Indonesian Journal of Global Health Research
Volume 4 Number 4, November 2022
e-ISSN 2715-1972; p-ISSN 2714-9749
http://jurnal.globalhealthsciencegroup.com/index.php/IJGHR

DO YOU FEEL RUSHING IN THE MORNING TRAVEL? THE EVIDENCE OF DAILY TRAVEL PATTERN ACTIVITY DURING IRREGULAR TRAFFIC CONDITIONS IN POST COVID-19, CASE STUDY SOUTH BALI INDONESIA

I Made Sukmayasa[1]*, Efendhi Prih Raharjo[1], Octaviani Ariyanti[2], Aris Budi Sulityo[3], Putu Diva Ariesthana Sadri[4]
[1]Road Transport Management, Politeknik Transportasi Darat Bali, Jl. Cemp. Putih, Samsam, Tabanan, Bali 82111, Indonesia
[2]Road Transport Authorithy Bali and NTB, Jl. Raya, Mengwitani, Mengwi, Badung, Bali 80351, Indonesia
[3]Automotive Technology, Politeknik Transportasi Darat Bali, Jl. Cemp. Putih, Samsam, Tabanan, Bali 82111, Indonesia
[4]Logistic Management, Politeknik Transportasi Darat Bali, Jl. Cemp. Putih, Samsam, Tabanan, Bali 82111, Indonesia
*sukmayasa@poltradabali.ac.id

ABSTRACT
Congestion during rush hours has always been a significant problem for the government, impacting travel time, vehicle operations and air pollution, and health problems. The government has proposed some policies through traffic engineering management and other management applications with the latest technology to overcome such issues. Research related to travel patterns during peak hours is beneficial, which will impact road users' decision-making, particularly during these days when everyone's activities are starting again after COVID-19 restrictions. In this paper, data processing (from Google Maps Distance Matrix API, Typical Google Maps, and Community Mobility Reports) was carried out for almost one month to obtain data on speed and travel time. These data are gathered from four pairs of locations with specific origin/destination of travel patterns in the southern Bali region. The community's travel pattern can be explained based on the one-way ANOVA with Bonferroni and the Kruskal Wallis Test. This paper found that people are in a hurried movement in the morning compared to other busy times, marked by the differences in speed and travel time in the morning commute to afternoon and evening commute during rush hours. This condition illustrates the irregular traffic flow after the Covid-19 restriction rules; thus, drivers can still choose the desired speed to travel. The irregular traffic flow can be seen on community mobility data and typical green traffic during peak hours. This result is significant because of the importance of traffic management during peak hours to optimize the level of road service.

Keywords: google api distance matrix api; tranvel pattern; velocity

First Received	Revised	Accepted
02 August 2022	08 August 2022	15 September 2022

Final Proof Received	Published
28 October 2022	28 November 2022

How to cite (in APA style)
Sukmayasa, I. M., Raharjo, E., Ariyanti, O., Sulistyo, A., & Sadri, P. (2022). Do You Feel Rushing in the Morning Travel? The Evidence of Daily Travel Pattern Activity During Irregular Traffic Conditions in Post Covid-19, Case Study South Bali Indonesia. *Indonesian Journal of Global Health Research, 4*(4), 883-894. https://doi.org/10.37287/ijghr.v4i4.1279.

INTRODUCTION

Many studies have observed related to travel behavior related to mode choice (Ding, Ling; Zhang, Ning (2016) by considering various causative determinants such as age and gender (Valentina et al., 2016), environment, route choices (Peng et al., 2018), land use and housing type (Schwanen et al., 2005). Furthermore, how travel behavior is directed to find out users' activity patterns, such as the purpose of the trip, time, duration, location, participants, expenditure, and structure of the trip (Axhausen, 2007). Understanding travel behavior measurement uses statistical and econometric methods based on Vehicle mile traveled (VMT), Person Mile Traveller (PMT), Mode Share, Telecommuting, Trip Purpose, Demographic, Attitudes, and Vehicle Occupancy. Yet, not many measures of travel behavior are based on traffic performance, such as speed, travel time, and travel distance.

It is common to see that travel patterns and post-demic traffic conditions still vary, and we can see this based on the COVID-19 community mobility report data. Community mobility is still not expected from the baseline data. Although many factors can cause it, it can indicate that people's mobility conditions have not been able to return to normal. Some observers in the economic sector consider that the economic impact post-demic will take time to become normal. The recovery of the economic sector may be related to transportation, where economic movements will affect people's mobility (Bonaccorsi et al., 2020). Congestion during rush hours has always been a significant problem for the government. The impact of this problem is not only travel time and vehicle operations but also air pollution and health problems (Seedam et al., 2017). Many policies have been implemented to reduce congestion during rush hours, including traffic engineering management and management application with the latest technology (Yan et al., 2017). Knowledge related to vehicle movement patterns during rush hours is beneficial for road users (Wemegah et al., 2018). Research related to travel patterns during peak hours will impact decision-making since people are just starting their activities again from the restrictions due to COVID-19.

Measurement of traffic performance in road service analysis is very commonly used in a study. The volume, speed, and travel time in traffic are calculated to determine road conditions, such as variations in rush hour and total volume, and the ratio of capacity volumes for road planning and evaluation. Data collection methods also vary significantly from manual collection to the latest technology (Zheng & McDonad, 2012). Generally, the relationship of volume-velocity-density can describe the existing traffic conditions, yet, cannot describe people's travel behavior. This study wanted to find out how the duration of activity patterns on community mobility seen from variations in speed and travel time with a fixed travel distance every hour can provide an overview of people's daily mobility behavior. Does the community in carrying out mobility have a particular travel pattern? This hypothesis was formulated to determine whether there are differences in road users' behavior activity patterns that have specific characteristics at different peak hours every day.

LITERATURE REVIEW

Traffic flow consists of the interaction between the transportation system in which the movement of vehicles, drivers interact with each other, and the road infrastructure. Since each driver behaves differently, it is impossible to describe the traffic flow singly. Nevertheless, we still need quantitative techniques to assess operational measures. Speed, flow, and density are all related to each other. The relationship between velocity and density is not difficult to observe in the actual condition, while the effects of velocity and density on flow are not as apparent. Under uninterrupted flow conditions, velocity, density, and flow are all related. Flow, velocity, and density are the main macroscopic traffic flow characteristics. *Flow rate* is a variable that quantifies demand. This is the number of vehicles that want to use a particular facility during a specific time. Speed is an essential measure of effectiveness that determines service levels for many facilities. TRB, Highway Capacity Manual 2000]. Density is a critical parameter for uninterrupted flow facilities because it characterizes the quality of traffic operations (TRB, Highway Capacity Manual 2000). The relationship between these three variables is called the traffic flow model. The traffic flow model provides a fundamental relationship of the main macroscopic traffic flow characteristics for uninterrupted flow. Since the flow is the product of velocity and density, flow is equal to zero when one or both of these terms are zero. It is also possible to conclude that the flow is maximized at some critical combination of velocity and density. Two common traffic conditions describe these points. The first is modern traffic jams, where traffic density is high, and speeds are very low. This combination results in a very low flow. The second condition occurs when the traffic density is very low, and the driver can obtain free-flow speed without undue stress caused by other vehicles on the highway. The low density compensates for the high speed, and the resulting flow is deficient.

The Google Maps API is a set of programming tools that allow programs to communicate with other programs or operating systems and help software developers create their applications (i.e., pieces of software) (Oxford University Press, n.d.). "Web API" means an API for a web server or web browser. With web APIs, users can use various web services from web browsers, software, or other HTTP clients. Google currently offers various web API services for maps, places, and routes within the Google Maps Platform framework. Distance Matrix API is a service that provides distance and travel time for the origin and destination matrices. As Calculated By The Google Maps API, the API returns information based on the recommended route between the start and endpoints and consists of rows containing each pair's duration and distance values . Required parameters, destination, One or more locations to use as endpoints to calculate travel distance and time. The options for the destination parameter are the same as for the origin parameter. Origins, The starting point for calculating travel distances and times. It can provide one or more locations separated by characters in the form of a place ID, address, or latitude/longitude coordinates. Google Maps Platform (2020a) explains that the service calculates the most efficient route taking travel time and other factors. The number of destinations and origins can be one or more. Theoretically, a maximum of 40,000 requests are available for free each month (Google Maps Platform, 2020c). The QPS limit is 1,000 (Google Maps Platform, 2019). The API has some limitations. As per our investigation, the details of the calculation algorithm are not published. In addition, traffic information is not available without meeting the specified requirements (Google Maps Platform, 2020b).

Some researchers used this method. Fahui Wang & Yanqing Xu (2011) Estimating O–D travel time matrix by Google Maps API found that Dynamically updated transportation network data and the routing rules maintained by Google and obtain a reliable estimate of O–D travel time matrix. The results are compared with those computed by the ArcGIS Network Analyst module to demonstrate its advantages. Haitao J et al., (2019). Open cloud services such as Google Direction API may serve as alternative public transit accessibility measurement solutions. Transit researchers and agencies may take advantage of such open API services to avoid the tediousness of collecting and processing geographic data sets on transit facilities. Mohan et al. (2017). Observational surveys were carried out at four locations in Delhi to observe traffic flow and vehicle occupancy data. Speed data were extracted for 38 origin-destination pairs during the January phase and 66 pairs using the April phase using a sample of roads from all over Delhi using Google Map API (Application Programming Interface). During the experimental period, car flow rates on roads were reduced by less than 20%, but motorized two-wheeler, bus, and auto ricksha rates increased. There was an insignificant rise in car occupant rates showing that most car owners did not opt for car sharing.
The Community Mobility Report shows movement trends by region across different categories. (Community Mobility Reports, 2022a). For each category in a region, the report

shows changes in 2 different ways by Comparing the mobility between the report date and the base day of measurement, calculating for the report date (unless there are gaps), and reporting as a positive or negative percentage. Furthermore, the percentage changed six weeks prior to the date of the report. Personally identifiable information such as an individual's location, contact, or movement will not be made available. This report is generated with an aggregated and anonymized data set from users who have the Location History setting turned on (Community Mobility Reports, 2022b), which is disabled by default. The measurement basis of this data represents the change in the number of visitors (or duration of time spent in) different categories of places compared to the measurement base day. The base day of the measurement represents the expected value for that day, where the measurement is the median value taken over five weeks between January 3 and February 6, 2020. The measurement base is not a single value for each regional category but seven individual values. (Community Mobility Reports, 2022c).

METHOD

The objective of this part was to explain the data collection procedure and preparation of the data for analysis. Data were collected by using Google Maps distance matrix API, Typical traffic google Maps, and mobility report index. During this stage, data is collected in normal conditions. The collected data were arranged and processed in a suitable form to be statistically analysed.

Determination of study sections

The first stage is to determine the pair of origin and destination coordinates in collecting data at the study location. The study location points are in the southern Bali region, divided into several centroids, including Pesanggaran, Kuta, Airport, and Nusa Dua (Tabel 1). The distance between centroids varies. The shortest distance is from Airport to Kuta at 3,412 meters, and the highest distance traveled is 12,534 meters from Kuta to Nusa Dua. Based on the distance traveled between zone, it portrays the route choice from origin and destination is mostly difference. The exact distance just from Pesanggaran to Nusa Dua and from Nusa Dua to Pesanggaran, which can explain the route choice for these trips is only once. Then, data collection is carried out with the help of the Google Maps distance matrix API, which is carried out every 24 hours on weekdays and holidays from March 21 to April 10, 2022. The data collected is the average speed, distance, and travel time to four origin-destination pairs compared with typical traffic volume data from Google Maps. Furthermore, the data is entered into Python, which automates the following process. Travel time is estimated between one origin and one destination in each round by calling the Google Direction Distance Matrix API. Each request is sent by a script, which builds a Uniform Resource Locator (URL) using the following parameters (Hananto,2020): Origin longitude (required), Origin latitude (required), Destination longitude (required), Destination latitude (required), Travel mode (optional), Departure date and time (optional).

Tabel 1.
Coordinat location and distance travelled in meter between origin and destination

Zone	Name	Xcoord	Ycoord
1	Nusa Dua	-8.798391	115.222982
2	Airport	-8.744668	115.179079
3	Kuta	-8.719439	115.183796
4	Pesanggaran	-8.716454	115.215218

O/D	1	2	3	4
1	-	9,187	11,930	11,644
2	9,790	-	3,412	6,199
3	12,534	3,966	-	4,212
4	11,664	6,525	4,881	-

The subsequent stage is to collect data from the Covid Mobility Index data based on reports from people in the Bali area in general to get data on community mobility in the Bali area, where there are several characteristics, including mobility at retail & recreational locations, pharmacies, parks, public transportation, workplaces, and settlements. Compared to the baseline data. The basic data was obtained from the initial measurement before the covid, January,3 – 6 February 6 2020. This data is used to determine how the community travels to represent the study location—observation period. Testing of the data results is carried out by presenting descriptive data through the speed and travel time average and standard deviation of the rush hour travel pattern compared to the travel pattern in 24 hours. An analysis is carried out with a combination of parametric and non-parametric tests. Due to the results of data extraction from google maps distance matrix API is not normally distributed, one-way ANOVA test by Bonferroni test and Kruskal Wallis test is used to determine whether there is a difference between the characteristics of the morning (06.00-09.00), afternoon (12.00-15.00) and afternoon (17.00-1900) trips.

RESULTS

The highest average travel speed for 24 hour data comes from zones 2 to 1 (Airport-Nusa Dua), reaching 51.5 km/hr (N=254, SD= 1.8 km/hr), and the lowest is from zones 4 – 3 (Pesanggaran-Kuta) at 39.8 km/hr (N=254, SD= 2.5km/hr). the comparison of average speed between overall, morning, noon, and afternoon show clearly that the velocity of the morning travel is higher than any other group for all origin and destination. The highest velocity of morning travel is from zone 2 (Airport) to zone 1 (Nusa Dua) (M=52,6, SD=1,2) and the lowest average speed is from zone 3 (Kuta)to zone 2 (Airport) (M=38,2, SD=0,7). In some cases, the velocity in noon travel is higher than in afternoon travel but less than morning and overall velocity. The average travel time in table 2 saw a similar pattern, where the morning commute is faster than other groups. Furthermore, the statistical test uses to understand the difference between the group.

This study uses a parametic test (one-way ANOVA) and non parametric test (Kruskal Wallis Test). Mix analysis combined with typical traffic data and the covid mobility index. The combination of these methods is used to describe the conditions in the study area. Therefore, the average speed and travel time data can be calibrated with the conditions in the field obtained from typical traffic data that describes the traffic conditions during the morning, afternoon, and evening trips. Furthermore, the covid mobility index data is used to describe the general mobility condition of the community at the study location. Although the picture of the mobility data results shows Bali island's condition, it can still represent the study area because the southern Bali region is an area with high mobility. Based on the results of data analysis using the Google map distance matrix API, a graph of the speed and travel time of each day of the origin and destination pairs in the study period can be generated. For example, in figure 1, from the travel time graph from Nusa Dua to the airport every hour for 24 hours. There are variations in travel time (seconds) in each hour. In general, from 12.00 - 15.00 and 19.00-21.00, the travel time to the destination is longer than in the early morning until noon. With a travel time range of 600 – 760 seconds with a distance of 9,187 meters.

The highest average travel speed for 24 hour data comes from zones 2 to 1 (Airport-Nusa Dua), reaching 51.5 km/hr (N=254, SD= 1.8 km/hr), and the lowest is from zones 4 – 3 (Pesanggaran-Kuta) at 39.8 km/hr (N=254, SD= 2.5km/hr). the comparison of average speed between overall, morning, noon, and afternoon show clearly that the velocity of the morning travel is higher than any other group for all origin and destination. The highest velocity of morning travel is from zone 2 (Airport) to zone 1 (Nusa Dua) (M=52,6, SD=1,2)

and the lowest average speed is from zone 3 (Kuta)to zone 2 (Airport) (M=38,2, SD=0,7). In some cases, the velocity in noon travel is higher than in afternoon travel but less than morning and overall velocity. The average travel time in table 2 saw a similar pattern, where the morning commute is faster than other groups. Furthermore, the statistical test uses to understand the difference between the group.

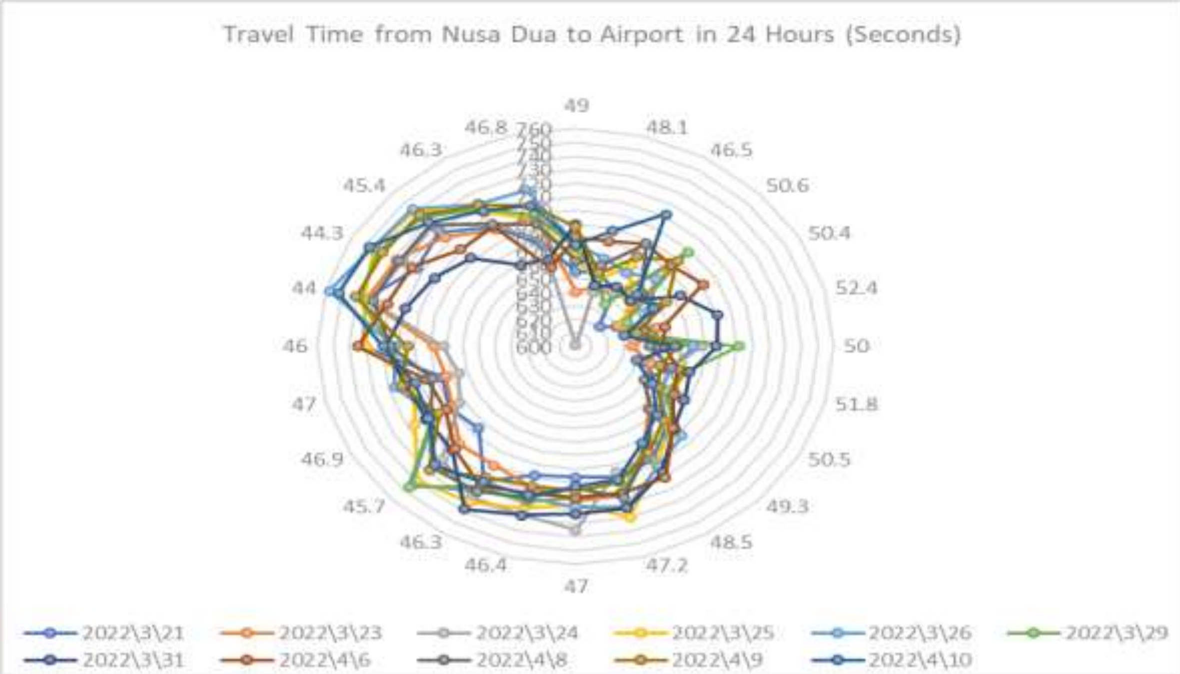


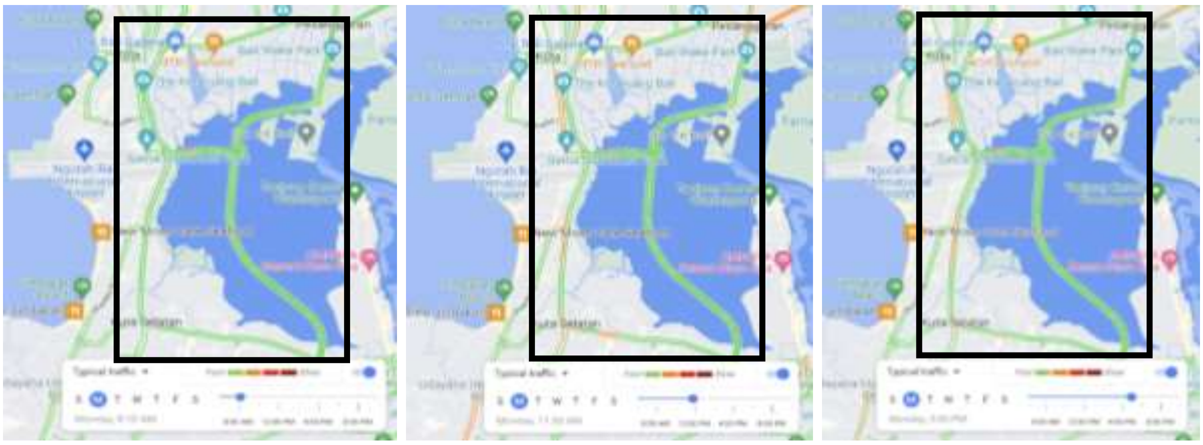
Figure 1. Travel time example from Zone 1 to 2 Generated from Google Map Distance Matrix API in 24 Hours

Tabel 2.
Descriptive Data of Speed Average and Travel Time From Origin to Destination in 24 Hours

Zone Name	Variabel	Overall 24 Hrs		Morning		Noon		Afternoon	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
1-2	Travel Time	691.1	31.2	662.2	13.7	715.8	10.3	715.8	20.8
	Speed	48.0	2.2	50.0	1.0	46.2	0.7	46.2	1.3
1-4	Travel Time	875.1	54.8	834.0	33.1	911.5	42.9	51.0	1.1
	Speed	48.9	2.7	50.9	1.7	47.3	2.4	47.1	2.0
1-3	Travel Time	870.6	51.7	828.5	27.3	903.5	43.7	903.7	46.9
	Speed	48.6	2.6	51.0	1.1	46.7	1.7	46.7	2.0
2-1	Travel Time	679.8	23.5	665.1	15.4	693.0	6.8	687.8	13.2
	Speed	51.5	1.8	52.6	1.2	50.4	0.5	50.8	1.0
2-4	Travel Time	490.8	13.8	479.0	11.7	498.5	4.5	488.8	9.0
	Speed	45.6	1.2	46.6	1.1	44.8	0.4	45.7	0.8
2-3	Travel Time	297.4	20.4	276.3	9.3	320.8	6.5	313.5	6.0
	Speed	41.5	2.9	44.5	1.5	38.3	0.8	39.2	0.7

Zone Name	Variabel	Overall 24 Hrs		Morning		Noon		Afternoon	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
4-1	Travel Time	796.3	35.7	772.8	19.5	816.8	13.1	812.1	18.2
	Speed	52.7	2.3	54.4	1.4	51.4	0.8	51.7	1.2
4-2	Travel Time	508.8	17.7	484.0	9.4	519.1	5.3	511.5	11.7
	Speed	46.2	1.6	48.5	0.9	45.3	0.5	45.9	1.0
4-3	Travel Time	443.1	27.0	406.5	12.0	467.8	7.6	467.4	10.1
	Speed	39.8	2.5	48.5	0.9	45.3	0.5	45.9	1.0
3-1	Travel Time	901.4	36.7	868.5	19.6	926.5	12.9	925.4	18.1
	Speed	50.1	2.1	52.0	1.2	48.7	0.7	48.8	1.0
3-2	Travel Time	356.0	21.0	335.7	18.0	374.3	7.4	371.8	7.6
	Speed	40.3	2.5	42.6	2.2	38.2	0.7	38.4	0.8
3-4	Travel Time	366.9	19.9	335.7	18.0	374.3	7.4	371.8	7.6
	Speed	41.4	2.3	44.5	1.4	39.8	0.7	39.5	1.0

Typical traffic in google maps is extracted to find an overview related to traffic conditions based on color differences. As shown in figure 2, overview related to low speed is highlighted in green, and poor speed performance is highlighted in red. From the observations in the black box, it can be seen that the road speed performance at the study location is still typical in the morning, afternoon, and evening which is marked in green, although in some places, there is a yellow color which is dominated by queue in intersections with traffic lights control. Technically, performance data is usually collected by means of a traffic volume survey and a speed survey, but it cannot describe the cumulative traffic conditions displayed on typical traffic on Google Maps.



Firgue 2. Typical traffic using google maps at 3 differents Times in Study Area

Mobility data based on Google Covid-19 Community Mobility Reports is used to determine whether people's movements have entered regular times or are still affected by Covid-19. The data in figure 3, is taken according to the time speed and travel time from March 20-April 4, 2022. Mobility data at residential locations have movement above average, and it shows that the mobility pattern is centralized in the residential area. This pattern affects the other locations, as transit stations, workplaces, shops, parks, and recreation locations are still below normal. Some data may still be questionable because the mobility at transit stations is far below the baseline data, yet, In Bali, people are less using public transport unless long journey transit.

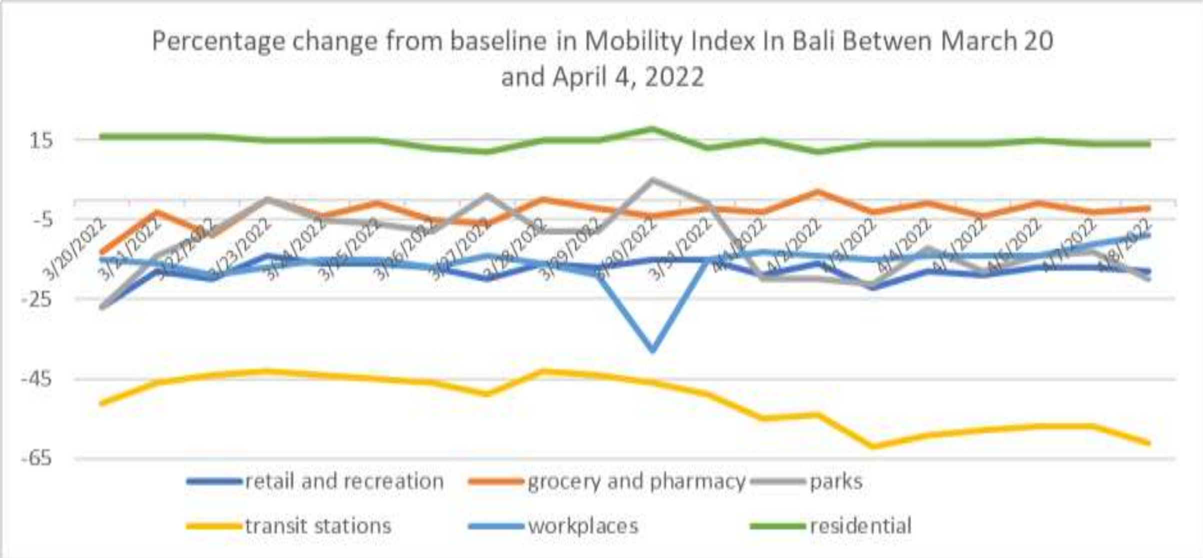


Figure 3. Percentage change from baseline in Mobility Index In Bali Betwen March 20 and April 4, 2022 Based on Google Covid-19 Community Mobility Reports

The results of the one-way ANOVA analysis of the difference in time and speed on the morning, afternoon, and evening trips. The four origin-destination pairs with two variables. Analysis of Test of Homogeneity of Variances resulted in four data with the same significant variance > 0.05. the result of Bonferroni test shows that the four data show differences between morning to afternoon trips and morning to evening trips, but there is no difference between trips from afternoon to evening and vice versa (see tabel 3). For pairs that do not have the same variance, a non-parametric test by the Kruskal Wallis test is carried out. From all available data, it can be seen that there are differences in Asymp's journey. Sig. < 0.05, hower, from the results of this test cannot be concluded which time is different.

Tabel 3.
One-way ANOVA and Kruskal Wallis test result from origin and destination

Zone Name	Variable	Test of Homogeneity of Variances		Anova		Siginificant level of Post hoc test (Multiple Comparisons)			Kruskal Wallis Test
		Levene Statistic	Sig.	F	Sig.	Peak 1-2	Peak 1-3	Peak.2-3	Asymp. Sig.
1-2	Speed	6.038	0.003	138.402	0.000				.000
	Travel time	7.399	0.001	130.418	0.000				.000
1-4	Speed								.000
	Travel time	5.045	0.008	37.023	0.000				.000
1-3	Speed								.000
	Travel time	8.843	0.000	38.352	0.000				.000
2-1	Speed	11.389	0.000	47.852	0.000				.000
	Travel	10.025	0.000	47.328	0.000				.000

Zone Name	Variable	Test of Homogeneity of Variances		Anova		Siginificant level of Post hoc test (Multiple Comparisons)			Kruskal Wallis Test
		Levene Statistic	Sig.	F	Sig.	Peak 1-2	Peak 1-3	Peak.2-3	Asymp. Sig.
	time								
2-4	Speed	9.443	0.000	37.373	0.000				.000
	Travel time	8.410	0.000	37.481	0.000				.000
2-3	Speed	8.929	0.000	325.099	0.000				.000
	Travel time	2.977	0.056	338.334	0.000	.000**	.000**	.710**	
4-1	Speed	2.057	0.133	66.795	0.000	.000**	.000**	1.000**	
	Travel time	1.301	0.277	65.086	0.000	.001**	.002**	1.000**	
4-2	Speed	13.532	0.000	134.037	0.000				.000
	Travel time	12.874	0.000	132.030	0.000				.000
4-3	Speed	9.642	0.000	391.384	0.000				.000
	Travel time	3.978	0.022	388.521	0.000				.000
3-1	Speed	4.726	0.011	122.068	0.000				.000
	Travel time	2.948	0.057	119.434	0.000	.001**	.003**	1.000**	
3-2	Speed	22.398	0.000	104.062	0.000				.000
	Travel time	15.476	0.000	106.089	0.000				.000
3-4	Speed	4.265	0.017	230.857	0.000				.000
	Travel time	3.196	0.045	223.676	0.000				.000

Post hoc test : *Homogeneity of variance if Sig < 0.05 using Games-Howell test, Sig > 0.05** Using Bonferroni test, Peak 1. Morning travel (06.00-09.00), Peak 2. Noon travel (12.00-15.00),and Peak 3. Afternoon travel (17.00-19.00).

DISCUSSION

Traffic has a peak period that can occur at various times every day, and this condition varies and results in a travel pattern. The intervention allows changes in travel patterns such as accidents, road closures, and certain activities. The trips generated in the case study clearly illustrate the differences in speed and travel time, especially on the morning trip. This is based on the results of the one-way ANOVA, which describes the differences in the characteristics of movement in the morning compared to the afternoon and evening. The Kruskal Wallis Test supports the data results reflected in the Asymp value. Sig. < 0.05. although the results from non-parametric cannot clearly describe the different time groups, the descriptive data by Mean and standard deviation data on the average value of morning rush hour trips compared to afternoon and evening trips support these results. However, the noon and afternoon speed and travel time cannot be compared statistically as the data result is insignificant (Sig. < 0.05). This condition should be marked because people's travel patterns in the morning want to get to their destination faster than other busy travel times. In general, travel performance during rush hour is described as low, which can usually be seen from the relationship between speed, density, and traffic volume. Where volume and density are high, the driver cannot choose the desired speed, but the speed is determined by the current density and volume conditions.

In addition to using the Traffic flow models, describe vehicle flows using three primary parameters: average speed (v), density (k), and flow (q). Here we use another approach to see a detailed description of traffic conditions through the condition of community mobility from the covid mobility index data and the green color on typical traffic from the google map. From the results of this data, it can be said that the travel pattern is still not normal. There are still many trips below the baseline travel data where movement in residential areas dominates, indicating that community travel is still internal. However, it does not fully describe the existing conditions because many variables cause travel not to be normal, such as population movement, covid policies, economic improvement, land use, and others. This allows motorists to choose the speed they want during peak hours, especially in the morning commute. However, it is unknown why people are in a hurry in the morning compared to other peak hours, such as whether going to work and school activities require a shorter amount of time in the morning than traveling home from work in the afternoon. Further research is needed to determine the variables that cause this condition subjectively.

CONCLUSION

The combination of the Google Map Distance Matrix API, Typical Google Maps, and the Covid- 19 community mobility index is carried out to find out the mobility pattern of people in the destination area. The research discussion results from March 20th to April 10th 2022, concluded that community mobility in the morning was different from the afternoon and evening, with the difference in the travel time and travel speed. One-way ANOVA is used to describe the difference for normal data, and the Kruskal Wallis test is used for the data that are not normally distributed, which is supported by descriptive data on differences in average speed and rush hour travel time for the entire data. This combining method can be used to obtain community travel patterns compared to conventional methods. Further analysis is needed on answering question of why people in a hurry more on morning trips than in the afternoon, evening, and even in some locations at night because the results of this study have not been able to describe subjective data related to people's perceptions of driving at different times.

REFERENCES

Axhausen, Kay & Zürich, ETH. (2007). Concepts of Travel Behavior Research.

Ding, Ling; Zhang, Ning (2016). A Travel Mode Choice Model Using Individual Grouping Based on Cluster Analysis. Procedia Engineering, 137(), 786–795. doi:10.1016/j.proeng.2016.01.317

Basaric, Valentina & Vujičić, Ana & Mitrović Simić, Jelena & Bogdanović, Vuk & Saulic, Nenad. (2016). Gender and Age Differences in the Travel Behavior – A Novi Sad Case Study. Transportation Research Procedia. 14. 4324-4333. 10.1016/j.trpro.2016.05.354.

Peng, Jing & Zhao, Mengxuan & He, Meiling & Chen, Long. (2018). Travel Mode and Travel Route Choice Behavior Based on Random Regret Minimization: A Systematic Review. Sustainability (Switzerland). 10. 10.3390/su10041185.

Schwanen, Tim & Dijst, Martin & Dieleman, F.M.. (2005). The Relationship between Land Use and Travel Patterns: Variations by Household Type. Spatial Planning, Urban Form and Sustainable Transport.

Bonaccorsi, Giovanni; Pierri, Francesco; Cinelli, Matteo; Flori, Andrea; Galeazzi, Alessandro; Porcelli, Francesco; Schmidt, Ana Lucia; Valensise, Carlo Michele; Scala, Antonio; Quattrociocchi, Walter; Pammolli, Fabio (2020). Economic and social consequences of human mobility restrictions under COVID-19. Proceedings of the National Academy of Sciences, (), 202007658–. doi:10.1073/pnas.2007658117

Google Maps Platform. (2019). Google Maps Platform FAQ. Retrieved from https://developers.google.com/maps/documentation/distance-matrix/overview

Google Maps Platform. (2020a). Developer Guide - Directions API. Retrieved from https://developers.google.com/maps/documentation/distance-matrix

Google Maps Platform. (2020b). Developer Guide - Distance Matrix API. Retrieved from https://developers.google.com/maps/documentation/distance-matrix/start

TRB, Highway Capacity Manual 2000, National Research Council Washington D.C., 2000.

A.D. May, Traffic Flow Fundamentals, Traffic Engineering Handbook, Prentice-Hall, Englewood Cliffs, New Jersey (1990)

Pengjun Zheng; McDonad Mike (2012). An Investigation on the Manual Traffic Count Accuracy. , 43(none), –. doi:10.1016/j.sbspro.2012.04.095.

Seedam A, Satiennam T, Radpukdee T, Satiennam W, Ratanavaraha V (2017) Motorcycle on-road driving parameters influencing fuel consumption and emissions on congested signalized urban corridor. J Adv Transp 2017. https://doi.org/10.1155/2017/5859789.

Yan Y, Zhang S, Tang J, Wang X (2017) Understanding characteristics in multivariate traffic flow time series from complex network structure. Physica A: Statistical Mechanics and its Applications 477:149–160. https://doi.org/10. 1016/j.physa.2017.02.040.

Wemegah, T.D., Zhu, S. & Atombo, C. (2018) Modeling the effect of days and road type on peak period travels using structural equation modeling and big data from radio frequency identification for private cars and taxis. *Eur. Transp. Res. Rev.* **10,** 39. https://doi.org/10.1186/s12544-018-0313-9

Wang, Fahui & Xu, Yanqing. (2011). Estimating O-D Travel Time Matrix by Google Maps API: Implementation, Advantages, and Implications. Annals of GIS. 17. 199-209. 10.1080/19475683.2011.625977.

Haitao, Jin & Jin, Fengjun & Qing, Hao & He, Zhu & Xue, Yang. (2019). Measuring Public Transit Accessibility Based On Google Direction API. The Open Transportation Journal. 13. 93-108. 10.2174/1874447801913010093.

Mohan, Dinesh & Tiwari, Geetam & Goel, Rahul & Lahkar, Paranjyoti. (2017). Evaluation of Odd–Even Day Traffic Restriction Experiments in Delhi, India. Transportation Research Record: Journal of the Transportation Research Board. 2627. 9-16. 10.3141/2627-02.

Hananto P. 2020. Tutorial Pelatihan Geospatial dan Big Data Untuk Evaluasi Kinerja Transportasi dan Konektivitas.

Community Mobility Reports. (2022). Community Mobility Reports Help. Retrieved from https://support.google.com/covid19-mobility/answer/overview

Community Mobility Reports. (2022a). Community Mobility Reports Help. Retrieved from https://support.google.com/covid19-mobility/answer/Understand the data

Community Mobility Reports. (2022a). Community Mobility Reports Help. Retrieved from https://support.google.com/covid19-mobility/answer/calibrate your region