# Investigation of the Vehicle Driving Trajectory During Turning at Intersectional Roads Using Deep Learning Model 

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#### Abstract

Two-thirds of vehicle accidents in Malaysia occurred at the straight type of roads, followed by intersection-type roads. Despite the deployment of traffic lights on the road, accidents still occur which are caused by illegal maneuvers, speeding or misjudgment of other's actions. Hence, motivated by the lack of previous research regarding causes of accidents on intersectional roads, this study aims to observe the pattern of the vehicles' speed and turning angle during the right turn after the traffic stop at the intersection road. To obtain these parameters, video samples of vehicles at two types of intersections were obtained and analyzed via YOLOV7 and DeepSORT. The two road intersections researched are four-legged intersection and three-legged intersection. 153 and 35 vehicle samples were collected from these types of road intersections, respectively. It was observed that 78 and 75 vehicles exit towards the nearest and furthest lanes at four-leg controlled crossings on divided roads. While, at a single-lane to a dual carriageway road intersection, 26 and 9 vehicles exit towards the nearest and furthest lanes, respectively. From the research, $16.52-17.53 \mathrm{~km} / \mathrm{h}$ and $67.57^{\circ}-73.33^{\circ}$ are the most optimal turning speeds and angles respectively for vehicles at four-leg controlled crossings. Whereas $14.48-15.51 \mathrm{~km} / \mathrm{h}$ and $144.77^{\circ}-154.403^{\circ}$ are the most optimal turning speeds and angles respectively for vehicles at a single-lane to a dual carriageway road intersection.


Keywords: Vehicle accidents; Intersection roads analysis; Turning behavior; Vehicle trajectory patterns; YOLOV7

## 1. Introduction

Road accidents are among the leading causes of fatalities globally [1]-[3]. Among ASEAN countries, Malaysia had approximately 7000 road users affected by road accidents every year [4]-[6]. According to the Transport Ministry, 915,874 road
accidents were recorded in a period from 20212022. From the number, there were 545,588 road accidents in 2022 with 6,080 deaths and 370,286 road accidents in 2021 with 4,539 deaths. With the constant increase of road traffic hazards yearly [4], the government of Malaysia has spent RM 9 billion annually to mitigate this problem [7].

According to [1], [8] this issue has been considered one of Malaysia's major and unaddressed issues despite the rise of traffic accidents.

Malaysia has five different types of roads: straight, curved, roundabout, interchanges, and intersections. The straight road is identified as the most typical form of road where crashes frequently happened in the earlier investigations. As shown in Figure 1, $67 \%$ of traffic accidents occurred on straight roads. Compared to other road kinds, it has the highest representation [1]. The second type of road where crashes frequently happen is the intersection, followed by roundabouts and bend roads, with $14 \%$ and $1 \%$, respectively. Although the percentage of road accidents in the intersection is not too large, it still cannot be disregarded. When compared to international data, the study from [9] and [10] shows that most of the accidents in the intersection roads are in urban areas.

The data from the CARE crash database (ETSC, 2001) for 2003 to 2013 shows the accidents involved in the European Union. The data analysis discovered that every third traffic collision happens at an intersection [11]. At 43.2 percent, four-legged intersections possess the highest rate of fatal and severe injuries. It should be noted, though, that such percentages additionally rely on how exposed various junction types are. Four-legged intersections are typically riskier than three-legged intersections because of the more significant number of conflict spots [11]. Few crashes per million conflicts occur at multi-lane crossings (unsignalized) than at signalized crossroads. Rear-end and head-on crashes are the most common crash types at
signalized crossings, according to research [12]. However, research by [13] shows that this also relies on the number of lanes and traffic volume. Furthermore, angle collisions account for most accidents at unsignalized intersections [11], [14].

Traffic signals were deployed to decrease traffic accidents and enhance traffic safety at urban intersections [15][16]. However, severe traffic collisions continue at the urban signalized crossroads [12]. As a result, the urban signalized intersection was identified as the most hazardous area in the road network [1], [17]. The author of this paper [18] asserts that the human, vehicle, weather, and roadway elements were the four main components that contributed to the occurrence of traffic accidents.

There are several strategies to observe the vehicles' behavior, such as using traffic camera footage. Several researchers proposed MultiObject Tracking (MOT) to classify multiple vehicles throughout the video [19]. In MOT, there are three approaches, which are joint detection and tracking [19], attention mechanism [20] and tracking by detection [21]. The latter was deployed as it was the best approach to detect multiple vehicles per frame. First, it identifies the targets in each video frame. Then the targets were cropped in the frame according to the bounding box anchors set for each class. Despite the possible target correlation between the frames due to the ever-changing positions of the vehicles per frame, the Intersection over Union (IoU), appearance feature, Hungarian and greedy algorithms generate a similarity matrix to help to mitigate the issue. Hence, this method is popular since it's the most efficient way to detect and classify vehicles simultaneously [22].


Figure 1. Road traffic crashes according to the different road types in Malaysia [1]

Regarding detection, the YOLO framework is the most popular detection network as it can produce the bounding box and detection results immediately from a single frame in the video [23]. As of the time of writing, YOLOV8 was already released. For tracking algorithms related to the MOT field, SORT and DeepSORT were widely used. The former utilizes the Kalman filter and Hungarian matching to track the object. However, DeepSORT [24] improves detection by adding cascade matching, which maintains vehicle detection. This approach is widely used in various studies on vehicle detection in camera footage. For instance, [25] used YOLOV7 for vehicle multi-tracking on multiple parts of the city. Also, this method of utilizing YOLOV7 and DeepSORT was used by [26] for vehicle detection. Rodriguez et al. utilized YOLOv3 and Kalman Filter for vehicle detection and tracking [27]. The detected vehicles from a video would then be collected into a dataset which would then be separated by lane for speed estimation. Using five different statistical methods and three different machine learning methods, the speeds of the vehicles were estimated in real time. A similar approach was conducted by Sangsuwan et al. to obtain both vehicle speed and moving pattern but with DeepSORT in place of Kalman Filter [28].

This paper sets out to investigate the factors affecting the behavior of right-turning vehicles and to evaluate their contributions to the safety of signalized intersections in the context of the
vehicle's speed and turning angle. Lack of adequate past knowledge on the effect of vehicle dynamics behavior is the major approach to the safety of signalized intersections during right turning, which motivated this study. Several key contributions of this paper include:
a. The analysis of the vehicle's trajectory during turning at four-legged junctions and threelegged junctions from the traffic stop to the lanes.
b. The evaluation of the vehicle's speed and heading angle during turning at two types of intersections.
c. Observation on the relationship between the vehicle's heading angle and the turning direction of the vehicle during turning.
d. Evaluation of the vehicle's steering during turning at two types of intersection.

## 2. Method

### 2.1. Experiment Set-Up

The experiment was conducted at two places, namely Cyberjaya District and Pekan District. The Cyberjaya District, which lies in the southwest region of Selangor, Malaysia, served as the test location for vehicles' behavior on a four-legged junction, as shown in Figure 2. The areas selected for data collection were all four-leg controlled crossings on divided roads. The road included a divisional island in the middle to segregate the traffic moving in the opposite direction. The


Figure 2. Video inference set-up for Cyberjaya
chosen study site had consistent traffic control, allowing vehicles to turn left and right. Each site was selected to simulate a typical signalized intersection in Malaysia, with auxiliary lanes or channelizing and divisional islands to guide or impede the movement of turning vehicles, respectively. A diverse percentage of motorcycles and other vehicles were in the traffic mix. Figure 2 shows the research sites marked with lane identifications for video inference.

The second location, Taman Mentiga, a locality in Pekan's suburb of Pahang, Malaysia, was selected as the study location for a three-legged junction. The junction consists of a single lane that leads to a two-legged road, as shown in Figure 4. Also, the location had constant traffic control, which allowed us to observe the behavior of the vehicles during the exit. This site was chosen because it can simulate a regular signalized intersection and has a short waiting time of 15-20 seconds between traffic light changes.

### 2.2. Hardware Setup

The video footage at Cyberjaya is taken from roadside CCTV at Persiaran APEC, while for Taman Mentiga, the footage is taken from the drone. Both data were collected in the afternoon, during peak hours. For this research, the videos were recorded at 25 fps and were processed on a Legion Y545 laptop with an NVIDIA GeForce RTX 2060 as its GPU. Python 3.7 was utilized alongside the OpenCV2 library, Tensorflow, and DeepSORT.

### 2.3. Architecture of the Vehicle Detection Algorithm

The algorithm's architecture is illustrated in a block diagram shown in Figure 4 which is subdivided into three modules. First, the algorithm receives input from the video footage of the traffic intersection which would be directed to the Vehicle Detection Module. Then in that module, each vehicle identified by YOLOV7 will be bounded by a box via OpenCV in the video and then given classification according to the identified vehicle type (Car, Motorcycle and Truck) also via YOLOV7. The identified vehicles will then be tracked via the Vehicle Tracking module using DeepSORT, which tracks the vehicle's entry into the intersection and exit. The vehicle's entry into the intersection was visualized using OpenCV by drawing a golden line to represent the vehicle's entry into the intersection alongside a red and green markings corresponding to the nearest and furthest lane when the vehicle exits the intersection. An additional white line was then added to detect any vehicles that changed their initial lane. They are positioned based on observed trajectories of the vehicles. In most cases the vehicles will change their lane from the furthest to the nearest lane. To keep track of the number of detected vehicles, a vehicle counter was added to the top left of the screen. Also, to detect the vehicle's trajectory, the centroid of the bounding box will be used to visualize the vehicle's trajectory and assist in registering the vehicle's count when it


Figure 3. Video inference set-up for Taman Mentiga, Pekan, Pahang


Figure 4. Block diagram of the algorithm
enters and exits the intersection. Finally, the Vehicle Heading Angle and Speed Calculation Module will extract the respective vehicle's heading angle and speed upon exiting the intersection. The detailed flowcharts of each module are shown below at Figure 5 respective to the module.

### 2.4. Parameters for Data Collection and Data Analysis

### 2.4.1. Parameters for Data Collection and Data Analysis

To calculate the distance travelled by the vehicles to reach their respective lanes after the intersection, Eq. (1) to Eq. (3) were utilized. An average road width in Malaysia is 3.25 meters long at an intersection. Hence, to calculate the trajectory values at longitudinal, $x$ and lateral, $y$ for trajectory distance, the number of lanes was counted from the bottom-left corner of the intersection. As the vehicle's centroid represents the vehicle's trajectory, the lane's midpoint was
accounted for in the calculation instead. The disparity between the camera's perspective and the hypotenuse was used to represent the road distance. By applying Eq. (1) to Eq. (3), hypotenuses to represent the vehicles' trajectory to the left and right lanes are obtained in which N represents the number of lanes.

$$
\begin{equation*}
\text { Trajectory Distance }=\sqrt{x^{2}+y^{2}} \tag{1}
\end{equation*}
$$

$$
\begin{gather*}
x=3.25 \mathrm{~N}  \tag{2}\\
y=3.25 \mathrm{~N} \tag{3}
\end{gather*}
$$

### 2.4.2. Vehicle Heading Angle and Speed Calculation

The heading angle of the vehicles is calculated by obtaining the tangent between the car's previous position and its current position per frame using Eq. (4) to Eq. (6). The vehicle's heading angle was written into a .csv file via the algorithm.


Figure 5. Flowchart of the algorithm split into flowcharts for vehicle detection module, vehicle tracking module and vehicle heading angle and speed calculation module

$$
\begin{gather*}
x=x_{b}-x_{a}  \tag{4}\\
y=y_{b}-y_{a}  \tag{5}\\
\tan \alpha=\frac{y}{x} \tag{6}
\end{gather*}
$$

As shown in Eq. (4) to Eq. (6), the coordinates $\left(x_{b}, y_{b}\right)$ and the coordinates $\left(x_{a}, y_{a}\right)$ represents the coordinates at the exit of the intersection and the entrance of the intersection respectively. From there, the heading angle is calculated by obtaining the tangent between the coordinates mentioned.

The steps to obtain vehicle speed were shown in Eq. (7) to Eq. (9). The values of frame end and frameentrance corresponds to the frame number when the vehicle exits and enters the intersection. From there, the difference between frame end and frame entrance is represented as framer. Framer represents the distance of the vehicle in the video as there's no method to directly obtain the distance from the video itself. From there, the predicted duration of the vehicle turn was calculated by obtaining the dividing the framer value against the fps value. The value of fps is set to 25 as it is the total frames per second of the video.

The vehicle's velocity was obtained by dividing the trajectory distance with the duration before multiplying the product by 3.6 to convert it from metres per second to kilometres per hour as shown in Eq. (9). The vehicle velocity was then rounded up to three decimal points.

$$
\begin{gather*}
\text { framer }^{=} \text {framer }_{\text {end }}-\text { framer }_{\text {entrance }}  \tag{7}\\
\text { duration }=\frac{\text { framer }}{\text { fps }}  \tag{8}\\
\text { velocity }=\frac{\text { trajectory distance }}{\text { distance }} \times 3.6 \tag{9}
\end{gather*}
$$

### 2.4.3. Vehicle Steering Evaluation Method

Then to determine the vehicle's tendency to understeer or oversteer while exiting the lanes, the detected vehicle's entry and exit coordinates are first plotted on a graph. Then, the corresponding midpoints of the entry and exit coordinates would serve as the reference curve.

The criteria of the vehicle to oversteer or understeer depends on the reference curve. If the vehicle exits under the reference line, then it's
classified as oversteer while if the vehicle exits above the reference line, then it's classified as understeer. The distance between the midpoint and the exit coordinates of the respective lanes will determine the values of understeer and oversteer. Distance between coordinates will be calculated using Eq. (10).

## 3. Result and Discussion

### 3.1. Average Vehicle Heading Angle and Speed

Based on the video analysis conducted for both locations, 153 vehicles and 35 vehicles were identified in the videos for Cyberjaya and Taman Mentiga, respectively. The number of vehicles at Taman Mentiga is lower than that of Cyberjaya because a drone was used to record the video footage. Due to the drone's battery capacity, it can fly for only 15 minutes, and the captured footage is just 6 minutes. However, this data is valuable because the location is strategic as it is the busy area, which is a residential area to the main road.

Table 1 below shows the length of the roads for the value of vehicle trajectory, which fulfills Equation 9. Based on this table, the number of lanes and distances for vertical and horizontal lanes at Cyberjaya and Taman Mentiga are the same. This information is important to ensure the road follows the standard. In addition, the number of lanes and distance can affect the driver's behavior while exiting the junction.

The heading angles and vehicle speed results for Cyberjaya are plotted in a bar graph in Figure 6 and Figure 7. At Cyberjaya, there are two lanes at the exit junction and two lanes at the entry junction. The possibility of the vehicle changing lanes while exiting the intersection is almost impossible, especially with heavy traffic. From the results, vehicles heading towards the left lane have an average heading angle of 73.33 degrees, while vehicles heading towards the right lane have an average heading angle of 67.57 degrees. Their average vehicle speeds towards the left lane are $16.52 \mathrm{~km} / \mathrm{h}$, and towards the right lane are $17.53 \mathrm{~km} / \mathrm{h}$.

Taman Mentiga has only one lane at the entry junction and two lanes at the exit junction. In this road condition, the driver will have two options either to exit to the left or right lanes. Figure 8 and Figure 9 show the results for Taman Mentiga.

$$
\begin{equation*}
\text { Distance }=\sqrt{\left(x_{\text {exit coordinates }}-x_{\text {midpoints }}\right)^{2}+\left(y_{\text {exit coordinates }}-y_{\text {midpoints }}\right)^{2}} \tag{10}
\end{equation*}
$$

Table 1. Length of the roads for trajectory calculation

|  |  | Cyberjaya |  | Taman mentiga |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Direction | Destination | Number <br> of lanes | Distance <br> $(\mathbf{m})$ | Number <br> of lanes | Distance <br> $(\mathbf{m})$ |
|  | Vertical distance from <br> entrance to exit (y) | 3.5 | 11.375 | 3.5 | 11.375 |
| Furthest | 2.5 | 8.125 | 2.5 | 8.125 |  |
|  | Horizontal distance from <br> entrance to exit (x) <br> Vertical distance from <br> entrance to exit (y) | 4.5 | 14.625 | 4.5 | 14.625 |
|  | Horizontal distance from <br> entrance to exit $(\mathrm{x})$ | 3.5 | 11.375 | 2.5 | 8.125 |

Graph of Vehicle Speed and Heading Angle of each vehicle entering the left lane


Figure 6. Bar graph of vehicle speed and vehicle heading angle for each vehicle on the left lane for Cyberjaya Graph of Vehicle Speed and Heading Angle of each vehicle entering the right lane


Figure 7. Bar graph of vehicle speed and vehicle heading angle for each vehicle on the right lane for Cyberjaya

Graph of Vehicle Speed and Heading Angle of each vehicle entering the left lane


Figure 8. Bar graph of vehicle speed and vehicle heading angle for each vehicle on the left lane for Taman Mentiga

Graph of Vehicle Speed and Heading Angle of each vehicle entering the Right Lane


Figure 9. Bar graph of vehicle speed and vehicle heading angle for each vehicle on the right lane for Taman Mentiga

The results at Taman Mentiga show that the vehicles heading towards the left lane have an average heading angle of 154.403 degrees, while the vehicles heading towards the right lane have an average heading angle of 144.77 degrees. The heading angles of both lanes at Taman Mentiga are greater than those of Cyberjaya because the trajectory from the single lane to the two lanes is more significant than from the two lanes to the two lanes. The number of entry and exiting lanes also affects the vehicle's speed. At Taman Mentiga, the average vehicle speeds are 15.51 $\mathrm{km} / \mathrm{h}$ for the left lane and 14.48 km for the right
lane, slightly slower than those at Cyberjaya due to the smaller intersection size.

It was also observed that throughout all footage, no vehicles diverted their initial course at Cyberjaya due to the number of lanes being the same at the exit and entry the junction. However, in Taman Mentiga, 26 out of 35 vehicles drive to the left, which is the slow lane, while 9 vehicles drive to the right, the fast lane. The reason for that could be due to the destination of each vehicle. One of the reasons the vehicle takes a slow lane is that the exit from the junction leads to the main road heading into the residential area. Figure

10 shows the map of the location at the junction at Taman Mentiga, where it can be seen that there is a junction to exit the main road to the residential area. In contrast, for the fast lane, the driver wants to stay on the main road and has no intention of exiting the main road in a short time.

### 3.2. Evaluation of the Vehicle's Steering Behaviour

Upon analysis of the vehicle's trajectory from the entry to the intersection exit, the average
midpoints of the vehicle's initial entry and exit were tabulated in Table 2 below and drawn in Figure 11 and Figure 12 below. The reference trajectory, which is the center line from the entry to exit the lane, was drawn in a black curve, as shown in Figure 11 and Figure 12. Cyberjaya's reference line is drawn based on each lane because the entry and exit intersection has two lanes. However, Taman Mentiga's center line is drawn from the same entry lane to the two exit lanes, either to the fast or slow lanes.


Figure 10. Intersection at Taman Mentiga


Figure 11. Vehicles' reference curve visualized in black for Cyberjaya


Figure 12. Vehicles' reference curve visualized in black for Taman Mentiga, Pekan, Pahang
Table 2. Average coordinates of vehicles trajectory at entry and exit for both study sites

|  | Cyberjaya |  | Taman Mentiga |  |
| :---: | :---: | :---: | :---: | :---: |
| Direction | Entrance | Exit | Entrance | Exit |
| Left | $(650,401)$ | $(739,700)$ | $(983,262)$ | $(653,420)$ |
| Right | $(745,358)$ | $(909,738)$ | $(1028,259)$ | $(685,502)$ |

From the reference line, the vehicle steer characteristic can be determined as understeer or oversteer. The vehicle is classified as understeer if the trajectory is above the reference line and oversteer if the trajectory is below the reference line. Table 3 shows the results of vehicle steer characteristics. From this result, it can be seen that at Cyberjaya, the number of vehicles that oversteer is higher than understeer for both left and right lanes. This steer characteristic is safe when driving at the junction because the driver will keep the vehicle in the same lane, and the possibility of the vehicle entering the other lane is low. For Taman Mentiga, the left lane shows the same value for understeer and oversteer. The left lane, which is the slow lane, is different from the fast lane (right lane) because some of the drivers will exit the main road after the junction. Figure 13 shows the example of the vehicle immediately changing from the right to the left lane after leaving the intersection. As a result, the value of the understeer in the left lane is high, and if there is a motorcycle in the left lane, the possibility of a collision to occur is high. However, for the right or fast lane, the oversteer characteristics are higher than the understeer,
which is a safe characteristic for maintaining the vehicle in the same lane.

Further analysis at Taman Mentiga has been done because only Taman Mentiga vehicles have changed lanes from fast to slow. The midpoint coordinates are defined by the average coordinates of the vehicles at entry and exit lanes. Then, the entry and exit junction distance is measured based on equation (10). In the analysis, if the distance from the lane's midpoint is more than 25 , then the vehicle's trajectory changes, while for the right lane, if the vehicle's distance from the lane's midpoint is more than 40 , the vehicle's trajectory changes too. The plotted graph of the vehicle's trajectories at Taman Mentiga is shown in Figure 14 and Figure 15 for the right or fast lane and left or slow lanes, respectively. From the samples obtained, three vehicles diverted from the right lane to the other lane, while two vehicles diverted from the left lane to the right lane. The driver changes from the fast to the slow lane and vice versa because of the destination; either the driver wants to exit the main road or continue at the main road and increase the speed.

Table 3. Quantity of vehicles that oversteer and understeer for both study sites

|  |  | Cyberjaya |  | Taman Mentiga |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Direction | Understeer | Oversteer | Understeer | Oversteer |  |
| Left | $28(18.3 \%)$ | $50(32.7 \%)$ | $13(37.1 \%)$ | $13(37.1 \%)$ |  |
| Right | $27(17.6 \%)$ | $48(31.4 \%)$ | $3(8.6 \%)$ | $6(17.2 \%)$ |  |



Figure 13. Example of vehicle understeering from its course
Graph of Vehicle Entry and Exit for Vehicles Heading to the Furthest Lanes (Right) for Taman Mentiga


Figure 14. Graph of vehicle entry and exit for vehicles heading to the nearest lanes (left) for Taman Mentiga

Graph of Vehicle Entry and Exit for Vehicles Heading to the Nearest Lanes (Left) for Taman Mentiga


Figure 15. Graph of vehicle entry and exit for vehicles heading to the furthest lanes (right) for Taman Mentiga

## 4. Conclusion

In this study, an algorithm was developed for vehicle's classification and trajectory tracking. From the algorithm, the classified vehicle's velocity and heading behaviour can be analysed while making a right turn at the intersection. YOLOV7 is proven to be a reliable object detection model for video inference whereas DeepSort is reliable in classifying and sorting the classified vehicles in the video. Also, the vehicles' trajectory was successfully visualized via OpenCV library. Based on results obtained from the research, for a four-legged intersection the optimal vehicle speed from the intersection entrance are $16.52 \mathrm{~km} / \mathrm{h}$ and 17.53 $\mathrm{km} / \mathrm{h}$ for the nearest lane and furthest lane of the intersection respectively. Whereas the optimal heading angles for the vehicles heading out of the intersection entrance are 73.33 degrees and 67.57 degrees respectively measured from the exit. Meanwhile for three- legged intersection type of road, the optimal vehicle speed from the intersection entrance are $15.51 \mathrm{~km} / \mathrm{h}$ and 14.48 $\mathrm{km} / \mathrm{h}$ for the nearest lane and furthest lane of the intersection respectively. Whereas the optimal heading angles for the vehicles heading out of the intersection entrance 154.403 degrees and 144.77 degrees respectively measured from the exit. It is observed that drivers in Cyberjaya follow the
dedicated lane because the entry and exit lanes are the same. However, in Taman Mentiga, drivers can choose to exit into either the fast or slow lane since there is a single entry lane but two exit lanes at the intersection. This study also found that drivers choose their lane based on their destination. Those exiting the main road after the junction take the slow lane, while those continuing on the main road take the fast lane and increase their speed after exiting the junction.

For future study, the 3D machine learning algorithm can be used to enhance the accuracy of the result and potentially to visualise the 3D vehicle dynamics data. Also, the yaw, roll and pitch angles of each vehicle can be derived to obtain better results accuracy.

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## Author's Declaration

## Authors' contributions and responsibilities

The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation and discussion of results. The authors read and approved the final manuscript.

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## Availability of data and materials

All data are available from the authors.

## Competing interests

The authorsdeclare no competing interest.

## Additional information

No additional information from the authors.

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