Using street imagery and crowdsourcing internet marketplaces to measure motorcycle helmet use in Bangkok, Thailand

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Received 31 October 2018
Revised 4 January 2019
Accepted 7 January 2019

To cite: Merali HS, Lin L-Y, Li Q, *et al*. *Inj Prev* Epub ahead of print: [*please include* Day Month Year]. doi:10.1136/injuryprev-2018-043061

ABSTRACT

Introduction The majority of Thailand's road traffic deaths occur on motorised two-wheeled or three-wheeled vehicles. Accurately measuring helmet use is important for the evaluation of new legislation and enforcement. Current methods for estimating helmet use involve roadside observation or surveillance of police and hospital records, both of which are time-consuming and costly. Our objective was to develop a novel method of estimating motorcycle helmet use.

Methods Using Google Maps, 3000 intersections in Bangkok were selected at random. At each intersection, hyperlinks of four images 90° apart were extracted. These 12 000 images were processed in Amazon Mechanical Turk using crowdsourcing to identify images containing motorcycles. The remaining images were sorted manually to determine helmet use.

Results After processing, 462 unique motorcycle drivers were analysed. The overall helmet wearing rate was 66.7 % (95% CI 62.6 % to 71.0 %). Taxi drivers had higher helmet use, 88.4% (95% CI 78.4% to 94.9%), compared with non-taxi drivers, 62.8% (95% CI 57.9% to 67.6%). Helmet use on non-residential roads, 85.2% (95% CI 78.1 % to 90.7%), was higher compared with residential roads, 58.5% (95% CI 52.8% to 64.1%). Using logistic regression, the odds of a taxi driver wearing a helmet compared with a non-taxi driver was significantly increased 1.490 ($p<0.01$). The odds of helmet use on non-residential roads as compared with residential roads was also increased at 1.389 ($p<0.01$).

Conclusion This novel method of estimating helmet use has produced results similar to traditional methods. Applying this technology can reduce time and monetary costs and could be used anywhere street imagery is used. Future directions include automating this process through machine learning.

INTRODUCTION

Road traffic injuries are a leading cause of death with 1.2 million deaths globally each year.[1] Significantly, nearly half of these deaths are among vulnerable road users including pedestrians, cyclists and motorcyclists. In addition, it is estimated that 50 million people suffer non-fatal injuries as a result of road traffic collisions.[1] In order to address this growing problem, the United Nations created two Sustainable Development Goals (SDGs) in 2015 targeting road traffic safety. SDG 3.6 aims to half the number of road traffic deaths by 2020, and SDG 11.2 aims to provide safe and accessible transport for all by 2030.[1] If we are to make progress towards these goals, then known interventions for preventing road traffic deaths must be implemented.

The issue of motorcyclists as vulnerable road users is particularly problematic in South East Asia. Between 2010 and 2013, there has been a 27% increase in the number of motorised two-wheeled vehicles[1] and motorcyclists comprise the largest proportion of road traffic deaths in the South East Asian and Western Pacific regions.[1] In 2012, it was estimated that Thailand had a road traffic mortality rate of 36.2 per 100 000 population per year, and the vast majority, 73%, were riders of two-wheeled or three-wheeled motorised vehicles.[1] Hospital data in Thailand have shown that up to 80% of people hospitalised for a road-traffic collision were motorcyclists.[2] Road traffic collisions also affect the economy with losses equivalent to 3.0% of Gross Domestic Product (GDP) in Thailand.[1] If Thailand is to achieve the goal for the *Decade of Action for Road Safety* and reduce the mortality to under 10 per 100 000, significant road safety improvements must be made, especially those targeting motorcyclists.[3]

The most important method of decreasing injuries and deaths for motorcyclists is increasing helmet use. Studies from multiple countries including Thailand have demonstrated an increased risk of injury and death from not wearing a helmet.[4–6] Data from high quality studies included in a Cochrane review demonstrate that motorcycle helmets reduce the risk of death by 42% and of head injury by 69%.[4] Despite this significant reduction in morbidity and mortality, helmet wearing rates remain a significant problem in Thailand. Since the Helmet Act of 1994 was enacted, wearing a helmet in Thailand while operating a motorcycle has been mandatory. There is also an additional penalty to any driver who carries a non-helmeted passenger.[2] Despite this law, however, national data from 2012 demonstrated that the driver helmet wearing rate in Thailand was only 52%.[1]

Accurate estimates of helmet use are important both for national policy and enforcement. This, however, has been challenging in many countries including Thailand where helmet use estimates vary widely. It has been demonstrated to be as low as 43.7% in the largest national study from 2010 which included 945 956 direct observations,[7] to 55.8% using observational data from four provinces during the Songkran Festival in 2007,[8] to 60% in a national interview-based study in 2009.[2] Bangkok has been shown to have the highest helmet wearing

rate among drivers at 93.2% with 100 randomly selected sites in 2010.[7] Part of the disparity in these estimates is a result of geographic location and the year of study, but part of it is also due to the methodology of helmet estimation. Currently, there are two methods of helmet data collection, road side observation[9] and surveillance of police and hospital records. The main deficit of surveillance data is underreporting in both police[10] and hospital records.[7] Severely injured motorcyclists who are killed may never be brought to the hospital, and those who have minor injuries may also not be brought to the hospital or have the police involved. Roadside observation is typically limited by only having a small number of observation sties.[11] In addition, both of these methods are time consuming and costly. This may explain the global lack of data on collecting helmet use rates with only 41% of countries having these data available in a recent WHO report.[1]

In an effort to reduce time and monetary costs in research in general, two powerful tools have emerged in recent years: street imagery and crowdsourcing internet marketplaces. Google Street View (GSV) is the largest street imagery platform and has been used for such diverse applications as assessing built environments in cities,[12,13] city-level travel patterns,[14] vulture habitats,[15] roadside vegetation,[16] smoke free signage,[17] air pollution[18] and neighbourhood vectorborne illness risk.[19] A systematic review examining the use of GSV found seven articles related to injury prevention.[20] The second tool, crowdsourcing internet marketplaces, allow for a variety of tasks to be completed quickly and at low cost.[21] There are several companies that offer this service, including Amazon's Mechanical Turk (MTurk), which is commonly used for research purposes. MTurk allows researchers to collect and analyse data that requires Human Intelligent Tasks (HITs) and has been used previously to evaluate the built environment at the street level to identify bicycles and pedestrians.[22] In this study, our objective was to combine these two research tools to develop a novel method of estimating helmet use in Bangkok, Thailand that is both time and cost efficient.

METHODS

Data collection and processing

To obtain the images to be processed, a freely available shapefile of the Bangkok road network was first obtained from BBBike.org.[23] Shapefiles are digital files used to store geographic data associated with particular geographic points. The shapefile was then overlaid onto Google Maps using the Google Maps Application Programming Interface (API). The shapefile provided specific information on the types of roads at a specific point, and therefore, any point with more than one road was classified as an intersection. Using this method, we were able to obtain information on 153 650 intersections in Bangkok with the images available through Google Maps API. From this database, we randomly selected 3000 intersections (see figure 1). Then, using the Google Maps API and Street View function, we obtained hyperlinks of four images 90° apart at each of these intersections for a total of 12 000 images. Using information from both the shapefile and Google Maps, each image contained data on the coordinates, the heading, the date the image was taken, and the types of roads contained at that point. The resulting 12 000 images were taken from September 2011 to December 2016.

These 12 000 image hyperlinks were then submitted to MTurk for processing. Our HIT included one simple question: 'Do you see one or more motorcycle or motorised scooter in this image?'. The users only had the option to select 'yes' or 'no'. Specifically, we asked users to include motorcycles and motorised scooters and to exclude bicycles, cars and trucks (see figure 2). Each image analysed was a separate HIT and processed by one user. In order to increase accuracy, we only used MTurk Master Workers. These users are given this qualification by Amazon if they can consistently demonstrate a high degree of success performing HITs across a large number projects.[24]

All of the images processed through MTurk which were labelled either 'yes'or 'no answer' were then reviewed by a researcher (HM). The validity of each image was then determined on the basis of their being at least one motorcycle with a driver who had a clear view of their head to see if the individual was wearing a helmet or not (see figure 2). A determination of whether the driver was a taxi driver was also made by the researcher (HM) based on clearly identifiable coloured vests worn by motorcycle taxi drivers in Bangkok. Images where there was either no motorcycle, a parked motorcycle or the helmet status of the motorcycle driver could not be determined were excluded at this stage.

Finally, each image was classified based on the type of intersection in one of three categories, either residential, non-residential or other. In order to ensure non-residential images were classified appropriately, only one of the roads in the image needed to be non-residential in order for that particular image to be classified as such.

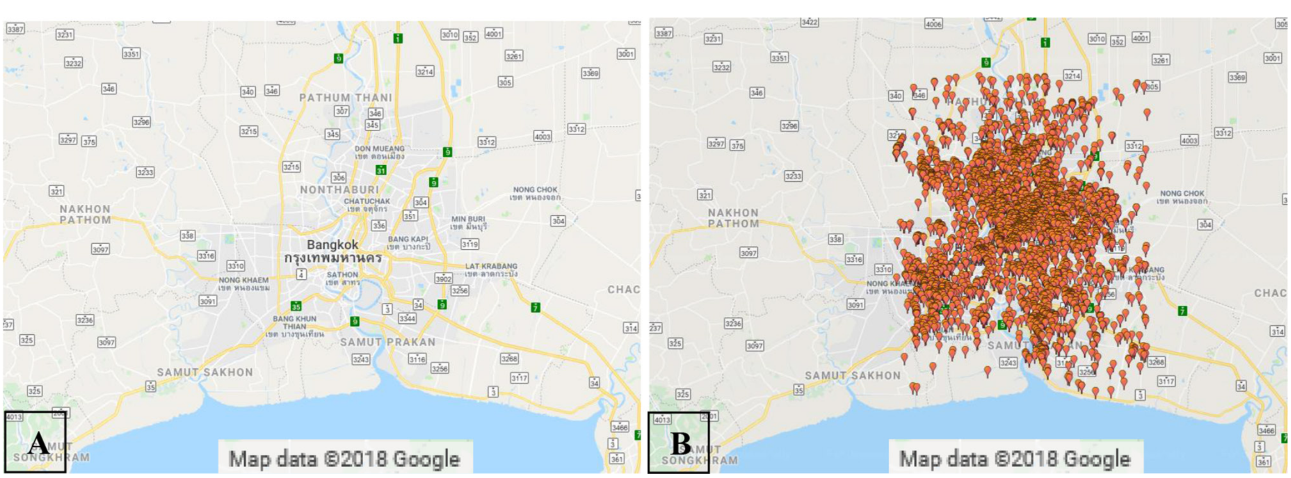

Figure 1 Google Maps view of Bangkok (A) and shapefile overlay showing 3000 randomly selected intersections (B).

Figure 2 Sample image from Google Street View demonstrating two motorcycle drivers wearing helmets in Bangkok.

Statistical analysis

Both descriptive statistical methods and multivariate logistic regression were used to analyse the data. Confidence intervals in univariate descriptive statistics were calculated using a binomial distribution, which is the default approach for count data.[25] The intervals reflect the uncertainty when a sample is used to make an inference about a parameter in the population. For bivariate analysis, a proportion test based on a binomial distribution was used to test the statistical significance of difference between groups.[26] For multivariate logistic regression, the following model was used:

$$logit\left(y_i\right) = X_i\beta$$

where i indexes occupant; $y_i = 0/1$ is an indicator of occupant i not wearing (0) or wearing[1] helmet; X_i is the vector of covariates for occupant i including an intercept; β is the vector of regression coefficients. Covariates included in the model are type of vehicle (taxi vs non-taxi) and type of road (residential, non-residential and other).

All data analyses were conducted in Stata 15 SE.[27]

RESULTS

MTurk

In total, 178 unique workers completed between 1 and 248 HITs each. Each worker spent an average of 38 s completing each task, and the total time it took for the entire project to be completed was 89 min and 22 s. Of the 12 000 image hyperlinks submitted to MTurk, 9440 were labelled as not having a motorcycle or motorised scooter, 2559 were labelled as having a motorcycle or motorcycle scooter and 1 was labelled as not having an answer. Similar to the original database, these images also ranged in date from September 2011 to December 2016.

Manual processing

All of the 2560 images labelled 'yes' or 'no answer' were manually examined and 378 of these images were determined to be valid, while 2182 were determined to be invalid. Of the 2182 images that were invalid, the reasons for invalidity were: 1049 (48.1%) did not have a motorcycle or motorised scooter in the image, 882 (40.4%) displayed parked motorcycles and 251 (11.5%) had motorcycles with drivers but their helmet status was unable to be determined. Within the 378 valid images, each image contained between 1 and 4 motorcyclists, and a total of 462 unique motorcycle riders were analysed. Of the 378 valid images, 146 (38.6%) were from 2011, 227 (60.1%) from 2012, 1 (0.3%) from 2014 and 4 (1.1%) from 2016 (see figure 3).

Final analysis

After analysis of the 462 motorcycle drivers, the overall helmet wearing rate was 66.7% (95% CI 62.6% to 71.0%). Of the 462 total drivers, 69 were taxi drivers and they had higher helmet use, 88.4% (95% CI 78.4% to 94.9%), compared with non-taxi drivers, 62.8% (95% CI 57.9% to 67.6%). Helmet use on non-residential roads, 85.2% (95% CI 78.1% to 90.7%), was higher compared with residential roads, 58.5% (95% CI 52.8% to 64.1%) (see table 1).

In the bivariate analysis, the difference in the helmet wearing rate between taxis and non-taxis was found to be statistically significant ($p<0.001$ per Fisher's exact test). Similarly, the difference in helmet wearing rate between the three types of road was also statistically significant ($p<0.001$ per Fisher's exact test).

Using logistic regression, the odds of a taxi driver wearing a helmet compared with a non-taxi driver was significantly increased 1.490 ($p<0.01$). The odds of helmet use on non-residential roads as compared with residential roads was also increased at 1.389 ($p<0.01$) (see table 2).

DISCUSSION

There is a large global gap in helmet use estimates making it challenging for countries to implement changes in policy and enforcement. Furthermore, data gathered using different methodologies have made it difficult to compare helmet usage rates over time as well as between regions and countries.[1] Current methods involving roadside observation or police and hospital record surveillance are costly and time-consuming and if these barriers were reduced, it is likely that more regions would be able to estimate helmet use.

Measurement of helmet use using location data can be particularly important to law enforcement who wish to target low-helmet use wearing areas. Vercino-Ortiz *et al* demonstrated that helmet use enforcement could potentially save 9882 lives annually across 84 countries affecting the poorest billion people.[28] Enforcement of motorcycle helmet laws has also been included in the recent SAVE Lives technical package as one of the proven interventions that could reduce road traffic collision mortality.[29] Enforcement can also be useful to increase police presence in general via helmet checkpoints. In a study of 2429 Thai motorcycle drivers and 1328 passengers, the prevalence of helmet use was higher among people who frequently observed police checkpoints, regardless of whether they were a driver or passenger.[2] In the largest Thai helmet use study to date, law enforcement activities were found to be significantly associated with helmet use.[7] As a country, however, the law enforcement rating for motorcycle helmet use in Thailand is only 6 out of a possible 10, where 8 is 'good'.[1] With limited enforcement resources, geographic helmet-use data could be useful for police to provide targeted enforcement. In addition to law enforcement, helmet estimates are useful to track helmet usage rates over time. With legislation, public service campaigns and new enforcement, obtaining low-cost, time-efficient helmet use data can more easily demonstrate the impact of such interventions.

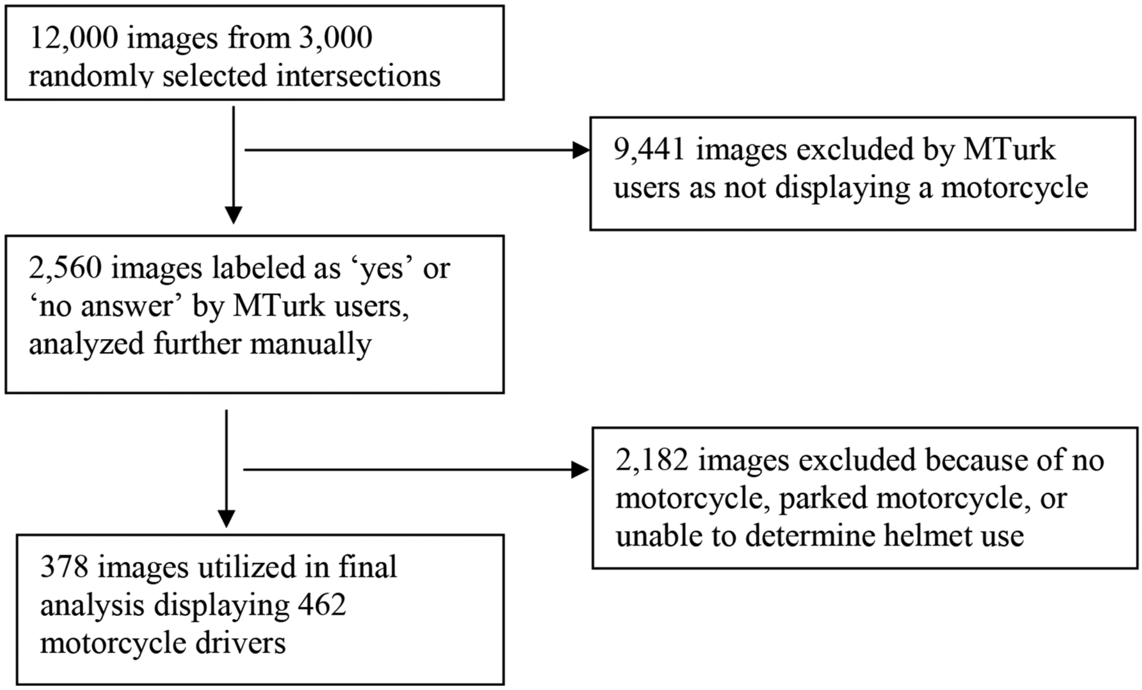

Figure 3 Flowchart of GSV image selection. GSV, Google Street View.

This study demonstrates that using images from GSV, combined with crowdsource analysis through MTurk, can provide helmet use estimates in Bangkok, Thailand. Our estimate of the overall motorcycle driver helmet use of 66.7% in Bangkok is similar to national studies demonstrating 55.8% helmet use using observational data,[8] and 60% helmet use in an interview-based study.[2] However, our estimate is lower than the single study that has previously been done using roadside observations and surveillance data examining Bangkok.[7] This study found the driver helmet use in Bangkok to be 93.2% (95% CI 92.8 to 93.5).[7] This could be due to a number of different factors. First, the data in that study are older, and there are likely changes in helmet use over time. Second, the authors of this study sampled 100 sites in Bangkok,[7] whereas our final database contained 378 sites. Having more geographical sites represented in the dataset is more likely to produce an accurate assessment. Finally, it is likely that given our study was able to examine more geographical sites, we likely had more residential areas represented in our study sample, lowering the overall helmet use rate. It is unlikely that the authors of the previous study did roadside observations on smaller residential roads, but this is not specifically commented on in the article.[7] Excluding residential areas in our study yielded a helmet wearing rate of 85.2% (95% CI 78.1% to 90.7%), which is closer to the previous studies' finding.[7] It should be noted also that the authors of the previous study found poor correlation and no agreement between roadside data and sentinel injury surveillance.[7] Our results demonstrating higher helmet use in taxi drivers compared with non-taxi drivers are consistent with a previous study from Guangdon, China using questionnaire data.[30] Results demonstrating higher helmet use rates on non-residential roads is also consistent with previous literature demonstrating increased helmet use on larger roads.[31 32]

Our study also demonstrates the time and cost efficiency of this novel method. Street imagery applications are especially useful because they allow for the potential of cost-savings versus on the ground, and in person, surveillance.[15 16] In one roadside vegetation assessment using GSV, Deus *et al* found that the assessment only required 9% of the funds as compared with an on the ground car survey.[16] Other advantages of using GSV include time savings and easily accessible data.[20] In this study, using GSV in combination with MTurk provided additional cost and time savings. The vast majority of our images were processed within MTurk in less than 90 minutes and at a cost of only US$360.00. In an assessment of 35 articles that used MTurk, the authors concluded that MTurk, compared with conventional data

Table 1 Descriptive statistics of motorcycle driver helmet use

Variable	Number of motorcycles	Helmet wearing rate	95% CI
All	462	66.7	62.2 to 71.0
Taxi			
Yes	69	88.4	78.4 to 94.9
No	393	62.8	57.9 to 67.6
Road type			
Residential	311	58.5	52.8 to 64.1
Non-residential	135	85.2	78.1 to 90.7
Other	16	68.8	41.3 to 89.0

Table 2 Logistic regression of driver helmet use

Variable	Driver helmet use
Taxi (Ref: non-taxi)	1.490* (0.397)
Road type (Ref: residential)	
Non-residential	1.389* (0.272)
Other	0.611 (0.553)
Constant	0.177 (0.122)
Observations	462

SEs in parentheses.
*p<0.01.

collection methods, was efficient, cost-effective and reliable in generating comparable results to conventional methods.[33]

There are several limitations to this study. In general, the quality of the images is one significant limitation in GSV. In a study by Clews *et al*, the authors found GSV images to be less sensitive than in person observation when examining visible drinkers.[34] In our study, it is unlikely that a helmet would have been completely missed, however, it is possible that certain types of hats may have been misclassified as helmets or vice versa. This is especially important in regions that allow the use of cap type helmets. Another imaging limitation of the study was that GSV, in order to protect a person's identity, will distort the facial features of identifiable persons. In doing so, it was sometimes the case that the top of the head and helmet area were also distorted and an assessment of helmet use was not able to be determined. GSV is also limited by how frequently areas are updated in the database. Our dataset contained a large range of data from 2011 to 2016 and therefore point prevalence was not able to be estimated. Another limitation of this study is that we were unable to assess the quality of the helmets being worn which is important as substandard helmets can limit their effectiveness.[1] The use of human workers with Mechanical Turk is also a limitation, demonstrated by the large number of false-positive images. This is potentially due to users not understanding the instructions properly as many of these images displayed bicycles. In future research, it would be helpful to do inter-rater reliability testing as well as an analysis of the false-negative results to see if any motorcycles were missed.

Future research in this field would benefit from methodologies to completely automate this process using a convolutional neural network. With this technology, images could be analysed automatically for helmet use, further reducing the time and cost for helmet estimates. This has been done by a research team using Microsoft's Common Objects in Common data and found to be 94.7% accurate when detecting helmet use,[35] although not attempted to date using GSV. A larger dataset generated from the methodology described in this paper could be used for subanalyses to examine helmet use by season, time of day and day of the week.

What is already known on the subject

- Half of the worlds' 1.2 million annual road traffic deaths are among vulnerable road users, including motorcyclists.
- Wearing a helmet can significantly reduce morbidity and mortality among motorcyclists and accurately measuring helmet use is important for law enforcement, and for governments to measure the effects of new legislation.
- Current methods for estimating helmet use involve roadside observation or surveillance of police and hospital records, both of which are time-consuming and costly.

What this study adds

- This study combines two powerful research tools, street imagery and crowdsourcing internet marketplaces, to estimate helmet use in Bangkok, Thailand.
- This novel method of helmet use estimation significantly reduces the time and cost of traditional estimation techniques.
- This methodology can be applied to any city or region in the world that has street imagery, potentially allowing a greater number of countries to be able to estimate helmet use.

CONCLUSION

This study presents a novel method of estimating motorcycle helmet use in Bangkok, Thailand. Using a combination of GSV and Amazon's Mechanical Turk, we were able to estimate motorcycle driver helmet use as well as obtain additional information on helmet use based on the type of road travelled on and whether the driver was a taxi driver. This method presents both a cost and time savings compared with traditional methods and could be applied to any region where street imagery is used. This is important considering the number of regions globally without helmet use data. Further research is needed to explore biases and accuracy of this method.

Funding Funding for this study was provided by the Alpha Chapter of the Delta Omega Public Health Honors Society at Johns Hopkins University.

Competing interests None declared.

Patient consent for publication Not required.

Provenance and peer review Not commissioned; externally peer reviewed.

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