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Exploring Daily Activity Pattern Using Spatio-Temporal Statistics with R for Predicting Trip Production

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ABSTRACT

Spatio-temporal data modelling is one of the methods in data analysis that uses space (spatial) and time (temporal) approaches. This study used Spatio-temporal statistical modelling to observe the daily activity patterns of people. Spatio-temporal modelling selected for support activity-based transportation demand. This research identifies community mobility patterns that will provide trip production data for transportation demand prediction. Using Spatio-temporal statistical modelling benefit this study because statistical this model can make model components in a physical system appearing to be random. Even if they are not, the models are helpful as they have accurate and precise predictions. In this study, descriptive analysis was used. Incorporating statistical distributions into the model is a natural way to solve the problem. This research collects daily activity data from 400 respondents recorded every 15 minutes. From this data, a pattern of respondents' daily activities was formed, which was analyzed using R. Software R also visualizes data on daily activities of the community in Spatio-temporal modelling. This research aims to depict the daily activity patterns to predict trip production. This research found three clusters of trip production patterns with specific groups member and specific patterns between workdays and holidays.

1. Introduction

Travel-related patterns are the main topic in transportation research, combining human behavior and transportation modelling [1]–[3]. Along with the increasing population, especially in modern cities, day-to-day activity-travel patterns directly affect the increase in travel activity. According to [4], people's desires to carry out daily and other episodic activities drive the demand for transportation services. Exploring daily activity patterns is very important to analyze transportation behavior. In the daily activity pattern, recording a person's activity can identify patterns related to transportation behavior. Many factors, such as demographics and lifestyle, can influence a time-activity pattern [5]. Several previous studies have used daily activity patterns in studies related to travel production [2], [3], [5]–[7].

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This research was conducted with a Spatio-temporal approach to analyze travel behavior. This approach explains the phenomenon of space (spatial), namely in the form of a stopover location in a travel activity and time (temporal), which is the time spent in a travel production.

The data extracted from the daily activity pattern involved 400 respondents. Researchers realize that extracting data from daily activities and converting it into spatial and temporal data takes time. However, this method is one of the most precise ways to get a person's activity patterns, especially individual movement patterns. Since transportation, especially in Indonesia, is very volatile, changes in human movement can occur in a brief time and large numbers. Therefore, the analysis using a Spatio-temporal approach aims to determine the movement of humans from one place to another (spatial) within a specific time (temporal). The role of statistics in transportation problems is crucial and inseparable. The role of statistics in transportation problems is crucial and inseparable.

The application of statistics in this study, among others, is to calculate the movement and formation of clusters and form the data into daily travel patterns. In applying statistics, the Rstudio software was used. Rstudio is an IDE from the R programming language. R roles include initial processing data, cluster formation and visualization consisting of daily activity graphs, cluster distributions, and trip patterns extracted from each cluster based on the K-Means Clustering algorithm. Hopefully, the result of this research can meet the goals of identifying Spatio-temporal daily activity, determining the cluster pattern, and forming the travel production duration based on daily activities.

Studies using spatiotemporal analysis are important to be carried out in research in the field of transportation, specifically for traffic analysis. This is because spatiotemporal analysis emphasizes spatial exploration (place) and temporal (time) of individuals, so that we can find out the statistics of human movement from one place to another within a certain period of time. Spatiotemporal analysis data can be used for further analysis of traffic congestion [8], [9], Optimization of public transportation routes [10], [11], and vehicle emission analysis [12], [13].

2. Literature Review

Often, humans cannot meet their needs in their place [14]. This condition causes humans to need to move from one place to a particular destination to meet their needs [15]. If each individual does the same thing, a significant movement will cause traffic flow (traffic congestion). Traffic flow is a major transportation problem rooted in activities that fulfil human needs [16]. So, it states that if someone makes traffic predictions, they should be able to assess the characteristics of everyday human activities. This daily activity pattern could be used to determine the origin and destination of movement [17].

Characterizing human mobility patterns is critical for a better understanding of the consequences of human movement. The influence of population dynamics in the city, for example, cannot be comprehended without such a definition [18]. Sometimes, a specific group of communities also have their travel patterns, such as university communities [3], health utilization [19], and port communities [20], which will form travel patterns based on intra-personal variability and intra-household activities.

A travel pattern is a typical behavior caused by numerous elements during travel as a collective attribute of travel [21]. Several previous studies have revealed what factors could influence travel patterns, including global health situations such as pandemics [22], [23], geographical conditions [24], socioeconomic factors [25], [26], as well as from socio-demographic factors [27]. Understanding people's travel patterns is essential for route planning. Several studies were conducted with a Spatio-temporal approach to analyze travel patterns and travel behavior [21], [28]–[30], and especially, the study conducted by Li (2021) revealed Spatio-temporal patterns for analyzing travel and commuting behavior.

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The description of the Spatio-temporal analysis method using time-geography revealed by the study [31]. This study addressed that the Spatio-temporal analysis using a time-geography approach initially developed by Torsten Hägerstrand and associates in 1970 determines the interdependence relationship between nature and technology. Delafontaine (2011) revealed that in analyzing the Spatio-temporal pattern of human movement, the time geography model plays a role in describing the conceptual perspective.

Spatio-temporal is more attractive when we use point of interest and drop-off location as the point that makes trip production. A meaningful reference for transportation demand prediction can be achieved by combining K-means clustering from data on essential activities and the time spent making trip production [30]. In this study, home, school, restaurant, store, and workplace were used as the point of interest that makes trip production.

Furthermore, previous research from Kwan [32] elaborates the development of time-geographic modelling for Spatio-temporal analysis from 2D to 3D based graphics to provide interactive geo-visualization of activity-travel patterns as a methodological exploration with an extensive data set. Then, the use of time-geographic models with 3D-based graphics and 2D-based graphics was also applied to the study [29] to analyze large-scale time geographic based on compressed linear reference.

The extensive use of the Spatio-temporal analysis approach and the power of Spatio-temporal to elaborate much travel pattern behavior and travel production ensure that this research meets its purposes. Furthermore, combining with R to process the K-means clustering algorithm will make this research result contribute to and enrich the finding from previous studies.

3. Material and Methodology

The research was conducted in a series starting from data collection, data processing, and statistical analysis using R tools, as shown in Fig. 1.

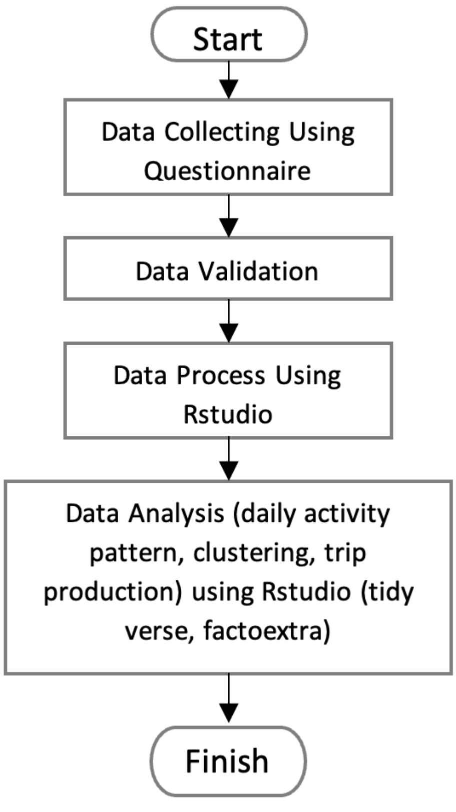

Fig. 1 Research flow chart.

3.1. Material

A survey involving 400 respondents was held in Yogyakarta Province to collect the data for three months in early 2022. The survey recorded the daily activity of each respondent every 15 minutes and formed an activity diary. The activity diary explains each respondent's daily activities starting from the respondent's initial activities at the beginning of the day to the respondent's last activities at the end of the day. The activity diary recording process followed the classification of activity choices provided in the recording guidance. The data collected is heterogeneous, so daily recording activities based on the options provided aim to make it easier for researchers to classify types of activities and reduce data outliers that can interfere with the research process.

Respondent data recorded in the activity diary survey has a demographic distribution in the form of quite varied ages, starting from 17 years old as the youngest to 82 years old as the oldest. The daily activity survey in the study also obtained spatial data (locations) recorded from each respondent as well as temporal data in the form of the period traversed by the respondents in the survey. Moreover, this survey succeeded in getting patterns in the form of activity and travel patterns.

3.2. Method

First, 400 respondents in Yogyakarta Province were hired in a survey to fulfil the activity diary. Four hundred respondents recorded their daily activities in an activity diary for four days. The activity diary was divided into two working days and two holidays. After the respondents completed the daily activity diary, the data from the survey was recapitulated into a Microsoft Excel file as initial data before being analyzed using the Rstudio software. The initial recapitulation of activities in the daily activity diary was then codified into numeric numbers to facilitate analysis in the Rstudio software.

Processing data analysis started by making several groups from the data according to the age of the respondents. Then, calculate the amount of time (minutes) spent in each activity for 24 hours in each age group. The next step was dividing the time by the number of respondents in each age group to obtain the average time spent on each activity. After this, the initial data from the average time were inputted into the Rstudio software for further analysis.

In Rstudio, the initial process was to visualize the daily activity pattern. The visualization was in the form of a graph consisting of the x-axis representing the time for 24 hours, the y-axis representing the number of respondents in each activity, and a line representing the respondents' activities. The graph shows an initial picture of the respondents' activity and movement/travel patterns.

Moreover, the activity diary data in the form of the average time in each activity from respondents groping into several clusters based on identifying the respondent's activity pattern. The type of cluster used is the K-means cluster. The K-means algorithm, which solves the well-known clustering problem, is one of the most prominent unsupervised learning techniques [33].

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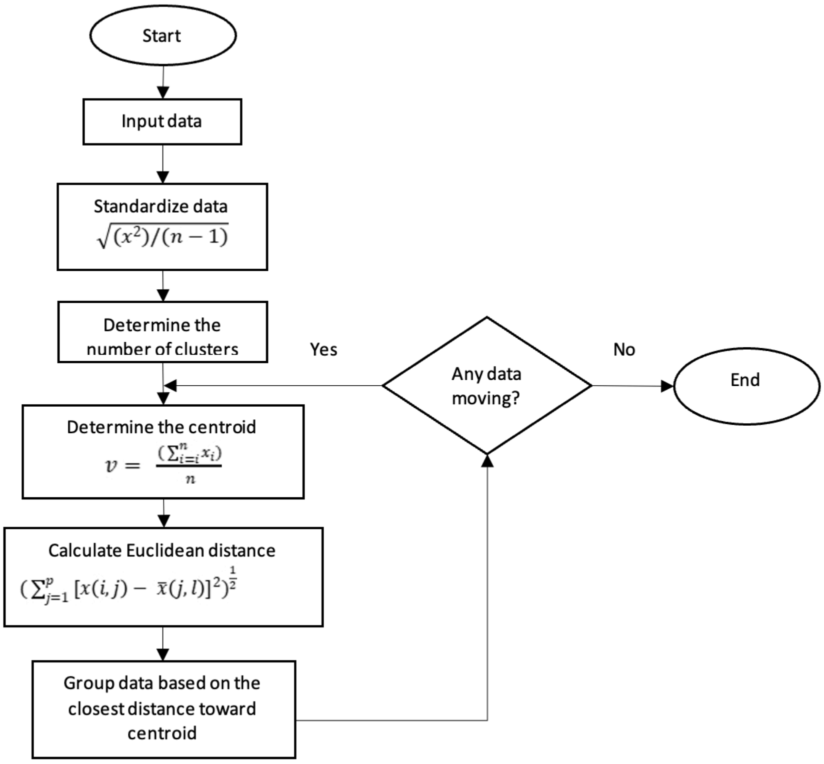

Fig. 2 K-means clustering algorithm.

The steps for grouping K-means (Fig. 2) are as follows:

1. The first step in clustering using the K-Means method is to input the data to be processed first.
2. The second step is to standardize the data to uniformize the values in the inconsistent data. The formula used in data standardization is based on references from [34], where x is a vector of the non-missing values and n is the number of non-missing values.

$$\sqrt{(x^2)/(n-1)} \tag{1}$$

3. The third step is to determine the desired number of clusters.
4. The fourth step is to determine the centroid of the cluster. The formula used in:

$$v = \frac{(\sum_{i=i}^{n} x_i)}{n} \tag{2}$$

- V = centroid pada cluster
- X_i = object to – i
- N = number of objects

5. The fifth step is to calculate the Euclidean distance with a formula based on the reference from [35], namely, where:

$$(\sum_{j=1}^{p} [x(i,j) - \bar{x}(j,l)]^2)^{1/2} \tag{3}$$

- *d(i,l)* = Euclidean distance
- *x(I,j)* = I-th object value on the j-th variable
- $\bar{x}(j,l)$ = the mean of the I-th object in the j-th variable
- *i* = number of objects

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- j = number of variables
- l = number of clusters

6. The sixth step is to group the data by the closest distance to the centroid.
7. The seventh step is to ascertain whether any data is switching clusters or not. If yes, repeat the fourth step to determine the centroid; if the data has not moved clusters, then the clustering is complete.

After clustering the data, several clusters containing age groups based on similar activity patterns emerged from the process. The travel activity of respondents in each cluster was analyzed to determine the difference in travel activity patterns between clusters. The activity pattern was processed based on spatial data in the form of the location visited by the respondent and temporal data in the form of the respondent's time in activities for 24 hours. Visualizing the activity pattern using time-geographic modelling to get a Spatio-temporal picture was meant to read the respondent's activity pattern more effortlessly. In the time-geographic graph, a y-axis represents the activities carried out by respondents, and an x-axis represents the time elapsed for 24 hours.

4. Result and Discussion

4.1. Visualization of Daily Activity Pattern

The initial data from the activity diary was visualized in a graph to get the pattern of the activities carried out by the respondents for four days. The spatial data appear in lines forming a pattern of the respondent's movement for 24 hours. The temporal data waa visualized on the graph's x-axis, representing the time of the activities carried out by the respondents for 24 hours.

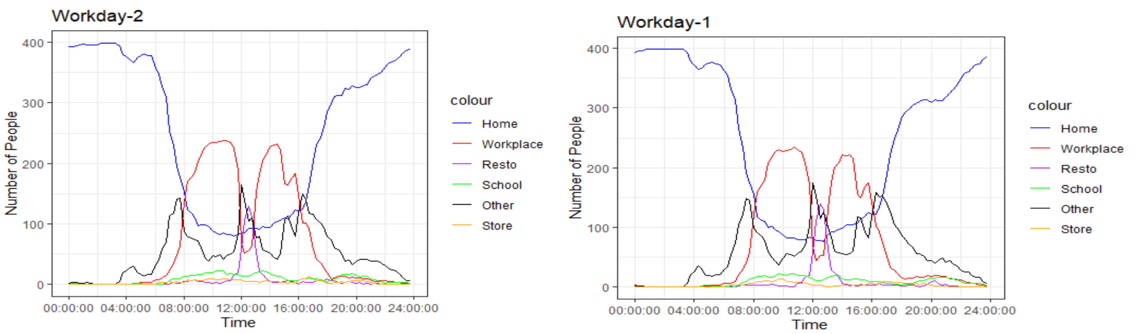

Fig. 3 Daily activity pattern on working day-1 and working day-2.

From the daily activity pattern chart on working day one and working day two (Fig. 3), there is no significant difference in the activity pattern undertaken by the respondents. The two data visually tend to have similar patterns. Busy hours of movement from respondents in large numbers are marked by two or more lines on the graph that coincide. This busy time is predicted at 08.00, 12.00, 13.00, and 16.00.

There are differences in the behavior of the respondents' activities on daily activity patterns during the holiday. Respondents will have more free time during holidays than working days. This phenomenon in the graph where the line representing activities at home tends to experience lower fluctuations than the graph on a working day, even if the line does not intersect with other lines. The line that represents other activities on holiday tends to have more stable fluctuations in the time range of 08.00 – 16.00 compared to a working day. There is a significant difference in the activities carried out at work on holiday-1 and holiday-2. The pattern is depicted in a line representing activities at work, where on holiday 1, the line tends to be more stable than the line on holiday 2, which tends to be more volatile (Fig. 4).

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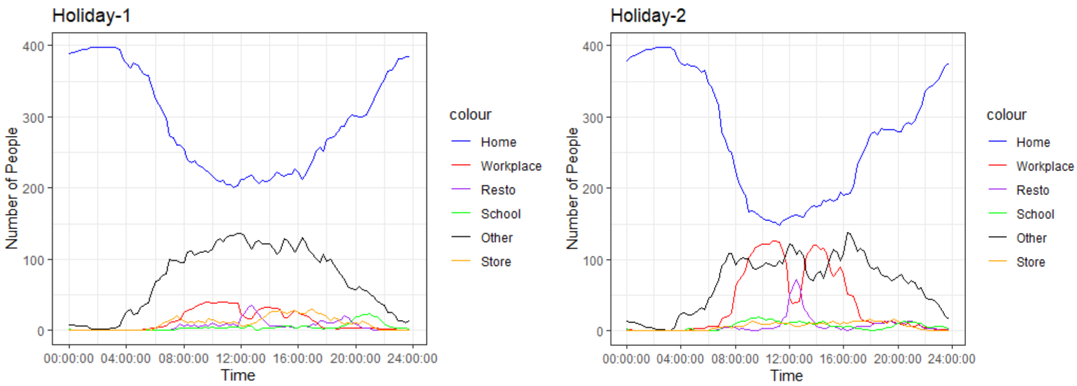
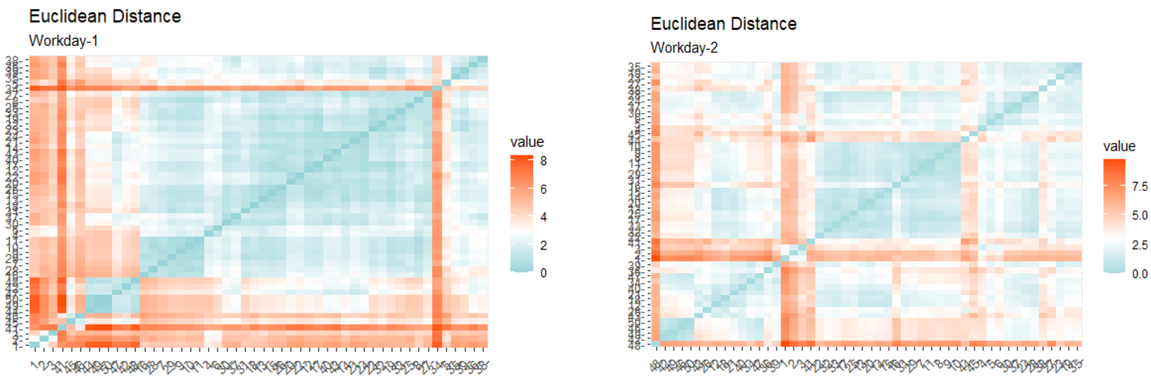


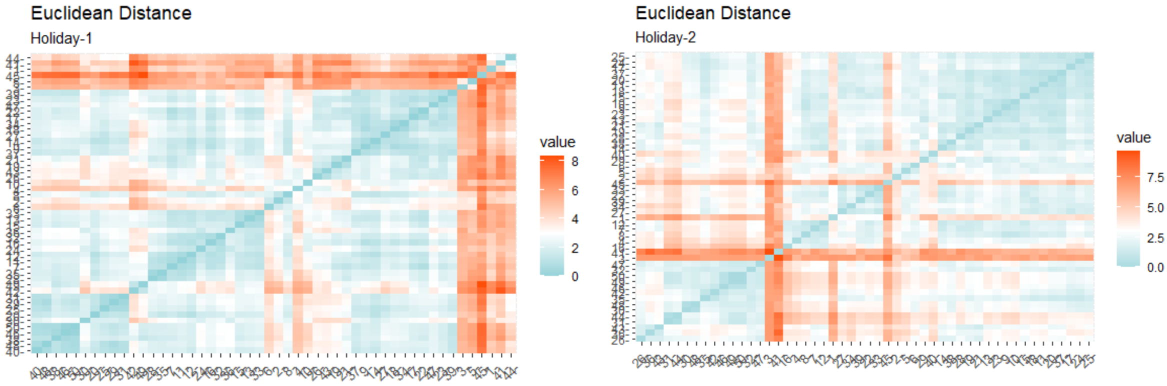
Fig. 4 Daily activity pattern on holiday-1 and holiday-2.

4.2. K-Means Clustering

At the clustering stage, the type of cluster used is the K-means cluster, which is included in the unsupervised modelling learning. The number of clusters used was three, as the center of the cluster (centroid). Data from the average time in each activity carried out by the respondent was scaled, then calculated the Euclidean distance. The data with Euclidean distance were grouped into clusters based on the proximity of the distance to the centroid with 25 iterations.



(a) Working day



(b) Holiday

Fig. 5 Visualization of Euclidean distance of K-means clustering in working day and holiday.

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After the data from the average respondent's activities are scaled, then the Euclidean distance is calculated from the scaled data. Then the visualization of the Euclidean distance is visualized in the form of a heatmap (Fig. 5). The the detail of the centroid of each cluster is in Table 1.

Table 1 Cluster Centroid

Cluster	Home	Workplace	School	Resto	Store	Other
		Cluster Centers Working Day-1				
1	-0.04	0.44	0.16	0.16	-0.22	-0.27
2	-1.39	-0.69	0.68	-0.49	1.35	1.75
3	1.61	-1.56	-1.51	-0.35	-0.21	-0.39
		Cluster Centers Working Day-2				
1	-1.87	-0.45	1.53	-0.51	1.06	-1.87
2	-0.40	0.46	0.14	-0.12	0.27	-0.40
3	1.12	-0.80	-0.55	0.33	-0.72	1.12
		Cluster Centers Holiday-1				
1	-2.32	-0.87	0.66	1.33	2.34	-2.32
2	0.41	-0.05	-0.22	-0.09	-0.26	0.41
3	-0.93	0.80	0.85	-0.25	0.14	-0.93
		Cluster Centers Holiday-2				
1	-0.48	0.32	0.33	0.24	0.28	-0.48
2	1.26	-0.72	-0.75	-0.58	-0.64	1.26
3	-0.75	-1.31	-1.23	-0.19	-0.96	-0.75

Rstudio software made clusters to read which age groups were included in certain cluster groups. There was a cluster change between working day 1 and working day 2, where on working day 1, cluster 1 had more cluster members than cluster 1 on working day 2. A significant difference also occurred in cluster 3, where the number of members of cluster 3 on working day 2 was more than the number of cluster members on working day 1 (Fig. 6).

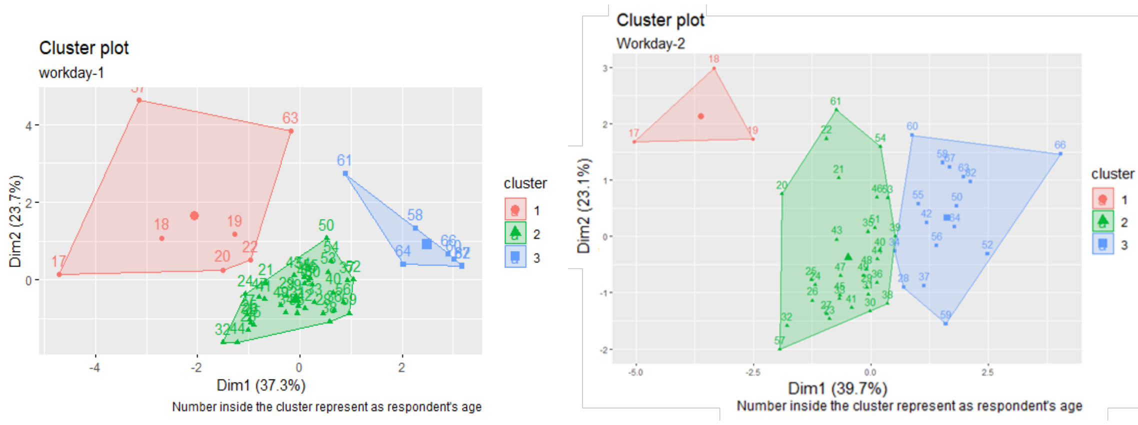

Fig. 6 Workday clustering plot using Rstudio.

In the visualization of clusters on holiday 1 and holiday 2, there was a very significant difference in the number of cluster members. In clusters 1 and 2, there was the differences in cluster members. Whereas, in clusters 1 and 2 at holiday 1, they were less than the number of members in holiday 2. In contrast, in cluster 3, the number of cluster members on holiday 1 was more than the number of cluster members on holiday 2 (Fig. 7).

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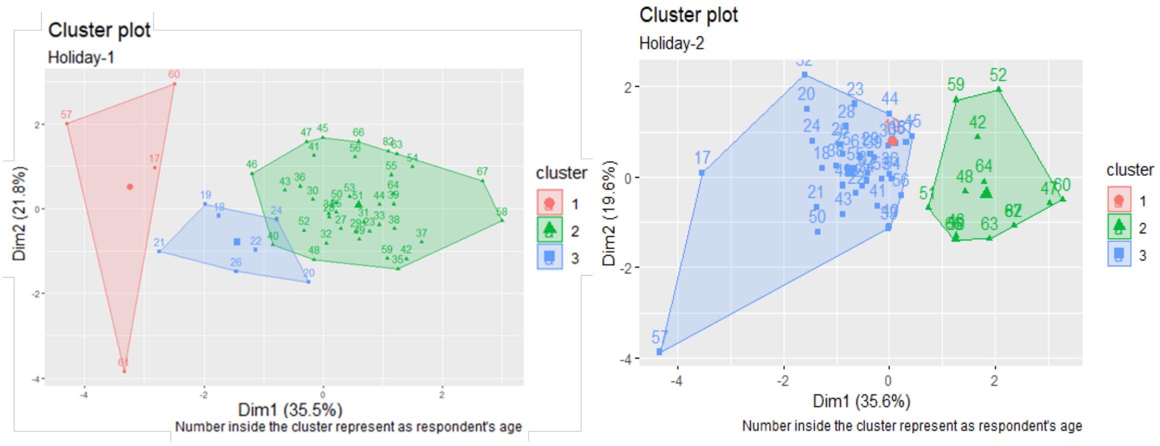

Fig. 7 Holiday clustering plot using Rstudio.

4.3. Visualization of Clusters in 3D

Visualization of clusters in 3D aims to determine the relationship between clusters and activities carried out by respondents.

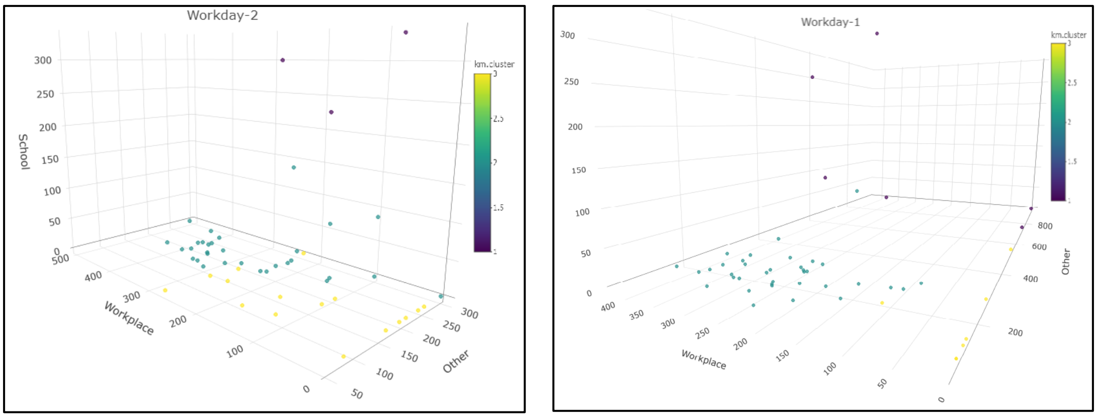

Fig. 8 3D Workday clustering plot using R.

Visualizing clusters in a 3D scatterplot on working day 1 and day 2 (Fig. 8) visualizes the relationship between activities carried out by respondents, namely activities at school, workplace and others with clusters that have been formed. In the visualization, on working day 1 and working day 2, there was no significant change between the two graphs. Visually, cluster 1 is generally filled with respondents who spend more time on activities at school, and cluster 2 is filled with more time by respondents who spend time in the workplace. In contrast, in cluster 3, there is no link between school or workplace activities.

In holiday-1 and holiday-2, the cluster visualized in a 3D scatter plot (Fig. 9) shows the relationship between activities at home, others, and the store. Visually, the cluster division between holiday-1 and holiday-2 in terms of activities spent at home tends to be similar, where cluster 3 was at the top level, and cluster 2 had lower levels than cluster 3. The difference was depicted in cluster

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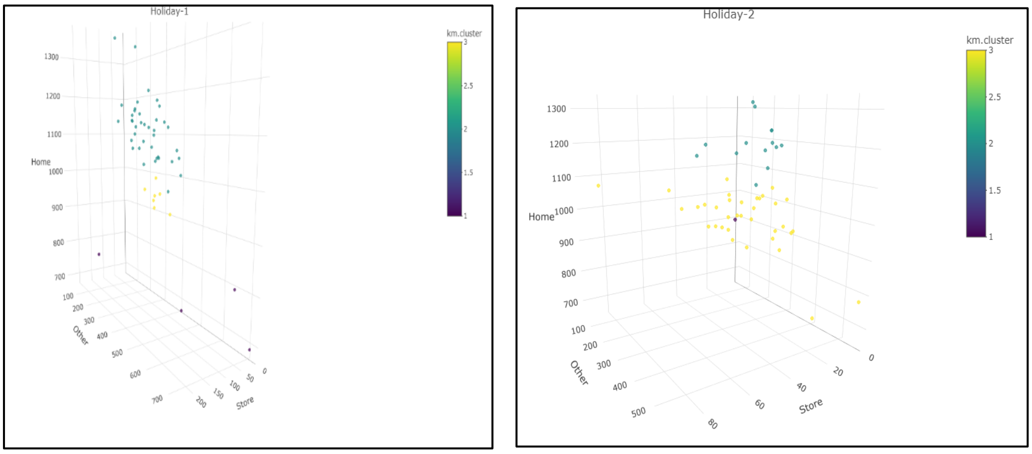


Fig. 9 3D Holiday clustering plot using R.

1 on working day 1, where the position of cluster 1 was lower than clusters 2 and cluster 3, while on working day 2, cluster 1 had the same level as cluster 2.

4.4. Activity & Travel Pattern

Respondents' travel patterns were obtained from the extraction results. The data originated from each cluster on working days and holidays. The travel pattern was visualized using time-geographic modelling, representing spatial and temporal modelling. The x-axis represents a time of 24 hours, and the y-axis represents the types of activities carried out by the respondent.

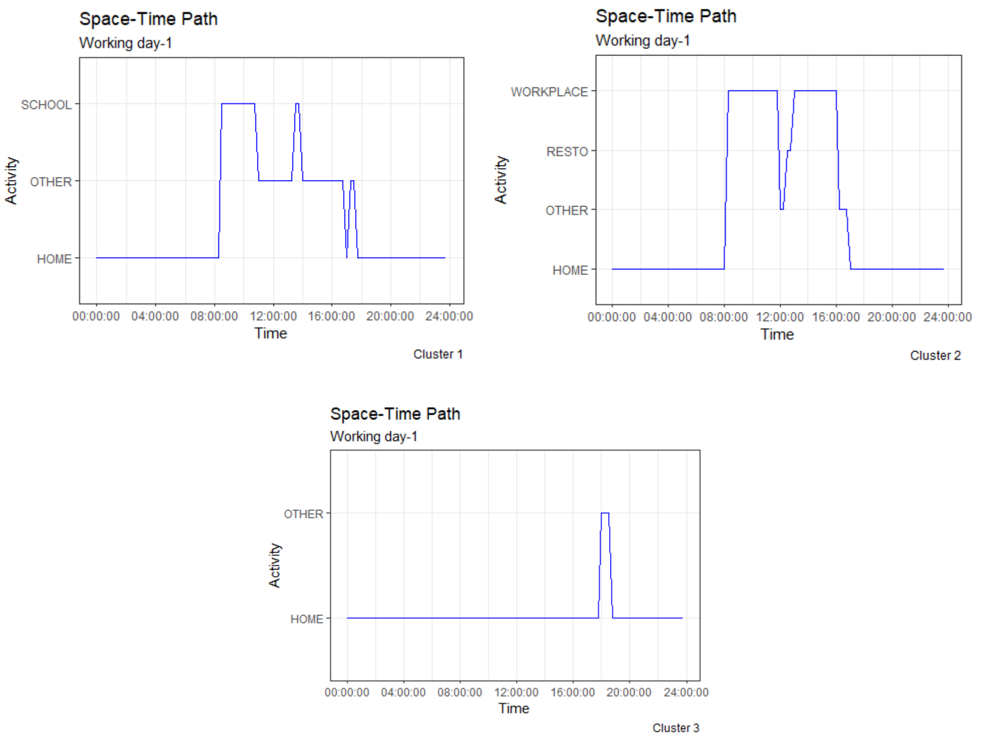


Fig. 10 Workday-1 travel pattern in each cluster.

On working day 1 (Fig. 10), each space-time path graph had a different pattern based on the activity behavior of each cluster, where each cluster contained respondents with similar travel and activity patterns. As in cluster 1, most cluster members came from the student age group, so the more dominant activities at 08.00 until 16.00 were in schools/educational institutions. In cluster 2, most cluster members were filled by the age group of workers, so the dominant activity at 08.00 until

16.00 was in the workplace. Meanwhile, in cluster 3, the majority of cluster members were made up of post-productive age groups where the dominant activity for 24 hours was only at home, and there was no significant fluctuation in the travel pattern in cluster 3.

On working day 2 (Fig. 11), the space-time path of travel and the respondent's activity pattern tended to be the same, and there was no significant difference between the space-time path of the travel & activity pattern on working day 1.

In holiday-1 (Fig. 12), cluster 1 tended to have fluctuations in the travel & activity pattern with a higher intensity than cluster 2 and cluster 3. In clusters 2 and 3, there were no fluctuations in travel and activity patterns and the dominant activity carried out by respondents was located there.

There was no difference between cluster 2 and cluster 3 on holiday 2 (Fig. 13). Meanwhile, in cluster 1, fluctuations in the travel and activity pattern had a lower intensity than in cluster 1 on holiday-1.

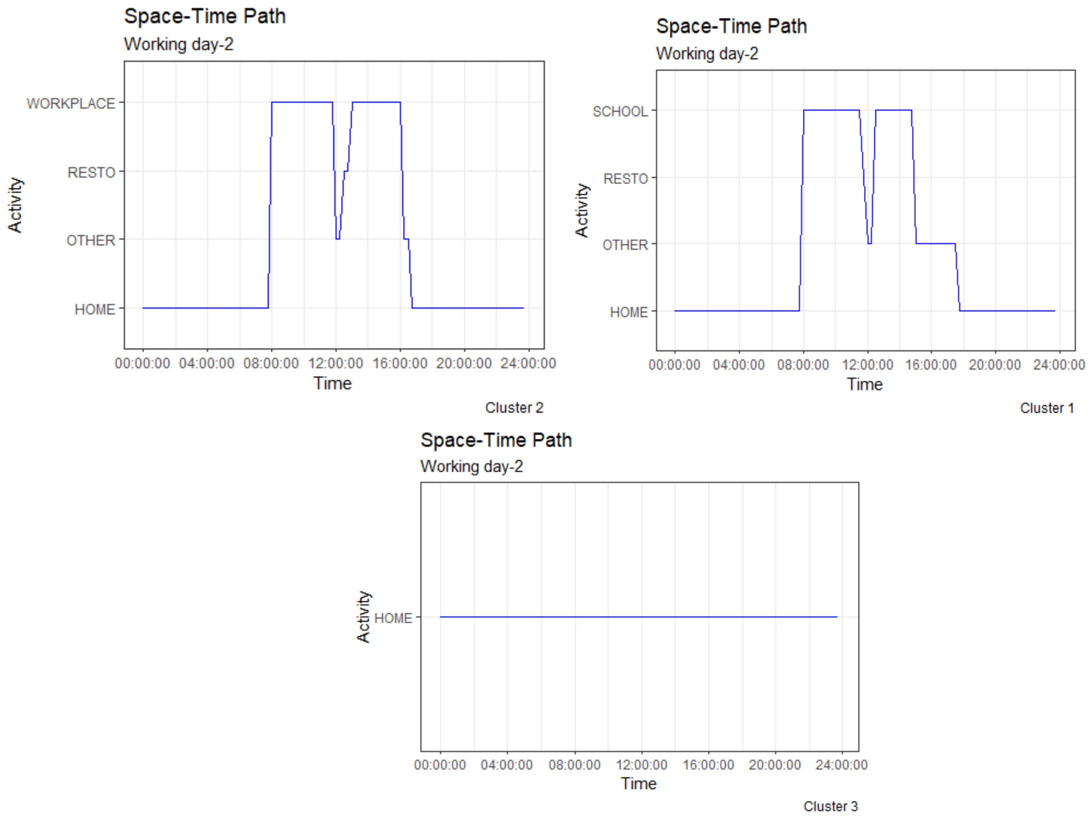
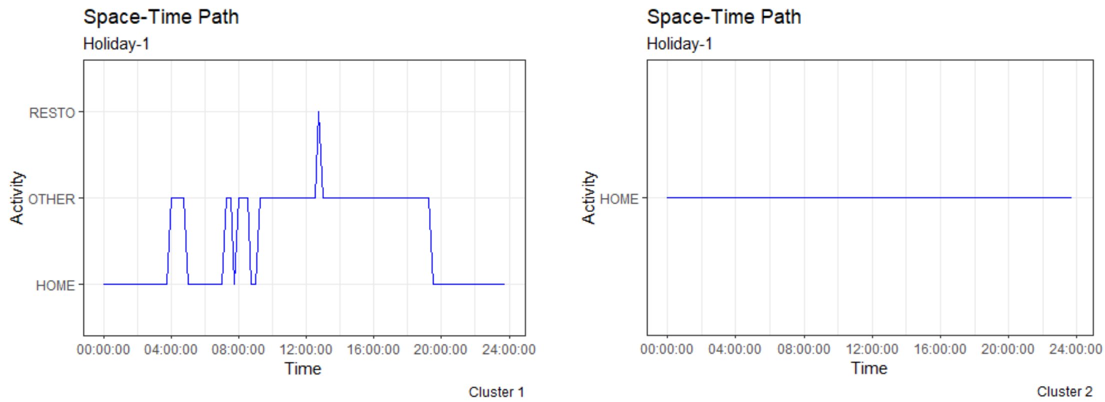


Fig. 11 Workday-2 travel pattern in each cluster.



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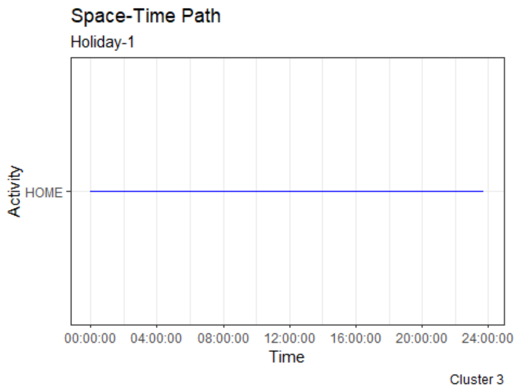

Fig. 12 Holiday-1 travel pattern in each cluster.

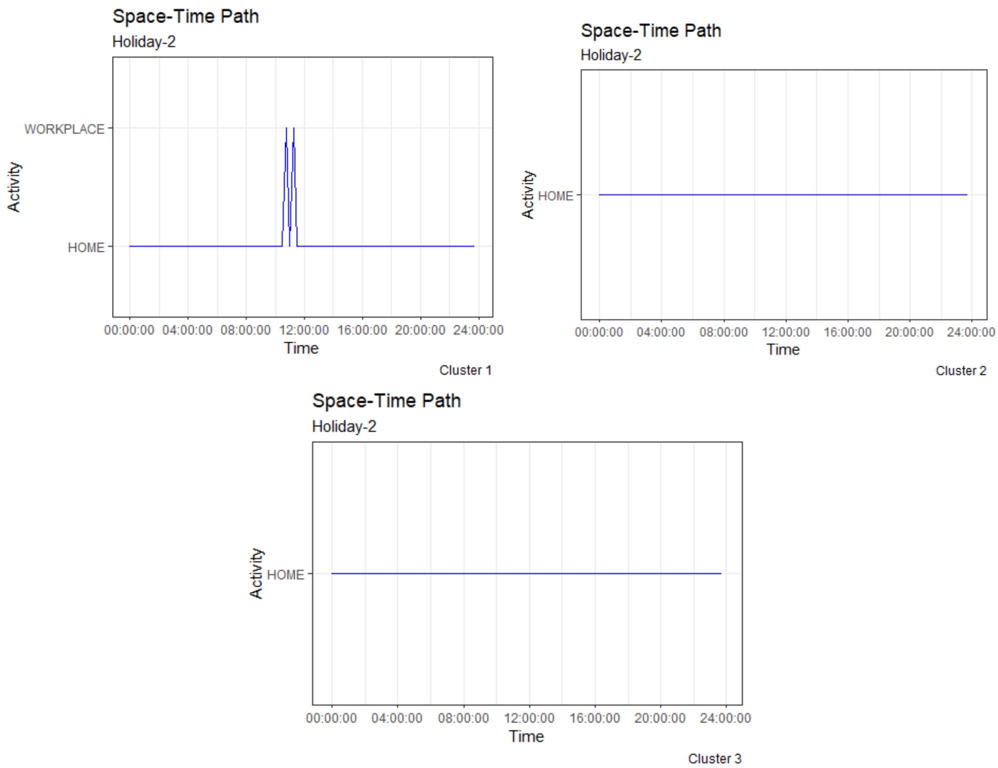

Fig. 13 Holiday-2 travel pattern in each cluster.

5. Conclusions

Discussing daily activity patterns related to transportation remains interesting since trip production can bring problems to human mobility. Statistical modelling with precise algorithms combined in R software can be a tool recommended and widely used to predict travel patterns. Based on the research finding, the purposes of the research meet the expectation of mapping daily activities with a Spatio-temporal approach. Based on the result and discussion, there were three clusters with specific groups member and specific patterns between workdays and holidays. The differences may vary between the clusters; some are likely similar, and others are contrastingly different, depending on the respondent's dispersed activities.

This study uses R to explore daily activity patterns to predict travel production with a Spatio-temporal approach. The data studied in this study came from the daily activity diaries of 400 respondents for four days. The activity diary was divided into two working days and two holidays.

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This study reveals the analysis of differences in the travel production of respondents from three clusters that were made for four days. As a result, the pattern of travel production on working day-1 and working day-2 had a significant difference. This significant difference resulted from optimally formed clusters, where between these clusters, there were apparent differences between cluster members in terms of age groups. Among others, in cluster 1, the majority was filled by student age. In cluster 2, the majority was filled by working age. Cluster 3 was mostly filled by post-productive age. While in holiday-1 and holiday-2, the difference in patterns of travel production was not too significant, the activities carried out by respondents tended to be carried out only at home. However, an analysis of the differences between clusters can still be done in terms of the activity pattern carried out. In contrast, at home, including cluster 2 was filled by respondents who did the most activities at home, cluster 3 was filled by respondents who did fewer activities at home but more than cluster 1, and cluster 1 was filled with people who did the least number of activities at home.

Several shortcomings from this research are notified, including the absence of further analysis regarding the determination of the optimal cluster, especially in cases when the data tends to have a homogeneous pattern, which in this study occured in holiday 1 and 2 data. Further research can use the elbow method and gap statistics to determine the optimal number of clusters in the analysis. Demographic analysis is also limited to age groups and has not led to other things such as gender and occupation.

The main contribution of the research is forming information for readers regarding the use of activity diary data. It can be used to predict trip production patterns in the following assessment. The difference in the pattern of trip production can be analyzed using a Spatio-temporal approach extracted from the processed data of the respondent's activity diary that forms in some clusters. This study also illustrates that research on Spatio-temporal can work effectively using statistical science-based software, namely Rstudio.

Rstudio is one software widely used in studies discussing Spatio-temporal and related GIS (Geographic Information System). This research contribution hopefully benefits transportation science, where Spatio-temporal modelling is needed in the field to find where and when a person travels. This study also applies to social statistics, where there are differences in the behavior of the respondent's activity pattern and each cluster, especially on working day 1 and working day 2, which have optimal clusters in terms of age groups. The fact-finding notifies that there are differences in behavior from the activity pattern.

Although it has a limitation, this statistical method and the software can use in further research by referring to the shortcomings, benefits, and applications described previously. Future research regarding the prediction of trip production using a Spatio-temporal approach, such as analysis to determine the optimal cluster, as well as further analysis by exploring demographic data in terms of gender, occupation, and other socio-demographic factor can use this method.

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