Available online at www.CivileJournal.org

Civil Engineering Journal

(E-ISSN: 2476-3055; ISSN: 2676-6957)

Vol. 12, No. 01, January, 2026

A Multivariate Analysis of Smartphone Use Behavior Among Motorcyclists at Urban Intersections

Ekarin Surinaud [1], Phongphan Tankasem [2*], Anuchat Leeanansaksiri [1]

[1] *Department of Civil Engineering, Faculty of Engineering, Northeastern University, Khon Kaen, Thailand.*

[2] *Department of Civil Engineering, Faculty of Engineering, Mahasarakham University, Mahasarakham, Thailand.*

Received 23 April 2025; Revised 09 December 2025; Accepted 17 December 2025; Published 01 January 2026

Abstract

The increasing use of smartphones while riding motorcycles poses significant safety risks, particularly in urban environments of middle-income countries with high motorcycle usage. Despite growing global concerns, limited research has examined the combined influence of individual, behavioral, and environmental factors on smartphone use among motorcyclists at signalized intersections. This study investigates the determinants of smartphone use behavior—both hand-held and hands-free—among motorcyclists in Khon Kaen City, Thailand. A total of 31,648 riders were observed using video surveillance across eight intersections with varying geometric and land-use characteristics. As part of the methodological approach, binary and multinomial logistic regression models were applied to analyze factors associated with smartphone use. The results show that 7.7% of motorcyclists used smartphones while riding, with 6.2% using hand-held and 1.5% using hands-free modes. Significant predictors included riding alone, being male, not wearing a helmet, riding during nighttime or weekdays, and stopping at red lights. Delivery riders were particularly likely to use smartphones, especially in hands-free mode. These findings highlight the multifaceted nature of distracted riding and suggest the need for comprehensive, context-sensitive policy interventions. The insights gained from this study can inform strategic planning and safety enforcement not only in Thailand but also in other urban areas across middle-income countries where motorcycles remain a dominant mode of transport.

Keywords: Smartphone Use; Distracted Riding; Logistic Regression; Motorcyclists; Signalized Intersections.

1. Introduction

Road traffic injuries have posed a long-standing public health challenge in Thailand, particularly among users of two- and three-wheeled vehicles. According to the Global Status Report on Road Safety 2023 [1, 2], motorcyclists account for the highest fatality rate among all vehicle users in the country, representing 51% of all road traffic deaths. The fatality rate for these vehicle types stands at 12.95 deaths per 100,000 population, ranking first globally [3]. Moreover, data from the Department of Land Transport of Thailand reveal that over 1.8 million new motorcycles have been registered annually from 2010 to 2024 [4].

The primary causes of motorcycle-related accidents in Thailand are associated with risky behaviors, including not wearing helmets, exceeding speed limits and using mobile phones while riding [5]. The use of mobile phones while operating a vehicle, whether driving or riding, is considered a major source of distraction that compromises road safety. Prior research has shown that mobile phone use is more prevalent in urban areas, especially on city streets, than on rural roads or highways [6]. While hands-free phone use is permitted in many countries, including Thailand, the use of hand-held devices while riding or driving remains illegal.

* Corresponding author: phongphan.t@msu.ac.th

https://doi.org/10.28991/CEJ-2026-012-01-08

Mobile phone usage while riding is strongly associated with individuals who engage in other risky behaviors. Past behavior has a significant positive effect on mobile phone addiction and behavioral intention of riders [7]. For instance, drivers with a history of reckless conduct are more likely to use their phones compared to cautious drivers [8, 9]. Numerous studies have demonstrated that using a mobile phone while riding or driving significantly reduces concentration and impairs the operator's ability to control the vehicle [10–12]. It diverts attention from the road and the critical tasks required for safe driving, significantly affecting gaze behavior [13,14], particularly the focus on the rear-view mirror [15]. In some cases, mobile phone use can be more distracting than driving with a blood alcohol content of 80–100 mg/dL [16]. Communication with phone conversation partners also carries more cognitive risk than with in-vehicle passengers, who are aware of the driving context and can help mitigate distractions [17]. Despite awareness of legal restrictions and safety concerns, drivers often prioritize the perceived urgency or importance of mobile communications [18, 19].

1.1. Behavioral and Contextual Factors Influencing Mobile Phone Use

A growing body of literature has explored the situational and demographic factors associated with mobile phone use while operating vehicles. Studies have consistently shown that drivers or riders traveling alone are more likely to use mobile phones than those accompanied by passengers [6, 20, 21]. Furthermore, drivers are more likely to use their phones at intersections [22], particularly when stopped at red lights or in congested traffic, than when traveling at higher speeds [21].

Time of day and day of the week have also emerged as influential factors. Motorcyclists are more likely to use phones on weekdays—possibly due to work-related communication—than on weekends [19]. Additionally, phone use tends to be higher during daylight hours, although some studies suggest the contrary [23]. Gender is another relevant variable, with male riders generally reporting higher mobile phone use [10, 18].

Interestingly, some studies have reported counterintuitive findings regarding safety gear. For example, motorcyclists who wear helmets may exhibit higher rates of risky behaviors, such as using phones while riding, compared to those who do not wear helmets—suggesting a potential risk compensation effect [24].

1.2. Smartphone Use Patterns and Enforcement Gaps

Legal frameworks in many countries, including Thailand, permit hands-free mobile phone use but prohibit hand-held use. In practice, however, weak law enforcement has led to widespread violations. This distinction—between hand-held and hands-free usage—has prompted researchers to classify phone use accordingly [6, 13, 21, 25, 26]. While hands-free devices reduce physical distraction, they may still impose significant cognitive loads, potentially compromising attention, and decision-making [6, 26, 27].

In recent years, the rise of motorcycle-based delivery services has further amplified the issue. Since 2012, the popularity of food and goods delivery via motorcycles has increased rapidly due to speed and affordability. Between 2014 and 2019, Thailand's food delivery market grew by an average of 10% annually [28], and since 2021, following COVID-19, order volumes on delivery platforms have surged by 44% [29]. For these workers, smartphones are essential tools for navigation, communication, and task management—making their use while riding nearly unavoidable.

1.3. Research Objectives and Rationale

Although previous studies have investigated various behavioral and contextual determinants of mobile phone use, limited empirical research has focused specifically on motorcyclists at signalized intersections, particularly within urban environments of middle-income countries where motorcycles dominate daily travel. Furthermore, this study examines delivery riders, addressing a gap in the literature that has not previously been explored.

This study addresses this research gap by examining the key factors influencing both hand-held and hands-free smartphone use among motorcyclists in Khon Kaen City, Thailand. By applying binary and multinomial logistic regression models, the study aims to provide insights that can inform targeted policy, enforcement strategies, and technological solutions to improve traffic safety in similar urban settings.

2. Methodology

2.1. Study Sites

This study was conducted at eight signalized intersections located within Khon Kaen City, Thailand. These intersections were strategically selected based on two primary criteria: (1) a high volume of motorcycle traffic and (2) variation in geometric and operational characteristics. Specific factors considered during the site selection process included traffic signal cycle length, street classification, intersection configuration (e.g., cross, T-shaped, or skewed), and adjacent land use types such as commercial, institutional, and residential zones. A summary of the characteristics of each site is presented in Table 1, and their geographic locations are illustrated in Figure 1.

Table 1. Geometric and contextual characteristics

No.	Type of intersecting street	Type of intersection	Land use	Latitude, Longitude
1	Major Arterial – Minor Arterial	Cross intersection or 4 legs intersection	Central business district, shopping mall, medical center, commercial area, residential area, public space.	16.432087, 102.823623
2	Collector – Local	T-intersection	Campus, commercial area, cafeteria, campus residential area, athletic facilities.	16.477637, 102.819333
3	Minor Arterial – Collector	Cross intersection or 4 legs intersection	Medical center, campus, commercial area, residential area.	16.441003, 102.819148
4	Bypass Road – Collector	Cross-Skewed intersection	Commercial area, residential area, industrial area.	16.406018, 102.784259
5	Minor Arterial – Collector	T-intersection	Campus, commercial area, residential area.	16.441688, 102.814592
6	Major Arterial – Collector	Cross-skewed intersection	Retail complex, commercial area, campus, industrial area.	16.415010, 102.818730
7	Major Arterial – Collector	Cross intersection or 4 legs intersection	Campus, commercial area, residential area.	16.421430, 102.820578
8	Major Arterial – Collector	T-intersection	Campus, commercial area.	16.476052, 102.832616

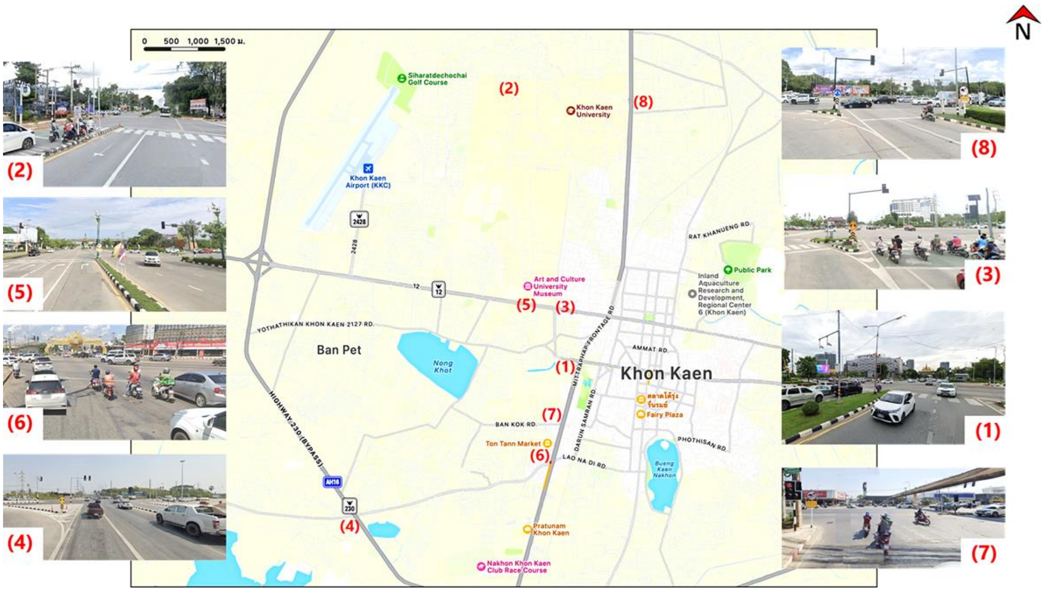

Figure 1. Overview of Study Locations in Khon Kaen City

2.2. Data Collection

The data collection process in this study involved recording both the geometric and environmental characteristics of each intersection, as well as the behavioral patterns of motorcyclists. Video cameras were strategically installed to capture motorcycle traffic from all approach directions during predefined observation periods. These recordings were subsequently analyzed to extract behavioral indicators and intersection attributes. Usage patterns were classified based on observable behavior, and only riders whose actions could be clearly identified were included in the analysis. Cases with ambiguous classification were excluded. Hands-free use was identified when smartphones were placed in holding devices installed on motorcycles. An example of camera placement and field of view is illustrated in Figure 2.

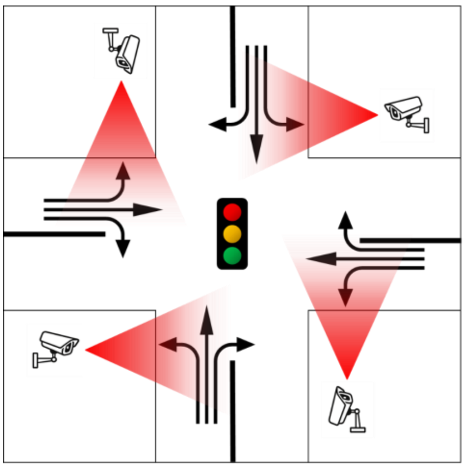

Figure 2. Typical camera placement and field of view at a signalized intersection

Each intersection was observed over two separate days—one weekday and one weekend day. On each day, four time periods were surveyed to account for traffic variation: daytime peak, daytime off-peak, nighttime peak, and nighttime off-peak hours. To ensure that data reflected typical traffic conditions, national holidays and long weekends were deliberately excluded from the observation schedule. This approach also minimized the inclusion of irregular travelers who may not frequently use the selected intersections.

2.3. Data Analysis

Pearson's Chi-square test was initially employed to assess the association between smartphone use while riding and the selected independent variables [30, 31]. Variables found to be statistically significant at a level of $p < 0.05$ were subsequently included in the regression modeling process [32].

To examine the factors influencing smartphone use behavior among motorcyclists, logistic regression analysis was conducted. Two types of logistic regression models were utilized: Binary logistic regression (BLR) and multinomial logistic regression (MLR). The BLR model analyzed smartphone use behavior categorized into two groups: use and non-use. The MLR model extended this classification into three categories: hand-held, hands-free, and non-use. Both models were estimated with a 95% confidence level to ensure statistical robustness and interpretability.

Figure 3 shows the flowchart of the research methodology through which the objectives of this study were achieved.

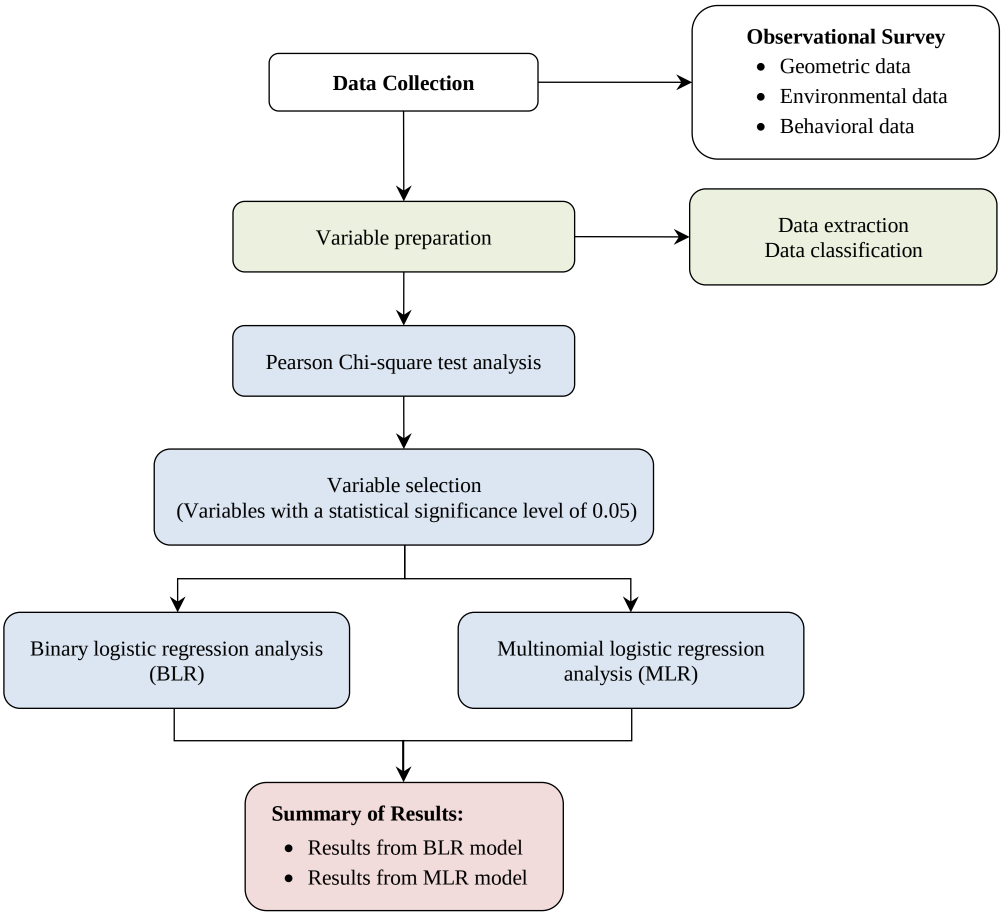

Figure 3. The research methodology flowchart

Logistic regression models are used to predict the probability of an event, considering the relationship between the dependent variable and independent variables [33, 34]. The logistic regression model is represented by the function in Equation 1 and is further described by Equation 2 [35].

$$f(x) = \frac{e^x}{1+e^x} \quad (1)$$

where: e is Euler number, x is linear combination.

$$P(event\ of\ Y) = \frac{e^{\beta_0+\beta_1 X_1+\cdots+\beta_n X_n}}{1+e^{\beta_0+\beta_1 X_1+\cdots+\beta_n X_n}} \quad (2)$$

where: P is probability of an event, Y is the dependent variable, X is independent variables, β_0 is intercept, β_1 is Logistic Regression Coefficient of X_1, β_n is Logistic Regression Coefficient of X_n.

The variables used for data analysis were classified into dependent and independent variables. The dependent variable represented the type of smartphone use behavior among motorcyclists and was categorized into three mutually exclusive groups: hand-held use (HH), hands-free use (HF), and non-use (NU). The independent variables were grouped into two major domains: (1) demographic and behavioral factors and (2) environmental factors.

Variables of demographic and behavioral factors consisted of six variables, including passenger status (riding alone, riding with a passenger), gender (male, female), helmet use (wearing, not wearing), riding characteristics while using a smartphone (using smartphone while stopping due to red lights, using smartphone while riding through the intersection), occupation (delivery rider, other occupations), and engine capacity (engine capacity >150 cc., engine capacity ≤150 cc.). Variables of environmental factors consisted of five variables, including Intersection type (Cross Intersection, Cross-Skewed Intersection, T-intersection), Time of day (night, day), peak hour (peak hour, off-peak hour), day of week (weekend, weekday) and intersection location (site 1 to site 8). The characteristics of these variables are shown in Table 2.

Table 2. Variable characteristics

Variable	Category / Coding	Reference
Dependent Variable		
Mobile phone use characteristics (Y)	0 = Non-use [NU] 1 = Hand-held [HH] 2 = Hands-free [HF]	[6, 13, 21, 25, 26]
Independent Variable		
Passenger status	0 = Riding without passenger 1 = Riding with a passenger	[6, 20, 21]
Gender	0 = Male 1 = Female	[9, 13, 18]
Helmet use	0 = Not wearing 1 = Wear	[24]
Riding characteristics while using a smartphone	0 = Stopping 1 = Riding	[21]
Time of day	0 = Nighttime 1 = Daytime	[23]
Peak hour	0 = Off-peak hour 1 = Peak hour	[23, 32]
Day of week	0 = Weekend 1 = Weekday	[20]
Occupation	0 = Delivery rider 1 = Other	This study
Engine capacity	0 = Capacity > 150 cc. 1 = Capacity ≤ 150 cc.	[32]
Intersection type (Dummy variable)		This study
Cross Intersection	0 = Yes 1 = No	
Cross-Skewed Intersection	0 = Yes 1 = No	
T-Intersection	Redundant	
Location (Dummy variable)		This study
1	0 = Yes 1 = No	
2	0 = Yes 1 = No	
3	0 = Yes 1 = No	
4	0 = Yes 1 = No	
5	0 = Yes 1 = No	
6	0 = Yes 1 = No	
7	0 = Yes 1 = No	
8	Redundant	

3. Results

3.1. Prevalence of Smartphone Use Among Motorcyclist

Among the 31,648 motorcyclists observed across all study sites, 2,433 riders (7.7%) were found to be using smartphones while riding. This proportion is slightly lower than the 8.4% reported in a previous study conducted in Vietnam [19]. Specifically, 1,955 riders (6.2%) were classified as hand-held users, while 478 riders (1.5%) were identified as hands-free users. Table 3 presents the distribution of smartphone use behavior across all independent variables, along with the results of Pearson's Chi-square test. The Chi-square analysis revealed that most independent variables were significantly associated with smartphone use behavior ($p < 0.05$). However, three variables—peak hour, engine capacity, and intersection type—did not show statistically significant associations ($p > 0.05$). All independent variables were subsequently included in further analysis using binary logistic regression (BLR) and multinomial logistic regression (MLR) models to examine their effects on smartphone use behavior. The regression results are summarized in Tables 4 and 5, respectively [32].

Table 3. Distribution of smartphone use by variable category with Chi-square significance

Variable	Variable characteristics	No. of sample (%)	Smartphone use characteristics (no. of sample (%))		
			Hand-held	Hands-free	Non-use
Passenger status **	Riding alone	24,697 (78.0%)	1,737 (7.1%)	454 (1.8%)	22,506 (91.1%)
	Riding with a passenger	6,951 (22.0%)	218 (3.2%)	24 (0.3%)	6,709 (96.5%)
Gender **	Male	23,609 (74.6%)	1,498 (6.4%)	459 (1.9%)	21,652 (91.7%)
	Female	8,039 (25.4%)	457 (5.7%)	19 (0.2%)	7,563 (94.1%)
Helmet use **	Not wearing	8,617 (27.2%)	473 (5.5%)	18 (0.2%)	8,126 (94.3%)
	Wear	23,031 (72.8%)	1,482 (6.4%)	460 (1.0%)	21,089 (91.6%)
Riding characteristics while using a smartphone **	Stopping	15,157 (47.9%)	1,824 (12.0%)	440 (2.9%)	12,893 (85.1%)
	Riding	16,491 (52.1%)	131 (0.8%)	38 (0.2%)	16,322 (99.0%)
Time of day**	Night	13,835 (43.7%)	1,012 (7.3%)	278 (2.0%)	12,545 (90.7%)
	Day	17,813 (56.3%)	943 (5.3%)	200 (1.1%)	16,670 (93.6%)
Peak hour	Peak hour	18,516 (58.5%)	1,092 (5.9%)	236 (1.3%)	17,188 (92.8%)
	Off-peak hour	13,132 (41.5%)	863 (6.6%)	242 (1.8%)	12,027 (91.6%)
Day of week *	Weekday	18,018 (56.9%)	1,118 (6.2%)	270 (1.5%)	16,630 (92.3%)
	Weekend	13,630 (43.1%)	837 (6.2%)	208 (1.5%)	12,585 (92.3%)
Occupation **	Delivery rider	2,675 (8.4%)	311 (11.6%)	423 (15.8%)	1,941 (72.6%)
	Other	28,973 (91.6%)	1,644 (5.7%)	55 (0.2%)	27,274 (94.1%)
Engine capacity	> 150 cc.	2,863 (9.0%)	198 (6.9%)	59 (2.1%)	2,606 (91.0%)
	≤ 150 cc.	28,785 (91.0%)	1,757 (6.1%)	419 (1.5%)	26,609 (92.4%)
Intersection type	Cross Intersection	12,887 (40.7%)	949 (7.4%)	224 (1.7%)	11,714 (90.9%)
	Cross-Skewed Intersection	8,225 (26.0%)	542 (6.6%)	97 (1.2%)	7,586 (92.2%)
	T-Intersection	10,536 (33.3%)	464 (4.4%)	157 (1.5%)	9,915 (94.1%)
Location **	1	4,065 (12.8%)	486 (12.0%)	95 (2.3%)	3,484 (85.7%)
	2	3,810 (12.0%)	126 (3.3%)	59 (1.5%)	3,625 (95.1%)
	3	3,038 (9.6%)	245 (8.1%)	59 (1.9%)	2,734 (90.0%)
	4	3,028 (9.6%)	224 (7.4%)	68 (2.2%)	2,736 (90.4%)
	5	2,365 (7.5%)	136 (5.8%)	49 (2.1%)	2,180 (92.2%)
	6	5,197 (16.4%)	318 (6.1%)	29 (0.6%)	4,850 (93.3%)
	7	5,784 (18.3%)	218 (3.8%)	70 (1.2%)	5,496 (95.0%)
	8	4,361 (13.8%)	202 (4.6%)	49 (1.1%)	4,110 (94.2%)
Total		31,648 (100.0%)	1,955 (6.2%)	478 (1.5%)	29,215 (92.3%)

Note: * Statistical significance level <0.05; ** Statistical significance level <0.01.

Table 4. Binary logistic regression estimates and odds ratios for factors associated with smartphone use while riding

Variable	Category	β	p-value	Odds ratio
Passenger status	Riding alone	1.010	< 0.001	2.747
	Riding with a passenger	Reference		1.000
Gender	Male	0.155	0.008	1.167
	Female	Reference		1.000
Helmet use	Not wearing	0.209	< 0.001	1.233
	Wear	Reference		1.000
Riding characteristics while using a smartphone	Stopping	2.930	< 0.001	18.730
	Riding	Reference		1.000
Time of day	Night	0.261	< 0.001	1.298
	Day	Reference		1.000
Day of week	Weekday	0.102	0.030	1.107
	Weekend	Reference		1.000
Occupation	Delivery riders	1.872	< 0.001	6.501
	Other	Reference		1.000
Intersection-1	Yes	0.767	< 0.001	2.154
	No	Reference		1.000
Intersection-2	Yes	-0.753	< 0.001	0.471
	No	Reference		1.000
Intersection-3	Yes	0.398	< 0.001	1.489
	No	Reference		1.000
Intersection-4	Yes	0.245	0.013	1.277
	No	Reference		1.000
Intersection-5	Yes	-0.127	0.247	0.881
	No	Reference		1.000
Intersection-6	Yes	-0.126	0.183	0.882
	No	Reference		1.000
Intersection-7	Yes	-0.561	< 0.001	0.571
	No	Reference		1.000
Intercept		-6.062	0.000	

Table 5. Multinomial logistic regression results comparing hand-held and hands-free use with non-use

Variable	Category	Hand-Held			Hands-free		
		β	p-value	Odds ratio	β	p-value	Odds ratio
Passenger status	Riding alone	1.026	< 0.001	2.790	1.042	<0.001	2.834
	Riding with a passenger	Reference		1.000	Reference		1.000
Gender	Male	0.114	0.043	1.121	0.745	0.004	2.107
	Female	Reference		1.000	Reference		1.000
Helmet use	Not wearing	0.278	< 0.001	1.320	-0.619	0.019	0.538
	Wear	Reference		1.000	Reference		1.000
Riding characteristics while using a smartphone	Stopping	2.942	< 0.001	18.953	2.933	<0.001	18.782
	Riding	Reference		1.000	Reference		1.000
Time of day	Night	0.285	< 0.001	1.329	0.087	0.043	1.091
	Day	Reference		1.000	Reference		1.000

Day of week	Weekday	0.089	0.044	1.093	0.197	0.032	1.217
	Weekend	Reference		1.000	Reference		1.000
Occupation	Delivery riders	1.040	< 0.001	2.830	4.765	<0.001	117.349
	Other	Reference		1.000	Reference		1.000
Intersection-1	Yes	0.743	< 0.001	2.102	0.835	<0.001	2.306
	No	Reference		1.000	Reference		1.000
Intersection-2	Yes	-0.901	< 0.001	0.406	-0.267	0.226	0.766
	No	Reference		1.000	Reference		1.000
Intersection-3	Yes	0.357	< 0.001	1.429	0.595	0.008	1.812
	No	Reference		1.000	Reference		1.000
Intersection-4	Yes	0.060	0.571	1.062	1.606	<0.001	4.984
	No	Reference		1.000	Reference		1.000
Intersection-5	Yes	-0.257	0.031	0.773	0.514	0.031	1.672
	No	Reference		1.000	Reference		1.000
Intersection-6	Yes	-0.026	0.789	0.974	-1.044	<0.001	0.352
	No	Reference		1.000	Reference		1.000
Intersection-7	Yes	-0.615	< 0.001	0.541	-0.333	0.114	0.717
	No	Reference		1.000	Reference		1.000
Intercept		-6.079	0.000		-10.109	<0.001	

3.2. Binary Logistic Regression Model: Factors Influencing Smartphone Use

Table 4 presents the results of the binary logistic regression (BLR) analysis, which examined the effects of independent variables on the likelihood of smartphone use while riding, relative to non-use. Several variables were found to significantly predict smartphone use behavior among motorcyclists at urban signalized intersections. The model's regression coefficients and corresponding odds ratios (ORs) provide insight into how each demographic, behavioral, and environmental factor contributes to the probability of smartphone use. These findings enhance the understanding of risk-related behaviors and can inform targeted interventions aimed at reducing distracted riding.

Riders without a passenger were 2.747 times more likely to use smartphones while riding compared to those with a passenger ($p < 0.001$). This finding aligns with previous studies conducted in Germany [6], Vietnam [20], and the Netherlands [21]. Male riders demonstrated a higher likelihood of smartphone use than female riders ($OR = 1.167$, $p < 0.01$), consistent with findings from China [18]. Similarly, riders who did not wear helmets were 1.233 times more likely to engage in smartphone use than those wearing helmets ($p < 0.001$), consistent with findings from Vietnam [8] and Australia [9] that indicated that riders who had a history of risky behavior were more likely to use a smartphone while riding. Smartphone use was significantly more prevalent among riders who were stopped at red lights, with an odds ratio of 18.730 compared to those riding through the intersection without stopping ($p < 0.001$). This supports earlier findings from the Netherlands [21], which suggest that drivers are more inclined to use mobile phones when their vehicles are stationary. The reduced cognitive demand during idling periods may increase the likelihood of engagement with smartphones. Nighttime riding was associated with a 1.298-fold increase in smartphone use compared to daytime riding ($p < 0.001$), which contrasts with studies from the United States [23], where daytime smartphone use is reportedly more common.

Weekday riders were also more likely to use smartphones than those riding on weekends ($OR = 1.107$, $p < 0.05$), echoing patterns reported in Vietnam [20]. Among occupational groups, delivery riders showed the highest likelihood of smartphone use, being 6.501 times more likely to engage in such behavior than other riders ($p < 0.001$). Intersection-specific effects were also observed. Riders at Intersection-1 were 2.154 times more likely to use smartphones than those at other locations ($p < 0.001$). This intersection, located in the central business district (CBD) of Khon Kaen City, is one of the busiest areas in the study, which may contribute to the elevated rates of smartphone use observed at this site.

3.3. Multinomial Logistic Regression: Smartphone Use Behavior Characteristics

Table 5 presents the results of the multinomial logistic regression (MLR) model, which examined the effects of independent variables on hand-held and hands-free smartphone use among motorcyclists, using non-use as the reference category. The model identifies several demographics, behavioral, and environmental factors that significantly predict the likelihood of engaging in either hand-held or hands-free smartphone use while riding. By disaggregating the dependent variable into these two distinct modes of use, the analysis offers a more nuanced understanding of the behavioral patterns underlying distracted riding. The regression coefficients and odds ratios describe the direction and strength of the relationship between each independent variable and smartphone use behavior across the two outcome categories: 1. Hand-held use vs. non-use and 2. Hands-free use vs. non-use. This model extends the binary analysis by identifying whether specific factors are more strongly associated with one form of smartphone use over the other.

3.3.1. Demographic and Behavioral Factors

Several demographic and behavioral variables were found to significantly influence both hand-held and hands-free smartphone use behavior. The variable "engine capacity" was excluded from the MLR analysis due to a lack of statistical significance in the preceding bivariate test.

Passenger status: Riders traveling alone were significantly more likely to use smartphones compared to those riding with a passenger. The odds of hand-held use were 2.790 times higher ($p < 0.001$), and the odds of hands-free use were 2.834 times higher ($p < 0.001$). These results are consistent with the findings from the binary logistic regression model. A plausible explanation may be that the presence of a passenger increases riders' safety awareness or riding complexity, thereby reducing opportunities or willingness to use smartphones.

Gender: Male riders were 1.121 times more likely to engage in hand-held smartphone use ($p < 0.05$) and 2.107 times more likely to use smartphones in hands-free mode ($p < 0.01$) than female riders. These findings are in line with prior research from Vietnam [20] and China [18], and are consistent with the BLR model results.

Helmet use: Riders who did not wear helmets were 1.320 times more likely to use hand-held smartphones ($p < 0.001$), whereas the odds of hands-free use were significantly lower ($OR = 0.538$, $p < 0.05$). This contrast suggests that riders who prioritize safety (e.g., wearing helmets) may also be more inclined to adopt safer modes of smartphone use, such as hands-free devices. The results of this analysis support the binary logistic analysis of this study and the conclusions of previous studies in Vietnam [8] and Australia [9], which concluded that those who prioritize safety are less likely to use smartphones while riding than those who frequently engage in risky behaviors.

Smartphone use context: Riders who used smartphones while stopped at red lights had dramatically higher odds of use than those who used smartphones while riding through intersections. The odds were 18.593 times higher for hand-held use and 18.782 times higher for hands-free use ($p < 0.001$ for both). These findings support earlier studies from the Netherlands [21] and align closely with the BLR model. The similarity in odds ratios across both categories implies that stopping at red lights equally encourages both forms of smartphone use.

Occupation: Delivery riders exhibited the most pronounced differences. They were 2.830 times more likely to engage in hand-held use ($p < 0.001$) and 117.349 times more likely to engage in hands-free use ($p < 0.001$) compared to other occupational groups. The substantial odds ratio for hands-free use may be attributed to the common use of phone holders among delivery riders, enabling easier access to smartphones while riding. Moreover, delivery riders often rely on smartphones for navigation, customer communication, and order management, which may increase both the necessity and frequency of hands-free use despite potential safety concerns. By contrast, the use of smartphone holders among the general public remains limited. Taken together, these factors—including the occupational necessity of smartphone use, the reliance on smartphones for work-related context, and the limited adoption of phone holders among the general public—explain why hands-free smartphone use is significantly higher among delivery riders than in other occupations.

3.3.2. Environmental Factors

Three environmental variables—time of day, day of week, and intersection location—were found to be significantly associated with smartphone use behavior among motorcyclists. The variables peak hour and intersection type were excluded from the multinomial logistic regression model due to lack of statistical significance in the bivariate analysis.

Time of day: Riders were more likely to use smartphones at night than during the day. The odds of hand-held use were 1.329 times higher ($p < 0.001$), while hands-free use was 1.091 times higher ($p < 0.05$). This may reflect less stringent law enforcement or lower traffic density during nighttime hours, which may encourage smartphone use while riding.

Day of week: On weekdays, riders had 1.093 times higher odds of hand-held use ($p < 0.05$) and 1.217 times higher odds of hands-free use ($p < 0.05$) compared to weekends. These findings are consistent with prior studies in Vietnam [20] and align with the binary logistic regression results. A possible explanation is that weekday riding—particularly among delivery riders—involves work-related communications and navigation, resulting in a greater need for hands-free device usage.

Intersection location: Riders at Intersection-1 had the highest odds of hand-held smartphone use, being 2.102 times more likely to engage in such behavior compared to riders at other locations ($p < 0.001$). In contrast, Intersection-4 showed the highest odds of hands-free use, with riders being 4.984 times more likely to use smartphones in this manner ($p < 0.001$). These variations may reflect differences in traffic volume, land use context, or rider purpose at each site.

4. Conclusion

This study identified key demographic, behavioral, and environmental factors associated with smartphone use while riding motorcycles in Khon Kaen City, Thailand. By employing Binary Logistic Regression (BLR) and Multinomial Logistic Regression (MLR) analyses, the research provides a comprehensive understanding of distracted riding behavior in an urban Southeast Asia context.

Among demographic and behavioral variables, riders traveling alone, male riders, and those not wearing helmets were significantly more likely to use smartphones while riding. Riders who used smartphones while stopped at red lights or during nighttime also showed elevated likelihoods. Delivery riders, in particular, exhibited a disproportionately high prevalence of smartphone use, especially in the hands-free mode, likely due to the occupational necessity of smartphone use and the reliance on smartphones for work-related context. Regarding environmental factors, smartphone use was significantly more prevalent at night and on weekdays compared to daytime and weekends, respectively. Intersection-1, located in the central business district, showed the highest incidence of smartphone use, likely due to increased traffic volume and rider idling time. These findings emphasize that smartphone use while riding is shaped by a complex interplay of personal, occupational, and situational influences. The high prevalence among specific rider groups—such as delivery riders and those at high-traffic intersections—suggests the need for targeted countermeasures.

To address this critical safety issue, the following strategic interventions are recommended: Public education campaigns to raise awareness of the risks associated with smartphone use while riding. Policy reforms and stricter enforcement, particularly for hand-held use, which remains illegal and highly risky. Infrastructure improvements at high-risk intersections to reduce opportunities for distracted riding and enhance rider focus.

Future research should investigate the psychological and situational drivers behind smartphone use, such as perceived safety, boredom, and notification responsiveness—especially during stops at red lights or nighttime riding. Additionally, expanding the study to include diverse geographic and cultural contexts, additional study sites or cities, as well as variations in traffic light characteristics, will help generalize the findings. Longitudinal research evaluating behavioral changes in response to stricter enforcement, new policy implementation, or the deployment of smartphone-restriction technologies is also encouraged. Given the exceptionally high OR. explored among delivery riders, future studies should also explore the occupational necessities, technological dependencies, and work-related incentives that may explain their reliance on smartphones while riding.

5. Declarations

5.1. Author Contributions

Conceptualization, E.S. and P.T.; methodology, E.S.; software, E.S.; validation, P.T. and A.L.; formal analysis, E.S., P.T., and A.L.; investigation, E.S., P.T., and A.L.; resources, E.S., P.T., and A.L.; data curation, E.S.; writing—original draft preparation, E.S. and A.L.; writing—review and editing, E.S., P.T., and A.L.; visualization, E.S.; supervision, P.T. and A.L.; project administration, E.S., P.T., and A.L.; funding acquisition, P.T. and A.L. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

This research project was financially supported by Mahasarakham University.

5.4. Conflicts of Interest

The authors declare no conflict of interest.

6. References

[1] WHO. (2018). Global Status Report on Road Safety 2018: Thailand Report. World Health Organization (WHO), Geneva, Switzerland.

[2] WHO. (2023). Global Status Report on Road Safety. World Health Organization (WHO), Geneva, Switzerland.

[3] WHO. (2024). Road safety Thailand 2023 country profile. World Health Organization (WHO), Geneva, Switzerland.

[4] Department of Land Transport of Thailand. (2024). Annual Report on New Vehicle Registrations in Thailand. Department of Land Transport of Thailand, Bangkok, Thailand.

[5] Ministry of Transport of Thailand. (2024). Road Accident Situation Analysis Report. Ministry of Transport of Thailand. Bangkok, Thailand.

[6] Metz, B., Landau, A., & Hargutt, V. (2015). Frequency and impact of hands-free telephoning while driving - Results from naturalistic driving data. Transportation Research Part F: Traffic Psychology and Behaviour, 29, 1–13. doi:10.1016/j.trf.2014.12.002.

[7] Liu, J., & Chen, X. (2023). Analysis of college students' phone call behavior while riding e-bikes: An application of the extended theory of planned behavior. Journal of Transport & Health, 31. doi:10.1016/j.jth.2023.101635.

[8] Truong, L. T., Nguyen, H. T. T., & De Gruyter, C. (2018). Correlations between mobile phone use and other risky behaviours while riding a motorcycle. Accident Analysis & Prevention, 118, 125–130. doi:10.1016/j.aap.2018.06.015.

[9] Rahmillah, F. I., Tariq, A., King, M., & Oviedo-Trespalacios, O. (2023). Is distraction on the road associated with maladaptive mobile phone use? A systematic review. Accident Analysis & Prevention, 181, 106900. doi:10.1016/j.aap.2022.106900.

[10] Chee, P., Irwin, J., Bennett, J. M., & Carrigan, A. J. (2021). The mere presence of a mobile phone: Does it influence driving performance? Accident Analysis and Prevention, 159, 106226. doi:10.1016/j.aap.2021.106226.

[11] Hakzah, H., Damayanti, A., Misbahuddin, & Rahman, A. (2025). Predicting Speeding Behavior of Long-Haul Freight Truck Drivers Using Machine Learning Models. Civil Engineering Journal, 11(11), 4709–4723. doi:10.28991/CEJ-2025-011-11-015.

[12] Li, X., Yan, X., Wu, J., Radwan, E., & Zhang, Y. (2016). A rear-end collision risk assessment model based on drivers' collision avoidance process under influences of cell phone use and gender—A driving simulator based study. Accident Analysis & Prevention, 97, 1–18. doi:10.1016/j.aap.2016.08.021.

[13] Jiang, K., Yang, Z., Feng, Z., Sze, N. N., Yu, Z., Huang, Z., & Chen, J. (2021). Effects of using mobile phones while cycling: A study from the perspectives of manipulation and visual strategies. Transportation Research Part F: Traffic Psychology and Behaviour, 83, 291–303. doi:10.1016/j.trf.2021.10.010.

[14] LoBue, S. A., Martin, C. R., Catapano, T. M., Coleman, K. M., Martin, S., Plascencia, S., Shelby, C. L., & Coleman, W. T. (2024). Texting while driving is a visual problem influenced by phone viewing angle and working distance in young individuals. Heliyon, 10(19), 38657. doi:10.1016/j.heliyon.2024.e38657.

[15] Boulagouas, W., Catalina, O. C. A., Mariscal, M. A., Herrera, S., & García-Herrero, S. (2024). Effects of mobile phone-related distraction on driving performance at roundabouts: Eye movements tracking perspective. Heliyon, 10(8), 29456. doi:10.1016/j.heliyon.2024.e29456.

[16] WHO. (2011). Mobile phone use: a growing problem of driver distraction. World Health Organization (WHO), Geneva, Switzerland.

[17] Schlehofer, M. M., Thompson, S. C., Ting, S., Ostermann, S., Nierman, A., & Skenderian, J. (2010). Psychological predictors of college students' cell phone use while driving. Accident Analysis & Prevention, 42(4), 1107–1112. doi:10.1016/j.aap.2009.12.024.

[18] Shi, J., Xiao, Y., & Atchley, P. (2016). Analysis of factors affecting drivers' choice to engage with a mobile phone while driving in Beijing. Transportation Research Part F: Traffic Psychology and Behaviour, 37, 1–9. doi:10.1016/j.trf.2015.12.003.

[19] Useche, S. A., Alonso, F., Faus, M., Trejo, A. C., Castaneda, I., & Oviedo-Trespalacios, O. (2024). ‘“It's okay because I'm just driving”': an exploration of self-reported mobile phone use among Mexican drivers. PeerJ, 12, 16899. doi:10.7717/peerj.16899.

[20] Truong, L. T., Nguyen, H. T. T., & De Gruyter, C. (2016). Mobile phone use among motorcyclists and electric bike riders: A case study of Hanoi, Vietnam. Accident Analysis and Prevention, 91, 208–215. doi:10.1016/j.aap.2016.03.007.

[21] Christoph, M., Wesseling, S., & van Nes, N. (2019). Self-regulation of drivers' mobile phone use: The influence of driving context. Transportation Research Part F: Traffic Psychology and Behaviour, 66, 262–272. doi:10.1016/j.trf.2019.09.012.

[22] Alagbé, J. A., Xu, C., Wang, R., & Jin, S. (2023). The intersection of phones and traffic lights: Analysis of usage and contributing factors. Proceedings of the Institution of Civil Engineers: Transport, 177(7), 467–478. doi:10.1680/jtran.23.00012.

[23] Xiong, H., Bao, S., & Sayer, J. R. (2014). Factors affecting drivers' cell phone use behavior: Implications from a naturalistic study. Transportation Research Record, 2434(1), 72–79. doi:10.3141/2434-09.

[24] Graham, J. D. (1984). Technology, behavior, and safety: An empirical study of automobile occupant-protection regulation. Policy Sciences, 17(2), 141–151. doi:10.1007/BF00146925.

[25] Benedetti, M. H., Li, L., Shen, S., Kinnear, N., Delgado, M. K., & Zhu, M. (2022). Talking on hands-free and handheld cellphones while driving in association with handheld phone bans. Journal of Safety Research, 83, 204–209. doi:10.1016/j.jsr.2022.08.016.

[26] Larsen, H. H., Scheel, A. N., Bogers, T., & Larsen, B. (2020). Hands-free but not Eyes-free. Proceedings of the 2020 Conference on Human Information Interaction and Retrieval, 63–72. doi:10.1145/3343413.3377962.

[27] Yan, W., Xiang, W., Wong, S. C., Yan, X., Li, Y. C., & Hao, W. (2018). Effects of hands-free cellular phone conversational cognitive tasks on driving stability based on driving simulation experiment. Transportation Research Part F: Traffic Psychology and Behaviour, 58, 264–281. doi:10.1016/j.trf.2018.06.023.

[28] Chartchawalitsakul, P. (2020). The service quality affecting customer loyalty toward food delivery service in Thailand. Master Thesis, Chulalongkorn University, Bangkok, Thailand. doi:10.58837/CHULA.IS.2020.99.

[29] Kasikorn Research Center. (2022). Food delivery becomes an essential sales channel even in the face of high challenges. Econ Digest. Kasikorn Research Center, Bangkok, Thailand. Available online: https://www.kasikornresearch.com/en/analysis/k-social-media/Pages/Food-Delivery-FB-20-09-2022.aspx (accessed on December 2025).

[30] Siegel, A. F., & Wagner, M. R. (2022). Chi-Squared Analysis. Practical Business Statistics, 531–547, Academic Press, Cambridge, United States. doi:10.1016/b978-0-12-820025-4.00017-8.

[31] Rayat, C. S. (2018). Chi-Square Test (χ2 – Test). Statistical Methods in Medical Research. Springer, Singapore. doi:10.1007/978-981-13-0827-7_9.

[32] Jantosut, P., Satiennam, W., Satiennam, T., & Jaensirisak, S. (2021). Factors associated with the red-light running behavior characteristics of motorcyclists. IATSS Research, 45(2), 251–257. doi:10.1016/j.iatssr.2020.10.003.

[33] Nayebi, H. (2020). Logistic Regression Analysis. Advanced Statistics for Testing Assumed Causal Relationships. University of Tehran Science and Humanities Series, Springer, Cham, Switzerland. doi:10.1007/978-3-030-54754-7_3.

[34] Schonlau, M. (2023). Logistic Regression. Applied Statistical Learning. Statistics and Computing, Springer, Cham, Switzerland. doi:10.1007/978-3-031-33390-3_4.

[35] Borucka, A. (2020). Logistic regression in modeling and assessment of transport services. Open Engineering, 10(1), 26–34. doi:10.1515/eng-2020-0029.