# Factors affecting carsharing accessibility behavior in Bangkok

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## Abstract

Carsharing is a new mode of travel that has become increasingly popular in several countries. Due to the features of the service that can support and connect with the public transport networks. A number of factors can influence user behavior and accessibility of the service, both of which vary in many different contexts. This study therefore focuses on factors that affect the accessibility behavior of carsharing in Bangkok. The results showed that those factors, including access distance to a carsharing station and vehicle ownership, have significant impacts on accessibility and user behavior in terms of public transport use, personal transport use and walking. In this study, accessibility of the carsharing users was analyzed through a set of statistical models, it was found that the artificial neural network model (ANN) proved to be more effective than the multinomial logistic regression model (MLR) in predicting the results of the user behavior and the accessibility of carsharing. The finding in this study can be as a guideline to determine the location of carsharing stations and improve the quality of carsharing service in Bangkok.

**Keywords:** carsharing, accessibility, transportation model, artificial neural network model, multinomial logistic regression model

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## Introduction

Shaheen, & Cohen (2016) described carsharing as a form of car rental whereby people rent vehicles for short periods of time and for their particular purposes, with the full utility of the rented vehicle. It is also a mode of transport that is popular in many countries. A study found that carsharing has become instrumental in decreasing car ownership. Carsharing users can have access to rental vehicles at stations through online applications. It is considered one of the modern modes of travel in Thailand.

Generally, carsharing stations are located near 24-hour parking lots where different modes of travel, including public bus and rail transit, can be interconnected to facilitate urban travel. In some countries, one-way carsharing services are available for users who travel from one particular starting point to the destination.

The locations of carsharing stations, together with the integrated networks of transport in different countries, have thus been the major factors that affect user behavior and accessibility of carsharing. For instance, if a carsharing station is located next to a rail transit system or a bus stop, users of carsharing are more inclined to use those modes of public transport in order to access carsharing services. In some countries, it is found that people tend to opt for bikesharing to access carsharing services if bike lanes are available. Studies on factors influencing travel behavior have also been conducted in many countries in order to develop transport models.

Faghri, & Hua (1992) applied the artificial neural network (ANN) model in the transport engineering problems. The study aimed to analyze trip generation models based on vehicle travel data on tollways in northern Texas, the United States. The result showed that factors of travel distance and travel time had a considerable effect on travel volumes. The MLR model and the ANN model were also created as the trip generation models to compare prediction errors of the data. It was found that the ANN model is more effective than the MLR model in predicting the results, with minimum error values. The ANN model thus proved more suitable for analyses on transport engineering.

Rao, Sikdar, Rho, & Dhingra (1998) analyzed mode choices of transport, which include walking, public bus, motorcycle, car and taxi, in the Indian city of Mumbai. Socio-demographic data, waiting time for public bus and taxi services, travel time and expenses incurred from traveling were considered in the study. Following the interview of 4,335 commuters, it was found that socio-demographic data had a considerable influence on those mode choices. The comparison between the application of the MLR model and the ANN model was also made, with the result illustrating that the efficacy of the ANN model is greater than the MLR model by 12%.

Hussain et al. (2017) also studied mode choices of transport in Baghdad, Iraq, using data on public bus and public van (instead of private vehicles). Factors of socio-demographic data, driver's license, car ownership, travel distance and travel time from a residence to an office played pivotal roles in shaping the decisions over mode choices of public bus and public van. The interview of 620 private car users also showed that these factors influenced a shift from private vehicles to mode choices of public bus and public van. This led to a comparison between the MLR model and the ANN model, with the prediction results illustrating that the former was 76.2% accurate, whereas the latter was 80.9% accurate.

Lee, Derrible, & Pereira (2018) studied mode choices of transport in Chicago, the United States by using travel data and Travel Diary. The data derived from a sample of 10,500 cases included socio-demographic data, number of household vehicles, travel time, travel modes and travel expenses. The result showed that factors of socio-demographic data and travel expenses influenced decisions on mode choices. A comparison between both transport models was also made for the prediction results, showing that the accuracy values of the MLR model and the ANN model were 83.3% and 82.9%, respectively.

Assi, Nahiduzzaman, Ratrout, & Aldosary (2018) studied transport models in Khobar, Saudi Arabia by determining students' mode choices for commuting to school. The data applied in this study was garnered from a sample of 1,000 students, aged 16-18. They included socio-demographic data, household income, travel time, travel modes between home and school. It was found that factors of household income and travel time impacted decisions on mode choices, which included walking and private vehicle use. A comparison between the MLR model and the ANN model was subsequently made. The ANN model proved more effective in predicting the result, with 78% accuracy value, while the MLR model yielded 69%.

Nowadays, there is a new transportation model for sharing vehicle (such as bicycle, scooter and car). Reiffer, Worle, Heilig, Kagerbauer, & Vortisch (2020) analyzed user behavior that affected the accessibility of carsharing in Karlsruhe, Germany. Accessibility patterns were divided into 6 groups: 1) walking 2) bicycle 3) bike sharing 4) public transport 5) driver's private vehicle and 6) passenger's private vehicle. This categorization was examined with factors of socio-demographic data, travel time and travel expenses. With the application of the MLR model, the result illustrated that factors of travel time and travel expenses affected the ways people accessed carsharing and the most popular method, which was bicycle. Its popularity was due to the features of the vehicle that allow users to travel short distances between carsharing stations. Moreover, the availability of bicycle lanes also encouraged users to access carsharing as a whole.

Due to the result of the aforementioned studies, it can be concluded that socio-demographic factors, travel distance and travel time influence user behavior that affect the accessibility of carsharing. Those factors also include locations of carsharing stations and transport networks, both of which play a role in shaping user behavior concerning the accessibility of carsharing. The studies also lead to the development of 2 transport models, the MLR model and the ANN model, which have become the widely acceptable tools for predicting user behavior concerning carsharing accessibility. The principal aim of these methods is to improve the quality of carsharing and make it more suitable for users' lifestyles.

## Methodology

For the data collection effort, we made an inquiry with regard to user behavior concerning carsharing accessibility. A sample of 484 carsharing users were expected to be interviewed over the phone during August-November 2021, although only 230 of them were actual participants, accounting for 47.52%. The interviews were conducted mainly during 6.00-7.00 pm., as it was outside working time, hence inducing the interviewees to participate.

Following the interviews of 230 carsharing users, the acquired data was filtered to remove some confidential details and collect useful ones for further analysis. The final data included 175 cases associated with socio-demographic data and accessibility data, as shown in (Table 1).

According to (Table 1), the interviewees are 114 men and 61 women, accounting for 65% and 35%, respectively. Age groups consist of 4 groups. The biggest age group comprises 107 carsharing users aged under 30, accounting for 61%. The 30-39 age group consists of 48 users, accounting for 27%. The 40-49 age group consists of 15 users, accounting for 9%. The 50-59 age group consists of 5 users, accounting for 3%. By education level, carsharing users can be divided into 2 groups. The high school level and below consists of 17 users, accounting for 10%, whereas the bachelor degree level and above consists of 158 users, accounting for 90%. There are 129 users who own at least one private car in their households, accounting for 74%, while 46 users do not own private cars in their households, accounting for 26%. Besides, the percentages of users who own motorcycles and those who do not own motorcycles are not distinctly different, with the former 93 users (53%) and the latter 82 users (47%), respectively. For occupation groups, 107 users are government officers and company employees, accounting for 61%. 46 users are business owners, accounting for 26%. 22 users are students, accounting for 13%. Of all interviewees, the percentages of users who use carsharing on weekdays and users who use carsharing on weekends are not distinctly different, with the former 96 users (57%) and the latter 76 users (43%), respectively.

**Table 1** Socio-demographic and carsharing access behavior data.

| variable | category | frequency | percentage |
|---|---|---|---|
| gender | male | 114 | 65 |
| | female | 61 | 35 |
| age | < 30 | 107 | 61 |
| | 30-39 | 48 | 27 |
| | 40-49 | 15 | 9 |
| | 50-59 | 5 | 3 |
| education level | high school level and below | 17 | 10 |
| | bachelor degree level and above | 158 | 90 |
| number of cars in household | none | 46 | 26 |
| | 1 or more than | 129 | 74 |
| number of motorcycles in household | none | 82 | 47 |
| | 1 or more than | 93 | 53 |
| occupation | student | 22 | 13 |
| | business owner | 46 | 26 |
| | government sector / private enterprise | 107 | 61 |
| monthly income | < 15,000 THB | 22 | 13 |
| | 15,001-25,000 THB | 44 | 25 |
| | 25,001-50,000 THB | 80 | 46 |
| | > 50,001 THB | 29 | 16 |
| day type of carsharing usage | weekday | 99 | 57 |
| | weekend | 76 | 43 |
| accessibility | public transport | 100 | 57 |
| | personal vehicle | 50 | 29 |
| | walk | 25 | 14 |
| access distance to carsharing station | 0-0.5 km. | 19 | 11 |
| | 0.51-5 km. | 86 | 49 |
| | 5.1-10 km. | 37 | 21 |
| | > 10 km. | 33 | 19 |

With regard to the user behaviors that affect the accessibility of carsharing, 57% of users access carsharing via modes of public transport, including public bus, rail transit, taxi and motorbike service. This is due to the advantageous locations of carsharing stations in Bangkok that can connect with and support other modes of public transport. Meanwhile, 29% of users access carsharing as drivers and passengers via private vehicles (within a radius of 0.5 kilometers and beyond). In addition, 14% of users, who commute from home to a carsharing station within 0-0.5 kilometers, access carsharing via walking.

In this study, we applied 2 efficient transport models to the analysis of the accessibility and factors that affect users' decisions on travel modes and behaviors. These transport models are the multinomial logistic regression model (MLR) and the artificial neural network model (ANN). The details of them are as follows:

**Multinomial logistic regression model (MLR)**

Multinomial logistic regression model (MLR) as a model suitable for analyzing factors that affect decisions over 3 or more options (McFadden, 1977). The analysis through this method considers all factors and options simultaneously, as well as specifying crucial factors that significantly impact decisions over different options, as shown in (Equation 1).

$$P_{ij} = \frac{e^{\beta' X_{im}}}{\sum_{k=1}^{M} e^{\beta' X_{ik}}} \tag{1}$$

where $P_{ij}$ is the probability that the person i access j mode to carsharing, $\beta'$ is a coefficient that indicates the variable influence, M is total number of access modes, and $X_{ijk}$ is the variable k that influences how the person i access j mode to carsharing.

In this study, we specify coefficients that influence carsharing access behavior for the analysis through the MLR model. The coefficients include 1) Qualitative Data, consisting of sex, age (30 and below=1, 30-39=2, 40-49=3, 50-59=4), education, vehicle ownership of car and motorcycle (None=0 and 1 or more than=1), occupation, monthly income (15,000 THB and below=1, 15,001-25,000 THB=2, 25,001-50,000 THB=3, 50,000 THB and above=4) and day of carsharing usage (weekday=0 and weekend=1) when carsharing is used, and 2) Quantitative Data on accessibility and carsharing use, consisting of travel distance to carsharing stations, actual hour and actual distance.

The results showed that carsharing access behavior can be divided into 3 types (Bucsky, 2020). They are as follows:

- Public transport: taxi, rail transit (BTS or MRT), public bus and motorbike taxi

- Private transport: car, motorcycle, (as a driver or a passenger)
- Walking to carsharing stations (Reference)

**Artificial neural network model (ANN)**

Artificial neural network model (ANN) development of the model was based on a model of animal behavior. It was further developed to study human brains, including learning paradigms. The knowledge is stored in a network as a weight value, which can be adjusted when more learning paradigms are added (McCulloch, & Pitts, 1943). The purpose of the model is to solve a wide range of problems. Generally, the ANN model is composed of:

- Input data: a collection of data stored during the knowledge-gathering process.
- Output data: the actual results from the learning process of the model.
- Weight value: a set of data acquired from the learning process of the model. It is recorded and varies according to input data.
- Summation data: a total sum of input data. In this study, the summation can be calculated in (Equation 2).

$$S = \sum_{i=1}^{n} a_i w_i \tag{2}$$

where S is a summation function, $a_i$ is a summation of input data, $w_i$ is a weight value.

According to the aforementioned process, a wide range of input data and output data of carsharing access behavior are analyzed through the multi-layered ANN model, with added hidden layers, to evaluate the weight value of each input data, as shown in (Figure 1).

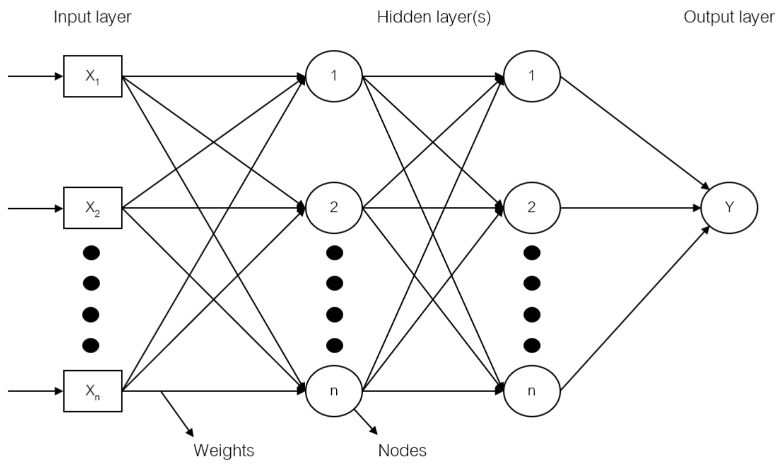


**Figure 1** Basic structure of artificial neural networks model. (Sairamya, Thomas George, Subathra, & Kumar, 2019)

## Results and discussion

Following the analysis through the SPSS program, the factors that influence carsharing access behavior can be summarized in the results from the 2 models below.

### 1. Results from the multinomial logistic regression model

Following those variables, the result of the analysis of carsharing access behavior can be illustrated in (Table 2).

**Table 2** Results from multinomial logistic regression model.

| accessibility | variable | coefficient | df | *P* value (sig.) | Exp (B) | 95% confidence interval for Exp (B) | |
|---|---|---|---|---|---|---|---|
| | | | | | | lower | upper |
| public transport | intercept | -3.80 | 1 | 0.11 | | | |
| | gender | 0.41 | 1 | 0.59 | 1.51 | 0.34 | 6.61 |
| | age | -1.77 | 1 | 0.07 | 0.17 | 0.03 | 1.16 |
| | education | 0.46 | 1 | 0.75 | 1.59 | 0.09 | 27.65 |
| | vehicle | 1.13 | 1 | 0.40 | 3.08 | 0.23 | 41.28 |
| | job | 1.69 | 1 | 0.14 | 5.42 | 0.57 | 51.33 |
| | income | -1.35 | 1 | 0.25 | 0.26 | 0.03 | 2.65 |
| | day | 0.11 | 1 | 0.90 | 1.11 | 0.23 | 5.46 |
| | distance to CS | 2.44 | 1 | 0.00* | 11.42 | 3.40 | 38.29 |
| | travel time | 0.01 | 1 | 0.82 | 1.01 | 0.93 | 1.10 |
| | travel distance | -0.01 | 1 | 0.63 | 0.99 | 0.99 | 1.01 |
| personal vehicle | intercept | -3.42 | 1 | 0.16 | | | |
| | gender | 0.30 | 1 | 0.70 | 1.36 | 0.29 | 6.33 |
| | age | -1.37 | 1 | 0.17 | 0.26 | 0.04 | 1.82 |
| | education | -0.75 | 1 | 0.61 | 0.47 | 0.03 | 8.11 |
| | vehicle | 3.08 | 1 | 0.03* | 8.03 | 0.49 | 132.61 |
| | hob | 0.89 | 1 | 0.46 | 2.38 | 0.25 | 23.20 |
| | income | -1.00 | 1 | 0.41 | 0.37 | 0.03 | 3.98 |
| | day | 0.26 | 1 | 0.75 | 1.30 | 0.25 | 6.72 |
| | distance to CS | 2.45 | 1 | 0.00* | 11.53 | 3.44 | 38.69 |
| | travel time | -0.01 | 1 | 0.92 | 0.99 | 0.91 | 1.09 |
| | travel distance | -0.01 | 1 | 0.24 | 0.99 | 0.99 | 1.00 |
| | No. of observation | 175 | | | | | |
| | -2 Log likelihood | 231.13 | | | | | |
| | Chi-square | 103.36 | 20 | 0.00 | | | |
| | Cox & Snell's R2 | 0.45 | | | | | |
| | Nagelkerke value | 0.52 | | | | | |
| | McFadden's value | 0.31 | | | | | |

*note: 95% confidence level and using type of walk reference in accessibility carsharing behavior model comparative analyzed.

According to (Table 2), significant variables are distance to a carsharing station and vehicle ownership. If the distance access to a carsharing station is within 0.50 kilometers, users are highly likely to opt for walking or users are highly likely to opt for public transport mode if carsharing stations are located in advantageous areas that can be easily accessible by public transport as their travel mode. In addition, users who opt for personal vehicles to access carsharing are highly likely to possess at least one car or one motorcycle. Nevertheless, there are no significant indicators of carsharing access behavior in other variables.

**2. Results from the artificial neural network model**

The structure of the multi-layered ANN model can be illustrated in (Figure 2).

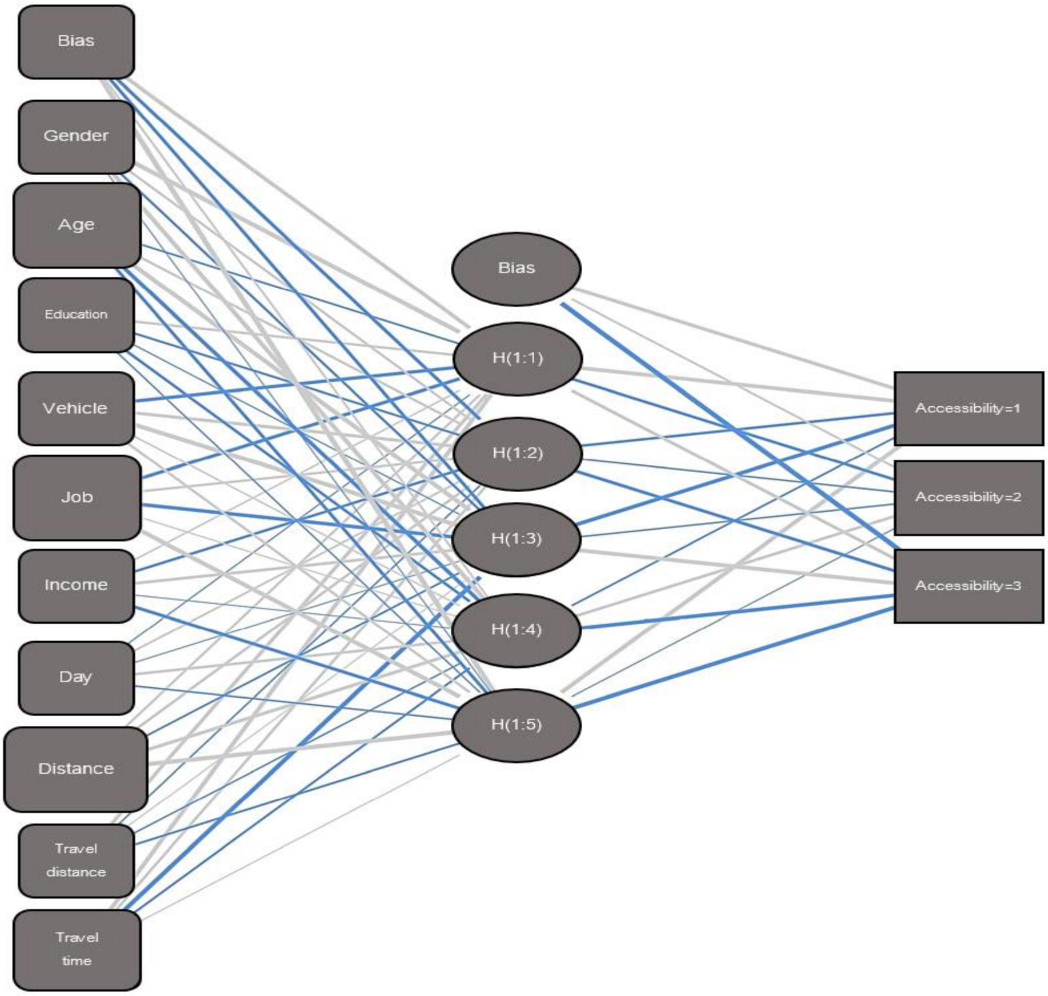


**Figure 2** Structure of ANN from SPSS program.

According to (Figure 2), the ANN model can be divided into 3 layers including:

- Input layers: from the data of gender, age, education, vehicle ownership, occupation, income, day (weekday and weekend), distance from a residence or office to a carsharing station, travel time and travel distance.
- Hidden layers: to evaluate the weight value in each node.
- Output layers: from the carsharing access behaviour data, which consists of Accessibility 1=Public Transport, Accessibility 2=Personal Vehicle and Accessibility 3=Walking.

Following those structures and variables of ANN, the result of the independent variable importance can be illustrated in (Table 3).

**Table 3** Independent variable importance from artificial neural network model.

| variable | importance | normalized importance |
|---|---|---|
| gender | 0.07 | 38.10 |
| age | 0.07 | 39.10 |
| education | 0.08 | 40.70 |
| vehicle | 0.15 | 81.10 |
| job | 0.05 | 27.90 |
| income | 0.08 | 45.40 |
| day | 0.02 | 12.50 |
| distance to CS | 0.18 | 100.00 |
| actual hour | 0.10 | 55.30 |
| actual distance | 0.09 | 50.40 |

According to (Table 3), Independent variables importance are distance to a carsharing station and vehicle ownership similar results from MNL model. Therefore, the analysis results from MNL and ANN models show distance to a carsharing station and vehicle ownership are factors that affects to carsharing accessibility.

3. Model discussion

The comparison between the MLR model and the ANN model in the analysis of all variables that affect carsharing access behavior comprises 2 datasets, which are Training Dataset (70%) and Testing Dataset (30%). The result illustrates that the ANN model proves better and more accurate in accessing carsharing access behavior than the MLR model, with the accuracy of the former 72.2% and the latter 69.1% as in (Table 4) (Hussain et al., 2017; Assi, Nahiduzzaman, Ratrout, & Aldosary, 2018). The efficacy of the ANN model is due largely to its more efficient learning process and evaluation of various sets of input data and output data on carsharing access behavior (public transport, private vehicle and walking).

**Table 4** Model comparison in forecasting the accessibility of carsharing services.

| | forecasting accuracy (%) | |
|---|---|---|
| accessibility | multinomial Logistic regression (MLR) | artificial neural network (ANN) |
| | 69.10 | 72.20 |

## Conclusion

This analytical study aimed primarily to analyze factors and carsharing access behavior in Bangkok. The components of the study include a range of factors that affect carsharing access behavior and modes of transport that users adopt to access carsharing. Two models, the MLR model and the ANN model, are applied for the analysis of user behavior acquired from a sample of carsharing users through the interviews over the phone. It was found that 57% of users, which constitute the largest proportion, opt for public transport (taxi, rail transit, public bus and motorbike taxi) as their travel mode to a carsharing station within 5 kilometers. This is because carsharing stations are located in advantageous areas that can be easily accessible by public transport. Furthermore, travel distance and vehicle ownership are the 2 factors that significantly impact carsharing access behavior. It is highly probable that carsharing users tend to opt for walking as their travel mode to a carsharing station if the travel distance is less than 0.5 kilometers, while carsharing users who own at least 1 private vehicle tend to commute to a carsharing station by their own vehicles, either as a motorbike rider parking the vehicle at the station or a passenger driven by others. However, there are no significant impacts of other factors on carsharing access behavior in Bangkok.

In analyzing carsharing access behavior through the SPSS program, the results showed that the ANN model proves to have higher accuracy than the MLR model in predicting user behavior affected by different variables. However, due to a limited amount of data, it was more difficult to analyze carsharing access behavior through a multi-layered model with high variances in data on all variables. The ANN model is thus a suitable tool that is more capable of assessing flexible input data and categorizing data on hidden layers. It is generally applied as a guideline for considering the location of a carsharing station to help improve service qualities and carsharing management system, thus developing Thailand's overall transport system in the future.

## Suggestion

Nowadays carsharing user in Thailand is still in an early stage. Therefore, there was a limited number of carsharing users during the study period. In addition, less than 50 percent of the users were willing to provide the carsharing usage to this study. Such limitations of the study have impacts on coefficients and other related significant indicators and can yield results that are less accurate than previous studies conducted with larger sample size. As a result, it is recommended that in the future another survey should be conducted once carsharing service gains popularity in Thailand.

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