

## Project overview:

The objective of this project is to analyze driving behaviors of Pakistan and identify any differences between genders. The project aims to understand how gender may influence various driving outcomes, such as accident rates, speeding violations, and adherence to traffic rules. By exploring these patterns, we can gain insights into potential gender-based disparities in driving behaviors.

## Importing Libraries

```
In [2]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind, chi2_contingency
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler, LabelEncoder

import warnings
warnings.simplefilter("ignore")
```

## Loading Dataset

The dataset used for this analysis contains information on a sample of drivers, including their demographic characteristics, driving history, and recorded incidents. The dataset includes variables such as age, gender, number of accidents, speeding violations, and other relevant driving-related attributes.

```
In [3]: df = pd.read_csv(r"C:\Users\razam\Downloads\Pak Data.csv")
```

Statistical Insights

In [4]:

df.head()

Out[4]:

	Driver ID	Name	Age	Gender	Years of Driving Experience	Location	Occupation	Marital Status	Socioeconomic Status	
0	1	Ali Hassan	35	Male	15	Lahore	Engineer	Married	Middle Class	
1	2	Fatima Khan	42	Female	20	Karachi	Doctor	Married	Upper Class	
2	3	Usman Ahmed	28	Male	5	Islamabad	Teacher	Single	Lower Class	
3	4	Asad Khan	55	Male	30	Peshawar	Business Owner	Married	Upper Middle Class	
4	5	Ayesha Malik	31	Female	10	Lahore	Lawyer	Divorced	Upper Class	

5 rows × 34 columns

```
In [5]: df.dtypes
```

```
Out[5]: Driver ID          int64
        Name             object
        Age              int64
        Gender           object
        Years of Driving Experience  int64
        Location         object
        Occupation       object
        Marital Status   object
        Socioeconomic Status  object
        Driver's License object
        Accident Type    object
        Accident Location object
        Date             object
        Time             object
        Weather Conditions object
        Road Conditions  object
        Accident Severity object
        Average Speed    int64
        Traffic Signal Violations  int64
        Distracted Driving Frequency  object
        Traffic Violations  int64
        Training Programs object
        Training Hours    int64
        Certifications   object
        Vehicle Type     object
        Vehicle Make     object
        Vehicle Model    object
        Vehicle Year     int64
        Road Type        object
        Speed Limit      object
        Traffic Signs Present  object
        Road Conditions.1  object
        Distance Traveled (km) float64
        Seatbelt Usage   object
        dtype: object
```

```
In [6]: df.describe()
```

Out[6]:

	Driver ID	Age	Years of Driving Experience	Average Speed	Traffic Signal Violations	Traffic Violations	Training Hours
count	1200.000000	1200.000000	1200.000000	1200.000000	1200.000000	1200.000000	1200.000000
mean	600.500000	36.447500	11.879167	57.300000	0.562500	2.246667	12.004167
std	346.554469	7.671133	6.447548	5.129840	0.575647	1.244500	7.232292
min	1.000000	22.000000	2.000000	40.000000	0.000000	1.000000	0.000000
25%	300.750000	32.000000	8.000000	55.000000	0.000000	2.000000	10.000000
50%	600.500000	35.000000	10.000000	55.000000	1.000000	2.000000	14.000000
75%	900.250000	39.000000	15.000000	60.000000	1.000000	2.000000	15.000000
max	1200.000000	63.000000	33.000000	75.000000	2.000000	7.000000	40.000000

## Check Missing Values

```
In [7]: df.isnull().sum()
```

```
Out[7]: Driver ID      0
        Name          0
        Age           0
        Gender        0
        Years of Driving Experience  0
        Location       0
        Occupation    0
        Marital Status 0
        Socioeconomic Status 0
        Driver's License 0
        Accident Type  0
        Accident Location 0
        Date          0
        Time          0
        Weather Conditions 0
        Road Conditions 0
        Accident Severity 0
        Average Speed  0
        Traffic Signal Violations 0
        Distracted Driving Frequency 0
        Traffic Violations 0
        Training Programs 0
        Training Hours 0
        Certifications 0
        Vehicle Type   0
        Vehicle Make   0
        Vehicle Model  0
        Vehicle Year   0
        Road Type      1
        Speed Limit    1
        Traffic Signs Present 1
        Road Conditions.1 1
        Distance Traveled (km) 1
        Seatbelt Usage 1
        dtype: int64
```

```
In [8]: # Option 1: Imputation: Replace missing values with mean of the column
        df_imputed = df.fillna(df.mean())
```

```
In [9]: # Option 2: Removal: Remove rows with any missing values
        df_removed_rows = df.dropna()
```

```
In [10]: # Remove columns with any missing values
         df_removed_cols = df.dropna(axis=1)
```

```
In [11]: # Print the resulting DataFrames
df_imputed.head()
```

Out[11]:

	Driver ID	Name	Age	Gender	Years of Driving Experience	Location	Occupation	Marital Status	Socioeconomic Status
0	1	Ali Hassan	35	Male	15	Lahore	Engineer	Married	Middle Class
1	2	Fatima Khan	42	Female	20	Karachi	Doctor	Married	Upper Class
2	3	Usman Ahmed	28	Male	5	Islamabad	Teacher	Single	Lower Class
3	4	Asad Khan	55	Male	30	Peshawar	Business Owner	Married	Upper Middle Class
4	5	Ayesha Malik	31	Female	10	Lahore	Lawyer	Divorced	Upper Class

5 rows × 10 columns



```
In [12]: # DataFrame with removed rows
df_removed_rows.head()
```

Out[12]:

	Driver ID	Name	Age	Gender	Years of Driving Experience	Location	Occupation	Marital Status	Socioeconomic Status
0	1	Ali Hassan	35	Male	15	Lahore	Engineer	Married	Middle Class
1	2	Fatima Khan	42	Female	20	Karachi	Doctor	Married	Upper Class
2	3	Usman Ahmed	28	Male	5	Islamabad	Teacher	Single	Lower Class
3	4	Asad Khan	55	Male	30	Peshawar	Business Owner	Married	Upper Middle Class
4	5	Ayesha Malik	31	Female	10	Lahore	Lawyer	Divorced	Upper Class

5 rows × 10 columns



```
In [13]: # DataFrame with removed columns
df_removed_cols.head()
```

Out[13]:

	Driver ID	Name	Age	Gender	Years of Driving Experience	Location	Occupation	Marital Status	Socioeconomic Status
0	1	Ali Hassan	35	Male	15	Lahore	Engineer	Married	Middle Class
1	2	Fatima Khan	42	Female	20	Karachi	Doctor	Married	Upper Class
2	3	Usman Ahmed	28	Male	5	Islamabad	Teacher	Single	Lower Class
3	4	Asad Khan	55	Male	30	Peshawar	Business Owner	Married	Upper Middle Class
4	5	Ayesha Malik	31	Female	10	Lahore	Lawyer	Divorced	Upper Class

5 rows × 28 columns



```
In [14]: # Convert data types
df['Years of Driving Experience'] = df['Years of Driving Experience'].astype(int)
df['Occupation'] = df['Occupation'].astype(str)
```

```
In [15]: # Normalize or scale numerical variables
scaler = MinMaxScaler()
df['Years of Driving Experience'] = scaler.fit_transform(df[['Years of Driving Experience']])
```

```
In [16]: # Encode categorical variables
encoder = LabelEncoder()
df['Occupation'] = encoder.fit_transform(df['Occupation'])
```

```
In [17]: # Print the transformed DataFrame
df.head()
```

Out[17]:

	Driver ID	Name	Age	Gender	Years of Driving Experience	Location	Occupation	Marital Status	Socioeconomic Status
0	1	Ali Hassan	35	Male	0.419355	Lahore	4	Married	Middle Class
1	2	Fatima Khan	42	Female	0.580645	Karachi	3	Married	Upper Class
2	3	Usman Ahmed	28	Male	0.096774	Islamabad	6	Single	Lower Class
3	4	Asad Khan	55	Male	0.903226	Peshawar	1	Married	Upper Middle Class
4	5	Ayesha Malik	31	Female	0.258065	Lahore	5	Divorced	Upper Class

5 rows × 10 columns



## Removing duplicates

```
In [18]: df.drop_duplicates(inplace=True)
```

```
In [19]: # Correcting inconsistent values
df['Occupation'].replace({'4': 'Doctor'}, inplace=True)
```



```
In [20]: # Print the cleaned DataFrame
df.head()
```

Out[20]:

	Driver ID	Name	Age	Gender	Years of Driving Experience	Location	Occupation	Marital Status	Socioeconomic Status
0	1	Ali Hassan	35	Male	0.419355	Lahore	4	Married	Middle Class
1	2	Fatima Khan	42	Female	0.580645	Karachi	3	Married	Upper Class
2	3	Usman Ahmed	28	Male	0.096774	Islamabad	6	Single	Lower Class
3	4	Asad Khan	55	Male	0.903226	Peshawar	1	Married	Upper Middle Class
4	5	Ayesha Malik	31	Female	0.258065	Lahore	5	Divorced	Upper Class

5 rows × 10 columns

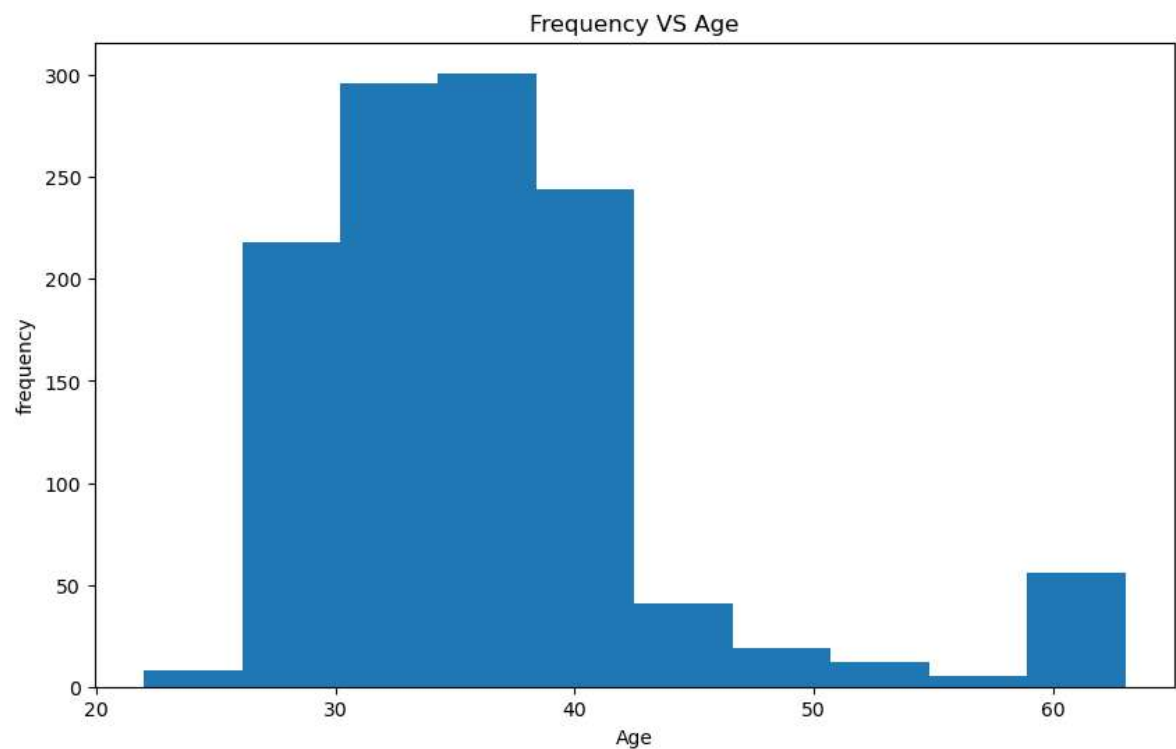
```
In [21]: # Summary statistics
df.describe()
```

Out[21]:

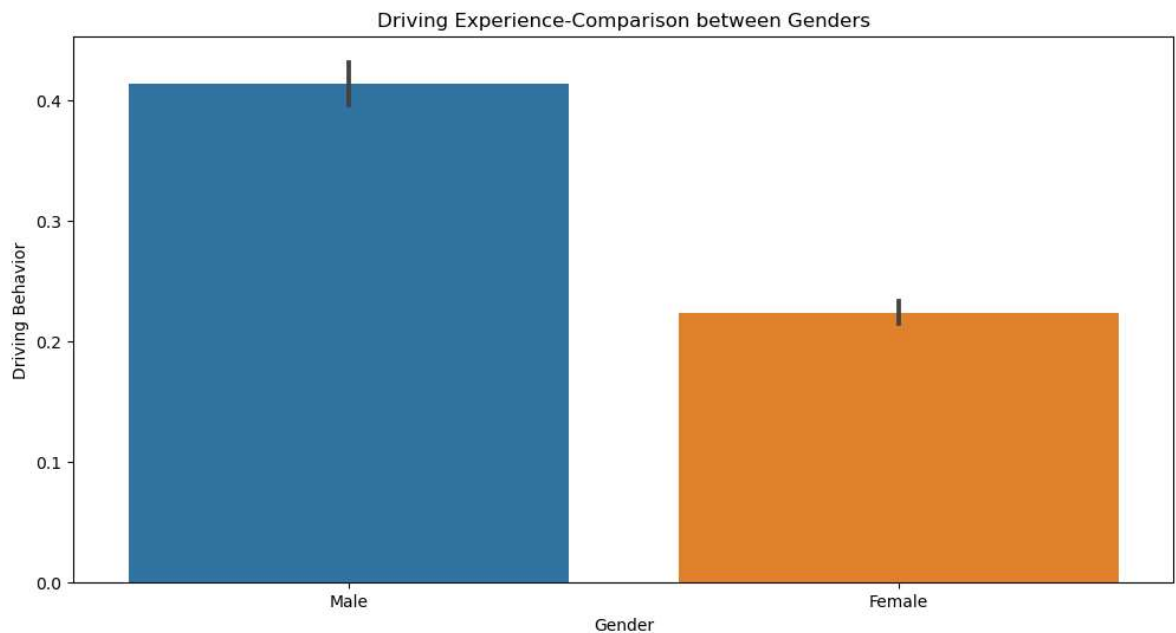
	Driver ID	Age	Years of Driving Experience	Occupation	Average Speed	Traffic Signal Violations	Traffic Violation
count	1200.000000	1200.000000	1200.000000	1200.000000	1200.000000	1200.000000	1200.000000
mean	600.500000	36.447500	0.318683	3.143333	57.300000	0.562500	2.246667
std	346.554469	7.671133	0.207985	1.870126	5.12984	0.575647	1.244500
min	1.000000	22.000000	0.000000	0.000000	40.000000	0.000000	1.000000
25%	300.750000	32.000000	0.193548	1.000000	55.000000	0.000000	2.000000
50%	600.500000	35.000000	0.258065	3.000000	55.000000	1.000000	2.000000
75%	900.250000	39.000000	0.419355	4.000000	60.000000	1.000000	2.000000
max	1200.000000	63.000000	1.000000	6.000000	75.000000	2.000000	7.000000

## Visualization

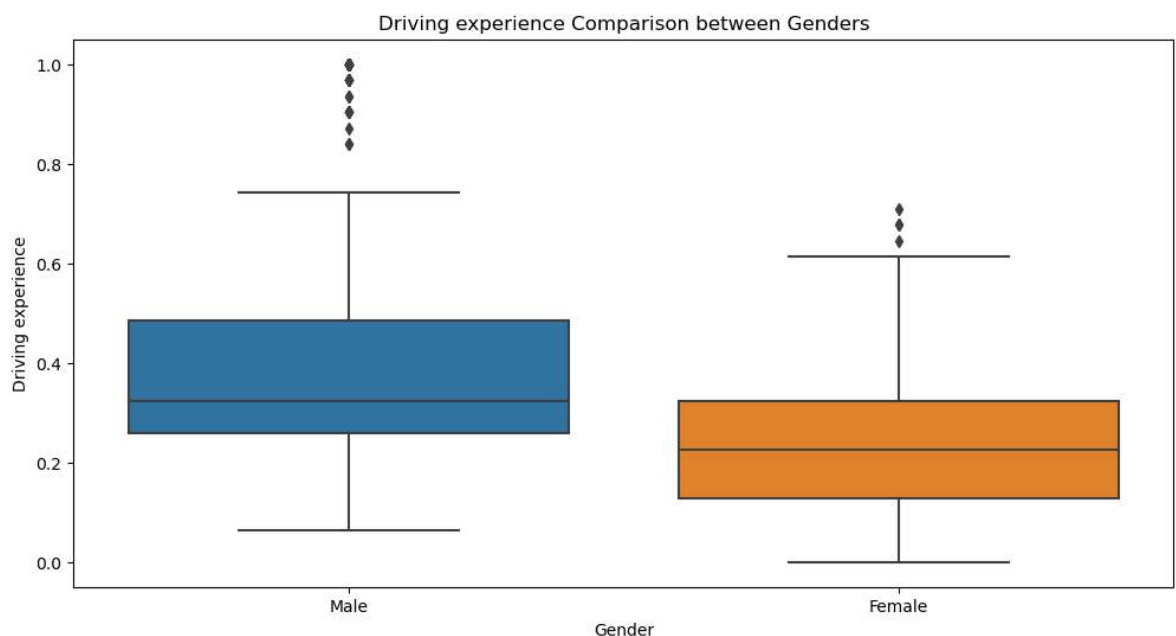
```
In [22]: # Create histograms for numeric variables
plt.figure(figsize=(10, 6))
plt.hist(df['Age'], bins=10)
plt.xlabel('Age')
plt.ylabel('frequency')
plt.title('Frequency VS Age')
plt.show()
```



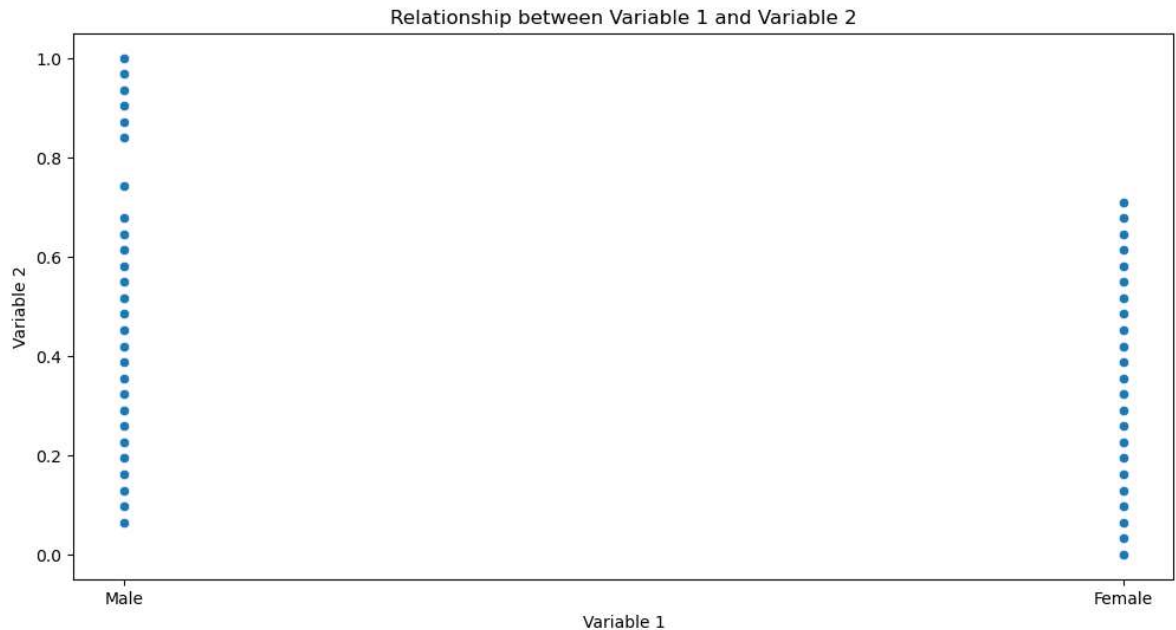
```
In [23]: plt.figure(figsize=(12, 6))
sns.barplot(x='Gender', y='Years of Driving Experience', data=df)
plt.xlabel('Gender')
plt.ylabel('Driving Behavior')
plt.title('Driving Experience-Comparison between Genders')
plt.show()
```



```
In [24]: # Create box plots to compare driving behaviors between genders
plt.figure(figsize=(12, 6))
sns.boxplot(x='Gender', y='Years of Driving Experience', data=df)
plt.xlabel('Gender')
plt.ylabel('Driving experience')
plt.title('Driving experience Comparison between Genders')
plt.show()
```



```
In [25]: # Create scatter plot to explore the relationship between two variables
plt.figure(figsize=(12, 6))
sns.scatterplot(x='Gender', y='Years of Driving Experience', data=df)
plt.xlabel('Variable 1')
plt.ylabel('Variable 2')
plt.title('Relationship between Variable 1 and Variable 2')
plt.show()
```



## Statistical Tests

```
In [26]: # Perform independent samples t-test
t_statistic, p_value = ttest_ind(df[df['Gender'] == 'Male']['Average Speed'],
                                  df[df['Gender'] == 'Female']['Average Speed'],
                                  equal_var=False)

# Print the results
print("t-statistic:", t_statistic)
print("p-value:", p_value)
```

```
t-statistic: -0.8697939346553197
p-value: 0.3845883625986757
```

```
In [27]: # Create a contingency table of observed frequencies
contingency_table = pd.crosstab(df['Years of Driving Experience'], df['Gender'])

# Perform chi-square test
chi2_statistic, p_value, _, _ = chi2_contingency(contingency_table)

# Print the results
print("Chi-square statistic:", chi2_statistic)
print("p-value:", p_value)
```

Chi-square statistic: 539.4795154833507  
p-value: 2.1380163596770716e-95

## Training --- Testing

```
In [28]: # Identify non-numeric columns
non_numeric_columns = ['Name', 'Gender', 'Location', 'Occupation', 'Marital Status',
                        'Accident Type', 'Accident Location', 'Date', 'Time', 'Distance Traveled (km)',
                        'Accident Severity', 'Distracted Driving Frequency', 'Vehicle Type', 'Vehicle Make', 'Vehicle Model', 'Road Conditions.1', 'Seatbelt Usage']
```

```
In [29]: # Perform one-hot encoding on non-numeric columns
df_encoded = pd.get_dummies(df, columns=non_numeric_columns)
```

```
In [30]: # Split the dataset into features (X) and target variable (y)
X = df_encoded.drop('Distance Traveled (km)', axis=1)
y = df_encoded['Average Speed']
```

```
In [31]: # Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
In [32]: # Print the shapes of the resulting datasets
print("Training set shape:", X_train.shape, y_train.shape)
print("Testing set shape:", X_test.shape, y_test.shape)
```

Training set shape: (960, 1076) (960,)  
Testing set shape: (240, 1076) (240,)

```
In [33]: # Create and train the logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)
```

```
Out[33]: LogisticRegression
LogisticRegression()
```

```
In [34]: # Predict on the testing set
y_pred = model.predict(X_test)
```

## Model Accuracy

```
In [35]: # Evaluate the model Accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

Accuracy: 0.8583333333333333

```
In [36]: # Generate classification report
print("Classification Report:\n")
print(classification_report(y_test, y_pred))
```

Classification Report:

	precision	recall	f1-score	support
50	0.00	0.00	0.00	12
55	0.88	1.00	0.94	166
60	0.80	0.74	0.77	38
65	1.00	0.44	0.62	9
70	0.62	0.57	0.59	14
75	0.00	0.00	0.00	1
accuracy			0.86	240
macro avg	0.55	0.46	0.49	240
weighted avg	0.81	0.86	0.83	240

## Conclusion:

### Are Females Really bad at Driving?

No, the belief that females are inherently bad at driving is a stereotype and a misconception. Driving abilities are not determined by gender, but rather by individual skills, knowledge, experience, and responsible behavior.

Research studies have consistently shown that there is no significant difference in driving abilities between genders. Factors such as training, experience, adherence to traffic rules, and individual driving habits have a more significant impact on driving skills and safety than gender alone.

It's important to recognize that generalizing an entire gender based on anecdotal experiences or stereotypes is unfair and can perpetuate bias and discrimination. Each individual's driving abilities should be evaluated on their own merits, irrespective of their gender.

Promoting safe driving practices, providing equal opportunities for driver education and training, and encouraging responsible behaviour on the road are more effective ways to improve overall road safety, regardless of gender. It's essential to challenge and debunk

stereotypes that perpetuate gender-based misconceptions and promote a fair and inclusive environment for all drivers.

### Why do most people have this misconception?

The misconception that females are bad at driving may stem from various factors, including societal norms, cultural beliefs, personal biases, and limited exposure to diverse experiences. Here are some reasons why this misconception may exist:

1. **Gender stereotypes:** Society has long perpetuated gender stereotypes, assigning certain traits or behaviours to specific genders. These stereotypes can create biases and assumptions about abilities, including driving skills. The belief that men are better drivers and women are worse drivers can be a result of these deeply ingrained stereotypes.
2. **Confirmation bias:** Confirmation bias is the tendency to seek or interpret information in a way that confirms pre-existing beliefs. If someone already believes that women are bad drivers, they may selectively remember or notice instances where they witnessed female drivers making mistakes or exhibiting poor driving behavior, while ignoring instances that contradict their belief.
3. **Media influence:** Media portrayals can reinforce gender stereotypes, including those related to driving abilities. Movies, TV shows, advertisements, and other forms of media often depict male characters as skilled and confident drivers, while portraying female characters as more prone to accidents or mistakes behind the wheel. These representations can influence people's perceptions and contribute to the misconception.
4. **Limited exposure:** Limited personal experiences or exposure to diverse drivers can contribute to the perpetuation of this misconception. If someone has had limited interactions with female drivers or has had negative experiences with a few female drivers, they may generalize those experiences to all female drivers without considering the larger context.
5. **Historical biases:** Historically, driving and transportation-related professions have been male-dominated. This may have led to a biased perception that men are more skilled or experienced drivers. As gender roles and societal dynamics evolve, it is important to challenge these historical biases and recognize that driving abilities are not determined by gender.

It is crucial to address and challenge these misconceptions by promoting accurate information, educating individuals about the diverse abilities of drivers across genders, and emphasizing the importance of evaluating driving skills based on individual merits rather than gender stereotypes.

### Explain the importance of addressing the misconception about female driving abilities

Addressing the misconception about female driving abilities is important for several reasons:

1. **Promoting gender equality:** The misconception about female driving abilities perpetuates gender stereotypes and biases. By challenging this misconception, we can promote gender equality and create a more inclusive society where individuals are treated fairly and without discrimination.
2. **Eliminating gender-based discrimination:** If the misconception about female driving abilities persists, it can lead to discriminatory practices such as higher insurance premiums or biased hiring decisions in certain industries. By debunking this misconception, we can

work towards eliminating gender-based discrimination in various aspects of life, including driving.

3. **Improving road safety:** The focus on addressing the misconception about female driving abilities is not about proving superiority or inferiority of one gender over the other. It is about acknowledging that safe driving is not dependent on gender but on individual skills, knowledge, and responsible behavior. By dispelling this misconception, we can shift the focus towards improving road safety for all individuals, regardless of their gender.
4. **Encouraging female empowerment:** Challenging the misconception about female driving abilities can empower women and encourage their active participation in various fields, including traditionally male-dominated areas such as transportation, logistics, and driving professions. It can contribute to breaking down gender barriers and fostering gender diversity and inclusivity.
5. **Enhancing social perceptions:** Addressing the misconception about female driving abilities can help reshape societal perceptions and attitudes towards women. It can challenge and change deeply ingrained stereotypes, leading to a more progressive and equitable society.

Overall, addressing the misconception about female driving abilities is crucial for promoting gender equality, eliminating discrimination, improving road safety, empowering women, and fostering positive social change. It is an important step towards creating a society where individuals are valued and treated based on their abilities, rather than preconceived notions based on gender.

## References:

<http://www.kaggle.com/competitions/kaggle-survey-2020>

(<http://www.kaggle.com/competitions/kaggle-survey-2020>).

[https://r.search.yahoo.com/\\_ylt=Awrle5n8uaFki5MpxhYM34lQ;\\_ylu=Y29sbwNpcjIEcG9zAzEEdn-analysis-and-visualization-with-jupyter-notebook-](https://r.search.yahoo.com/_ylt=Awrle5n8uaFki5MpxhYM34lQ;_ylu=Y29sbwNpcjIEcG9zAzEEdn-analysis-and-visualization-with-jupyter-notebook-22f6dcd25cc5/RK=2/RS=QbFAGeNMloYJfy.zSVaK7n9KuPs-)

[22f6dcd25cc5/RK=2/RS=QbFAGeNMloYJfy.zSVaK7n9KuPs-](https://r.search.yahoo.com/_ylt=Awrle5n8uaFki5MpxhYM34lQ;_ylu=Y29sbwNpcjIEcG9zAzEEdn-analysis-and-visualization-with-jupyter-notebook-22f6dcd25cc5/RK=2/RS=QbFAGeNMloYJfy.zSVaK7n9KuPs-)

([https://r.search.yahoo.com/\\_ylt=Awrle5n8uaFki5MpxhYM34lQ;\\_ylu=Y29sbwNpcjIEcG9zAzEEdn-analysis-and-visualization-with-jupyter-notebook-](https://r.search.yahoo.com/_ylt=Awrle5n8uaFki5MpxhYM34lQ;_ylu=Y29sbwNpcjIEcG9zAzEEdn-analysis-and-visualization-with-jupyter-notebook-22f6dcd25cc5/RK=2/RS=QbFAGeNMloYJfy.zSVaK7n9KuPs-)

[22f6dcd25cc5/RK=2/RS=QbFAGeNMloYJfy.zSVaK7n9KuPs-](https://r.search.yahoo.com/_ylt=Awrle5n8uaFki5MpxhYM34lQ;_ylu=Y29sbwNpcjIEcG9zAzEEdn-analysis-and-visualization-with-jupyter-notebook-22f6dcd25cc5/RK=2/RS=QbFAGeNMloYJfy.zSVaK7n9KuPs-)).

[https://r.search.yahoo.com/\\_ylt=Awrle5n8uaFki5MpyBYM34lQ;\\_ylu=Y29sbwNpcjIEcG9zAzIEdnF](https://r.search.yahoo.com/_ylt=Awrle5n8uaFki5MpyBYM34lQ;_ylu=Y29sbwNpcjIEcG9zAzIEdnF)

([https://r.search.yahoo.com/\\_ylt=Awrle5n8uaFki5MpyBYM34lQ;\\_ylu=Y29sbwNpcjIEcG9zAzIEdnF](https://r.search.yahoo.com/_ylt=Awrle5n8uaFki5MpyBYM34lQ;_ylu=Y29sbwNpcjIEcG9zAzIEdnF)

[https://r.search.yahoo.com/\\_ylt=Awrle5n8uaFki5Mp1BYM34lQ;\\_ylu=Y29sbwNpcjIEcG9zAzMEdr-dysphoria/RK=2/RS=Wrf4elx8V2GRXYzNNUUZJLJIIVk-](https://r.search.yahoo.com/_ylt=Awrle5n8uaFki5Mp1BYM34lQ;_ylu=Y29sbwNpcjIEcG9zAzMEdr-dysphoria/RK=2/RS=Wrf4elx8V2GRXYzNNUUZJLJIIVk-)

([https://r.search.yahoo.com/\\_ylt=Awrle5n8uaFki5Mp1BYM34lQ;\\_ylu=Y29sbwNpcjIEcG9zAzMEdr-dysphoria/RK=2/RS=Wrf4elx8V2GRXYzNNUUZJLJIIVk-](https://r.search.yahoo.com/_ylt=Awrle5n8uaFki5Mp1BYM34lQ;_ylu=Y29sbwNpcjIEcG9zAzMEdr-dysphoria/RK=2/RS=Wrf4elx8V2GRXYzNNUUZJLJIIVk-)

[dysphoria/RK=2/RS=Wrf4elx8V2GRXYzNNUUZJLJIIVk-](https://r.search.yahoo.com/_ylt=Awrle5n8uaFki5Mp1BYM34lQ;_ylu=Y29sbwNpcjIEcG9zAzMEdr-dysphoria/RK=2/RS=Wrf4elx8V2GRXYzNNUUZJLJIIVk-)).





