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Not the same: How delivery, ride-hailing, and private riders' roles influence safety behavior

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A R T I C L E I N F O

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A B S T R A C T

In recent years, the growth of motorcycle-based ride-hailing and delivery services has led to an increase in traffic crashes involving these riders. Previous studies have indicated that the behavior of ride-hailing and delivery riders is influenced by work demands and individual characteristics. However, the extent to which risky riding behaviors depend on the type of riding and the interaction between road traffic context and risky behaviors remains unclear. Addressing these gaps, this study investigates factors influencing risky behaviors among motorcycle riders in Hanoi, Vietnam. By examining various rider traits (such as rider type, gender, and age) and aspects of the road traffic environment (such as police presence, number of road lanes, and weather), we aim to understand their contribution to risky riding behaviors. Through the observation of 9164 motorcycle riders (i.e., delivery, ride-hailing, and private motorcycle riders) at 31 intersections and decision tree analysis, the study underscores the significant impact of rider type on risky behaviors. Key findings include a higher tendency for both delivery riders and ride-hailing riders to run red lights, neglect to use turn signals, and the notable distraction of mobile phone use. Additionally, private riders are found to show a higher incidence of not wearing helmets even in locations with a police presence. These findings highlight the critical need for strategies to enhance road safety for all motorcycle riders. However, it is essential to recognize that the reasons behind risky behavior vary across different groups of motorcycle riders, from private to commercial riders. Therefore, we need more targeted strategies that address the specific factors influencing each group to effectively improve road safety for all.

1. Introduction

Road trauma is a significant sustainability issue affecting nations worldwide. According to the latest road safety status report by the World Health Organization (WHO, 2023), 1.19 million people are fatally injured each year. Low- and middle-income countries (LMICs) are disproportionately affected by road trauma, accounting for most road traffic-related injuries globally (Haghani et al., 2022). In Southeast Asia, countries like Vietnam experience one of the highest incidences of road traffic casualties, largely associated with motorcycle riding, a common means of transport. In Vietnam, it is estimated that motorcycles comprise 85 % of registered vehicles (Trithucthoidai, 2016) and motorcycle-related crashes account for approximately 34 % of the total crashes (WHO, 2023). According to the Vietnam National Traffic Safety Committee (UBATGTQG, 2022), there were more than 11,400 traffic crashes in 2022, a situation that remains "alarming" and warrants concern among transport practitioners and academics.

The rapid advancement of online payment systems and the shared economy model has significantly impacted the global transportation industry, leading to the emergence of new services such as ride-hailing and delivery services. These services, often categorized under gig economy work, rely heavily on online payments and the principles of the shared economy. Their importance cannot be understated, as they contribute significantly to national economies. For instance, in 2021, delivery services in Vietnam generated 0.7 billion USD for the domestic economy and are projected to grow at a compound annual growth rate of approximately 24.1 % (Statista, 2023). Similarly, the ride-hailing sector recorded revenues of 2.4 billion USD, employing over 90,000 contract riders (VNA, 2022). From the riders' perspective, their income is primarily dependent on the number of trips completed or orders delivered,

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rather than a fixed salary. This gig economy work is praised for offering work flexibility and job opportunities (Healy et al., 2020), though the benefits are increasingly scrutinised (Galiere, 2020).

Delivery riders often operate under significant time pressure to meet tight delivery deadlines, which can increase their propensity for engaging in risky behaviors (Gupta et al., 2024; Nguyen-Phuoc et al., 2022; Zong et al., 2024). Similarly, ride-hailing riders face time constraints as they aim to maximize their earnings by completing more rides, potentially leading them to take risks to shorten travel times. Both groups spend substantial amounts of time on the road, frequently navigating dense urban environments. This high exposure to traffic not only raises their risk of crashes but also influences their riding behaviors. In this study, motorcycle riders working in the gig economy (e.g., delivery riders, ride-hailing riders) are considered to be commercial riders since they operate vehicles or modes of transport within a commercial or business context. In contrast, private riders use their vehicles primarily for personal purposes, resulting in typically less intense exposure to traffic and fewer job-related pressures. This difference can lead to distinct risk-taking behaviors compared to those whose livelihood depends on riding. However, studies exploring the differences among these three groups have been limited and rarely include more than a two-group comparison (e.g., private and food delivery riders) (Oviedo-Trespalacios et al., 2022).

Risky riding behaviors are a crucial factor in the chain of traffic safety–critical incidents, including motorcycle-related crashes. Research has identified various causes behind unsafe riding behaviors among delivery riders, ride-hailing riders, and private riders. Studies have shown, for instance, that using a mobile phone while riding is the most prevalent risky behavior among private riders in Vietnam, followed by speeding, not wearing a helmet, and running red lights (Truong et al., 2016). Interestingly, ride-hailing riders exhibit a lower incidence of risky behaviors and collisions compared to private riders (Nguyen-Phuoc et al., 2020a). However, there is a scarcity of research comparing the influence of different factors on unsafe riding behaviors across these three groups within the same context and timeframe, leading to a limited understanding of how the prevalence of risky behaviors varies by type of riding. Indeed, the interaction between the road traffic context, types of risky behaviors, and the nature of the riding activity remains underexplored.

This study aims to fill a gap in existing research by exploring whether factors influencing risky riding behaviors differ among food delivery, ride-hailing, and private motorcycle riders (Fig. 1). It seeks to provide a comprehensive overview of the prevalence of unsafe riding behaviors and to identify the traits that influence such behaviors within each specific group of riders. Previous research has predominantly utilized survey methods to examine psychological factors – such as attitudes, behavioral control abilities, and social influences – that affect rider behaviors (Nguyen et al., 2023;Chorlton et al., 2012; Nguyen-Phuoc et al., 2020b; Nguyen-Phuoc et al., 2022). However, this study adopts observational method to directly assess the occurrence of unsafe riding behaviors and to explore the potential demographic and contextual factors that may contribute to these behaviors. Observational methods enable researchers to capture the context in which risky behaviors occur, providing a deeper understanding of the situational factors that may influence these behaviors. This contextual data is essential for developing targeted interventions to enhance rider safety across different segments of the motorcycle-riding population.

2. Literature review

2.1. Methodological approaches to examine risky riding behaviors

There have been numerous studies analyzing typical risky riding behaviors using various research methods, including surveys, in-depth interviews, observations, and simulations. Surveys have been a common approach. For instance, in India, over 50 % of private riders reported involvement in traffic crashes due to unsafe riding behavior (Chouhan et al., 2021). A survey in Greece revealed that about 25 % of delivery riders had been in at least one serious crash (Papakostopoulos and Nathanael, 2021). In Vietnam, a survey of 602 ride-hailing riders found that 30 % had experienced at least one collision in the past year (Nguyen-Phuoc et al., 2020a). For commercial riders, including delivery and ride-hailing riders, time pressure and long working hours are significant factors contributing to unsafe riding behaviors (Nguyen-Phuoc et al., 2020a; Chen, 2023; Useche et al., 2024).

In-depth interview methods have also been utilized to study riding behaviors. This qualitative research technique helps to better explain, understand, and explore factors influencing participants' behaviors. In Vietnam, research by Nguyen et al. (2022) identified attention, cognitive function, and decision-making ability as the main predictors of risky riding behavior among private riders. According to Tunnicliff et al. (2011), private riders are aware of the potential dangers and "wrong things to do" while riding, yet they may still engage in unsafe behaviors.

The current study uses an observational method to gather data from three groups of motorcycle users, focusing on easily observable unsafe behaviors such as running red lights, not using a helmet, mobile phone distraction, and failing to signal when turning for analysis. Observational studies have long been recognized as a valuable approach in traffic and behavioral research due to their ability to capture real-time data on naturalistic behaviors in actual traffic environments. For instance, studies by Rusli et al. (2020), Yan et al. (2016) and Nguyen-Phuoc et al. (2019) have successfully used observational methods to

a. Delivery riders b. Ride-hailing riders c. Private riders

Fig. 1. Three groups of motorcycle riders in Vietnam.

examine traffic behaviors and compliance with traffic regulations, highlighting the method's effectiveness in understanding rider behavior in natural settings. Furthermore, observational methods allow researchers to gather data without the biases often introduced by self-reporting or experimental manipulation, ensuring a more accurate and reliable understanding of behaviors as they occur in real-world contexts (Sussman, 2016).

The method's appropriateness is further reinforced by its extensive use in similar studies examining risky behaviors among motorcyclists and cyclists. Previous studies conducted by Amegah et al. (2023), Jantosut et al. (2021) or Nguyen-Phuoc et al. (2019) employed observational techniques to explore the factors influencing risky driving behaviors. For example, an observation study at traffic intersections in China, the finding showed that private riders tent to run red lights on weekends and during off-peak hours (Yan et al., 2016). These studies provided robust evidence that supports the validity of using observational methods in traffic research. Additionally, the ability to systematically record and analyze behaviors across different times of day and traffic conditions makes the observational method particularly well-suited for this study's objectives, as it allows for a comprehensive analysis of how environmental factors influence rider behavior. As such, the methodological rigor and relevance of the chosen approach can be effectively demonstrated, thereby strengthening the overall credibility and impact of the findings.

2.2. Risky riding behaviors among motorcycle riders

2.2.1. Red light running

Running a red light is recognized as a hazardous and reckless traffic violation, posing significant safety risks (Yao et al., 2011; Hassan and Abdel-Aty, 2013). One of the primary reasons for this behavior, especially on major routes, is the frustration arising from prolonged waiting times at red lights, leading some riders to lose patience (Hsu et al. 2024, Richard et al., 2005; Shinar, 1998). Additionally, instances of red light violations may occur when riders are in a rush or become overly eager for the light to change to green (Jensupakarn and Kanitpong, 2018). Extensive research has been conducted to identify and analyze the factors influencing red light running among different groups of riders. Studies have shown that male private riders are more likely to exhibit impatience and run red lights compared to female riders (Chu et al., 2022; Tien, 2021). Conversely, older individuals tend to be more cautious and less likely to engage in this behavior, demonstrating greater awareness compared to younger riders (Porter and Berry, 2001). Additionally, external pressures, such as requests from customers, family, or friends, have been identified as triggers for red light running (Yan et al., 2016; Harith and Mahmud, 2020). Studies on ride-hailing riders reveal that riders who are students, non-migrant and work more than 50 h/week are more likely to engate in red light running behavior (Nguyen-Phuoc et al., 2020a). For delivery riders, the demand to meet delivery deadlines set by their employers significantly contributes to the prevalence of red light violations (Papakostopoulos and Nathanael, 2021; Chen, 2023; Oviedo-Trespalacios et al., 2022). Moreover, environmental factors such as road conditions (Jensupakarn and Kanitpong, 2018; Damani and Vedagiri, 2021) and weather conditions (Satiennam et al., 2018; Rusli et al., 2020) also play a crucial role in influencing the tendency to run red lights among these groups, further complicating the challenge of addressing this unsafe behavior.

2.2.2. Not using helmet

Helmet use has been shown to reduce the mortality rate of motorcyclists and passengers involved in road traffic crashes by approximately 40 % (Branas and Knudson, 2001). For instance, following the implementation of helmet usage regulations by the Vietnamese government, there was a 16 % decrease in head injuries and an 18 % reduction in motorcycle-related death rates (Pervin et al., 2009; Passmore et al., 2010). Research by Li et al. (2008) indicated that private riders typically wear helmets on weekdays and during morning and afternoon peak traffic hours. In rural areas, three factors, including perceived severity, action cues, and perceived benefits, were identified as influencing helmet use intentions and behaviors among private motorcyclists (Jomnonkwao et al., 2020). Another finding is that attitudes and subjective norms impact helmet usage, particularly among adolescents (Ali et al., 2011; Haqverdi et al., 2015; Ranney et al., 2010).

A study assesses helmet-wearing behaviors in Ho Chi Minh City, Vietnam was conducted between July 2015 and April 2019 (Li et al., 2020). Eight rounds of observations were carried out at six randomly selected locations, involving 479,892 motorcycle riders. The results reveal that over 90 % wore helmets (92.5 %–96.0 % across rounds), but correct helmet use (wearing a strapped standard helmet) declined from 80.8 % in round one to 55.6 % in round eight. Another study on app-based motorcycle taxi services was conducted in Vietnam, involving over 600 ride-hailing riders (Nguyen-Phuoc et al., 2020). According to the survey, 89 % of the participants stated that they always wear helmets. In contrast, only 4.3 % of the participants reported that they often do not use a helmet when making a ride. The findings also show that riders who are under 30 year olds, full-time workers and work more than 50 h/week are more likely not to wear helmets while riding. For delivery riders, wearing helmets while working is perceived to obstruct the ability to locate customers and causes thermal discomfort (Papakostopoulos and Nathanael, 2021).

2.2.3. Neglect signal when turning

Signal lights serve as the primary indicator of a vehicle's intended direction, whether it is turning at an intersection, entering or exiting a car park, navigating a roundabout, changing lanes, or pulling over (Ariffin et al., 2020). Typically, drivers or motorcyclists activate these lights manually, with the lights flashing to signal a turn or lane change. Research has delved into the various factors that influence the behavior of activating signal lights among traffic participants. Studies from Malaysia and Vietnam have found that female private riders are more consistent in using their turn signals compared to their male counterparts (Ariffin et al., 2020; Nguyen-Phuoc et al., 2019, 2020). Additionally, a study in Malaysia identifies a notable trend of failing to use turn signals, particularly among individuals aged 21–30 (Leong et al., 2021). Faw (2013) highlight that in areas with high traffic density, there is a significant tendency among private riders to omit turn signal use. For ride-hailing riders, a study in Vietnam show that the weekly working hours of riders affect turn signal neglection behavior. Riders working more than 50 h/week are likely to neglect to turn signals when making a turn. However, research specifically addressing signal light usage among delivery riders remains sparse.

2.2.4. Mobile phone distraction

Distraction from using a mobile phone while riding is quite common, especially among commercial riders. Delivery and rechilling receive notifications of available jobs through audible alerts from the mobile phone app and must tap the screen within a minute or two to accept the order, even though such actions are illegal in many countries (Oviedo-Trespalacios et al., 2022). In some instances, riders also receive calls from customers if they are late to arrive or deliver orders (Christie and Ward, 2023). Research by Truong et al. (2016) indicates that riders often use their phones while waiting for red lights at intersections, particularly when the red-light duration is longer. In the UK, delivery riders interviewed reported that phone-induced distractions were more frequent on rainy days (Christie and Ward, 2023). However, in developing countries, riders face greater challenges in using phones due to less developed infrastructure (e.g., potholes), as such usage can easily lead to traffic collisions (Rusli et al., 2020). Leong et al. (2021) found that young riders were often distracted by looking at their phones while riding. Conversely, the study by Truong and Nguyen (2019) suggests that older riders may be more prone to risks associated with distracted riding due to decreased reaction times, especially during riding activities involving mobile phones. According to studies by Nguyen-Phuoc et al. (2020c) and Nguyen et al. (2020), safety-related beliefs and attitudes significantly influence mobile phone usage while riding among private riders.

3. Method

3.1. Collecting data

An observational study was designed to examine the riding behaviors and the potential demographic of three particularly vulnerable and expanding groups (delivery riders, ride-hailing riders, and private riders) as well as contextual factors that may contribute to these behaviors. Observational methods allow researchers to collect data in real-time and natural settings, ensuring the authenticity and accuracy of the behaviors being studied. This approach minimizes the potential biases and inaccuracies that can arise from self-reported data.

The observation period spanned three weeks, from March 29, 2021, to April 19, 2021 in Hanoi city. Data were collected at 31 strategically selected intersections throughout the city to ensure a representative sample of various traffic conditions and behaviors. The locations of intersections were selected based on their representativeness of various types of intersections, considering specific characteristics such as the number of lanes, the number of approaches, the presence or absence of medians on approach roads, the presence or absence of traffic signals, the presence or absence of traffic police, and whether the intersection is located in the city center. Additionally, the selection of observation sites adhered to principles ensuring the safety of observers and the ability to effectively monitor traffic at the intersections. Observations were conducted across three distinct timeframes to capture variations in traffic and rider behavior throughout the day. The morning observation period spanned from 6:30 AM to 8:30 AM, coinciding with the typical morning rush hour. The noon observation period, from 11:00 AM to 1:00 PM, covered the late morning and lunch hours. The evening observation period took place from 5:00 PM to 7:00 PM, aligning with the evening rush hour. This approach ensured comprehensive coverage of daily traffic patterns and provided a robust dataset for analyzing unsafe riding behaviors among delivery, ride-hailing, and private motorcycle riders.

At each intersection, two trained observers were strategically positioned on either side of the intersection to systematically record data, focusing on multiple safety indicators simultaneously. These observers collected detailed information such as rider characteristics, helmet use, red-light running, and other relevant behaviors using systematic observation techniques. The observers randomly select motorcycle subjects in the innermost lane first and then select the next riders in the farther lane. This process is repeated to ensure that motorcycle subjects in all lanes approaching the intersection were observed. If an observed motorcycle subject was lost from view, the observer would initiate the selection process anew with a random choice, discarding the previously incomplete information sheet. Information pertaining to the chosen motorcycle subject was recorded in a checklist and standardized data collection sheets based on actual observations at the specific intersection location. This meticulous approach allowed observers to note specific behaviors, ensuring accuracy and consistency in the data collected. At the same intersection, the observers prioritized observing ride-hailing and delivery riders due to their relatively low proportion in the overall traffic flow. This selection allowed to gather sufficient data on these specific types of motorcyclists, which are of particular interest in our study. In cases where there were no ride-hailing or delivery riders present, normal riders were observed instead.

The data collection sheet was developed by the authors which included details related to the aspects of intersection (e.g., dedicated car lanes, pedestrian paths, number of lanes, presence of traffic signal lights, and whether the intersection was centrally located). The presence of police at intersections was systematically recorded due to their pivotal role in enforcing traffic regulations, promoting road safety, and bolstering public security measures. Law enforcement presence exerts a deterrent effect; the potential risk of being apprehended and subjected to penalties or punishment for misconduct compels individuals to actively seek out police in their surroundings and modify or conceal their behaviors to avoid detection (Truelove et al., 2023).

The data sheet documents the riders' motorcycle (e.g., type of motorcycles), rider traits (e.g., gender, estimated age, presence of accompanying people or goods) and riders' speed and direction of riding in the traffic flow (e.g., comparing traveling speed of riders to average speed of traffic flow, riding in the opposite direction). Additionally, other information such as the time of the survey (morning, noon, evening), weather conditions (sunny/normal, cloudy, rainy), and day of the week (weekend or weekday) was recorded, tailored to Hanoi's specific conditions. Recorded unsafe riding behaviors included helmet use (yes, no, wearing but not properly fastened), engagement in red light running (yes, no), and turn signal use (yes, no). Finally, observers noted the presence of mobile phones, and we have categorized this variable into three groups: handheld, cradle, and no. "Handheld" indicates that the cell phone is held in the hands of the riders, "cradle" refers to the cell phone being fixed on the front handle of the motorcycle, and "no" means that the rider is not using a cell phone while riding.

Observers underwent a training session conducted by the authors before starting the field survey. The methodology for observations and data collection was thoroughly explained, and observers were familiarized with the paper form used for recording data. They briefly reviewed the information to be recorded and were provided with several photographs depicting various subjects for reference during data collection. Upon completing their observations, the authors collected the observation sheets and performed preliminary quality checks. Due to the observer team's experience in similar studies, the quality of observations was highly effective, with most forms being fully completed. The observation forms were then numbered and entered into a spreadsheet by two research staff members. This data entry process was conducted in batches, with the author independently verifying the quality of each batch. Data analysis commenced once all sheets had been reviewed and confirmed to be free of data entry errors.

3.2. Analyzing data

The present study used two separate analyses to address the main research objectives. IBM SPSS software (Version 27) was used for statistical analysis. Descriptive statistics (frequency) conduct statistics on individual characteristics and unsafe riding behaviors. The relationship between unsafe riding behavior and factors related to rider traits (e.g., gender, age, type of rider, etc.) and road traffic environment characteristics has been investigated by applying the Decision Tree Method.

Decision trees are an approach used to support making useful decisions to discover previously unknown relationships between data, considered one of the most powerful tools that can address classification and prediction tasks (Kantardzic, 2011). Decision trees can be considered a non-parametric method because they do not rely on assumptions about class density and the tree structure or model is not predetermined prior to the tree growth process (Alpaydın et al., 2020). Since the present study seeks to analyze data from different intersection points, the data are heterogeneous, therefore, a non-parametric approach is required to analyze the data, overcoming the dependence between behaviors and positions (Holgado et al., 2016; Oviedo-Trespalacios et al., 2022).

Decision trees provide a clear and intuitive way to visualize and interpret the factors that influence risky riding behaviors. Unlike complex econometric models, decision trees can easily display how different variables interact and lead to specific outcomes, making it easier for stakeholders to understand the results and implications without needing advanced statistical knowledge. Additionally, decision trees are particularly effective in handling non-linear relationships between variables. Risky riding behaviors can be influenced by a combination of factors that do not follow a linear pattern. Decision trees can capture these complex interactions and provide insights into how different factors contribute to the likelihood of engaging in risky behaviors. The method also manages missing data effectively, ensuring robust and reliable analysis even when some data points are incomplete.

From an algorithmic perspective, decision trees seek to split variables into nodes, building a tree model through the growth of branches (Fig. 2). The root node is the starting point of the tree. In this study, the root node is unsafe riding behaviors where the dependent variable is the presence or absence of that behavior. Next, an internal node is a node that appears after the root node or prior internal node, it has only one incoming edge and at least two outgoing edges. In this study, the internal node represents the attribute characteristics that constitute the intention to perform unsafe riding behavior or not. Finally, leaf nodes (terminal nodes) are the bottom elements of the tree and often represent layers of the decision tree model.

The comprehensive data mining algorithm Chi-Squared Automatic Interaction Detection (CHAID) designed by Kass (1980) was used in the present model because it allows the tree to grow through sequential combination and division based on statistical Chi-Square test and corresponding p-value. The CHAID algorithm divides the sample into two or more groups from dependent variable categories (in this study, factors related to unsafe riding behavior). The selection of relevant independent variables from a set of input variables is in such a way that in the resulting ordered structure, the first independent variable for the selected input data partition is the one with the lowest and is most strongly associated with the dependent variable. In the hypothesis testing procedure, if the p-value is equal to or lower than the predetermined significance level α, then the alternative hypothesis showing the dependence between the variables is accepted. In the context of growing a tree, represent a split node using a certain independent variable. The tree-building process ends when the p-values of all observed independent variables are higher than a certain separation threshold. This approach provides insight into which factors are most significantly associated with risky riding behaviors.

4. Results

4.1. General characteristics of the observations

A total of 9164 motorcycle riders were observed including 3362 delivery riders, 2545 ride-hailing riders, and 3257 private riders. Table 1 presents the main characteristics of the sample. Observations were primarily conducted on weekdays, during sunny or normal weather conditions, and mostly in the evening (5:00 PM–7:00 PM). The majority of delivery and ride-hailing riders observed in the study were men. Most riders comply with red light signals and avoid using hand-held mobile phones while riding. In particular, the mobile phone in a cradle is not common among private riders.

The data for red-light running and turning signal usage are based on a partial sample due to the specific focus of the observations. In this study, observations included both riders stopping at red lights and those going at green lights, as well as riders making turns and those going straight at intersections. However, the sample in Table 1 specifically comprises riders who were observed at red lights, providing targeted data on red-light running behavior. Similarly, to accurately analyze turning signal behavior, the sample was narrowed down to include only those riders who made turns. This approach ensures that the data directly addresses the specific behaviors under investigation, allowing for more precise and relevant analysis.

4.2. Red light running

The present study analyzes decision trees to determine whether riders engaged in red light running (n = 536; 16.4 %) or not (n = 2,740; 83.6 %). The tree predicting red light running consisted of 3 layers (depth), 22 groups (nodes), and 13 terminal nodes, all of which are significant at $p < 0.05$ (see Fig. 3). The final tree predicts 83.5 % of all cases. The misclassification risk estimate was 0.164 (SE = 0.6 %). Private riders were more likely to run red lights (21.1 %) (node 3) than delivery riders (13.9 %) (node 1) and ride-hailing riders (10.0 %) (node 2).

Among delivery riders, in the afternoon, there was a higher likelihood of engaging in red light running (18.1 %) than in the morning or evening (11.4 %) (node 4, 5). Meanwhile, on weekdays, ride-hailing riders were more likely to red light running (13.3 %) than on weekends (5.1 %) (node 6, 7). Among private riders, in the morning or evening, motorcyclists have a higher frequency of red light running (23.3 %) than in the afternoon (16.1 %) (node 8, 9). Based on the behavior of delivery riders in the morning or evening, these individuals who both ran a red light and rode in the opposite direction account for a proportion (20.0 %), higher than those who did not ride in the opposite direction (10.6 %) (nodes 10, 11). Based on traffic flow characteristics, delivery riders in the afternoon, in locations with high traffic volume, were more likely to engage in red light running (26.3 %) (node 12) than in locations with normal or light traffic (14.7 %) (node 13).

For ride-hailing riders, on the morning or afternoon of weekends, these individuals were more likely to engage in red light running (7.7 %) (node 14); Meanwhile, they almost did not run red lights on weekend nights (0.0 %) (node 15). On the contrary, in the afternoon and evening of weekdays, ride-hailing riders were more likely to run a red light than in the morning, respectively: (25.9 %), (13.5 %), and (5.9 %) (corresponding nodes 16, 17, 18).

Among private riders, in the morning or evening on weekdays, motorcyclists were more likely to run a red light (25.5 %) (node 20) than on weekends (19.5 %) (node 19). In addition, in the afternoon, where there

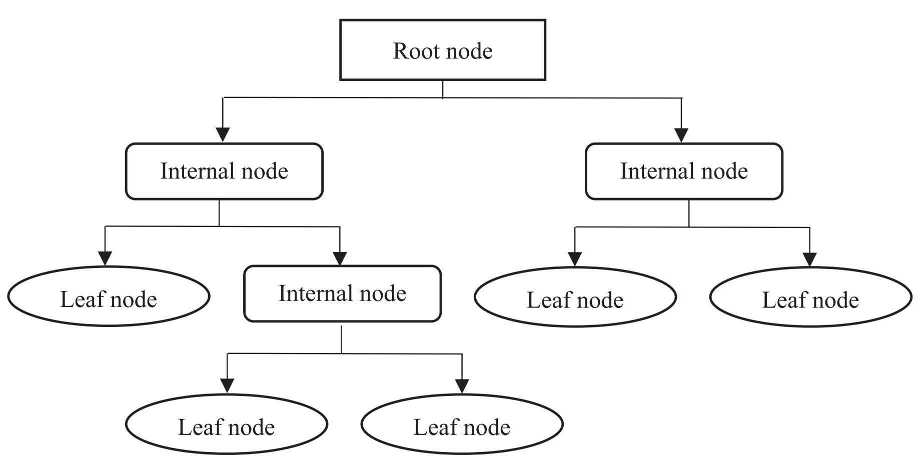

Fig. 2. Generalized decision tree model.

Table 1
Characteristics of observed data.

Observed characteristics		Group of subjects						Total
		Delivery riders		Ride-hailing riders		Private riders		
		n	%	n	%	n	%	
		3,362	36.7	2,545	35.5	3,257	27.8	9,164
Time	Morning	427	12.7	380	14.9	656	20.1	1,463
	Noon	1,025	30.5	536	21.1	770	23.7	2,331
	Evening	1,910	56.8	1,629	64.0	1,831	56.2	5,370
Weekend	Yes	1,312	39.0	705	27.7	975	29.9	2,992
	No	2,050	61.0	1,840	72.3	2,282	70.1	6,172
Weather	Sunny or Normal	1,352	40.2	1,037	40.8	1,688	51.8	4,077
	Rainy	816	24.3	833	32.7	846	26.0	2,495
	Cloudy	1,194	35.5	675	26.5	723	22.2	2,592
Gender	Male	3,173	94.4	2,392	94.0	1,998	61.3	7,563
	Female	189	5.6	153	6.0	1,259	38.7	1,601
Age	<25	1,802	53.6	1,164	45.7	1,595	49.0	4,561
	≥25	1,560	46.4	1,381	54.3	1,662	51.0	4,603
Wearing helmet	Having helmet and fastened	3,265	97.1	2,483	97.6	2,709	83.2	8,457
	Having helmet but not fastened	34	1.0	24	0.9	105	3.2	163
	Having no hemet	63	1.9	38	1.5	443	13.6	544
Red light running	Yes	146	13.9	71	10.0	319	21.1	536
	No	908	86.1	636	90.0	1,196	78.9	2,740
Turning signal	Yes	528	65.6	439	54.9	662	60.8	1,629
	No	277	34.4	360	45.1	426	39.2	1,063
Presence of mobile phone	Handheld	907	27.0	465	18.3	460	14.1	1,832
	In cradle	740	22.0	503	19.7	6	0.2	1,249
	No	1,715	51.0	1,577	62.0	2,791	85.7	6,083

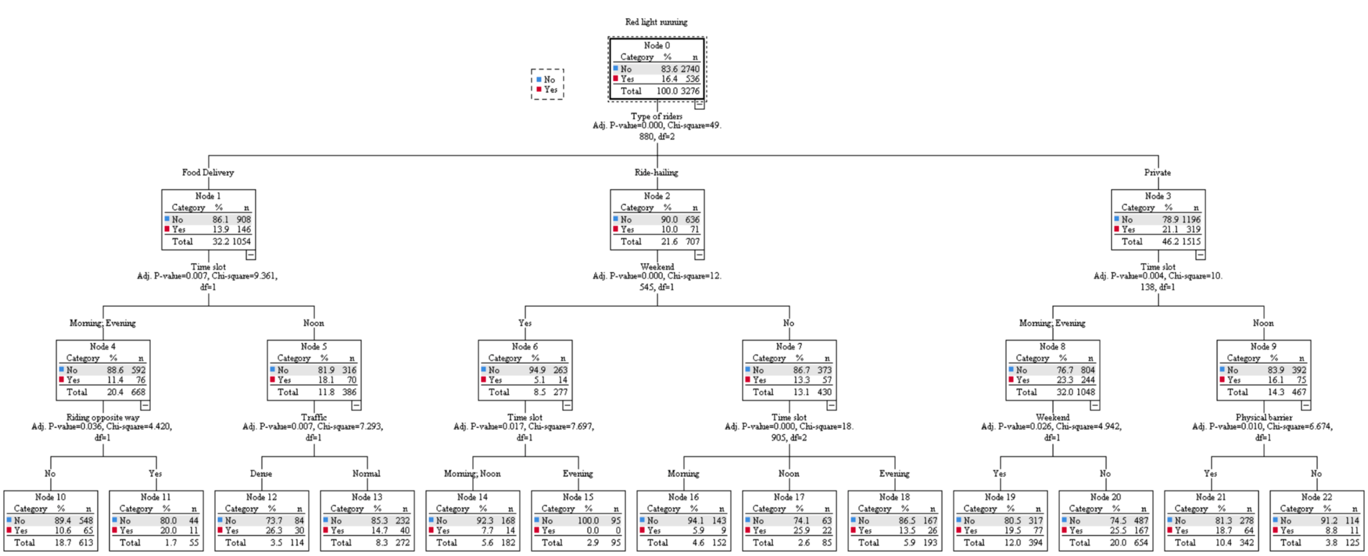

Fig. 3. Classification tree predicting red light running. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

was a physical barrier, private riders were more likely to engage in red light running (18.7 %) than when there was none (8.8 %) (node 21, 22).

In summary, delivery riders were highly likely to run red lights in the afternoon in places with dense traffic. Besides, in the morning or evening, riders who run red lights often have the habit of riding in the opposite direction. For ride-hailing riders, the rate of red light running is higher on weekdays, especially in the noon. Meanwhile, private riders are more likely to run a red light in the morning and evening; especially on weekdays.

4.3. Helmet using

This study conducted a decision tree analysis to determine the helmet-use behavior of traffic participants: wearing a helmet and fastened (n = 8,457; 92.3 %), wearing a helmet but not fastening (n = 163; 1.8 %), and did not use helmets (n = 544; 5.9 %). The tree predicting the likelihood of using a helmet includes 3 layers (depth), 12 groups (nodes), and 7 terminal nodes, all of which are significant at $p < 0.05$ as shown in Fig. 4. The final tree predicts 92.3 % of all cases. The misclassification risk estimate was 0.077 (SE = 0.3 %).

The most significant factor associated with helmet use was the type of riders (node 1, 2). The decision tree findings show that the delivery and ride-hailing riders combined under helmet use. It means that both groups have similar influential factors including: riding opposite way, police presence, time slot. Additionally, helmet use behavior might be relatively homogeneous across both groups, leading the decision tree to combine them into a single node for simplicity and clarity. Private riders have a higher rate of wearing helmets without fastened and not wearing helmets (3.2 % and 13.6 %) than delivery riders and ride-hailing riders (1.0% and 1.7 %).

Among delivery riders and ride-hailing riders riding in the opposite direction, the rate of wearing helmets without fastened and not wearing helmets is 2.3 % and 2.8 %, respectively (node 4); higher than when not riding in the opposite direction by 0.8 % and 1.6 %, respectively. On the other hand, commercial riders had a rate of 3.4 % and 1.8 % of not wearing a helmet or wearing one without fastened (node 8); higher than when there was no presence of police, 1.4 % and 0.7 % respectively (node 7). In the afternoon or evening, delivery riders and ride-hailing riders riding in the opposite direction had a higher rate of wearing helmets without fastened and not wearing helmets (3.2 % and 3.8 %) (node 10) than in the morning (0.0 % and 0.0 %) (node 9).

Among private riders, in places having the presence of police, motorcyclists had a higher rate of wearing helmets without fastened and not wearing helmets (15.6 % and 25.4 % respectively) than in places none (2.2 % and 12.6 %) (node 5, 6). In the morning, there was no presence of police, the rate of private riders not wearing helmets and wearing helmets without fastened was 17.8 % and 3.3 %, respectively (node 11); higher than in the afternoon and evening – corresponding to the ratio of 11.7 % and 2.0 % (node 12).

Results show that the majority of delivery riders and ride-hailing riders comply with the behavior of wearing helmets relatively well (97.3 %). Meanwhile, private riders were more likely to not wear helmets or wear them without fastened; especially in places where there was the presence of police and this rate increased in the morning.

4.4. Turning signal

The results of decision tree analysis of the behavior of turning signals among groups of riders were analyzed in this study, the results are shown in Fig. 5 below.

This study conducted decision tree analysis to determine whether traffic participants use turn signals (n = 1,629; 60.5 %) or not (n = 1,063; 39.5 %). The tree predicting turning signal use consisted of 3 layers (depth), 11 groups (nodes), and 7 terminal nodes, all of which are significant at $p < 0.05$ as shown in Fig. 5. The final tree predicts 61.2 % of all cases. The misclassification risk estimate was 0.388 (SE = 0.9 %).

The most significant behavior associated with turning signal use was the type of riders. That implies that traffic participants are the most important variable in their intention to turn on turn signals when making a turn. This division directs delivery riders to form node 1, ride-hailing riders to form node 2, and private riders to form node 3. Accordingly, ride-hailing riders had the highest rate of not turning signals (45.1 %), this rate for private riders were 39.2 % and delivery riders were 34.4 %.

Among delivery riders, node 1 was split by the presence of police, forming terminal nodes 4 and 5. The results show that: where there were police, delivery riders had a higher rate of turning on turn signals (77.1 %) than where there were none (64.3 %). According to the results at nodes 8 and 9, when riding faster or slower than the traffic flow, delivery riders have a higher rate of not using turn signals (43.9 %) than when riding at the same speed (31.5 %).

Among ride-hailing riders, by the presence of traffic lights at observed intersections, node 2 was split forming inner node 6 and terminal node 7. The results indicated that: in locations with traffic lights, ride-hailing riders signal when turning in a lower number (48.0 %) than in locations without lights (59.7 %). However, in places where traffic

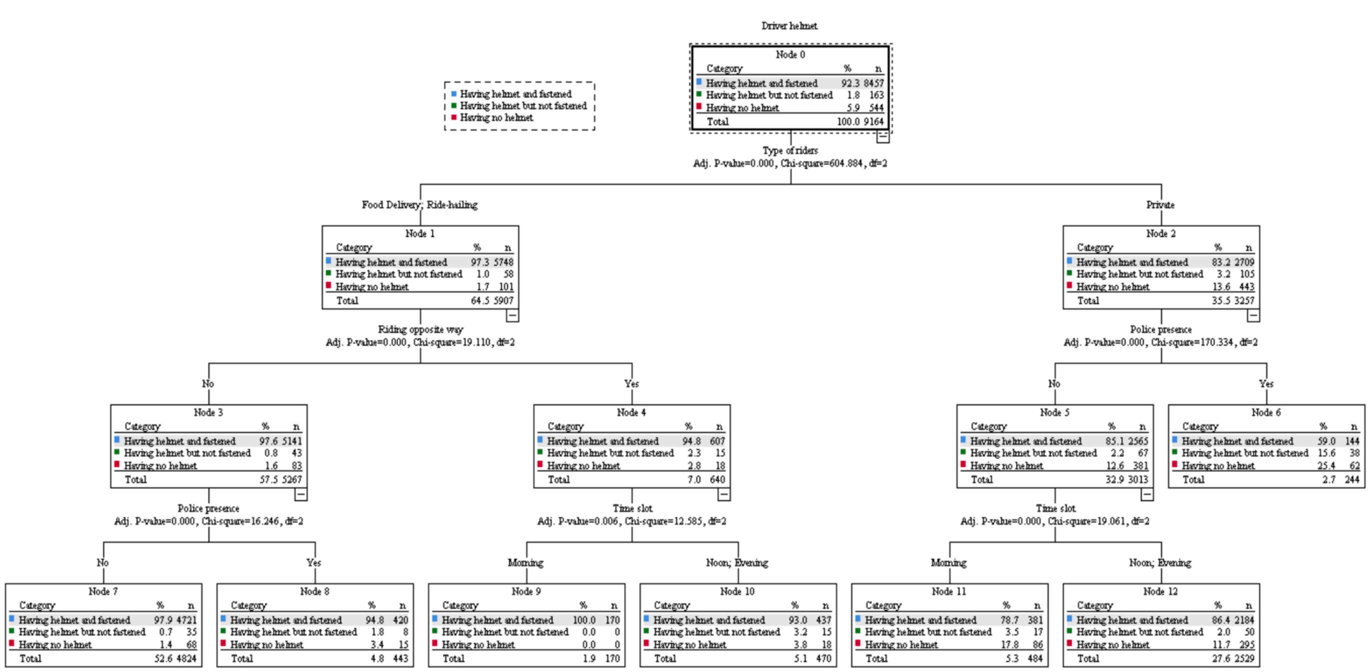

Fig. 4. Classification tree predicting helmet use.

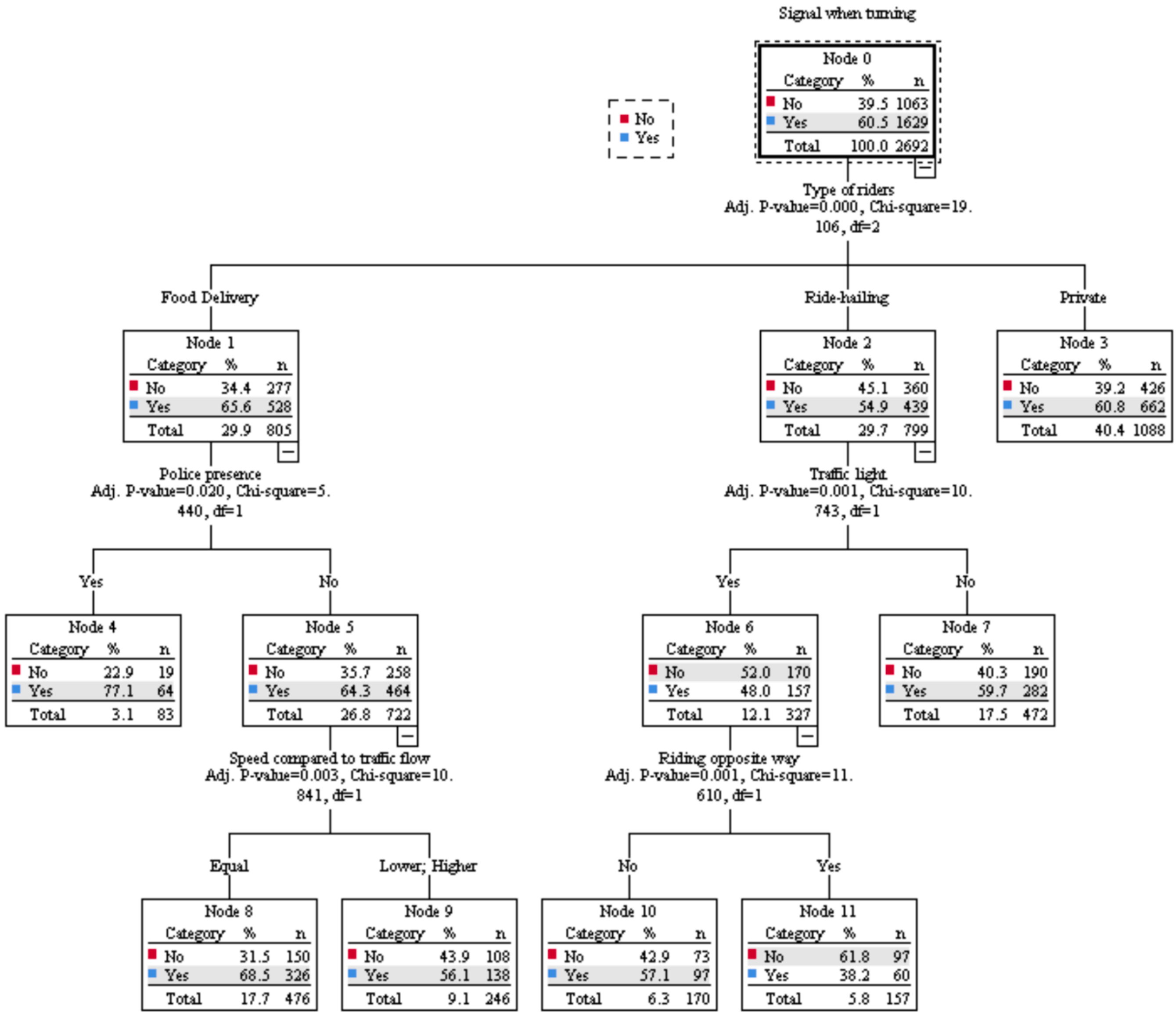

Fig. 5. Classification tree predicting turning signal when making a turn.

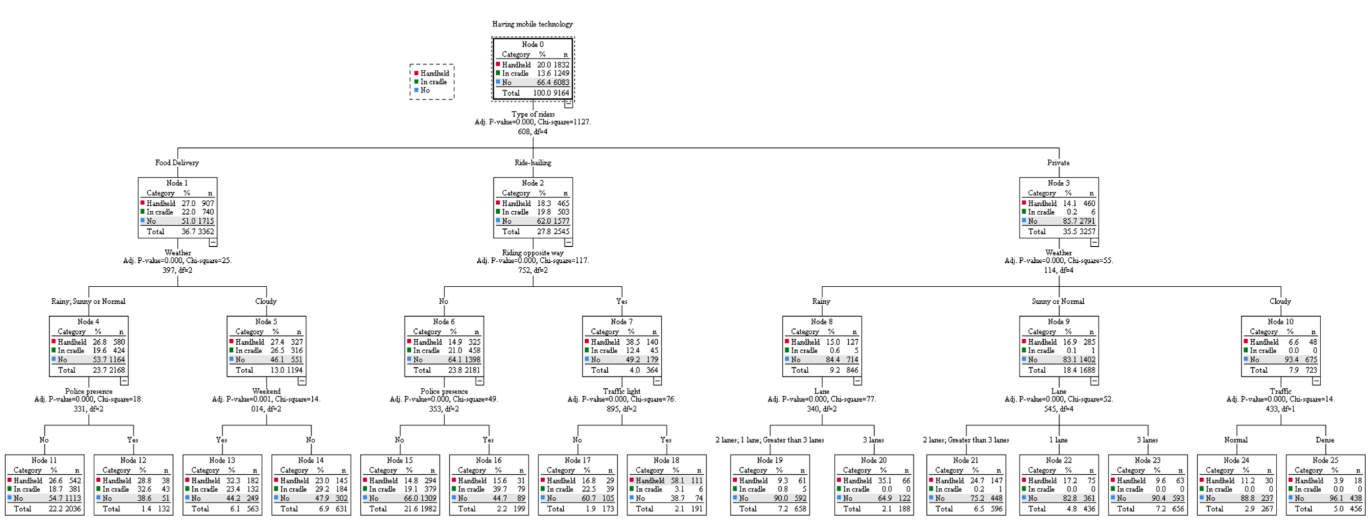

Fig. 6. Classification tree predicting mobile phone visibility.

lights are arranged, the group of delivery riders who turned signals when going in the opposite direction is lower (38.2 % – according to node 11) than riders going in the right direction (57.1 % – according to node 10).

In short, most delivery riders used turn signals when turning when riding at a different speed than the traffic flow in places where there was no presence of police. Ride-hailing riders have a lower rate of engaging in this behavior, especially when riding in the opposite direction at places with traffic lights.

4.5. The presence of a mobile phone

This study conducted a decision tree analysis to determine the presence of a mobile phone for vehicle riders: handheld (n = 1,832; 20.0 %), in a cradle (n = 1,249; 13.6 %), or no mobile phone on the vehicle (n = 6,083; 66.4 %). The mobile phone visibility prediction tree consisted of 3 layers (depth), 25 groups (nodes), and 16 terminal nodes; all were significant at $p < 0.05$, details are shown in Fig. 6. The final tree predicted 66.8 % of all cases. The misclassification estimated risk was 0.332 (SE = 0.5 %).

The most significant behavior associated with the presence of a mobile phone was the type of riders. That implies that traffic participants are the most important variable for intention to use mobile phones. This split directs delivery riders to form node 1, ride-hailing riders to form node 2, and private riders to form node 3. Delivery riders who had a handheld mobile phone were higher (27.0 %) than ride-hailing riders (18.3 %) and private riders (14.1 %).

Among delivery riders, based on weather characteristics (sunny, rainy, and cloudy), node 1 continues to be split, forming node 4 and node 5. The results show that on cloudy days, delivery riders were more likely to have a handheld mobile phone (27.4 %) than on sunny or rainy days (26.8 %). On sunny or rainy days, in places having the presence of police (node 12), delivery riders have a higher rate of holding phones in their hands (28.8 %) than in places without police (26.6 %, node 11). Meanwhile, on cloudy weekends (node 13), delivery riders had a handheld mobile phone rate of 32.3 %; higher than on cloudy days of the week (node 14) with this rate of 23.0 %.

Among ride-hailing riders, node 2 was split into nodes 6 and 7 based on whether the rider was going in the opposite direction or not. The results showed that ride-hailing riders riding in the opposite direction had a higher rate of having a handheld mobile phone (38.5 %) than when they did not (14.9 %). For riders who do not drive in the opposite direction, in places without the presence of police (node 15), the rate of having a handheld mobile phone is lower (14.8 %) than in locations with the presence (node 16, 15.6 %). On the other hand, ride-hailing riders had a higher rate of running in the opposite direction while having a handheld mobile phone (58.1 %)at intersections with traffic lights (node 18) than at intersections without traffic lights (16.8%, node17).

Among private riders, the highest rate of having a handheld mobile phone was when it was sunny (node 9), when it was rainy (node 8), and the lowest was when it was cloudy (node 10); corresponding to these rates were 16.9 %, 15.0 % and 6.6 %. The analysis results also show that road surface width was considered a road condition that affects the phone usage behavior of private motorcycle users. Specifically, when it rains, on 3-lane roads (node 20), the proportion of regular motorcyclists having a handheld mobile phone is higher (35.1 %) than on other roads (9.3 %, node 19). However, in the case of sunny weather, the rate of private riders traveling on 3-lane roads (node 23) had the lowest rate of phone use (9.6 %) compared to 1-lane roads (node 22) was 17.2 % and roads with 2 lanes or more than 3 lanes (node 21) were 24.7 %.

Besides, this study also considered the impact of traffic density (normal or dense) on ordinary motorcyclists on cloudy days; corresponding to node 24 and node 25. Analysis results show that when it was cloudy, in places with normal traffic density (node 25), private riders used phones more (11.2 %) compared to dense places (3.9 %).

In summary, the above analysis shows that delivery riders have the tendency to have a handheld mobile phone when riding on cloudy weekends. Simultaneously, ride-hailing riders often have this behavior and run in the opposite direction; especially when the weather is cloudy or rainy. Among private riders, on rainy days and on a 3-lane road, motorcyclists tend to the most of having a handheld mobile phone.

5. Discussion

This investigation delves into and contrasts the factors influencing unsafe riding behavior among delivery, ride-hailing, and private motorcycle riders. A comprehensive analysis of the results reveals that the primary determinant of the occurrence of the four risky behaviors investigated in this research is the type of motorcycle rider. Significantly, this category consistently emerged as the main variable predicting the occurrence of risky behavior with the greatest strength, positioning it as the foremost predictor for all types of risky behaviors examined. This further demonstrates that working as delivery or ride-hailing motorcyclists increases these individuals' vulnerability on the road. This increased vulnerability can be logically attributed to the fact that, while all three types of motorcyclists must navigate the demands of road traffic equally, those engaged in gig economy services also face additional work-related demands (Nguyen-Phuoc et al., 2023; Oviedo-Trespalacios et al., 2022). This finding highlights the importance of considering the intersectionality of factors when assessing the vulnerability of road users; in this case, the interplay between work and road traffic demands is crucial. Policies designed to meet the needs of all rider groups may not be equally effective for gig economy motorcyclists. This indicates a need for tailored approaches to improve their safety and for the industry to proactively take responsibility in the prevention of road crashes.

The present research also identifies distinct differences in the factors contributing to risky behavior across the four behaviors analyzed. This suggests that the underlying causes of unsafe practices vary significantly among the different types of risky behaviors, pointing to the complexity of addressing motorcycle rider safety. By acknowledging these differences, the findings advocate for more nuanced and targeted interventions that consider both the occupational and traffic-related challenges faced by motorcycle riders, especially those in the gig economy. This approach could lead to more effective strategies for reducing the occurrence of risky behaviors and, consequently, enhancing the overall safety of motorcycle riders on the road.

5.1. Red light running

The findings indicate that private riders are more likely to run red lights compared to delivery and ride-hailing riders. One possible explanation is that delivery and ride-hailing riders are more deterred by financial incentives to follow the rules, as violations can lead to fines, suspension, or termination. Additionally, their behavior is often monitored by employers through tracking systems, which can further discourage them from running red lights. In contrast, private riders, who lack such monitoring, may be more prone to taking risks. The study also reveals that private riders frequently run red lights during the morning and evening. In Vietnam, these times are peak periods, critical for commuting to work or school in the morning and returning home in the late afternoon (Waseem et al., 2019). One plausible explanation for this behavior is the heightened time pressure riders face during peak hours due to traffic congestion delays (Jha et al., 2011). The substantial volume of vehicular traffic during these periods often requires some vehicles to endure two or three light cycles to pass through an intersection (Liang et al., 2019). This extended wait time can lead to frustration and impatience among riders (Gupta et al., 2024), increasing the likelihood of running red lights as they attempt to make up for lost time.

In contrast, delivery riders and ride-hailing riders frequently run red lights in the noon (11 AM–1 PM). This observation aligns with findings from previous studies, which have identified a tendency among riders to engage in red light running during off-peak hours (Yan et al., 2016; Tien, 2021). This behavior can be attributed to Vietnam's tropical climate, where riders typically experience the highest temperatures of the day during the afternoon. The extreme heat during these hours can make waiting at traffic signals particularly uncomfortable, prompting riders to run red lights to reduce their exposure to the heat and to keep moving to stay cool. Given the nature of their service jobs, commercial riders spend a significant portion of their day in traffic (e.g., delivering food for lunch). This intense afternoon heat not only contributes to physical discomfort but also exacerbates the need to minimize idle time while waiting at traffic signals. This impatience can lead to risky behaviors, such as running red lights, as riders try to maintain their comfort and efficiency. Additionally, the pressure to complete deliveries on time quickly may further incentivize riders to take shortcuts, including ignoring traffic signals, to meet tight deadlines. Thus, the combination of high temperatures and job-related pressure significantly influences the propensity of delivery and ride-hailing riders to engage in risky riding behaviors during midday. Furthermore, delivery riders are prone to ignoring red lights during periods of high traffic volume. As Chen (2023) note, such tendencies may arise from the demands caused by riders behind them, possibly due to time pressure or a desire to maintain their position within the traffic flow.

5.2. Helmet using

In 2000, Vietnam introduced its first helmet legislation, mandating helmet use for motorcycle riders on certain major roads and highways. This initial legislation aimed to address the rising number of traffic accidents and related fatalities involving motorcyclists. In 2003, to bolster compliance, the government imposed fines ranging from 10,000 to 20,000 Vietnamese Dong (approximately 1 USD) for violations of the helmet law. However, evidence of the law's enforcement during this period was limited, and many riders continued to ignore the requirement. A pivotal observational study conducted by Hung et al. (2008) in 2006 in Hai Duong province revealed that only 29.9 % of motorcyclists were wearing helmets, highlighting the ineffectiveness of the initial enforcement measures. This study underscored the need for more robust enforcement and public awareness campaigns to improve helmet usage rates. In response to these findings and growing public safety concerns, Vietnam significantly intensified its efforts to enforce helmet legislation in December 2007. This period marked the beginning of widespread helmet enforcement, which included stricter penalties, increased police presence, and nationwide public education campaigns aimed at promoting the benefits of helmet use. As a result of these comprehensive measures, helmet usage rates saw a dramatic increase. The current study has found that helmet use among motorcyclists has risen significantly, with levels ranging from 83.2 % to 97.6 % as recently as 2021. The findings are consistent with those of previous studies which show a high prevalence of helmet use among motorcyclist (Li et al., 2020; Nguyen-Phuoc et al., 2020). These improvements demonstrate the effectiveness of the legislation and enforcement efforts, illustrating a successful public health intervention.

The findings of this study show that in locations with a police presence, private riders often show a higher incidence of not wearing helmets compared to when law enforcement is absent, contradicting prior research by Satiennam et al. (2020). Despite current Vietnam's road traffic law stipulating fines ranging from 400,000 to 600,000 VND (around 17–25 USD) for helmetless riders, enforcement by traffic police is infrequent, fostering a widespread disregard for helmet usage. Notably, intersections with high traffic often see traffic police primarily focused on regulation, while compliance with helmet-wearing regulations is higher among delivery riders and ride-hailing riders, potentially influenced by economic vulnerability as suggested by Oviedo-Trespalacios et al. (2022). Strict adherence to wearing a helmet is seen as a way to ensure safety in the workplace, avoid negative feedback from customers, and enhance competitiveness. This compliance also prioritizes receiving customers as per the policies of the service application management company. This observation could provide a basis for authorities to consider and adjust the level of fines; for example, by increasing or imposing harsher penalties for individuals with multiple traffic violations within a specific timeframe.

5.3. Signal turning

The current study also determined that delivery riders are more inclined to neglect the use of turn signals when navigating traffic at a speed different from the general flow, as opposed to when traveling at a consistent speed. This behavior is consistent with the findings of Leong et al. (2021), who identified that the desire to go faster contributes to motorcyclists not activating their signals while changing lanes, turning, or overtaking other vehicles. Delivery riders, under pressure to meet delivery times, may prioritize speed over safety, leading to the omission of signaling. Additionally, Faw (2013) noted that riding at a speed different from the general traffic flow increases susceptibility to distractions. These distractions can divert attention from essential safety practices like using turn signals. When riders deviate from the flow of traffic, they may focus more on maneuvering and maintaining their speed, inadvertently neglecting to signal their intentions to other road users.

We also found that ride-hailing riders at locations with traffic lights exhibit a higher tendency to neglect the use of turn signals when running in the opposite direction compared to those who follow the correct direction of the lane. This can be explained by the fact that engaging in one unsafe riding behavior, such as riding in the opposite direction, can lead to a cascade of other unsafe practices. Once a rider breaches one traffic rule, they may be more likely to disregard additional safety measures, including the use of turn signals. This compounding of unsafe behaviors highlights a critical area for intervention. Encouraging adherence to all traffic regulations, even under time pressure or when engaging in high-risk maneuvers, is essential for improving overall traffic safety. Understanding these patterns can help in designing targeted educational campaigns and enforcement strategies to promote the consistent use of turn signals among all rider categories, thereby enhancing road safety for the riders.

5.4. The presence of a mobile phone

Using a handheld mobile phone is identified as the most safety–critical distracted riding behavior. Riders using their phones by hand experience reduced control over their motorcycles and diminished situational awareness because they divide their attention between riding and the phone (Truong and Nguyen, 2019). While using a handheld cell phone is highly distracting, mounting a phone on a cradle can also cause brief but risky distractions (Oviedo-Trespalacios et al., 2022).

Commercial riders use mobile phones more frequently than private riders, likely because they depend on these devices for work-related tasks (Nguyen et al., 2024). In China, studies have shown that the commercial riders frequently check their phones for new orders or to communicate with customers (Wang et al., 2021; Xue et al., 2021). The riders often use phones for calls or navigation, especially during cloudy weather. In contrast, they focus more on riding during adverse weather conditions, due to increased difficulty in controlling the motorcycle and protecting the phone from damage (Truong et al., 2016). Additionally, the study found that ride-hailing riders are more likely to use their phones while riding in the wrong direction, indicating a correlation between this and other unsafe behaviors. Mobile phone use increases at intersections with traffic lights, where riders may use the waiting time to engage with their phones, potentially leading to distractions when they resume riding (Truong et al., 2016; Huth et al., 2015). This behavior can pose risks both during the wait at a red light and when continuing the journey after the light turns green.

5.5. Practical implications

Delivery riders and ride-hailing riders frequently run red lights, particularly in the afternoon, influenced by intense heat and time pressures while navigating traffic. They also show a higher incidence of neglecting turn signals when traveling at different speeds from the general traffic flow. This pattern of behavior suggests a need for increased awareness and adherence to traffic regulations, especially regarding signaling intentions while changing lanes or turning. Additionally, the distraction of mobile phone use is notable among delivery and ride-hailing riders, highlighting the importance of prioritizing safe riding practices over mobile phone use to mitigate associated risks.

To mitigate these risky behaviors and promote safer practices, delivery and ride-hailing companies should implement comprehensive training programs that emphasize safe riding practices, traffic regulations, and the importance of following company policies. However, it is important to recognize that education alone is not fail-proof and can only achieve so much. A broader approach is necessary, including changes in organizational culture and the creation of other incentives such as economic rewards or improved work design strategies to effectively change these behaviors. Furthermore, delivery riders are prone to ignoring red lights during periods of high traffic volume due to intense pressure to maintain schedules and the desire to stay ahead in traffic. Authorities can consider adopting measures such as adjusting light cycle times to better accommodate different times of day, thereby reducing the incidence of riders running red lights. Implementing dynamic traffic light systems that adapt to real-time traffic conditions could also help alleviate congestion and improve traffic flow. Additionally, stakeholders and policymakers can implement strategies to alleviate traffic congestion, such as encouraging organizations and schools to adopt staggered start and end times for the workday, which would spread out traffic demand more evenly. Enhancing police presence at key locations to monitor and address violations of traffic regulations can further promote safer riding behaviors during peak hours. By combining these strategies, authorities can create a more efficient and safer traffic environment for both delivery riders and the general public.

In the realm of ride-hailing and delivery services, our study advocates for a fundamental culture shift that places rider safety at the forefront of business values. This transformation involves integrating safety mechanisms directly into the tools and technologies that riders depend on daily. For instance, mobile applications essential to the operation of these services could be equipped with features that actively discourage phone use while in transit. These apps could serve as platforms for disseminating crucial safety information and tips, fostering a safety-conscious mindset among riders. Moreover, companies can establish robust monitoring systems that track and analyze rider behavior in real-time, receiving feedback from customers and flagging instances of risky riding behaviors such as running red lights or excessive speeding. By leveraging data analytics and machine learning algorithms, these systems can provide actionable insights to identify trends, patterns, and areas for improvement in rider safety. Additionally, fostering a sense of accountability among riders by implementing performance metrics related to safety can incentivize adherence to safety protocols. Recognizing and rewarding riders who consistently demonstrate safe riding behaviors through bonus programs or other incentives can further reinforce the importance of safety within the rider community.

Partnerships with local authorities and law enforcement agencies can enhance enforcement efforts and ensure compliance with traffic regulations. Collaborative initiatives, such as joint safety campaigns or targeted enforcement operations, can raise awareness about road safety issues specific to ride-hailing and delivery services. Additionally, integrating safety checkpoints and reminders within the app interface can serve as proactive measures to prompt riders to prioritize safety during their journeys. Ultimately, by fostering a safety-centric culture and implementing proactive measures at both organizational and technological levels, ride-hailing and delivery companies can significantly contribute to improving rider safety and reducing road traffic crashes.

Private riders, on the other hand, often neglect wearing helmets even in locations with a police presence. Despite existing fines for helmetless riding, enforcement is inconsistent, leading to widespread disregard for helmet usage. This non-compliance not only puts riders at risk of severe head injuries in the event of an accident but also undermines efforts to promote road safety. Additionally, private riders often run red lights in the morning or evening due to heightened time pressure caused by traffic congestion delays during peak hours. This behavior poses significant risks not only to the riders themselves but also to other road users. Authorities may need to review and adjust fine levels to incentivize compliance and ensure greater safety among private riders. Moreover, enhancing public awareness campaigns about the importance of helmet usage and adherence to traffic regulations could help reinforce the message of safety and foster a culture of responsible riding among private riders.

5.6. Limitations

This research encounters several limitations, primarily related to its observational data collection methods. One key limitation is the potential for human error in observing and recording behaviors, which could affect the accuracy and completeness of the data. Future research could benefit from integrating advanced technologies such as cameras equipped with artificial intelligence (AI) to capture and analyze data more effectively. This approach could significantly reduce human error and provide a more comprehensive and accurate dataset. However, in many countries, including Vietnam and Australia, video recording public behavior without consent poses privacy and legal challenges. Such recordings can potentially be used in legal proceedings, raising serious ethical concerns. Researchers must obtain proper data management permissions and ethical approvals, which can be a complex process. Therefore, the use of live observation methods, though less precise, was deemed more practical and compliant with ethical standards for this study. Second, while the decision tree has highlighted key differences and factors, the decision tree model alone cannot explain why these differences exist. Further qualitative research, such as focus groups and interviews, is needed to explore the underlying reasons why private, delivery, and ride-hailing riders engage in risky behaviors. This research can uncover motivations, pressures, and barriers faced by these three main groups of motorcyclists in Vietnam, providing a deeper understanding to inform more targeted and effective interventions to improve road safety. Third, we acknowledge that our study does not encompass all potential risky behaviors, such as speeding and weaving, which are critical factors in many traffic safety analyses. However, in the context of Vietnamese cities, speeding is less of a concern due to high congestion levels that inherently limit motorcycle speeds. Our focus on red-light running, helmet use, and signaling is based on their strong and direct links to negative safety outcomes, as supported by extensive literature. Future research should aim to incorporate a broader range of risky behaviors to provide a more comprehensive understanding of traffic safety issues. This would help in developing more effective and targeted interventions to enhance road safety. Finally, another limitation of this study is the potential for inaccuracies in age estimation resulting from collecting age data based on observers' judgment. Future studies should consider employing more precise methods for determining age, such as direct surveys or verification with identification documents. Additionally, incorporating technological tools like facial recognition software could enhance the accuracy of age data collection in observational studies. This would help to ensure that the demographic data used in the analysis is both accurate and reliable, thereby improving the validity of the study's findings and recommendations. Overall, addressing these limitations through the integration of advanced technologies and comprehensive qualitative research will enhance the robustness and applicability of future studies in understanding and mitigating risky riding behaviors among motorcyclists.

6. Conclusion

This study provides an comprehensive analysis of the factors influencing unsafe riding behaviors among three primary groups of motorcyclists in Vietnam: delivery riders, ride-hailing riders, and private riders. It delves into the distinct characteristics that predispose each group to engage in risky behaviours and examines the extent of traffic law violations. The findings highlight a concerning trend of risky riding behaviours, particularly among riders affiliated with commercial services like ride-hailing and delivery. This is significant because it underscores that not all riders are the same, and thus, policy interventions cannot be designed to be universal for everyone. While some safety measures may apply universally, it is crucial to understand the specific reasons behind behaviors, as this research clearly shows different systemic associations for each group. As such, targeted interventions become increasingly critical to curb unsafe riding habits and reduce traffic-related crashes among commercial motorcyclists. Additionally, this research underscores the necessity for authorities to revisit and potentially enhance the effectiveness of penalties and road safety programs, aiming to lower the incidence of traffic law violations among private riders. By addressing these key issues, there is a significant opportunity to improve road safety and protect the well-being of all road users.

CRediT authorship contribution statement

Duy Quy Nguyen-Phuoc: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nhat Xuan Mai:** Writing – original draft, Methodology. **Oscar Oviedo-Trespalacios:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

Fig. A1. Research data collection sites in Hanoi city (red dot)

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