In [2]:
```
# Importing Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [3]:
```
# Reading dataset using pandas
train = pd.read_csv('train.csv')
train.head()
```

Out[3]:

	trip_duration	distance_traveled	num_of_passengers	fare	tip	miscellaneous_fees	total_fare	surge_applie
0	748.0	2.75	1.0	75.00	24	6.300	105.300	
1	1187.0	3.43	1.0	105.00	24	13.200	142.200	
2	730.0	3.12	1.0	71.25	0	26.625	97.875	
3	671.0	5.63	3.0	90.00	0	9.750	99.750	
4	329.0	2.09	1.0	45.00	12	13.200	70.200	

In [4]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209673 entries, 0 to 209672
Data columns (total 8 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   trip_duration       209673 non-null  float64
 1   distance_traveled   209673 non-null  float64
 2   num_of_passengers   209673 non-null  float64
 3   fare                209673 non-null  float64
 4   tip                 209673 non-null  int64  
 5   miscellaneous_fees  209673 non-null  float64
 6   total_fare          209673 non-null  float64
 7   surge_applied       209673 non-null  int64  
dtypes: float64(6), int64(2)
memory usage: 12.8 MB
```

In [12]:
```
# Checking for duplicate and null records present in the dataset
print('Duplicate Records : ', train.duplicated().sum())
print()
print('Null Values :\n', train.isnull().sum())
```

```
Duplicate Records :  4325

Null Values :
 trip_duration         0
distance_traveled     0
num_of_passengers     0
fare                  0
tip                   0
miscellaneous_fees    0
total_fare            0
surge_applied         0
dtype: int64
```

In [13]:
```python
# Creating a function to data cleaning
def data_cleaning(data):
    # Drop Duplicate records
    data.drop_duplicates(inplace = True)

    # Removing collumns where trip duration is 0
    data.drop(data[data['trip_duration'] == 0].index, axis = 0, inplace = True)

    # Creating new feature
    data['speed_kmph'] =  ((data['distance_traveled'] * 1000 / (data['trip_duration'])) *

    return data
```

In [14]:
```python
data_cleaning(train)
```

Out[14]:

	trip_duration	distance_traveled	num_of_passengers	fare	tip	miscellaneous_fees	total_fare	surge_a
0	748.0	2.75	1.0	75.00	24	6.300	105.300	
1	1187.0	3.43	1.0	105.00	24	13.200	142.200	
2	730.0	3.12	1.0	71.25	0	26.625	97.875	
3	671.0	5.63	3.0	90.00	0	9.750	99.750	
4	329.0	2.09	1.0	45.00	12	13.200	70.200	
...	...	...	...	...	...	...	...	
209668	1617.0	8.42	1.0	150.00	47	5.800	202.800	
209669	438.0	1.29	1.0	48.75	12	34.575	95.325	
209670	571.0	2.82	1.0	63.75	0	6.000	69.750	
209671	491.0	2.16	1.0	56.25	0	13.500	69.750	
209672	3614.0	33.72	1.0	337.50	0	2.250	339.750	

205315 rows × 9 columns

In [15]:
```python
# Checking for duplicate and null records present in the dataset after cleaning the datase
print('Duplicate Records : ', train.duplicated().sum())
print()
print('Null Values :\n', train.isnull().sum())
```

```
Duplicate Records :  0

Null Values :
 trip_duration         0
distance_traveled     0
num_of_passengers     0
fare                  0
tip                   0
miscellaneous_fees    0
total_fare            0
surge_applied         0
speed_kmph            0
dtype: int64
```

In [19]:
```
train.describe().T.round(2)
```

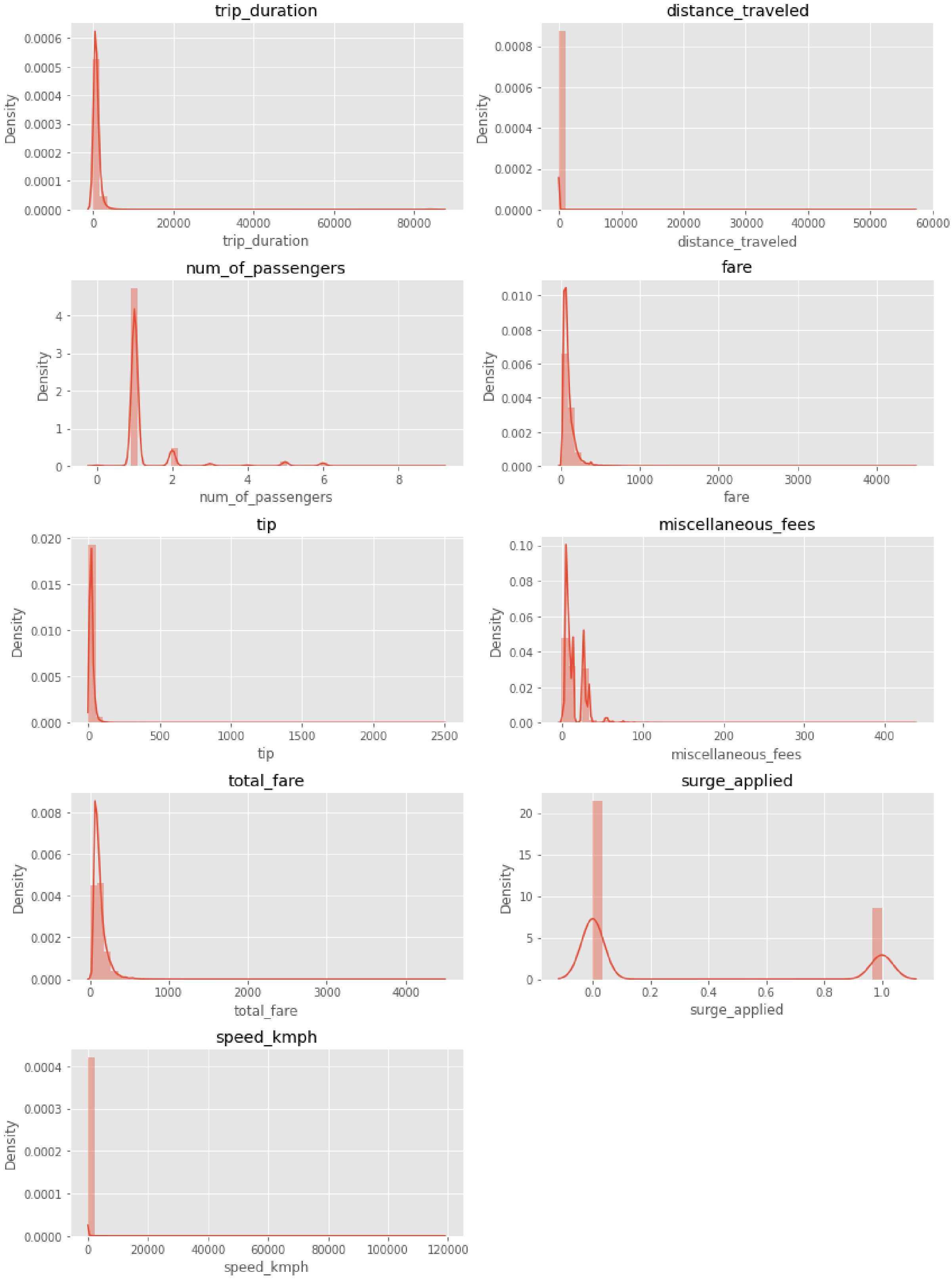
Out[19]:

	count	mean	std	min	25%	50%	75%	max
trip_duration	205315.0	1189.29	4824.67	1.00	454.00	717.00	1110.00	86387.00
distance_traveled	205315.0	5.12	126.54	0.02	2.00	3.25	5.81	57283.91
num_of_passengers	205315.0	1.30	0.94	0.00	1.00	1.00	1.00	9.00
fare	205315.0	100.65	86.13	0.00	52.50	78.75	116.25	4466.25
tip	205315.0	13.25	20.51	0.00	0.00	9.00	20.00	2500.00
miscellaneous_fees	205315.0	15.30	12.62	-0.50	6.00	9.75	26.53	435.00
total_fare	205315.0	129.19	99.27	0.00	73.12	103.50	153.45	4472.25
surge_applied	205315.0	0.29	0.45	0.00	0.00	0.00	1.00	1.00
speed_kmph	205315.0	24.42	347.07	0.00	13.57	17.06	22.26	118928.53

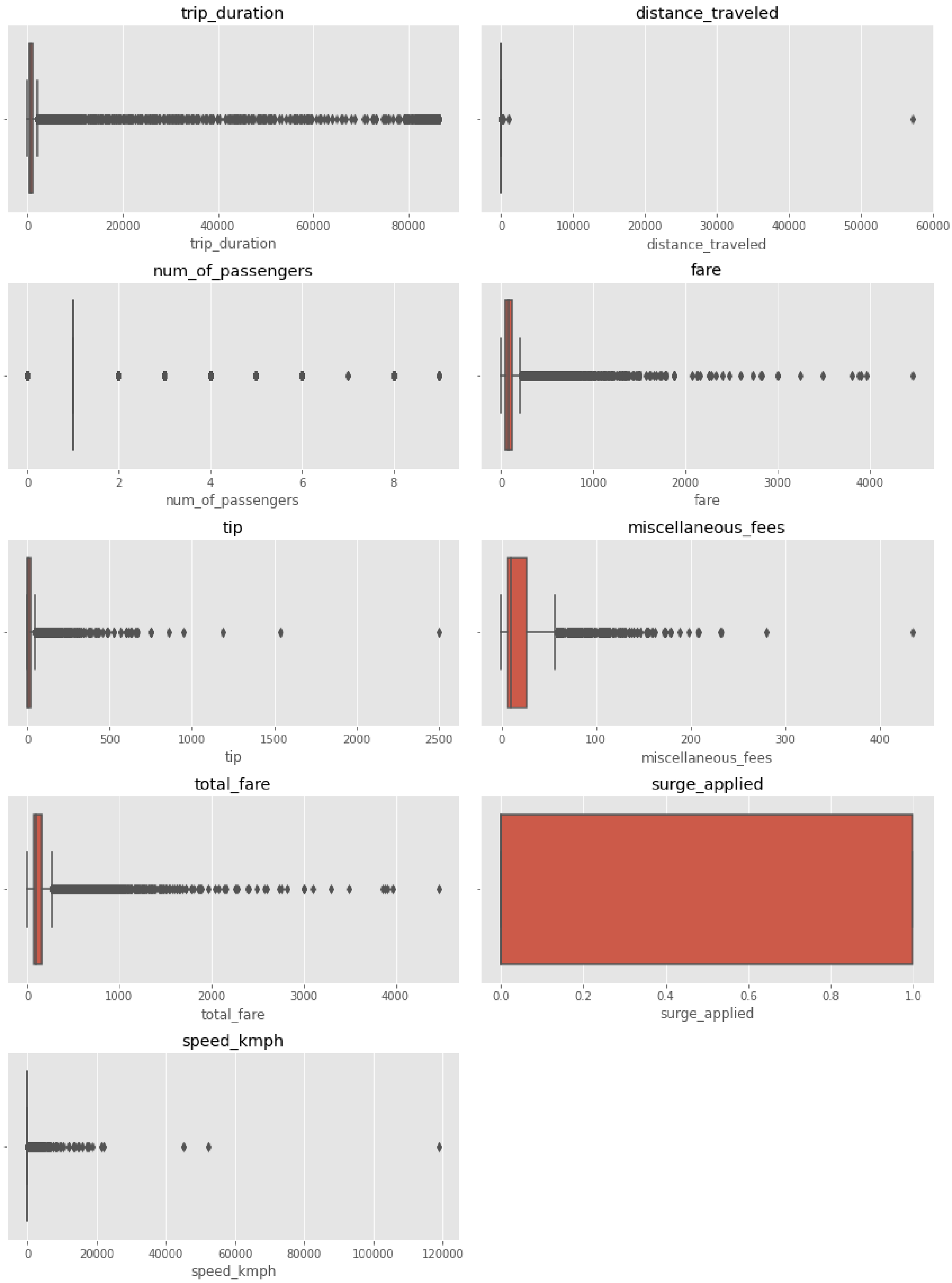
In [22]:
```
plt.style.use('ggplot')
```

In [54]:

```
# Plotting distribution plots of all variables in a dataset
plt.figure(figsize = (12, 16), layout = 'tight')
for i in range(len(train.columns)):
    plt.subplot(5,2, i+1)
    sns.distplot(train[train.columns[i]],)
    plt.title(train.columns[i])
plt.show()
```



In [57]:
```
# Plotting boxplots to check for outliers
plt.figure(figsize = (12, 16), layout = 'tight')
for i in range(len(train.columns)):
    plt.subplot(5,2, i+1)
    sns.boxplot(train[train.columns[i]])
    plt.title(train.columns[i])
plt.show()
```



- From the above distribution plots and boxplots we can observe that there are outliers in this datacand removing these outliers will help in the data normalization

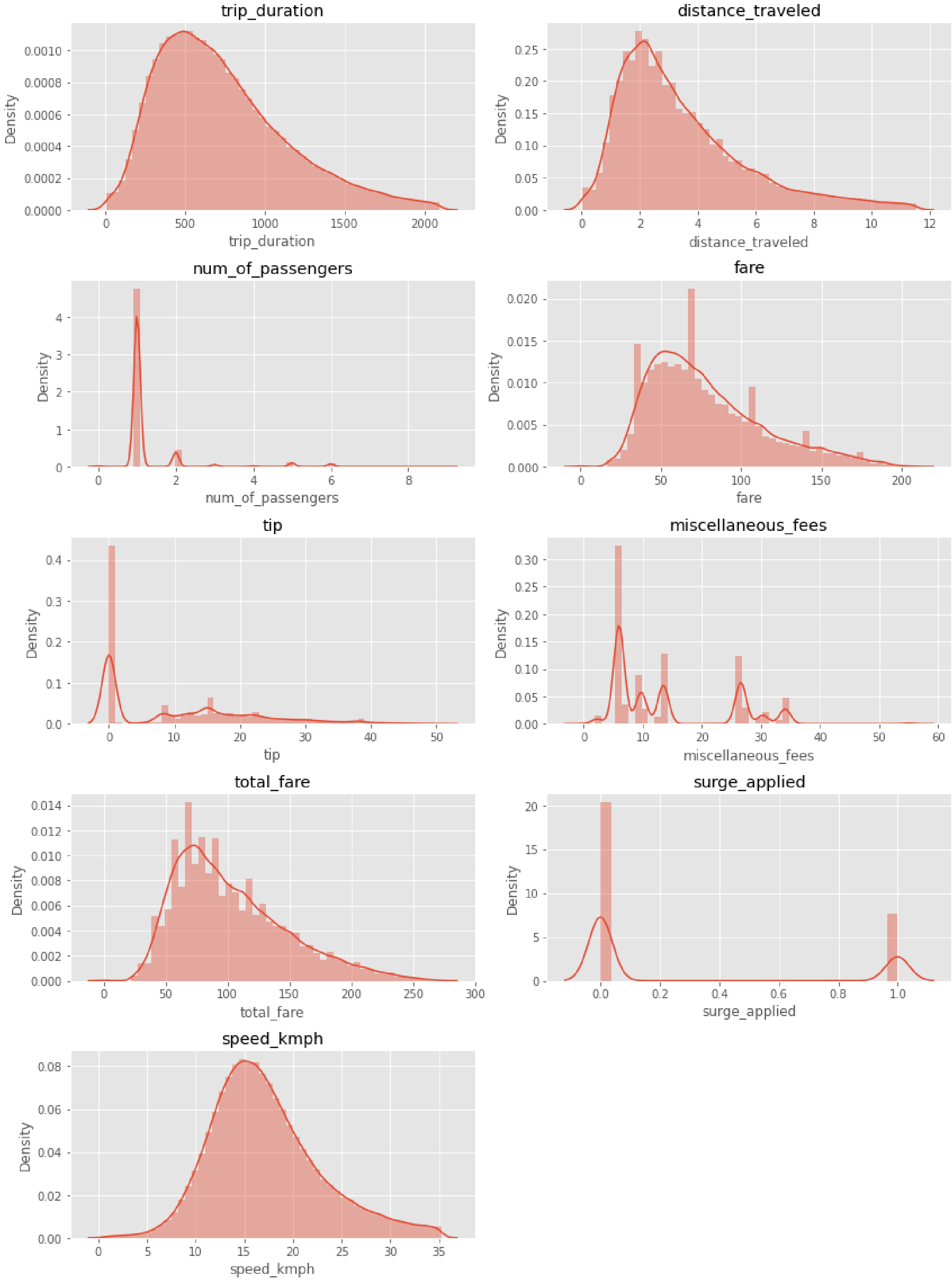
In [58]:

```
# Create a function to remove outliers from the data
def remove_outliers_from_dataframe(df, columns):

    # Select columns to consider for outlier removal
    if columns is None:
        columns = df.select_dtypes(include=[np.number]).columns

    # Create a copy of the original DataFrame
    cleaned_df = df.copy()

    # Iterate through selected columns and remove outliers
    for column in columns:
        # Calculate the first and third quartiles (Q1 and Q3)
        q1 = df[column].quantile(0.25)
        q3 = df[column].quantile(0.75)

        # Calculate the interquartile range (IQR)
        iqr = q3 - q1

        # Define the lower and upper bounds for outliers
        lower_bound = q1 - 1.5 * iqr
        upper_bound = q3 + 1.5 * iqr

        # Remove outliers from the selected column
        cleaned_df = cleaned_df[(cleaned_df[column] >= lower_bound) & (cleaned_df[column]

    return cleaned_df
```

In [60]:

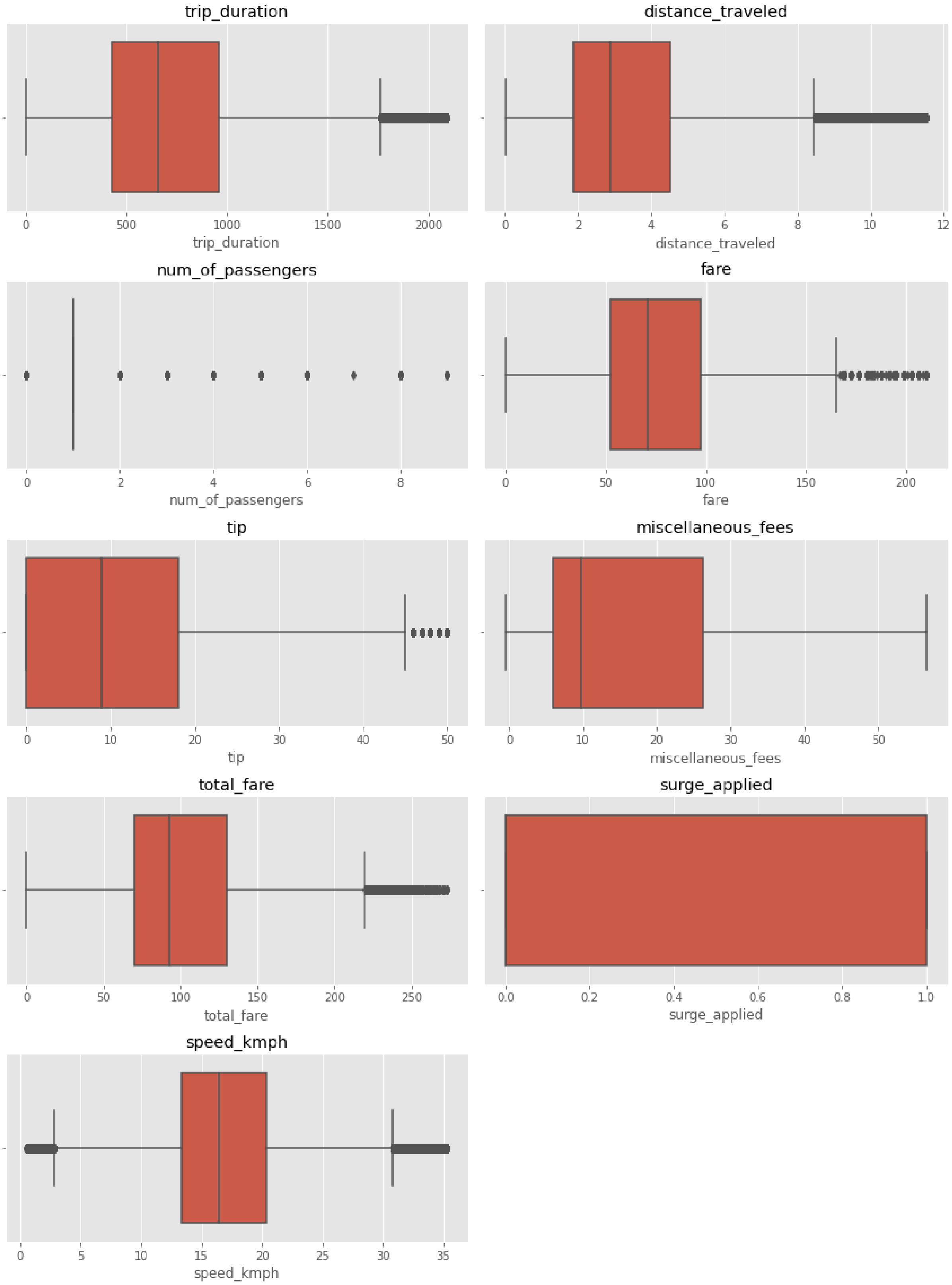
```
# Creating a new_train dataset which do not have any outliers
cols = ['trip_duration', 'distance_traveled', 'fare', 'tip', 'miscellaneous_fees', 'total_
new_train = remove_outliers_from_dataframe(train, columns = cols)
```

In [62]:
```python
# Plotting the distribution plots again to check if the outliers are removed or not
plt.figure(figsize = (12, 16), layout = 'tight')
for i in range(len(new_train.columns)):
    plt.subplot(5,2, i+1)
    sns.distplot(new_train[new_train.columns[i]])
    plt.title(new_train.columns[i])
plt.show()
```



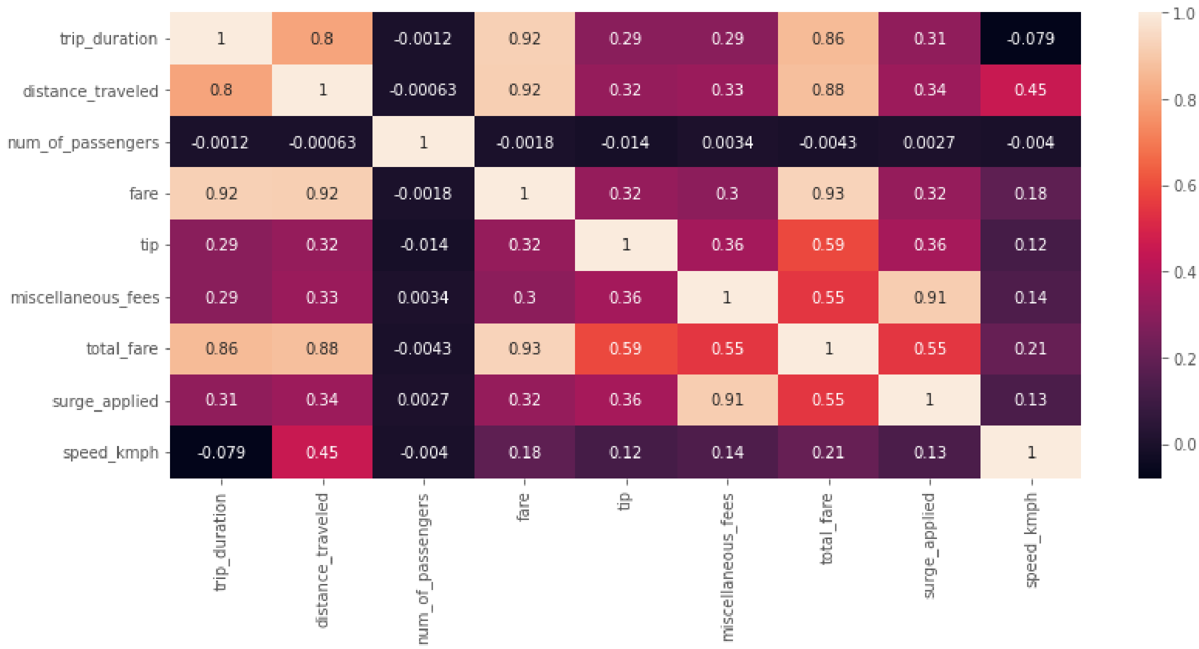
In [63]:

```
# Plotting boxplots again to check if the outliers are removed or not

plt.figure(figsize = (12, 16), layout = 'tight')
for i in range(len(new_train.columns)):
    plt.subplot(5,2, i+1)
    sns.boxplot(new_train[new_train.columns[i]])
    plt.title(new_train.columns[i])
plt.show()
```



In [67]:
```python
# Plotting a heatmap showing the correlation between the features
plt.figure(figsize =  (12, 6), layout = 'tight')
sns.heatmap(new_train.corr(), annot = True)
```

Out[67]:
```
<Axes: >
```



- Dropping the 'fare' column also since the target column and 'fare' column is highly correlated and it might affect the predictions after training the model.

In [68]:
```python
# Creating new datasets for dependent and independent variables
X = new_train.drop(['total_fare', 'fare'], axis = 1)
Y = new_train[['total_fare']].values

# Scaling the data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = scaler.fit_transform(X)

# splitting the data into training and testing sets
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size = 0.25, random_state =

print('Training Features Shape : ', x_train.shape)
print('Training Labels Shape   : ', y_train.shape)
print('Testing Features Shape : ', x_test.shape)
print('Testing Labels Shape   : ', y_test.shape)
```

In [74]:
```python
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

Decision Tree

In [76]:
```
from sklearn.tree import DecisionTreeRegressor
dt_regressor = DecisionTreeRegressor(max_depth = 500, random_state = 42)
dt_regressor.fit(x_train, y_train)

dt_pred_train = dt_regressor.predict(x_train)
dt_pred_test = dt_regressor.predict(x_test)

print('Training Score : ', r2_score(y_train, dt_pred_train))
print('Testing Score  : ', r2_score(y_test, dt_pred_test))
print()
print('Mean Absolute Error     : ', mean_absolute_error(y_test, dt_pred_test))
print('Root Mean Squared Error : ', np.sqrt(mean_squared_error(y_test, dt_pred_test)))
```

```
Training Score :  0.9997381943234211
Testing Score  :  0.9693139414137188

Mean Absolute Error     :  2.6048749568817122
Root Mean Squared Error :  7.956235255926912
```

In [79]:
```
from xgboost import XGBRegressor
xg_regressor = XGBRegressor(n_estimators = 800, max_depth = 300, random_state = 42)
xg_regressor.fit(x_train, y_train)

xg_pred_train = xg_regressor.predict(x_train)
xg_pred_test = xg_regressor.predict(x_test)

print('Training set score : ', r2_score(y_train, xg_pred_train))
print('Testing set score  : ', r2_score(y_test, xg_pred_test))
print()
print('Mean Absolute Error     : ', mean_absolute_error(y_test, xg_pred_test))
print('Root Mean Squared Error : ', np.sqrt(mean_squared_error(y_test, xg_pred_test)))
```

```
Training set score :  0.9997381940103195
Testing set score  :  0.9785926144343826

Mean Absolute Error     :  2.4812468830508667
Root Mean Squared Error :  6.64536556699745
```

In [95]:
```
from sklearn.ensemble import RandomForestRegressor
rf_regressor = RandomForestRegressor(n_estimators= 1000, max_depth= 300, random_state=100)
rf_regressor.fit(x_train, y_train)

rf_pred_train = rf_regressor.predict(x_train)
rf_pred_test = rf_regressor.predict(x_test)

print('Training Set Score : ', r2_score(y_train, rf_pred_train))
print('Testing Set Score  : ', r2_score(y_test, rf_pred_test))
print()
print('Mean Absolute Error     : ', mean_absolute_error(y_test, rf_pred_test))
print('Root Mean Squared Error : ', np.sqrt(mean_squared_error(y_test, rf_pred_test)))
```

```
Training Set Score :  0.9973772665291512
Testing Set Score  :  0.9815891979035146

Mean Absolute Error     :  2.125877628663771
Root Mean Squared Error :  6.162733904273959
```

- All the models performs very well on the dataset and the accuracy metrics scores also satisfied.
- Since random forest gave best results from all the above trained algorithms, it can be used as final model.

In [96]:
```
# Saving the model
import joblib
model = rf_regressor
filename = 'taxi_price_model.sav'
joblib.dump(model, filename)
```

Out[96]: ['taxi_price_model.sav']

In [128]:
```
# Reading the data for which we have to make predictions
val_data = pd.read_csv('test.csv')
val_data.head()
```

Out[128]:

	trip_duration	distance_traveled	num_of_passengers	fare	tip	miscellaneous_fees	total_fare	surge_applied
0	1076.0	4.18	1.0	0	0	13.500	0	0
1	429.0	1.48	4.0	0	0	13.500	0	0
2	856.0	4.15	1.0	0	24	6.000	0	0
3	622.0	3.22	1.0	0	15	5.625	0	0
4	507.0	3.98	1.0	0	0	2.250	0	0

In [131]:
```
predicted_data = val_data.copy()
```

In [133]:
```
val_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 89861 entries, 0 to 89860
Data columns (total 8 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   trip_duration       89861 non-null  float64
 1   distance_traveled   89861 non-null  float64
 2   num_of_passengers   89861 non-null  float64
 3   fare                89861 non-null  int64  
 4   tip                 89861 non-null  int64  
 5   miscellaneous_fees  89861 non-null  float64
 6   total_fare          89861 non-null  int64  
 7   surge_applied       89861 non-null  int64  
dtypes: float64(4), int64(4)
memory usage: 5.5 MB
```

In [134]:
```
# Data Cleaning and preprocessing
val_data.drop(['fare'], axis = 1, inplace = True)

val_data = scaler.fit_transform(val_data)
```

In [135]:
```
# Load the saved model
loaded_model = joblib.load(filename)

# Make predictions
val_prediction = model.predict(val_data)
```

In [137]:
```
predicted_data['Predicted_fare'] = pd.DataFrame(val_prediction)
```

In [138]:
```
predicted_data
```

Out[138]:

	trip_duration	distance_traveled	num_of_passengers	fare	tip	miscellaneous_fees	total_fare	surge_appl
0	1076.0	4.18	1.0	0	0	13.500	0	
1	429.0	1.48	4.0	0	0	13.500	0	
2	856.0	4.15	1.0	0	24	6.000	0	
3	622.0	3.22	1.0	0	15	5.625	0	
4	507.0	3.98	1.0	0	0	2.250	0	
...	...	...	...	...	...	...	...	
89856	435.0	2.24	1.0	0	13	13.700	0	
89857	519.0	2.61	1.0	0	7	13.850	0	
89858	450.0	2.24	1.0	0	0	26.625	0	
89859	919.0	4.12	1.0	0	25	30.200	0	
89860	441.0	3.52	1.0	0	23	6.175	0	

89861 rows × 9 columns

In [ ]: