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Road rules, infrastructure and risk – how law-abiding are e-scooter riders?

Scott N. Lieske[a,*,1], Richard Bean[a,b,2], Richard J. Buning[b,3]

[a] School of the Environment, the University of Queensland, St Lucia, Queensland 4072, Australia
[b] School of Business, the University of Queensland, St Lucia, Queensland 4072, Australia

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ABSTRACT

Use of both privately owned and shared e-scooters is continuing to proliferate in cities along with concerns about rider and pedestrian safety as well as compliance with road rules. The goal of this research was to understand e-scooter road rules compliance and contributing factors focusing on helmet use and speed limits. This paper documents a study of micromobility and active transport users across two years with observations captured by traffic cameras at eight sites in Brisbane, Australia. Machine learning was used for initial processing of more than 600,000 observations of e-scooter users, cyclists and pedestrians. In addition to transport mode (pedestrian, cyclist, e-scooter), observations included e-scooter ownership (shared *vs.* private), speed, helmet use, infrastructure type (footpath, traffic lane, bike lane, separated cycle track) as well as urban form and density (i.e., central business district, urban, suburban). Logistic regression is used to provide a robust model of the factors associated with e-scooter users road rules compliance. Speed compliance is highest on separated cycle tracks and is positively correlated with urban density and greater head protection. E-scooter riders wearing helmets rode faster than those not wearing helmets, and those with full-face helmets rode the fastest. Separated cycle tracks are associated with higher rates of helmet compliance than other infrastructure types for shared e-scooter riders. Private e-scooter riders were most likely to wear a helmet when riding on roads or bike lanes, potentially compensating for greater speeds on those infrastructure types. Overall, these findings reveal separated infrastructure encouraged road rules compliance and provide evidence of e-scooter users demonstrating risk compensation decisions around helmet use, speed and riding locations. The results here promote the importance of building separated cycling infrastructure in order to encourage road rules compliance.

1. Introduction

Since being introduced in Santa Monica, California in 2017 (Field and Jon, 2021) e-scooters have become increasingly popular in cities globally as a convenient and cost-effective transport method. Scholars report a wide range of benefits to communities and individuals from reduction in trip times and carbon emissions to improved well-being (Badia and Jenelius, 2023). As an alternative to automobiles for local travel, e-scooters can help mitigate problems with air pollution, noise and congestion (Gössling, 2020). E-scooters have the capacity to offer convenient, sustainable, cost-effective, and on-demand transport (Fan and Harper, 2022) with evidence suggesting slightly more less than half of e-scooter trips replace vehicle travel (Badia and Jenelius, 2023, Guo and Zhang, 2021).

At the same time there are numerous challenges with the integration of e-scooters in urban environments. There are concerns with excessive speed, driving under the influence of alcohol or drugs, carrying more than one person, underage riding as well as the frequency of injuries, especially head injuries, to e-scooter users (Rashed et al., 2022, Vallmuur et al., 2023, Ssi yan Kai et al., 2024). There are also concerns about e-scooter interactions with other road users, in particular, pedestrians. Based on accusations of being new and unproven, user conflicts including with pedestrians and other road users, as well as accident scholarship, problems with e-scooters are a popular topic in both the popular media and academic literature (Travers et al., 2024). Other negative perceptions and reasons for non-use are linked to a lack of dedicated infrastructure, convenience of other transport modes, and high costs (Dibaj et al., 2025; Teixeira et al., 2023).

* Corresponding author.
E-mail addresses: scott.lieske@uq.edu.au (S.N. Lieske), r.bean1@uq.edu.au (R. Bean), r.buning@uq.edu.au (R.J. Buning).
[1] https://orcid.org/0000-0001-6335-6117.
[2] https://orcid.org/0000-0002-1723-6760.
[3] https://orcid.org/0000-0002-0089-3967.

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As an emerging technology and transport mode where the fit with existing transportation modes and infrastructure remains uncertain, cities work to integrate these new forms of mobility within existing urban systems. Cities struggle to regulate where e-scooters can be legally ridden, at what speed, parking and sometimes helmet requirements. Cities also struggle to regulate the devices themselves including size, weight, power, maximum speed, stopping system (brakes), warning devices (bell), lights and reflectors (Queensland Government, 2024). The benefits of and concerns about e-scooter use along with cities ongoing regulatory struggles raise issues of user behavioural responses to regulatory requirements. Knowledge of e-scooter rider travel behavior is important but limited with numerous authors calling for additional research (Todd et al., 2019, Serra et al., 2021, Foissaud et al., 2022, Cicchino et al., 2024, Roberts et al., 2025).

2. Background

Electric scooters, known as e-scooters, are "scooters with a standing design with a handlebar, deck and wheels that are propelled by an electric motor" (Shaheen and Cohen, 2019p. 3) though some are equipped with seating (Beam Mobility n.d.). E-scooters can be divided in two major types based on ownership: those belonging to shared publicly accessible schemes (shared or hire e-scooters, sometimes referred to as public e-scooters) and private e-scooters.

The early phases of e-scooter introduction posed challenges to governments due to a sudden and rapid rise in e-scooter use. Rather than a gradual and negotiated entry, shared e-scooter providers swiftly flooded streets with their product in response to market opportunities (Riggs et al., 2021). Authorities had to act quickly and under a limited timeframe to regulate e-scooters, working to craft legislation to balance shared safety with new and innovative forms of mobility. An early example of e-scooter governance was in 2017 when the city of Santa Monica, California imposed an interim ban on the operation of a shared e-scooter provider, Bird, which had launched their product without permission (Field and Jon, 2021). The city then implemented regulations gradually, starting with a temporary permit and then a trial program that capped the number of e-scooters allowed (Lien and Etehad, 2018). On the stricter side, cities such as San Francisco followed Santa Monica's precedent (McFarland, 2019), first prohibiting public e-scooters on shared facilities, and then allowing a trial period. Paris adopted a more relaxed approach, allowing an estimated 20,000 e-scooters in the city from mid-2018 to 2019 (Field and Jon, 2021), but reversing the policy in September 2023 when Paris banned shared e-scooters due to safety, rider behaviour and parking issues (BBC News, 2023, Cities Today, 2024). At the same time as governments were working to respond to rapidly increasing e-scooter use, academic research developed in the areas of rider safety, rider behaviour and pedestrian safety. Key elements of rider behaviour are helmet use, travel speed, choice of infrastructure and risk perception.

Associations of helmets or lack thereof with accidents and injuries are frequently highlighted in e-scooter literature. Along with the influence of alcohol, internationally e-scooter injuries are most frequently associated with riders not wearing helmets (Phipps and Hamilton, 2024, Ssi yan Kai et al., 2024, Serra et al, 2021). In early work examining risky and illegal e-scooter rider behaviours as well as interactions with pedestrians, researchers at the Centre for Accident Research & Road Safety – Queensland (CARRS-Q) conducted observational studies in Brisbane on cyclists and e-scooter users, in February 2019 (Haworth et al., 2021a), October 2019 (Haworth et al., 2021b) and October 2021 (Haworth and Schramm, 2023). The studies involved manual observations of road users focusing on helmet use among other user and site characteristics. Observations were limited to the Brisbane central business district (CBD) on weekdays. The series of studies found correct helmet use, where helmet straps were worn and properly fastened, for shared e-scooter users ranged from 59.1 to 66.8%. Comparable helmet use for private e-scooter users was consistently higher ranging from 91.7% to 95.5%.

In San Francisco, Frye et al. (2024) compared helmet use rates of shared and private e-scooters and bicycles. They found shared e-scooters users wore helmets 70% less than private e-scooter users. The conclusion was that targeted safety regulations were urgently needed. Ssi Yan Kai et al. (2024) surveyed 360 adult e-scooter users in Canberra, Australia about helmet law compliance. Using logistic regression analysis, they also found shared e-scooter use was associated with helmet non-use. Kim et al. (2024) conducted an on-line survey, observation sessions at twelve sites, and interviews to understand reasons for risky behaviour. Observation results ($n = 131$) recorded sixteen risky behaviours with not wearing a helmet and footpath riding occurring most frequently. Interview results ($n = 10$) revealed e-scooter rider risky behaviours resulted from the trade-off with risk weighed against time and comfort. Janikian et al. (2024) conducted a scoping review of 81 papers examining safety issues around e-scooters use. They discussed helmet requirements, finding few e-scooter users wore helmets unless legally required. They also investigated alcohol and drug use, speed limits, rider demographics, environmental factors and injury patterns concluding with a need for interventions to reduce rider injuries. Using similar methods as the CARRS-Q papers, Roberts et al. (2025) conducted an observational study in Perth, Australia in order to see rider responses to new regulations. Data were collected on helmet use, rider infrastructure, e-scooter ownership, estimated speed and other rider characteristics. In spite of mandatory helmet laws, they found e-scooter rider helmet compliance decreased from 2022 to 2023 and was less than cyclist helmet compliance.

Other studies consider rider speed, often associated with infrastructure choice. Arellano and Fang (2019) conducted an observational study of e-scooter riders in San Jose, California in 2018 and 2019. They chose sites with street, footpath and mixed-use paths and measured speed using a stopwatch app, helmet wearing and distracted behaviour. Riders travelled faster on streets and slower on footpaths and mixed-used paths. The highest observed average speed was 25.9 km/h. Users did not generally wear helmets. Other research supports the finding that e-scooter riders travel more slowly on footpaths (Ma et al., 2021, Zuniga-Garcia et al., 2021). Cicchino et al. (2024) also focussed on rider infrastructure and rider speed. Their research accumulated 2,004 manual observations across sites in Washington D.C. and Austin, Texas. Key among their results was that "Over 80% of e-scooter users rode in bike lanes in both cities when they were available" (p. 171) and lower speed limits were associated with increased sidewalk riding potentially leading to greater conflict with pedestrians. However, these lower speeds also reduce the risk of injury. Combining these findings they observe, "Increasing bike lane availability could ease concerns about e-scooters moving to sidewalks when e-scooters are limited to lower speeds" (p. 179). The findings of Cicchino et al. (2024) on preferences for bike lanes are similar to those from NACTO (2019) and the Portland Bureau of Transportation (2024).

Risk also appears to play a role in rider behaviour. Focusing on rider infrastructure, Currans et al. (2022) investigated e-scooter rider behaviour and found bike lanes to be associated with lower e-scooter use on sidewalks. Although, "when riders were near larger roadways, we also observed more sidewalk riding behaviour, even when bike lanes were present." (p. i). Early e-scooter research in Portland, Oregon reports similar findings, that e-scooter users choose to ride on sidewalks as road speeds increase (Portland 2019). Currans et al. (2022) also note risk aversion based on rider experience, "Those who prefer riding on sidewalks were more likely to have experienced a crash of some kind, while those who prefer riding on bike lanes were less likely" (p. 2). Papers such as Kim et al. (2024) and Son et al. (2025) examined risk perception through surveys, observations, interviews and simulation studies. As noted, risky behaviour was perceived as a trade-off with time and convenience. The studies found road factors affecting safety, and risky behaviour were perceived differently depending on the assessment tool (e.g. video versus text) and user experience level. Although not developed in the e-scooter literature, the role of risk in rider behaviour suggests the potential influence of risk compensation theory, the addition of safety equipment and behaviour changes as compensation for risky behaviour (Adams and Hillman, 2001, Peltzman, 1975).

Although research is limited, a potential influence on e-scooter rider behaviour is weather. Noland (2021) aggregated City of Austin, Texas open data to look at e-scooter trip numbers, duration and distance. They found e-scooter trips numbers decrease in cold, rain, wind as well as with heat and high humidity. Kimpton et al. (2022) assessed the interface of weather and climate with over 800,000 shared e-scooter trips in Brisbane. They found e-scooter trip numbers decrease with precipitation and increase with heat. Alsulami et al. (2023), also looking at Austin, found precipitation and humidity decrease e-scooter demand.

Most e-scooter research is based on manual observations and/ or surveys. Prior use of video recording as an e-scooter research tool is limited. Notable exceptions are Todd et al. (2019) who used video to record observations of e-scooter riders in two communities in Los Angeles. They recorded observations of 171 shared scooter users including street *vs*. sidewalk riding, helmet wearing and traveling with *vs*. against traffic flow. Currans et al. (2022) combined video recording for traffic counts by mode with in-person observations of behaviour. Observation was limited to four hours at each of five sites yielding a total sample size of 232 scooter users. They also used survey data to develop a regression analysis focused on socioeconomic and demographic characteristics, trip purpose and alternative transport modes.

Numerous researchers have investigated e-scooter user helmet use, speed and other safety concerns. At the same time there are numerous gaps in e-scooter research. Few studies integrate big data sources. To the best of our knowledge only Noland (2021) and Kimpton et al. (2022) integrate weather with e-scooter rider behaviour. While risky behaviour is frequently explored in the e-scooter literature, the potential influence of risk compensation theory has yet to be explored.

The goal of this research was to understand e-scooter road rules compliance and contributing factors focusing on helmet use and speed limits. The approach is to use video technology to collect observations of e-scooter users at a range of locations at various times of day, while attempting to control for weather and other factors. Logistic regression of variables measured from recorded rider behaviour is employed to answer the following key questions: What are the rates of helmet use and speed compliance with road rules? What rider, location, or context factors significantly influenced road rules compliance? How did shared *vs*. private e-scooter riders differ in compliance behaviour? Did e-scooter rider infrastructure (footpaths *vs*. bike lanes *vs*. roads) and time factors affect rule compliance? The effect of localised precipitation on compliance is also assessed. A better understanding of e-scooter rider road rules compliance and contributing factors can support informed, effective and safe e-scooter management and governance and ultimately more sustainable urban mobility.

3. Methods and data

3.1. Study context

In Australia, the state of Queensland has been a leader in introducing shared e-scooter schemes, with Lime opening its system in late 2018 (ABC News, 2018), Neuron from 2019 and Beam from 2021 until 2024. Although levels of private e-scooter ownership are unknown, observational studies reveal increases in numbers of numbers of private scooters in the late 2010 s and early 2020 s (Haworth et al., 2021a, 2021b, Haworth and Schramm, 2023).

Though regulations have been in place in Queensland since the introduction of shared e-scooters, the safety of riders and pedestrians continues to be a concern, particularly for inexperienced, distracted or intoxicated riders. A submission to the June 2025 Queensland Parliamentary inquiry into e-mobility safety and use indicate 6,432 emergency department presentations or admissions in the one year from 1 April 2025 to 31 March 2025. Of these, 1,456 were admitted to hospital including 60 to intensive care (Queensland Health, 2025). To mitigate safety concerns and following local bicycling laws, the cornerstone of e-scooter regulation in Queensland is the legal requirement for e-scooter riders to wear helmets. In addition to the helmet requirement, in 2018 the Queensland government instituted strict restrictions on where e-scooters could be ridden through both geofencing and restrictions on rider infrastructure (ABC News, 2018, Neuron Mobility, 2020a). Brisbane has four infrastructure types that could be used by e-scooter riders: 1) footpaths (sidewalks), 2) on– road bicycle lanes, usually indicated with paint, 3) separated cycle tracks where there is some physical barrier between e-scooters or cyclists and motor vehicles and 4) general traffic lanes (Fig. 1). Bicycle lanes, separated cycle tracks and general traffic lanes are sometimes referred to collectively as on-road cycling infrastructure.

Initial regulations required e-scooters to be ridden only on footpaths or on separated paths with both pedestrian and cyclist lanes, but not in on-road bike lanes. E-scooter rider use of mobile phones and alcohol has always been forbidden. There was also guidance that an e-scooter should be parked in a “safe and responsible way” (ABC News, 2018). From December 2021, shared e-scooters were ‘locked out’ of Brisbane’s CBD

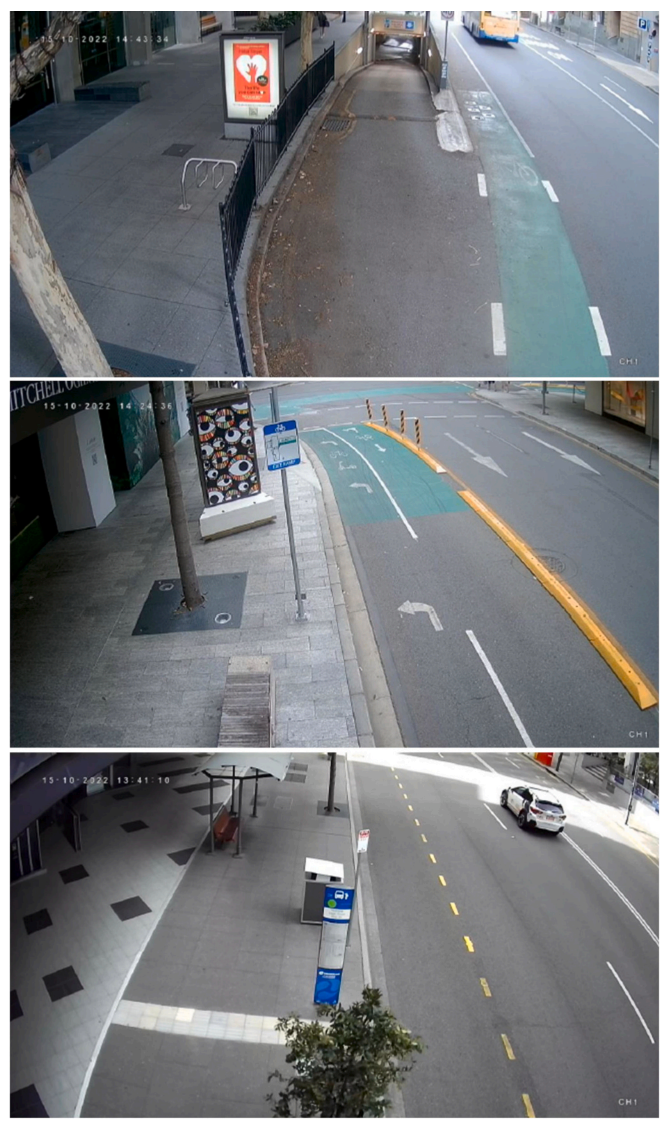

Fig. 1. 2022–2023 e-scooter conveyance infrastructure: footpath (each image, left), On-road bicycle lane (top), Separated cycle track (centre) and General traffic lane (bottom).

and Fortitude Valley meaning trips could end but not start in these areas from midnight to 5:00 am (ABC News, 2021). Shared helmets have been provided with shared e-scooters from the beginning, but were not physically attached to the devises. Neuron introduce the world's first e-scooter helmet lock in Brisbane in 2020. The helmet lock was controlled by the Neuron app that released helmets at the start of trips. The goals were to improve helmet availability and reduce problems of helmet theft and missing helmets (Neuron Mobility, 2020b).

With growing numbers of shared and private e-scooter users, new laws were enacted by the Queensland Government in November 2022. On 1 November 2022 the new laws limited e-scooter speeds on footpaths to 12 km/h (ABC News, 2022a, 2022b) after conflict between pedestrians and e-scooter users. The speed limit remained at 25 km/h elsewhere. Riders must be 16 years old to operate or 12 to 15 years old with adult supervision. All statements regarding speed and helmet compliance are derived from the official Rules for Personal Mobility Devices issued by the Queensland Government (Queensland Government, 2024).

3.2. Study sites and data collection

In order to understand e-scooter rider compliance with road rules for helmet use, speed limit and infrastructure type road users were observed in 2022 and 2023 using 15 cameras at eight different sites in Brisbane shown in Fig. 2. Characteristics of each site are presented in Table 1. Data were collected from 5:00 a.m. through 10:59p.m. in October 2022 on Saturday the 15th, Sunday the 16th, Tuesday the18th, Wednesday the 26th, Thursday the 27th and Saturday 29th and in October 2023 on Saturday the 14th, Tuesday the 17th, Wednesday the 18th, Thursday the 19th, Saturday the 21st and Sunday the 22nd. The weather was generally fine across the days of the study. In October 2022 the mean daily maximum temperature for Brisbane was 25.8 °C. The mean minimum temp for Oct 2022 was 16.5. In October 2023 the mean daily maximum temperature for Brisbane was 27.5 °C and the mean daily minimum temperature for Brisbane was 16.8 °C (Aus Bom, 2026a,b).

The sites can be classified according to urban form and density, from highest to lowest: CBD, urban or suburban. Additional site attributes include, e-scooter rider infrastructure (footpath along with on-road bicycle lane, separated cycle track, or general traffic lane), and posted speed limit (40, 50 or 60 km/h)."

3.3. Data processing

Video footage of cyclist, e-scooter and pedestrian activity was collected using high-definition cameras installed at the eight sites. Video footage was developed into a data set using Advanced Mobility Analytics Group (AMAG) Traffic AI commercial video analytics software for object recognition and recording of e-scooter and other traffic data. Data processing was based on classifications of public and private e-scooters as well as helmet use conducted using manual review of still images extracted from video. AMAG speed calculations are based on a series of points for each e-scooter trajectory. For each point speed is calculated as distance is divided by time. Speeds for all points in each e-scooter trajectory are then averaged resulting in a speed value for each e-scooter observation. Public e-scooters are identified and distinguished from private scooters by AMAG processing using colour and as a result did not provide reliable data after dark. Video data were processed to yield six different data dimensions:

- Class of user (e-scooter, cyclist, pedestrian)
- Speed of e-scooter user or cyclist

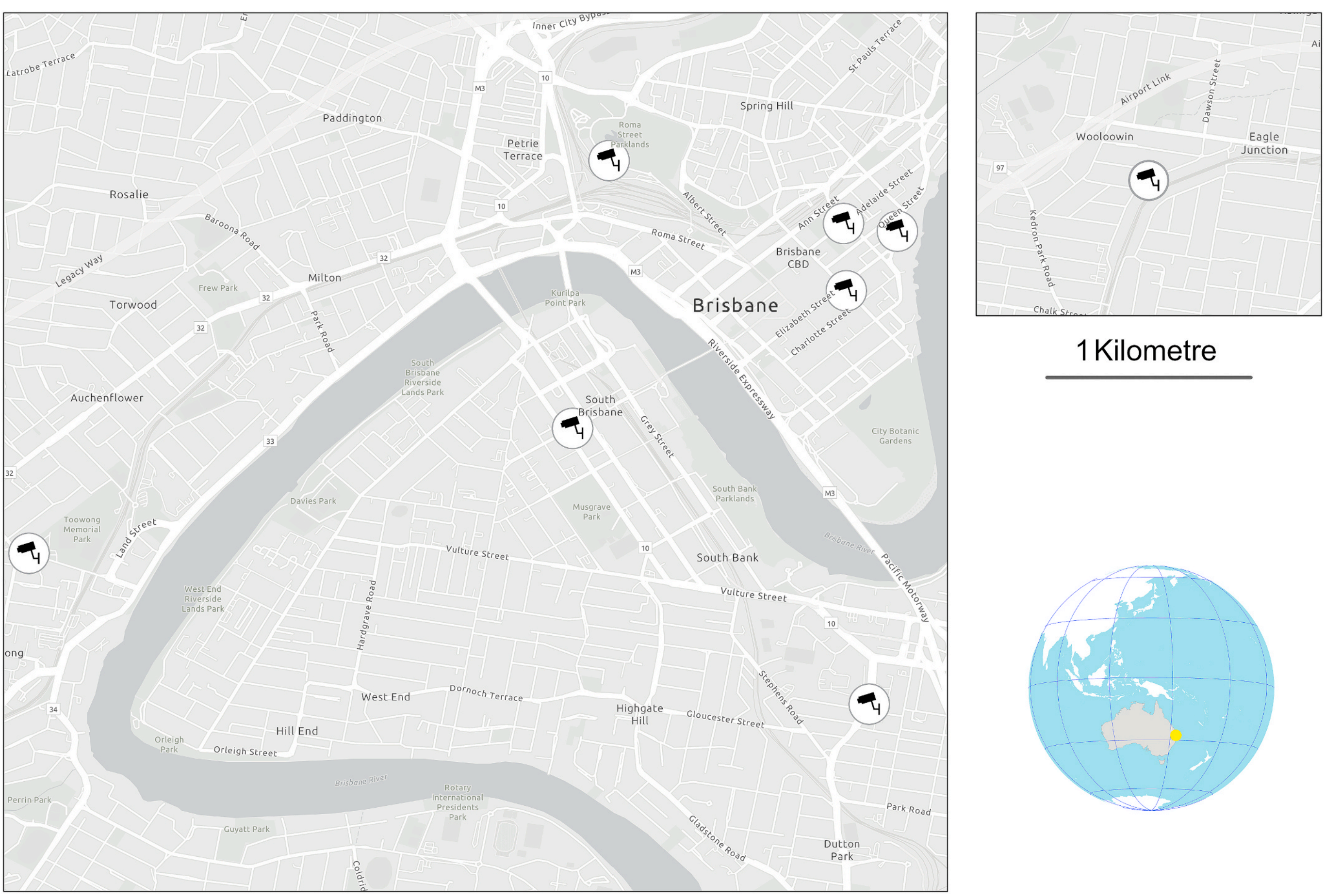

Fig. 2. Map of Survey Sites.

Table 1
Data collection sites and characteristics.

Site ID	Site Name	Category	Infrastructure Type	Posted traffic speed
1	Adelaide St, Brisbane CBD	CBD	On-road Bicycle Lane Southern Footpath	40 km/h
2A	Annerley Rd, Dutton Park	Urban	Separated cycle track Western Footpath	60 km/h
2B	Annerley Rd, Dutton Park	Urban	On-road Bicycle LaneEastern Footpath	60 km/h
3A	Melbourne St, South Brisbane	Urban	On-road Bicycle Lane Northern Footpath	40 km/h
3B	Melbourne St, South Brisbane	Urban	On-road Bicycle Lane Southern Footpath	40 km/h
4A	Sylvan Rd, Toowong	Suburban	On-road Bicycle Lane Southern Footpath	50 km/h
4B	Sylvan Rd, Toowong	Suburban	On-road Bicycle Lane Northern Footpath	50 km/h
5A	Dickson St, Wooloowin	Suburban	On-road Bicycle Lane Northern Footpath	60 km/h
5B	Dickson St, Wooloowin	Suburban	On-road Bicycle Lane (Southeast footpath)	60 km/h
6A	Elizabeth St west of Edward St, Brisbane	CBD	Separated cycle track Western Footpath	40 km/h
6B	Edward St south of Elizabeth St, Brisbane	CBD	Separated cycle track	40 km/h
7A	Eagle St, Brisbane CBD	CBD	General Traffic Lane Eastern Footpath	40 km/h
7B	Eagle St, Brisbane CBD	CBD	General Traffic Lane Western Footpath	40 km/h
8A	Parkland Boulevard, Roma St Parklands	Urban	General Traffic Lane Western Footpath	40 km/h
8B	Parkland Boulevard, Roma St Parklands	Urban	General Traffic Lane Eastern Footpath	40 km/h

- Age classification of e-scooter user
- Helmet use for e-scooter user or cyclist
- E-scooter ownership, shared or private
- Time and direction of travel

Manual data entry was used to augment automated processing in instances where public *vs.* private e-scooters and helmet use was not detectable by AI such as after dark. Age classification was a dichotomous choice categorical variable indicating adult or child. Due to the very small number of child observations age classification was excluded from analysis.

3.4. Descriptive analysis and logistic regression models

The total number of e-scooter observations was 18,874. Of these 9,989 were private e-scooters and 8,885 were public e-scooters. The number of e-scooters observations by site, category, ownership and year is presented in Table 2 and observations by infrastructure type are presented in Table 3. Summary statistics of e-scooter speeds are presented in Table 4. The distribution of e-scooter speeds is also presented visually in figure 3.

Table 3
Number of E-Scooter Observations by Infrastructure.

	Footpath	General Traffic Lane	On-Road Bicycle Lane	Separated Cycle Track	Total
Private E-Scooters	2533	1136	1689	4631	9989
Public E-Scooters	4036	279	937	3633	8885
Total	6569	1415	2626	8264	18,874

Table 4
Speed Summary (km/h).

	n	mean	min	max
Private E-Scooters	9989	18.37	0.0	58.76
Public E-Scooter	8885	15.11	0.0	57.35
Public E-Scooter over 25 km/h: 371 of 8,885 (4.2%)				

The first analytical steps were a series of descriptive analyses that provide a sense of helmet and speed compliance as well as infrastructure use. The second step was a series of regression analyses to study e-scooter helmet law compliance, user speed and the potential influence of precipitation. The analysis was conducted using the python "statsmodels.api" Logit and fit functions. Descriptive analysis is presented in a series of four plots:

1. Speeds for private and shared scooters (2022 *vs* 2023)
2. Helmet use by infrastructure type for private and shared scooters (2022 and 2023 combined)
3. Shared e-scooter speeds and private e-scooter speeds as histograms
4. Footpath and on-road usage proportion *vs.* footpath width

Variables used in the regression analysis are presented in Table 5. The regressions performed were:

1. Assessing helmet law compliance based on different variables: speed of travel, urban form and density (CBD/Urban/Suburban), ownership (private/shared), commuting hour (6am-9am and 3 pm-6 pm Monday to Friday), weekend/weekday travel, posted speed limit (40, 50, 60 km/h), and infrastructure type (bike lane, general traffic lane, separated cycle track).
2. Assessing speed limit compliance in the case of 12 km/h speed zones (e.g. footpath) with the same variables, including helmet compliance and excluding speed.
3. Assessing speed limit compliance in the case of 25 km/h speed zones (e.g. road, cycle track) with the same variables, including helmet compliance and excluding speed.

Each regression was developed both with and without precipitation as an independent variable. The regressions used the following baseline (reference) categories:

Table 2
Number of E-Scooter Observations by Site, Category, Ownership and Year.

Site	Category	Shared 2022	Private 2022	Shared 2023	Private 2023	Total
Adelaide St, Brisbane	CBD	529	201	502	243	1475
Annerley Rd, Dutton Park	Urban	302	671	561	690	2224
Melbourne St, South Brisbane	Urban	580	477	556	360	1973
Sylvan Rd, Toowong	Suburban	46	317	71	449	883
Dickson St, Wooloowin	Suburban	0	62	2	83	147
Elizabeth St / Edward St, Brisbane	CBD	1648	2227	1931	1756	7562
Eagle St, Brisbane	CBD	929	711	1020	682	3342
Parkland Blvd, Roma St Parklands	Urban	113	516	95	544	1268
Total		4147	5182	4738	4807	18,874

Table 5
Variables in regression analysis: reference, included and excluded.

Type	Variable	Included/Excluded/ Reference
Scooter Type	Private	Reference
	Shared	Included
Urban Form and Density	CBD	Reference
	Urban	Included
	Suburban	Included
Posted Speed Limit	40 km/h	Reference
	50 km/h	Included
	60 km/h	Included
Infrastructure Type	Separated Cycle Track	Reference
	On-road Bicycle Lane	Included
	General Traffic Lane	Included
Other Variables	Outside commuting hours	Reference
	During commuting hours	Included
	Weekday	Reference
	Weekend	Included
	Precipitation	Included
	Bicycle lane width	Excluded
	Site identifier (Site)	Excluded
	Speed	Included
	Helmet Compliance	Included
	Speed Compliance 12 km/h	Included
	Speed Compliance 25 km/h	Included

- e-scooters ownership type – private
- Density – CBD
- Posted speed limit – 40 km/h zones
- Infrastructure type – Separated Cycle Track
- Weekday
- Outside commuting hours

All regression results (odds ratios) were interpreted relative to these categories. Bike lane width and site identifiers were explicitly excluded from the regression models.

4. Results

4.1. Descriptive findings

Fig. 3 through 6 illustrate important descriptive findings for helmet and speed compliance as well as infrastructure type. A quantile plot of shared and private e-scooter speed results is shown in Fig. 3. Results indicate significant increases in speed of e-scooter users between 2022 and 2023 based on two-sample t-tests. For private e-scooters, the average speed significantly increased from 17.83 to 18.93 km/h ($p < 0.001$). For shared e-scooters, the average speed significantly increased but at a lower rate from 14.96 to 15.23 km/h (significant at $p < 0.1$, $p = 0.053$).

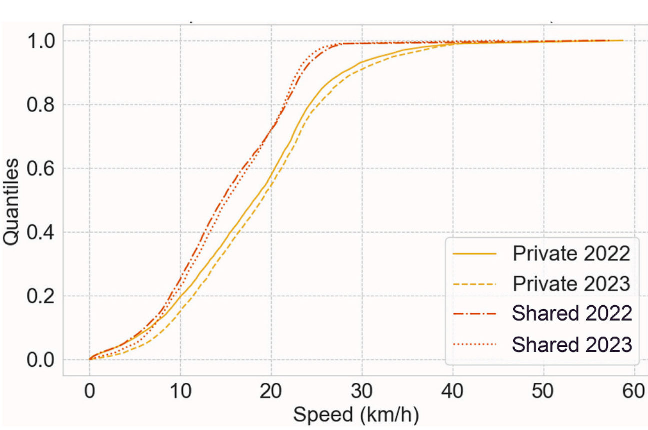

Fig. 3. Quantile plot of speeds for private and shared scooters (2022 *vs* 2023).

Helmet compliance as a percentage of total e-scooter users was 72.9% for footpath users and 83.3% for on road users (2022 and 2023 combined). Disaggregated by ownership, 76.4% of private e-scooter users and 71.0% of shared e-scooter users on footpaths and 87.7% of private e-scooter users and 76.9% of shared e-scooter users on road were compliant with helmet laws. Fig. 4 presents helmet use rates for shared and private e-scooter users by infrastructure type. Fig. 4 illustrates e-scooter users were more likely to wear a helmet when 'on road' (general traffic lane, bike lane, or separated cycleway) compared to being on a footpath. Private e-scooter users exhibit lower helmet usage on footpaths and increased helmet use as infrastructure progressively offers less protection for riders.

In addition, users who were speeding were complying with the helmet law at a higher rates than total e-scooter users. Users speeding on footpath (i.e. above 12 km/h) were complying with the helmet law at a rate of 73.4%, while users speeding on road (above 25 km/h) were complying at a rate of 90.7%. Adding full-face helmet observations to the study showed that users wearing a full-face helmet travelled on average faster than users wearing ordinary helmets, who in turn travelled faster than users not wearing helmets (25.6, 19.5, 17.7 km/h respectively). This suggested the possibility risk compensation was occurring.

Overall speed compliance was 82% on road and 52% on footpaths. Plotting shared e-scooter speeds as a histogram (Fig. 5A) shows a bimodal pattern. The clear peaks around 12 km/h and 22 km/h indicate the location limited 12 km/h and 25 km/h zones. The histogram of private e-scooter speeds (Fig. 5B) shows a single peak just under 25 km/h. Shared e-scooters are speed limited by the providers to 25 km/h. While the speed restrictions built into devices are imperfect, compliance with the 25 km/h speed limit is much higher for shared e-scooter users than for public e-scooter users. The higher proportion of private e-scooters in urban and suburban areas, in on-road environments, in the presence of faster-moving vehicles as well as risk compensation could all be plausible explanations for differences in speed compliance between shared and private e-scooter users.

4.2. Regression modelling results

On-road helmet law compliance regression results are presented in Model 1 (Table 6). The dependent variable in Model 1 is helmet compliance where 0 indicates non-compliance and 1 indicates compliance. Model 1 results indicate several factors significantly and positively influenced helmet compliance for on-road e-scooter riders. In order of influence these are: suburban location (odds ratio 3.75), travelling during commuting hours (odds ratio 1.80), urban location (odds ratio

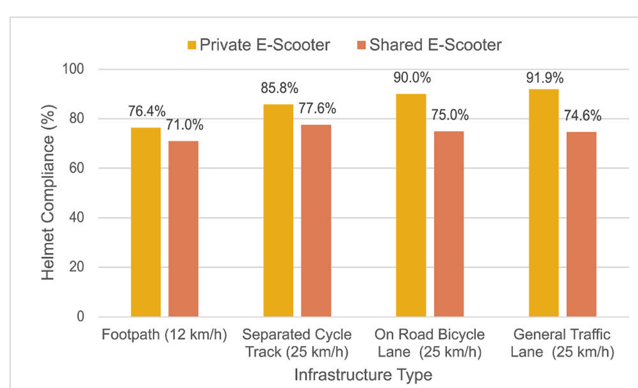

Fig. 4. E-scooter riders wearing helmet by ownership and infrastructure (2022 and 2023 combined).

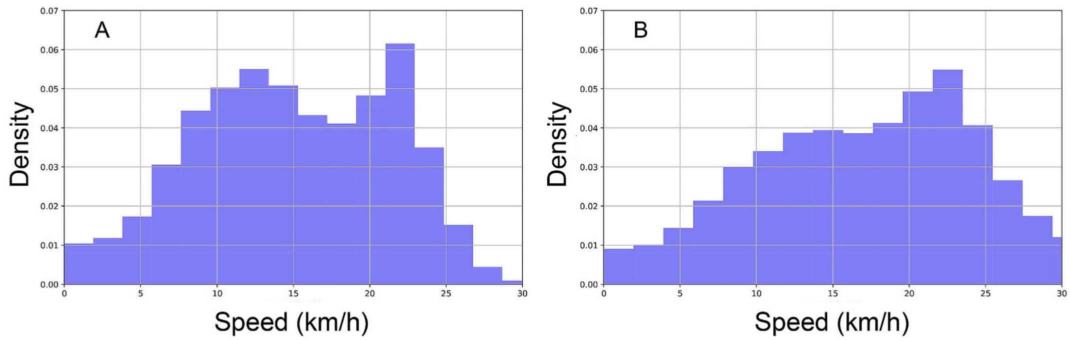

Fig. 5. Plot of (A) shared e-scooter speeds and (B) private e-scooter speeds as histograms.

Table 6
Model 1 On-Road Helmet Compliance Logistic Regression Results.

Variable	Odds ratio	95% CI	p-value
Density (vs CBD)			
CBD (Reference)	*1.00*	—	—
Suburban	3.75	1.42–9.90	0.008
Urban	1.49	1.21–1.83	<0.001
Time of day (vs Outside commuting hours)			
Outside commuting hours (Reference)	*1.00*	—	—
During commuting hours	1.80	1.56–2.07	<0.001
Infrastructure (vs Separated cycle track)			
Separated cycle track (Reference)	*1.00*	—	—
On-road bicycle lane	0.58	0.48–0.70	<0.001
General traffic lane	1.05	0.85–1.30	0.658
Scooter type (vs Private)			
Private (Reference)	*1.00*	—	—
Shared	0.62	0.56–0.68	<0.001
Day of week (vs Weekday)			
Weekday (Reference)	*1.00*	—	—
Weekend	0.64	0.57–0.72	<0.001
Posted speed limit (vs 40 km/h)			
40 km/h (Reference)	*1.00*	—	—
60 km/h	1.31	1.04–1.63	0.019
50 km/h	1.18	0.44–3.15	0.747
Speed (continuous, per 1 km/h)			
Speed	1.01	1.00–1.02	0.005
Constant (intercept)	*4.65*	*3.94–5.49*	*<0.001*

Table 7
Model 2 12 km/h Speed Zone Compliance Regression Results.

Variable	Odds ratio	95% CI	p-value
Posted speed limit (vs 40 km/h)			
40 km/h (Reference)	*1.00*	—	—
50 km/h	0.18	0.07–0.43	<0.001
60 km/h	0.28	0.19–0.40	<0.001
Density (vs CBD)			
CBD (Reference)	*1.00*	—	—
Urban	0.28	0.24–0.33	<0.001
Suburban	0.63	0.28–1.40	0.257
Infrastructure (vs Separated cycle track)			
Separated cycle track (Reference)	*1.00*	—	—
General traffic lane	0.30	0.25–0.36	<0.001
On-road bicycle lane	0.68	0.56–0.83	<0.001
Time of day (vs Outside commuting hours)			
Outside commuting hours (Reference)	*1.00*	—	—
During commuting hours	1.18	1.02–1.37	0.023
Scooter type (vs Private)			
Private (Reference)	*1.00*	—	—
Shared	0.91	0.81–1.01	0.078
Day of week (vs Weekday)			
Weekday (Reference)	*1.00*	—	—
Weekend	1.04	0.92–1.18	0.530
Helmet compliance (vs No helmet)			
No helmet (Reference)	*1.00*	—	—
Helmet worn	1.02	0.91–1.15	0.713
Constant (intercept)	*3.13*	*2.54–3.86*	*<0.001*

1.49), posted speed limit 60 km/h (odds ratio 1.31), and speed (odds ratio 1.01). These results illustrate that compared to 40 km/h speed zones, e-scooter users were significantly more likely to wear helmets when in a 60 km/h speed zone. For each additional 1 km/h increase in speed, the odds of helmet use increased by approximately 1%. This suggests a slight increase in the likelihood of helmet use with higher speeds, though the effect is small.

Model 1 regression results also indicate three statistically significant factors negatively influenced helmet compliance: shared scooter (odds ratio 0.62), weekend (odds ratio 0.64) and bike lane (odds ratio 0.58). Using a shared scooter decreased the odds of helmet use by about 38% compared to using a private scooter. Using an e-scooter on weekends, the odds of helmet use decreased by about 36% compared to weekdays, and using an on-road bicycle lane decreased the odds of helmet use by 42% compared to a separated cycle track. Helmet compliance regression results that include both footpath and on-road e-scooter riders are presented in Appendix I.

The factors influencing speed limit compliance in both the 12 km/h footpath and shared path speed limit zone and the 25 km/h speed limit zone for other bike paths and roads were also investigated. Summary results for the 12 km/h speed limit zone compliance regression are shown in model 2 (Table 7) Table 4 and results for the 25 km/h speed limit zone are shown in model 3 (Table 8). The dependent variable in models 2 and 3 is speed compliance (speed < speed limit) in the respective zones where 0 indicates non-compliance and 1 indicates compliance.

One factor significantly and positively influenced speed compliance in the 12 km/h speed limit zone: commuting hours (odds ratio 1.18). During commuting hours, 6am-9am and 3 pm-6 pm Monday to Friday, e-scooter riders were more likely to comply with the 12 km/h speed limit. Regression results also indicate five factors significantly and negatively influenced speed compliance in the 12 km/h speed limit zone: a posted speed limit of 50 km/h (odds ratio 0.18), a posted speed limit of 60 km/h (odds ratio 0.28), urban density (odds ratio 0.28), general traffic lane (odds ratio 0.30), and bike lane (odds ratio 0.38). These results suggest that higher posted automobile speed limits are associated with lower e-scooter speed compliance.

25 km/h speed zone compliance regression results are shown in model 3 (Table 8) Table 5. Results indicate four factors significantly and positively influenced speed compliance in the 25 km/h speed limit zone: scooter type shared (odds ratio 3.15), posted speed limit 50 km/h (odds ratio 2.44), posted speed limit 60 km/h (odds ratio 1.81) and weekend travel (odds ratio 1.18). These regression results also indicate five factors significantly and negatively influence speed compliance in the 25 km/h speed limit zone: helmet compliance (odds ratio 0.73), location type suburban (odds ratio 0.06), location type urban (odds ratio 0.13), bike lane (odds ratio 0.58), and general traffic lane (odds ratio 0.46).

25km/h speed zone compliance regression results suggest riders

Table 8
Model 3 25 km/h Speed Zone Compliance Regression Results.

Variable	Odds ratio	95% CI	p-value
Density (vs CBD)			
CBD (Reference)	*1.00*	—	—
Suburban	0.06	0.04–0.10	<0.001
Urban	0.13	0.11–0.16	<0.001
Scooter type (vs Private)			
Private (Reference)	*1.00*	—	—
Shared	3.15	2.75–3.61	<0.001
Posted speed limit (vs 40 km/h)			
40 km/h (Reference)	*1.00*	—	—
50 km/h	2.44	1.52–3.92	<0.001
60 km/h	1.81	1.48–2.22	<0.001
Infrastructure (vs Separated cycle track)			
Separated cycle track (Reference)	*1.00*	—	—
General traffic lane	0.46	0.37–0.58	<0.001
On-road bicycle lane	0.58	0.48–0.70	<0.001
Helmet compliance (vs No helmet)			
No helmet (Reference)	*1.00*	—	—
Helmet worn	0.73	0.61–0.87	<0.001
Day of week (vs Weekday)			
Weekday (Reference)	*1.00*	—	—
Weekend	1.18	1.03–1.36	0.016
Time of day (vs Outside commuting hours)			
Outside commuting hours (Reference)	*1.00*	—	—
During commuting hours	1.02	0.90–1.16	0.763
Constant (intercept)	*15.23*	*12.48–18.60*	*<0.001*

wearing a helmet were less likely to be compliant with the speed limits, likely due to risk compensation. Results also indicate that public e-scooter users are much more likely to be compliant with speed limits in 25 km/h zones, noting that public e-scooters are speed limited by the providers to 25 km/h. Compliance was higher on weekends than during the week. In contrast with the 12 km/h zone where posted speed limits of 50 or 60 km/h decrease speed limit compliance, in the 25 km/h zone these limits were associated with increased speed limit compliance. The 25 km/h regression also indicate that e-scooter users are more likely to be compliant with speed limits when using a separated cycle track rather than a bike lane or general traffic lane.

Although observations at each site were conducted in dry weather, the Bureau of Meteorology and the ERA5 reanalysis from the European Centre for Medium-Range Weather Forecasting (ECMWF) recorded precipitation in the Brisbane area on some of the days observations were recorded, which may have affected users' decisions on whether to ride. Riders do not base their decisions of transport mode solely on actual weather, but also on forecasts and their own subjective assessment of conditions.

Precipitation data were extracted from the European Centre for Medium-range Weather Forecasts (ECMWF, 2025) ERA5-Land model which has a resolution of approximately 9 km. The precipitation was then interpolated to the Brisbane General Post Office (GPO) location, the traditional centre of Brisbane, using bilinear interpolation (using oikolab.com data). The precipitation estimate is based on the average rainfall in the 9 km by 9 km square grid centred around the GPO. It does not reflect the likelihood of rain in any given location or study site. The measurement is the depth the water would have been if evenly spread over the grid box (ECMWF, 2025). According the Australian Bureau of Meteorology (BoM), significant precipitation is any amount exceeding 0.2 mm in 24 h. This amount was observed in the ECMWF data on three of six days in 2022 and 1 of 6 days in 2023. Further testing was performed by checking the correlation of observed BoM rainfall data at four sites in Brisbane (Mount Coot-tha, Raymond Park, Alderley, and Eagle Farm) to the modelled ECMWF precipitation data, observing a high correlation in each case.

Examination of the possible effect of precipitation on speed compliance regression results indicate precipitation was a significant variable in the 12 km/h speed zone (Model 4, Table 9). The dependent variable in model 4 is speed compliance where 0 indicates non-compliance and 1 indicates compliance. In the 12 km/h zone case, the odds ratio was 14.21 for the effect of precipitation on compliance ($p = 0.001$). Each additional millimetre of rain per hour had a significant effect on speed compliance. The interpretation of this result was that as precipitation increases, speed compliance is very likely for footpath riding, as this is a slippery environment. Precipitation was not significant in the 25 km/h zone on road infrastructure ($p = 0.409$). The effect of precipitation on helmet compliance gave an estimated odds ratio of 4.57 in the helmet compliance regression case ($p = 0.013$). Both speed reductions and increased helmet use linked with precipitation may be evidence of risk compensation as riders see the need for caution and safety equipment in a potentially more hazardous travel environment. Full details of all regressions are presented in appendix i.

5. Discussion

The goal of this research was to understand e-scooter road rules compliance and contributing factors focusing on helmet use and speed limits. Analysis was based on video recorded data capturing e-scooter user helmet use, speed, infrastructure type, ownership, travel date and time along with urban form and density. Helmet compliance as a percentage of total e-scooter users was 72.9% for footpath users and 83.3% for on road users. Overall speed compliance was 82% on road and 52% on footpaths. Logistic regression models combine to yield a series of findings around e-scooter user behaviour that illustrate both risk compensation and the role of infrastructure in supporting road rules compliance.

Several factors significantly and positively influenced helmet compliance, suburban location, travelling during commuting hours, urban location, posted speed limit 60 km/h, and speed. These results present a clear and positive association between helmet compliance and e-scooter rider speed. Three factors significantly and negatively influenced helmet compliance: shared e-scooter use, weekend riding and bike lane (Table 6). Shared e-scooter users were less likely to wear helmets,

Table 9
Model 4 Helmet and Speed Compliance Regression Results Including Precipitation.

Variable	Odds ratio	95% CI	p-value
Precipitation (continuous, per mm/h)			
Precipitation	14.21	2.83–71.45	0.001
Posted speed limit (vs 40 km/h)			
40 km/h (Reference)	*1.00*	—	—
50 km/h	0.18	0.07–0.44	<0.001
60 km/h	0.28	0.19–0.40	<0.001
Density (vs CBD)			
CBD (Reference)	*1.00*	—	—
Urban	0.28	0.24–0.33	<0.001
Suburban	0.62	0.28–1.39	0.248
Infrastructure (vs Separated cycle track)			
Separated cycle track (Reference)	*1.00*	—	—
General traffic lane	0.30	0.25–0.36	<0.001
On-road bicycle lane	0.68	0.56–0.82	<0.001
Time of day (vs Outside commuting hours)			
Outside commuting hours (Reference)	*1.00*	—	—
During commuting hours	1.17	1.02–1.36	0.030
Scooter type (vs Private)			
Private (Reference)	*1.00*	—	—
Shared	0.91	0.81–1.01	0.076
Day of week (vs Weekday)			
Weekday (Reference)	*1.00*	—	—
Weekend	1.07	0.94–1.21	0.323
Helmet compliance (vs No helmet)			
No helmet (Reference)	*1.00*	—	—
Helmet worn	1.02	0.90–1.15	0.760
Constant (intercept)	*3.03*	*2.45–3.75*	*<0.001*

perhaps because of availability and convenience issues, and because footpath riding in the CBD may feel safe enough to not require helmet use. Private e-scooter users are likely to own a helmet, mitigating hygiene concerns around shared helmets.

This evidence from Brisbane indicates that fast regular travel is positively associated with helmet use. Descriptive findings revealed users speeding on road (above 25 km/h) were complying with helmet requirements at a rate of 90.7%. Adding full-face helmet observations to the study showed that users wearing a full-face helmet travelled on average faster than users wearing ordinary helmet, who in turn travelled faster than users not wearing helmet. Lower helmet compliance rates for shared *vs*. private e-scooter users is demonstrated across all infrastructure types and is lower on footpaths than on road infrastructure (Fig. 4).

Specific to Brisbane, Haworth et al. (2021a, 2021b) and Haworth and Schramm (2023) found similar rates of helmet use and higher rates of compliance for private users versus shared users. The helmet compliance rates in Brisbane are also comparable to those presented in Roberts et al., 2025 who focused on Perth, Australia. Higher helmet compliance for private users compared with public users correspond with the findings from Canberra, Australia (Ssi Yan Kai et al., 2024) and internationally including Brussels, Belgium (Lefrancq, 2019), Vienna, Austria (Laa and Leth, 2020), and San Francisco, USA (Frye et al., 2024).

In addition to the emerging consensus around higher helmet use compliance for private users, the e-scooter literature also provides numerous examples of increased shared e-scooter use on weekends (Alsulami et al., 2023, Bieliński and Ważna, 2020, McKenzie, 2019). There are contrasting findings in Minneapolis in where shared e-scooter rider ridership was more stable across the week (Bai and Jiao, 2020). Looking at four cities in Europe, Foissaud et al., 2022 also provide a more nuanced and place-based interpretation of usage patterns across a week. To the extent a city experiences increased weekend shared e-scooter use the results here and elsewhere indicating lower helmet use for shared e-scooter users suggest lower helmet use rates in these times of high shared e-scooter demand.

A single factor significantly and positively influenced speed compliance in the footpath and shared paths 12 km/h speed limit zone: commuting hours. This result contrasts with Almannaa et al. (2021) and Zuniga-Garcia et al. (2021) who found e-scooter users travelled at higher speeds during commuting hours in Austin. Potential differences between Austin and Brisbane include public e-scooter riders traveling at low speeds on footpaths in the Brisbane CBD. Five factors significantly and negatively influenced speed compliance in the 12 km/h speed limit zone: a posted speed limit of 50 km/h, a posted speed limit of 60 km/h, location type urban, general traffic lane, and bike lane (Table 7). As noted above, speeds increase in areas of higher posted speed limits and when moving outward from the CBD to urban and then to suburban areas.

Four factors significantly and positively influenced speed compliance in the 25 km/h speed limit zone: scooter type shared, posted speed limit 50 km/h, posted speed limit 60 km/h and weekend travel. These results are similar to Zuniga-Garcia et al. (2021) who found e-scooter users travelled at higher speeds on weekdays in comparison with weekends. Given a large body of scholarship on the day of week and time of day of e-scooter travel and a similar level of concern around rider speed as a risky behaviour, further research linking speed compliance with travel times appears to be a natural next step in e-scooter research. Five factors significantly and negatively influence speed compliance in the 25 km/h speed limit zone: helmet compliance, location type suburban, location type urban, bike lane, and general traffic lane (Table 8). Speed compliance is greatest on separated cycle tracks, lower on bicycle lanes, lower still on general traffic lanes and lowest on footpaths. The finding of lower speed compliance in bike lanes aligns with Cicchino et al. (2024) who found riders moved most slowly on sidewalks, faster on roads and were fastest in bike lanes. They observe bike lanes provide space for e-scooters to ride where their speeds could more closely match other users (Cicchino et al., 2024). These results also align with Arellano and Fang (2019) who observed e-scooter riders travelled faster on streets than mixed-used (pedestrians, cyclists and e-scooters) paths.

Prior research incorporating precipitation focuses on the negative influence of precipitation on e-scooter usage. The focus here is not if rain impacts usage, but how rain impacts user behaviour. Precipitation was a significant positive influence on speed compliance and helmet compliance in the 12 km/h speed zone. Precipitation was not found to significantly impact behaviour in the 25 km/h zone.

Both descriptive findings and helmet compliance regression results accord well with the theory of risk compensation. Results indicated a positive correlation between greater head protection (no helmet, helmet, full face helmet) and higher speeds as well as greater helmet compliance at speed. The inverse relationship between helmet compliance and protection afforded by infrastructure, especially for private e-scooter users, (figure 4) also suggests risk compensation. Another example is seen in relation to urban density where helmet compliance and speeds increase when moving outward from the CBD to urban and then to suburban areas (tables 7, 8 and 9). In some situations, such as footpath riding, the effect of precipitation or the possibility of precipitation led to higher rates of speed limit compliance. Depending on the perceived risk, there is evidence users adjust their behaviour vis-à-vis speed and helmet law requirements, trading off safety, perceived risk and convenience.

6. Conclusion

Our study is the first to study e-scooter use based on automated classification of helmet use and speed measurement along with several additional data dimensions obtained from video data. There are a number of key findings that contribute to our understanding of e-scooter rider behaviour:

- These is a clear and positive association between helmet compliance and e-scooter rider speed. E-scooter riders wearing helmets rode faster than those not wearing helmets, and those with full-face helmets rode the fastest.
- Separated cycle tracks are associated with higher rates of helmet compliance than other infrastructure types for shared e-scooter riders.
- Private e-scooter riders were most likely to wear a helmet when riding on roads or bike lanes, potentially compensating for greater speeds on those infrastructure types.
- The results here confirm other research where private e-scooter riders where helmets at greater rates than public e-scooter riders.
- Speed compliance in the 25 km/h speed zone is highest on separated cycle tracks and is positively correlated with urban density and greater head protection.
- These findings provide evidence of e-scooter users demonstrating risk compensation decisions around helmet use, speed and riding locations.

The findings of this research improve our understanding of e-scooter road rules compliance, illuminate the factors influencing compliance and can inform policy development in Brisbane and internationally, for example for cities considering helmet requirements and what potential impacts may occur. While most of the findings here are supported with observations from cities around the world, caution is warranted when considering the degree to which aspects of these findings are broadly generalisable. The paucity of observational studies of e-scooter use compounded by the fact that instances of compulsory helmet use are limited internationally provide a limited basis of comparison for these results, especially helmet compliance. Expanding this research to additional cities, especially those with helmet requirements, would allow direct comparison of results and enhance generalizability.

There are several limitations to this study in addition to generalisability. Vendor specifications of the measurement accuracy (margin of error) of the Traffic AI speed estimates were not available, and this is a limitation of the study. As a consequence, the binary speed-compliance classifications may be subject to an unknown degree of misclassification, particularly for observations with true speeds close to the 12 km/h and 25 km/h regulatory thresholds, where a small measurement error can change the assigned compliance category. There is no reason to expect this error to differ systematically by ownership type, infrastructure type, site or time of day. Non-differential misclassification of the compliance outcome would be expected to attenuate the estimated associations toward the null (odds ratios biased toward 1.0). The statistically significant associations reported here are therefore likely to be, if anything, conservative estimates of the true effects.

Additional limitations include the accuracy and validation of the machine learning model, the absence of rider demographic data, and the omission of site-level effects in the models. There are also opportunities to consider device ownership distinguishing between shared, leased and private e-scooters. Distinctions between leased and private scooters are most likely to be in the area of device compliance but there may be follow-on behavioural impacts. There are also limits to the precipitation data as they are not site specific and we are unable to link precipitation data to the decision-making processes and revealed behaviours of e-scooter riders. The observational nature of the study also limits developing conclusions around causation.

These limitations, however, all suggest opportunities for future research. The theory of risk compensation appears to be relevant to many of the findings here. Whether users can correctly assess risks of helmet, speed and location combined is a study in risk perception versus reality. There are opportunities for survey and simulation to develop a more accurate picture of e-scooter users' risk perceptions and subsequent behaviour. Risk perception and behaviour can also be contrasted with alternate transport modes, especially cycling. Both risk compensation theory and risk perception are potentially fruitful areas for future research. Expanding the temporal scope of the study to include both additional years and additional months of the year would allow refining the findings here, potentially also improving generalisability. There are also opportunities in future research for multi-dimensional observational data to be integrated with other local data such as hospital admissions and police infringements. For example, Cittadini et al (2023) examined helmet use in the context of e-scooter riders and hospital admissions. Gan-El et al (2022) looked at e-scooter user injuries by time of day. The implication could be that harm could be mitigated depending on observed patterns, particularly if the observations were integrated with hospital admission data or enforcement data. Although, in Queensland, police and hospital data can be difficult to obtain in a useful form due to fragmentation between health services, privacy and legal concerns. Reasons for not wearing helmets such has heat, hygiene, are infrequently seen in the literature and also opportunities for future investigations.

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CRediT authorship contribution statement

Scott N. Lieske: Writing – review & editing, Writing – original draft, Resources, Project administration, Funding acquisition, Formal analysis. **Richard Bean:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Richard J. Buning:** Writing – review & editing, Resources, Project administration.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tbs.2026.101352.

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