0.285***	<0.001	0.650***	<0.001
Heterogeneity in the means of random parameters						
INTERSEC & DENSPOP[a]	-	-	-	-	1.386*	0.017
DAYTIME & DENSPOP[b]	-	-	-	-	0.910**	0.048

***, **, *: represent statistically significant at 1%, 5%, 10% levels, respectively.
[a]: means crash occurred at the intersection of densely populated area.
[b]: means crash occurred in densely populated area during daytime.

From **Table 9,** when fatalities occurred at rail crossing, the crash type was more likely to be tram-involved than non-tram-involved. Conversely, crashes that occur during the daytime, at intersection, at road which is narrower than 5.5 m are more likely to be a non-tram crash. When there are median between different directions, it also increases the tendency of non-tram crash.

The variables INTERSEC and DAYTIME do not exhibit statistical significance in the Fixed Probit model and Random Parameter Probit model, whereas they demonstrate significance in the Random Parameter with Heterogeneity in Means model, attributable to the influence of certain unobservable variables, resulting in mean differences across categories and consequently affecting distribution differences. Specifically, among crashes occurred at intersection,1.06% of individuals are more likely to involve tram; this likelihood increases to 87.17% for crashes occurring in densely populated area. During daytime, 0.00% of crashes are more likely to involve tram. However, when it is in densely populated area, this proportion rises to 99.98%.

In the process of model estimation of effecting factors of tram fatalities, whether a tram crash leads to fatality or not is selected as the dependent variable, independent variables which are not statistically significant at the 0.1 level of significance were removed. **Table 8** lists the parameter estimation results for the Fixed Probit, Random Parameter Probit, and Random Parameter Probit Model with heterogeneity in means. The Log-likelihood at coverage of Random Parameter with Heterogeneity in Means is -205.150, McFaddenR^2 of the model is 0.416, AIC of the model is 271.442. The results reveal the following:

Crashes occurred in spring or winter, at rail crossing, and in densely populated areas have a positive impact on the probability of fatal crashes, when these factors are present, the probability of a tram fatality crash will increase. Additionally, when the victim is aged over 35 years or is a pedestrian, motorcyclist, bicyclist, or electric bicycle user, the probability of a fatal crash increases. Conversely, crashes happening during the daytime or on roads with dry surfaces or median separators to delineate different directions are associated with a reduced probability of a fatal outcome.

For parameter estimates, **Table 10** shows that two explanatory variables: RCROSSING and AREA yielded random parameters as their standard deviations were statistically different from zero, which indicates that the safety effect of these factors varied across observations due to unobserved heterogeneity. Furthermore, the two random parameters, RCROSSING and AREA, produced significant heterogeneity in their means. Specifically, the parameter for crashes at rail crossings involving a cyclist as the other party exhibited a significant difference in the mean compared to the overall crash parameter. Similarly, the mean value changed significantly when a median separator was present in crashes occurring in densely populated areas.

Table 10. Models for fatal tram crash (vs. non-fatal tram crash)

Variables	Fixed Probit		Random Parameter Probit		Random Parameter with Heterogeneity in Means	
	Coefficient	Prob.|z|>Z*	Coefficient	Prob.|z|>Z*	Coefficient	Prob.|z|>Z*
Constant	-2.392***	<0.0001	-17.809***	<0.001	-9.181***	<0.001
Road and environment						
SEASON14	0.317*	0.085	3.886***	<0.001	1.598***	<0.001
DAYTIME	-0.278	0.429	-2.790**	0.014	-1.127*	0.086
DRY	-0.351	0.136	-2.540**	0.003	-1.056**	0.021
MEDIAN	-0.426	0.288	-3.091**	0.016	-41.793*	0.060
RCROSSING (Means)	1.798***	<0.001	17.539***	<0.001	8.750***	<0.001
RCROSSING (S.D.)	-	-	11.623***	<0.001	5.285***	<0.001
AREA (Means)	0.290	0.139	2.996***	<0.001	0.705*	0.065
AREA (S.D.)	-	-	4.430***	<0.001	0.671**	0.020
Victim classification						
OLDAGE	0.260	0.340	2.409***	0.009	1.252**	0.019
MIDDLE	0.342	0.231	2.560***	0.009	1.629***	0.006
TRUCK	0.109	0.721	1.922	0.103	0.912	0.232
CYCLE	1.117***	0.004	12.179**	<0.001	7.791***	<0.001
PED	1.497***	<0.001	13.019***	<0.001	6.324***	<0.001
Heterogeneity in the means of random parameters						
RCROSSING & CYCLE[a]	-	-	-	-	-2.768*	0.067
DENSPOP & MEDIAN[b]	-	-	-	-	42.428*	0.056

***, **, *: represent statistically significant at 1%, 5%, 10% levels, respectively.

[a]: means crash occurred at rail crossing and another part is motorcycle, bicycle or e-bicycle

[b]: means crash occurred in densely populated area and consist median to separate different directions

4.2 Model performance comparison

The performances of models for (1) tram crash (vs. non-tram); and (2) fatal tram crash (vs. non-fatal tram crash) are summarized in in **Table 11** and **Table 12**, respectively.

Table 11. Comparison of explanatory effects on factors to tram crash occurrence characteristics (vs. non-tram)

Model statistics	Probit	Random Parameter Probit	Random Parameter with Heterogeneity in Means
Number of parameters (k)	7	9	11

Number of observations	3344	3344	3344
Log-likelihood at constant-only	-1018.70	-1018.70	-1018.70
Log-likelihood at coverage	-239.636	-239.436	-225.110
McFadden's pseudo R^2	0.765	0.756	**0.779**
Akaike information criterion (AIC)	493.273	496.872	**472.219**

Table 12. Comparison of explanatory effects of fatal tram crash (vs. non-fatal tram crash)

Model statistics	**Probit**	**Random Parameter Probit**	**Random Parameter with Heterogeneity in Means**
Number of parameters (k)	12	14	16
Number of observations	304	304	304
Log-likelihood at constant-only	-205.150	-205.150	-205.150
Log-likelihood at coverage	-128.745	-125.191	-119.721
McFadden's pseudo R^2	0.372	0.390	**0.416**
Akaike information criterion (AIC)	281.491	278.38	**271.442**

Based on the McFadden pseudo-R-squared and Akaike Information Criterion (AIC), the estimated random parameter binary probit model with heterogeneity in means exhibit better overall statistical fit compared to models using fixed parameters and random parameters, respectively. In particular, incorporating individual heterogeneity through a mean heterogeneity approach significantly improves the statistical fit of crash data in this study.

5. Discussion

5.1 Characteristics of tram crash

In the previous section, the research revealed the influencing factors of tram occurrence crashes using a random parameter model that considers mean heterogeneity. Results of **Table 9** showed that crashes at railway crossing and those involving fatal injuries are more likely to be tram crashes compared to non-tram crashes. In contrast, crashes that happen during daytime, at intersections, or on roads narrower than 5.5 m are more likely to be classified as non-tram crashes compared to tram crashes. Additionally, when a median separates opposing directions, compared with tram crash, the likelihood of a non-tram crash increases. In this section, we will critically compare and discuss the results of **Table 9** in conjunction with existing studies.

5.1.1 Environmental factors

Trams can only operate on fixed tracks, and their speed is relatively uniform with other motor vehicles, which makes them less affected by the complex traffic flow during the daytime. In contrast, other road users, primarily motor vehicles, are more prone to crashes such as rear-end collisions due to frequent changes in driving routes and acceleration in complex traffic environments. However, at night, visibility is reduced due to insufficient light, making it difficult for drivers and pedestrians to timely observe surrounding hazards. The fixed route and heavier mass of trams make it challenging for them to maneuver quickly, while other road users can more flexibly adjust their driving routes and speeds.

5.1.2 Road conditions

At intersections, the trend of tram crashes is decreasing, while crashes at rail intersections are increasing, which may be related to the composition of traffic participants. The traffic conditions at intersections are relatively complex, with a greater variety and number of participants. However, compared to other traffic participants, trams have predictable trajectories, possess right-of-way, and maintain stable speeds (Choi et al., 2021), making non-tram crashes more likely at regular intersections. Conversely, at rail crossings, there are fewer types of traffic participants, and the likelihood of tram presence is higher, which increases the occurrence of tram-related crashes at these intersections. Similarly, the presence of a median that separates opposing traffic flows to minimize traffic conflicts between tram and other road users can effectively mitigate the occurrence of tram crashes. These findings are consistent with previous researches. Zhou et al. (2018) find that complex traffic flows increase the likelihood of trams-involved crashes. It has been repeatedly confirmed in existing research, the presence of medians that separate opposing traffic flows can reduce the probability of tram crashes (Currie and Shalaby, 2007). The installation of tram lines also affects the crashes, and narrow road segments often do not have the conditions to accommodate tram lines. Straight and flat sections of road typically serve as major thoroughfares with higher traffic volumes and more complicated conditions, which are common routes for trams. In contrast, narrower roadways tend to have lower traffic volumes and simpler conditions. Under more complex traffic situations, trams, with their fixed routes and stable operating speeds (Choi et al., 2021), have a lower probability of crashes compared to non-tram vehicles.

5.1.3 Injury severity

Compared to other vehicles, trams exhibit greater mass and longer braking distances, consequently leading to a higher fatality rate in traffic crashes (Maempel et al., 2018; Castanier et al., 2012; Hedelin et al., 1996). Particularly, the placement of stations increases the exposure of vulnerable groups, such as pedestrians, to trams (Wong et al., 2007).

5.1.4 Heterogeneity analysis

The results indicate that both daytime and intersection factors show a random distribution trend concerning tram crashes compared to ordinary crashes, with a positive mean value. Individuals positively influencing the occurrence of tram crashes constitute only 0.00% and 1.06% of the total population. However, in densely populated areas, the proportion of individuals positively influencing tram crashes rises significantly to 99.98% and 87.17%, respectively. In densely populated urban areas, the exposure frequency of pedestrians and cyclists is higher, with over 60% of tram crash victims being from vulnerable groups. Additionally, the traffic conditions in densely populated areas are more complex, making tram crashes more likely to occur in such intricate, restricted, and mixed traffic environments.

5.2 Factors affecting tram fatality

Results of **Table 10** showed that crashes that occur in spring or winter, at rail crossing, and in densely populated areas positively influence the likelihood of tram fatal crashes. Furthermore, the probability of a fatal crash increases when the victim is over 35 years old or belongs to vulnerable group. In contrast, crashes that happen during the daytime or on roads with dry surfaces and median separators that separate different traffic directions are linked to a lower probability of tram fatal outcomes. The following discussion presents an analysis of the functional modes of factors based on a comprehensive review of existing literature and the findings presented in **Table 10**.

5.2.1 Environmental factors

The season did not appear to influence tram-related fatalities in previous studies. However, seasonal differences in crashes have been confirmed (Gill and Goldacre, 2009). In Japan, crashes occurring in winter or spring have a positive effect on deaths. It can be attributed to a combination of factors. The reduced visibility due to winter conditions such as snowfall and fog can increase the likelihood of crashes involving trams. Additionally, the lower temperatures during winter may lead to icy road conditions, making it more challenging for trams to operate safely. In spring, the transition period from winter to warmer weather can bring about unpredictable weather patterns, potentially leading to hazardous conditions for tram operations. Furthermore, factors such as increased pedestrian activity during these seasons and potential changes in daylight hours can also contribute to the elevated risk of tram-related fatalities in Japan during winter and spring. In addition to seasonal differences, variations in time and road surface have a more direct impact on the probability of fatal crashes. Crashes occurring during daytime can contribute to a reduction in tram crash fatalities. The enhanced visibility during daylight hours allows for better detection of potential hazards by tram operators and other road users, leading to improved reaction times and crash prevention. Additionally, the increased ambient light levels during the day can enhance visibility of tram tracks and signals, reducing the likelihood of crashes caused by obscured or poorly visible tram infrastructure. Tram-involved crashes occurring on dry surface exhibit an inverse correlation with fatality rates in tram crashes. Firstly, dry conditions offer increased traction and stability for tram vehicles, reducing the likelihood of skidding or loss of control that could lead to crashes. This enhanced grip on the road surface can improve the overall handling and braking capabilities of trams (Zhao et al., 2017), thereby decreasing the risk of collisions and fatalities. Good lighting conditions and a dry road surface provide both parties involved in tram crash with the condition to perceive risks and take action. Compared to crashes that occur suddenly, the probability of fatalities in tram crashes that follow a deceleration or change in direction is significantly reduced.

5.2.2 Road conditions

Differences in the road conditions affect the types and behaviors of traffic participants, thereby influencing the probability of tram-related fatalities.

The probability of fatalities in tram crashes occurring on roads with measures separating traffic flows in different directions is lower. According to previous research, the reasons can be explained in two aspects: firstly, the physical barrier provided by the median serves as a protective divider between tram tracks and lanes of opposing traffic, reducing the likelihood of opposite collisions between trams and vehicles traveling in different directions (Tarko et al., 2008), while opposite crash is much more serious (Bareiss et al., 2019) than other angles. Secondly, the division of traffic flows enhances overall road safety by reducing the potential for conflicts and interactions between vehicles moving in different directions. By providing clear demarcation between lanes, the separation promotes orderly traffic patterns, and decreases the probability of crashes caused by erratic driving behaviors (Naznin et al., 2016a).

The occurrence at rail crossings has a positive impact on tram fatalities and rail crossing are found to be random parameters. Firstly, intersections serve as points of potential conflict where the paths of trams intersect with other vehicles, pedestrians, or cyclists. This increases the likelihood of collisions at higher speeds, which can result in more severe outcomes. The presence of multiple tracks at intersections can lead to complexities in tram movements and interactions, potentially causing confusion for both tram operators and other road users. This complexity may reduce the time available for effective decision-making and increase the risk of crashes with fatal consequences. Additionally, the design of intersections may not always prioritize tram safety, leading to inadequate infrastructure or signaling systems that fail to adequately address the unique needs of tram operations. These combined factors contribute to the heightened fatality rate in tram crashes at intersections.

The occurrence of fatal crashes involving trams in densely populated areas is positively correlated and found to be random parameters. The high volume of pedestrian and vehicular traffic in dense urban settings increases the likelihood of interactions between trams and other road users, leading to a higher probability of crashes. Moreover, the presence of numerous distractions in crowded urban environments, such as noise, visual stimuli, and a multitude of road users, can impact the focus and attention of tram operators, increasing the risk of crashes.

5.2.3 Classification of victims

Differences in the age and type of victims show significant differences in the likelihood of fatal crashes. Victims aged over 35 are more likely to suffer fatal outcomes in crashes involving trams due to several factors. This is consistent with numerous findings from previous studies. Older individuals may have slower reaction times and decreased physical resilience compared to younger counterparts, making them more vulnerable to the impact of a collision. Additionally, older victims may have pre-existing health conditions or vulnerabilities that can exacerbate the severity of injuries sustained in a tram crash (Oxley et al., 1997). Furthermore, psychological factors such as increased fear or panic in older individuals during high-stress situations can impede their ability to react effectively and mitigate the consequences of the crash (Finn and Bragg, 1986). When the other party involved in the crash belongs to vulnerable road users (such as cyclists, electric vehicle users, motorcyclists, or pedestrians), the probability of fatalities in tram crashes is higher (Vandenbulcke et al., 2014). Vulnerable road users, such as pedestrians and cyclists, are less protected compared to occupants of motorized vehicles, making them more vulnerable to severe injuries in the event of a collision with a tram. Their limited of physical protection and absence of certain safety warning devices (such as robust cockpit structure, reflective materials and lighting system) leaves them more exposed to the impact forces involved in tram crashes (Naznin et al., 2016b).

5.2.4 Heterogeneity analysis

In tram rail crossing-related crashes, 55.67% exhibited an increased likelihood of resulting in fatalities. However, when the victims involved are on motorcycles, bicycles, or e-bicycles, the average value of the RCROSSING parameter decreases by 14.22, reducing the probability of a crash leading to fatality to 32.27%. Nevertheless, this does not conclusively indicate that cyclists are safer in tram-involved crashes. Regarding the composition of crash victims, over half (54%) were pedestrians, while 35% were motorists, including car and truck drivers, and 6% were cyclists. This suggests that, compared to the overall victim population, cyclists may be relatively safer when involved in crashes at tram intersections.

Tram-related crashes in densely populated areas have also been shown to exhibit mean heterogeneity. However, due to software limitations, further analysis and quantification of this heterogeneity could not be performed.

5.3 Policy implications

According to the result of parameter estimation, the study suggests two key measures to improve tram safety: improving the road environment for trams and enhancing protection for vulnerable groups.

Improving the road environment for trams: establishing physical separation between tram tracks and lanes, such as using barriers or raised curbs, to minimize the risk of collisions with other vehicles. Measures such as increasing the separation of trams from other traffic participants have been shown to be effective in previous studies (Marti et al., 2016; Lee et al., 2019). Additionally, implementing regular monitoring of track conditions to ensure adequate dryness and suitability for safe tram operations, and providing sufficient illumination along tram routes to enhance visibility for both tram operators and other road users, especially during nighttime or adverse weather conditions.

Enhancing protection for vulnerable groups: designating dedicated waiting areas with physical barriers for passengers at tram stops, constructing pedestrian walkways separated from tram tracks, and creating designated bike lanes to ensure the safety of cyclists. Furthermore, increasing the presence of warning signs and signal lights at tram stops and intersections to alert both tram operators and other road users to the presence of vulnerable groups, particularly in areas with complex traffic flows or high pedestrian activity. Many studies have proved that strengthening the design of tram stations (Currie and Smith, 2006) and protecting the vulnerable groups (Shi et al., 2017) can significantly improve the severity of tram crashes

These measures are proposed based on the analysis of the contributing factors to fatal tram crashes and aim to provide practical solutions for enhancing tram safety.

6. Conclusions

Policies promoting sustainable transportation systems have led to an increase in the presence of trams and tramlines in many countries. However, due to the operational and organizational characteristics of trams, as well as the allocation of road rights, trams are more prone to collisions with other road traffic participants, especially vulnerable groups such as pedestrians, resulting in more severe injuries and fatalities, although risk perception in road traffic safety has been extensively studied, there is a lack of research on tram crashes in Asian countries. Therefore, this paper focuses on Japan as a case study to address this gap. The main objectives of this paper are to investigate the disparities between tram and non-tram crashes, and to analyze the factors contributing to fatal tram crashes in Japan.

This research employed a binary random parameter probit model that accounts for heterogeneity to investigate the main characteristics of tram crash and the primary factors influencing fatal crashes. Stratified sampling was used to build the dataset of tram crashes and non-tram crashes. Results showed that the presence of fatalities, crash occurred at rail-crossing have a positive effect on the occurrence of tram crash. Conversely, crashes that occur during the daytime, at intersection, at road which is narrower than 5.5m are more likely to be a non-tram crash. When the crash involves two vehicles, or when there are median between different directions, it also increases the tendency of non-tram crash, the crash occurred at intersection and during daytime exhibit random effects due to the influence of certain unobservable variables, resulting in mean differences across categories and consequently affecting distribution differences. Also, results indicate that fatal crashes are more likely to occur in spring or winter, particularly in densely populated areas or at railway crossings. Furthermore, victims over the age of 35, pedestrians, or cyclists are more likely to be involved in fatal tram crashes. Additionally, the likelihood of fatal crashes is lower when trams operate during the day, on dry road surfaces, and on roads with separate directions. Crashes occurring at rail crossing and in densely populated area exhibit mean heterogeneity due to unobserved factors. Notably, when motorcycle, bicycle, or e-bicycle involved in crashes at rail crossings, victim may face a higher probability of fatal outcomes compared to other types of victims. The study also proposes two key measures regarding how to improve the operating environment for trams and how to enhance the protection of vulnerable road users during tram operations.

In conclusion, the findings of this study could aid authorities in reducing tram-related fatalities, leading to financial benefits and increased commuter safety. Moreover, the study's findings offered valuable insights for tram operating authorities, drivers and other vulnerable road users, such as strengthening road segregation measures in different directions, monitoring track dryness and visibility, and enhancing protective barriers and warning signals based on segregation strategies. It can enable them to better understand the high-risk areas and situations involving trams and take necessary precautions to prevent crashes.

One of the limitations of this study is the data, which lack relevant information about the vehicles and the gender, age, and driving experience of tram operators and other road users involved in crashes. Subsequent research should aim to comprehensively explore tram crashes with more comprehensive data from other countries or regions.

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Author Contributions

The authors confirm contribution to the paper as follows: conceptualization, methodology, formal analysis, writing- review & editing, Investigation, funding acquisition: Jaeyoung Jay Lee; Literature search and review, model formulation and estimation, writing-original draft, writing review & editing: Yefan Yang; Methodology, writing- review & editing: Suyi Mao; Methodology, writing- review & editing: Marco Bassani; Model formulation and estimation, writing- review & editing: Emanuele Sacchi; The authors reviewed the results and approved the final version of the manuscript.

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