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How Well Machine Learning Can Help In Predicting Gender Preferences Among Travel Modes?

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Abstract

Understanding gender-specific travel preferences is crucial for designing inclusive urban mobility systems. This study investigates how effectively machine learning models can predict and interpret gender-based travel mode preferences among young adults aged 17 to 24 in Karachi, Pakistan. Data collected through a questionnaire-based survey was analysed, with 92.8% of the dataset retained after pre-processing. The eXtreme Gradient Boosting (XGBoost) algorithm was implemented to predict gender based on travel mode, distance, and purpose, achieving an accuracy of 82.3% with optimised hyperparameters and cross-validation. SHapley Additive exPlanations (SHAP) were used to interpret the model, identifying travel mode as the most influential feature. The model uncovered distinct gender patterns: males favour motorcycles and private cars, whereas females prefer public transport and shuttle services, primarily due to safety concerns. In contrast, males prioritize time efficiency and cost. The model not only achieved high predictive accuracy but also provided interpretable insights into gender-specific travel behaviour. These findings support the development of gender-sensitive urban mobility policies and emphasize the potential of interpretable machine learning in transport planning.

Keywords: Explainable AI, Gender-based transportation, Machine Learning, TreeSHAP, Transportation Modelling, Urban Mobility Patterns,

1. Introduction

Understanding travel behaviour and mode choice is crucial for developing efficient and equitable transportation systems, as these choices directly impact urban mobility and accessibility. A wide array of factors influences these decisions, including socioeconomic status, travel distance, safety, reliability, convenience, and individual preferences (Degeras and Suliman, 2021). Each of these elements interacts uniquely with individual circumstances, shaping travel patterns that mirror broader societal and infrastructural dynamics. Notably, gender stands out as a critical determinant, profoundly influencing travel behaviour. Men and women often face distinct mobility challenges and priorities,

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which shape their decisions when choosing modes of transport, highlighting the need for tailored, inclusive transportation solutions (Tsai, 2023).

In developing countries, particularly in South Asia, gender disparities in travel behaviour are often pronounced due to cultural norms, safety concerns, and access to resources. Men tend to have greater access to private modes of transport like motorcycles and cars, whereas women are more reliant on public transportation or shared modes, primarily due to lower vehicle ownership rates and safety concerns (Zahid, 2023). This dynamic creates an uneven transportation experience and highlights the need for a deeper understanding of how gender influences mode choice.

Recent advances in machine learning (ML) and predictive modelling have opened new avenues for analysing gendered patterns in travel behaviour with greater precision (Omrani, 2015). By processing large, complex datasets, ML techniques uncover subtle interactions between factors that traditional statistical methods might overlook. Algorithms like eXtreme Gradient Boosting (XGBoost) are particularly effective in predicting outcomes with high accuracy, especially for imbalanced or high-dimensional data. Gender-based differences in transportation preferences –shaped by concerns like safety, cost, and convenience –pose challenges that ML models are uniquely suited to address. For researchers and policymakers, these models provide actionable insights into the gendered dynamics of urban mobility, enabling more informed decision-making to design equitable transportation systems.

Focusing on Karachi, Pakistan, a densely populated megacity with a diverse yet challenging transportation network, this study explores gender-specific mode choice preferences. Karachi's transportation system spans private vehicles, public transport options, and shared services; however, it is plagued by inefficiencies, safety concerns, and limited accessibility, particularly for women. By targeting young adults aged 17 to 24 through a questionnaire-based survey, this research leverages XGBoost to predict gender based on travel-related factors like mode choice, distance, and trip purpose. The analysis is further enhanced with SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017), which provide interpretable insights into the features influencing gender-specific travel behaviours. These findings aim to contribute to the design of inclusive urban mobility policies and address the gender disparities within Karachi's complex transportation ecosystem.

2. Literature Review

Machine learning (ML) models offer substantial potential for predicting gender preferences among travel modes by enabling nuanced analyses of gendered travel behaviours. Studies reveal that machine learning can identify and predict distinct preferences and tendencies in travel mode choices between men and women. Gender-specific preferences are shaped by various factors such as safety concerns, convenience, trip chaining, and environmental considerations (Limanond et al. 2011). Women, for example, often prioritize safety and flexibility, favouring public or shared transport options, while men show a higher tendency for private vehicle use, influenced by time efficiency and cost factors (Haynes et al. 2019). These differences reflect distinct travel behaviours, with women frequently making shorter and more chained trips and men undertaking more direct, work-focused trips (Ng and Acker, 2018). Such gendered patterns make machine learning an ideal tool to assess and predict travel modes effectively, especially with techniques that can highlight specific influences on decision-making.

Random forest models, for instance, have consistently outperformed traditional models, such as the multinomial logit (MNL) model, in predicting mode choice due to their ability to handle complex interactions among numerous variables. Hagenauer and Helbich (2017) found random forests highly accurate in modelling travel mode choice, with meteorological factors and trip distance emerging as key determinants. Additionally, more advanced techniques, such as Light Gradient Boosting Decision Trees (LightGBDT), which demonstrated even greater predictive power, allow for deep insights into factors influencing gendered travel behaviours, including age, income, vehicle ownership, and density of destinations (Kashifi et al. 2022).

Advanced machine learning models also bring interpretability to predictions, crucial for gender-focused studies. SHapley Additive exPlanations (SHAP) values in LightGBDT models have proven effective for unpacking variable importance, thus elucidating gender differences in preferences. For instance, Kashifi et al. (2022) showed that women's choices were influenced more by safety and route flexibility, while men prioritized cost and efficiency. Such interpretability methods within machine learning enhance our understanding of gender-based choices, allowing for more informed transport policy development aimed at equitable urban mobility.

Neural networks (NNs), while typically less interpretable than ensemble methods, have demonstrated strong predictive capacity. Ali et al. (2021) found that NNs could better classify choices between public and private transport for both men and women than traditional logistic regression models. These high-performing models offer predictive benefits across gender categories but tend to struggle with interpretability in explaining the behavioural rationale behind gender-based choices. By employing feature importance analyses, researchers have made strides in clarifying some underlying factors within NNs, although ensemble methods generally remain more interpretable for understanding gender influences in travel behaviour.

Machine learning models can also address environmental factors that affect gender-specific travel choices. Zhao et al. (2020) found that random forest models could capture gendered responses to environmental conditions, such as air quality and weather changes, which heavily influence women's travel choices in favour of enclosed or public transport modes. Additionally, machine learning can model individual heterogeneity within gender categories. By incorporating preference variability, ML models provide a nuanced view of mode-switching behaviours under new transit scenarios, such as mobility-on-demand systems, where men's and women's choices differ significantly in response to service characteristics.

Despite ML's predictive advantages, traditional models still play an essential role in explaining behavioural insights due to their interpretive strengths. Studies comparing ML techniques and classical discrete choice models underscore that while machine learning models like extreme gradient boosting (XGBoost) offer higher predictive accuracy, traditional models retain better explanatory power regarding the behavioural dimensions of gendered mode choices (Wang and Ross, 2018). To bridge this gap, researchers often combine ML models with statistical approaches, using ensemble models to gain accuracy while employing traditional models for interpretability, especially in gender-focused research. Table 1 presents a comparison of studies utilizing different modelling techniques with the eXtreme Gradient Boosting (XGBoost).

Table 1 Comparison of Studies Utilizing Different Modelling Techniques with the eXtreme Gradient Boosting (XGBoost)

Reference	*Method Used*	*Key Findings*	*Drawbacks Compared to XGBoost*	*Suitability of XGBoost*
(Wang and Ross, 2018)	XGBoost and Multinomial Logit (MNL)	XGBoost provided higher predictive accuracy for travel mode choices, especially on imbalanced datasets. MNL offered interpretability but with lower predictive accuracy.	MNL is less effective with high-dimensional data, making it inadequate for capturing complex gendered interactions in travel behaviours.	XGBoost is highly suitable due to its robustness with imbalanced and complex data, enabling it to capture interactions relevant to gendered travel preferences.
(Kashifi et al. 2022)	Light Gradient Boosting Decision Trees (LightGBDT), Random Forest, Decision Tree, Logistic Regression, and Multilayer Perceptron	LightGBDT outperformed other models, with key influencing factors identified as trip distance, age, and vehicle ownership.	Random Forest and LightGBDT models can overfit on larger datasets without proper regularization, and Logistic Regression lacks the capacity to model non-linear relationships critical for gendered insights.	XGBoost's regularization features help prevent overfitting, while feature importance analysis (SHAP) provides deeper interpretability for gender-based predictions.
(Hagenauer and Helbich, 2017)	Random Forest, MNL, and SVM	Random Forest provided the highest accuracy in predicting mode choice. SVM was helpful for specific mode predictions like public transport but was less effective overall.	Random Forest can be computationally intensive on high-dimensional data, and SVM lacks scalability and interpretability.	XGBoost is computationally efficient, highly scalable, and offers robust handling of complex data, making it more suitable for gender-focused travel mode studies.
(Ali et al.. 2021)	Neural Network (NN) and Binary Logistic Regression	NN achieved high accuracy, especially for public vs. private transport choices. Logistic Regression was interpretable but less accurate overall.	NNs provide limited interpretability, making it challenging to discern gender-specific factors. They also risk overfitting with limited data.	XGBoost combines NN's accuracy with improved interpretability and regularization, making it more suitable for gender-based travel predictions, where explainability is essential.

(Zhao et al. 2020)	Random Forest and Logit Models (MNL and Mixed Logit)	Random Forest achieved higher predictive accuracy than logit models, though it initially showed behaviourally inconsistent outputs.	Logit models lack the flexibility to capture complex variable interactions, while Random Forest without tuning may yield behaviorally implausible results.	XGBoost can capture complex, nuanced relationships while using regularization to maintain behavioural consistency, which is crucial for gendered analysis.
(Ng and Acker, 2018)	Qualitative analysis and statistical models	Highlighted gendered patterns in urban travel behaviour, with women preferring public transport and men favouring direct routes.	Statistical models have limited predictive power and may miss complex, gendered patterns in large datasets.	XGBoost, with its machine learning power, can model subtle gender-specific preferences in travel behaviour, providing both high accuracy and meaningful insights.
(Haynes et al. 2019)	Qualitative data synthesis with ML	Found that gender differences in travel are tied to subjective safety for women and objective efficiency for men.	Qualitative synthesis lacks predictive capacity and generalizability for large datasets.	XGBoost's SHAP values allow for a detailed interpretation of gender-specific factors, providing actionable insights that qualitative methods lack.

One primary reason XGBoost is well-suited for gender prediction based on travel data is its ability to handle interactions between numerous heterogeneous variables, such as mode choice, travel distance, environmental factors, and demographic indicators. In travel behaviour studies, gendered preferences emerge from intricate relationships among these variables, with nuanced differences in the weights or importance of each feature for men versus women. Wang et al. (2018) found that XGBoost provided more accurate predictions in a multi-class travel mode choice problem compared to MNL, particularly with imbalanced datasets. For gender-based predictions, this capacity to accommodate imbalances is crucial, as the dataset may exhibit varied travel patterns and choices due to the gender distribution.

XGBoost also surpasses other machine learning techniques, such as random forests or support vector machines (SVM), due to its computational efficiency and ability to manage large, high-dimensional datasets without overfitting. Its regularization parameters reduce overfitting by penalizing overly complex models, which is advantageous in gender prediction since travel behaviour data often includes a wide array of both categorical and continuous variables that might otherwise lead to model overfitting. For example, Kashifi et al. (2022) demonstrated that XGBoost's regularization strength helped improve predictive accuracy while maintaining robust interpretability through feature importance, allowing for insights into the factors most strongly associated with gender-based travel choices.

Another key advantage of XGBoost for predicting gender preferences is its capability for interpretability through tools such as SHapley Additive exPlanations (SHAP) values, which offer detailed insights into feature importance at the individual prediction level. SHAP values are particularly helpful for understanding how specific travel factors, such as trip distance, cost, or vehicle ownership, influence gendered mode choices. This interpretability is crucial in applications where explaining model predictions is as important as accuracy. By comparing feature contributions for different genders, XGBoost enables targeted insights into the underlying factors driving travel preferences, supporting more precise recommendations for gender-sensitive transportation planning.

In comparison to neural networks (NNs), which also provide high predictive accuracy, XGBoost retains an edge in interpretability and computational efficiency. NNs are often seen as “black-box” models, and while they excel in predictive power, they are challenging to interpret, especially in studies aiming to understand gender-specific factors in travel mode choice. XGBoost, by contrast, can achieve comparable predictive performance while remaining interpretable, making it preferable in contexts like gender-based travel analysis, where actionable insights are required for policy development.

Thus, XGBoost stands out as a suitable choice for predicting gender based on mode choice and travel-related factors due to its balance of accuracy, handling of complex and imbalanced data, computational efficiency, and interpretability. These advantages position XGBoost as a valuable tool in analysing and predicting gendered travel preferences, ultimately supporting more effective, data-driven transportation policies.

3. Methodology

3.1 Study Area and Dataset Collection

The study was carried out in Karachi City, Pakistan, to investigate the combined impact of gender-based personal preferences on mode choice (Figure 1). The dataset was collected through a structured, questionnaire-based survey. A google form was shared among the respondents. The collected data was then verified through in-person interview. A total of 333 students voluntarily participated in the survey, with ages from 17 to 24 years. This exercise was conducted between July to August 2023. The survey form is divided into two sections: (a) sociodemographic information, including variables such as name, age, gender, address, and vehicle ownership status, and (b) travel-related information, such as preferred mode of transport, reason for the preference, and destination.

Figure 1. Location of Study Area: Karachi City, Pakistan

Based on the provided locations, the average distance travelled (DD) to the destination was estimated. The dataset includes three input variables: distance travelled (DD), purpose or reason for preference (R), and travel mode (MoT), with the target variable being gender (G). MoT is categorized into ten classes, each reflecting a different level of privacy, capacity, and convenience. For example, Motorcycle (=0) and Car (=1) are private modes, whereas Bus (=9) represents a shared, less convenient public option. The *Qingqi* (=6), a shared motorcycle rickshaw (Tahir, 2017), differs from a standard rickshaw (=4) in terms of number of occupants (3 passengers and one driver in Rickshaw, 8 passengers and one driver in Qingqi), structure, operation and user experience. Table 2 outlines the variables definitions. After removing 7.2% of redundant entries, 92.8% of the dataset was retained for model training and analysis.

Table 2 Statistical Summary and Definitions of Variables Used in the Gender Prediction Model.

Variable	*Definition*	*Percentage*	*Min.*	*Max.*	*S.D.*
Name	Respondents' name in text, unique information	/	/	/	/
Age	Respondents' age in years, count	20.7	17	24	1.06
Gender (G)	0 = Female 1 = Male	34.3 65.7	0	1	0.47
Name of Town	Respondents' area or town information, text	/	/	/	/
Travel Distance (DD)	Travel distance between home to destination, continuous (km)	9.63	1	29.5	5.88
Vehicle ownership status	0 = Ownership. Owns vehicle for transportation, e.g., car or motorcycle	63.6	/	/	/
	1 = non-owner. No ownership of the vehicle and uses public transport	36.4	/	/	/
Travel mode (MoT)	0 = Motorcycle. The respondent favoured the motorcycle over other modes.	37.9	0	9	3.58
	1 = Car. The respondents favoured cars over other modes.	12.9			
	2 = BRHS. The respondents favoured Bike ride-hailing services over other modes.	2.6			
	3 = RHS. The respondents favoured (car) ride-hailing services over other modes.	0.64			
	4 = Rickshaw. The respondents favoured rickshaw over other modes.	4.86			
	5 = Van. The respondents favoured Van over other modes	3.2			
	6 = *Qingqi*. The respondents favoured *Qingqi* over other modes	8.1			
	7= Minibus. The respondents favoured minibuses over other modes.	3.9			
	8 = Shuttle. The respondents favoured the shuttle (university shuttle services) over other modes	15.9			
	9 = Bus. The respondents favoured bus/coach services over other modes	10			
Purpose (R)	1 = Cost. The respondents who favoured 'cost' over other reasons	13.6	1	6	1.53
	2 = Time Saving. The respondents who favoured 'time saving' over other reasons	7.4			

	3 = Safety. The respondents who favoured ‘safety’ over other reasons	11.9		
	4 = Reliability. The respondents who favoured ‘reliability’ over other reasons	7.1		
	5 = Convenience. The respondents who favoured ‘convenience’ over other reasons	56		
	6 = Other. The respondent who considers other than above reasons	4		

Note: Min. = minimum, Max. = maximum, S.D. = Standard Deviation.

3.2 XGBoost Model Development

Based on insights from existing literature, the eXtreme Gradient Boosting (XGBoost) algorithm was selected for predictive modelling. The model was first introduced by Friedman (2001). The input features include MoT, R, and DD, with G as the target variable. The model’s objective is to predict the gender of a decision-maker, with gender serving as a binary class-dependent variable. Consequently, the model was trained using the “binary logistic” function for binary classification. After label encoding the dataset, it was split into training and testing sets in an 80:20 ratio before being fed into the model.

Hyperparameter tuning is critical for optimizing the training process in terms of both performance and efficiency. Four key hyperparameters were fine-tuned: learning rate, column sampling per tree, maximum tree depth, and the number of estimators (Wade and Glynn, 2020). A grid search cross-validation technique with k = 5 folds was employed to identify the optimal hyperparameter settings. Table 3 outlines the hyperparameters along with their ranges and the optimal values at which the model achieved the best performance.

Table 3 Optimal Hyperparameters and Definitions for the XGBoost Gender Prediction Model

Name and definition		*Hyperparameters*	*Best parameter*
Max. depth	Determines the length of the tree.	Range(2:8)	7
Colsample_bytree	Randomly selects particular columns according to the given percentage.	0.9/0.8/0.7/0.6/0.5	0.9
Learning rate	Shrink the contribution of individual trees by limiting their influence when building a model	0.5/0.3/0.1/0.05/0.03	0.5
n_estimator	The number of trees in the ensemble.	10/20/30/40/50/60/70	20

3.3 Performance Evaluation Metrics

To assess the model’s performance and reliability, the following evaluation metrics were employed, as outlined in Table 4. The labels in Equations (1) – (4), TP, TN, FP, and FN correspond to true-positive, true-negative, false-positive, and false-negative, respectively. These metrics provide a comprehensive understanding of the model’s accuracy and effectiveness in predicting outcomes.

Table 1 Performance Evaluation Metrics

Evaluation metric and definition		*Equation*
Accuracy	is the measure of correct predictions made out of total predictions	$\frac{TP+TN}{TP+FP+TN+FN}$ (1)
Precision	is the measure of how consistent the prediction is.	$\frac{TP}{TP+FP}$ (2)

Recall or Sensitivity	is the measure of false negative classifications made by the model	$\frac{TP}{TP+FN}$ (3)
F1- score	is the harmonic mean of exactness and completeness of classification	$2 \times \frac{Precision \times Recall}{Precision+Recall}$ (4)

3.4 SHAP experimental setup

The interpretability of machine learning classifier models is crucial for researchers aiming to enhance model performance. Post hoc analysis plays a vital role in understanding feature importance and building trust in model predictions (Kashifi et al. 2022). SHapley Additive exPlanations (or SHAP), developed by Lundberg and Lee (2017), offers a unified measure for feature attribution based on cooperative game theory. SHAP ranks feature importance by calculating the mean SHAP values across all dataset instances using Equation (5).

$$Importance_j = \frac{1}{N} \sum_{i=1}^{N} \left| \phi_{i,j} \right| \qquad (5)$$

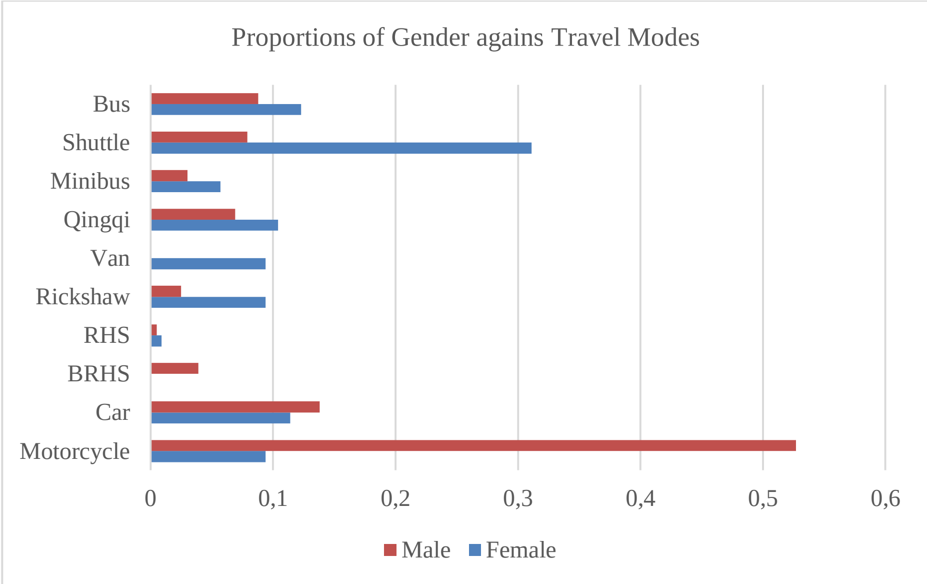
Where $\phi_{i,j}$ represents the SHAP value of sample i for feature j,
N is the number of samples.

SHAP's Python packages provide various plots for visualizing model behaviour, offering comprehensive insights into how each feature influences the model's prediction for a given instance. In this study, we utilized the TreeExplainer tool from the SHAP package (version 0.44.1). TreeExplainer is specifically designed to work with tree-based models (Lundberg et al. 2018) and uses the TreeSHAP algorithm, an optimized method for calculating SHAP values efficiently within gradient boosting models.

4. Results and Discussion

4.1 Statistical Analysis

The prediction of gender, based on factors like travel mode, distance, and the reason for choosing a particular mode, reveals distinct patterns. Figure 2 presents the proportions of feature distribution correlated with gender. 'Van' usage is predominantly linked to female students, while bike ride-hailing services are more commonly used by males, indicating a gender-specific preference in transportation choices. Females are more likely to opt for shuttle services and buses, with 0.311 and 0.123, respectively, whereas males show a strong preference for motorcycles, with 0.527 favouring this mode. In terms of reasons for mode selection, convenience is the primary factor for both genders, with 0.519 of females and 0.581 of males prioritizing it. Females rank safety as their second most important factor, while males prioritize cost, with safety being the least important consideration from them at 0.074. These patterns underscore the role of cultural context in shaping gender-based travel preferences, which is critical for accurately predicting gender in the model.



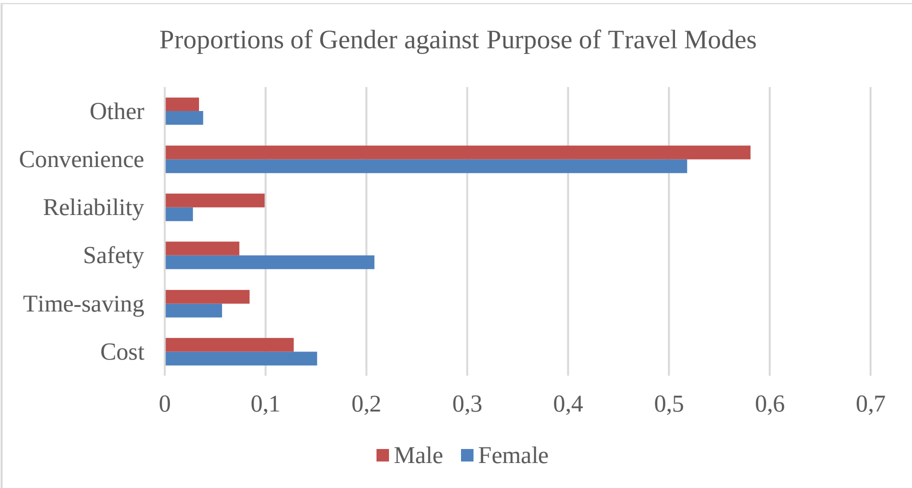


Figure 2 Proportions of Feature Distribution for Individual Gender Class *vs* Travel Modes, Purpose of Travel Modes

4.2 Model performance evaluation

The initial XGBoost model achieved an accuracy of 77.3%. To enhance its performance, a two-phase optimization approach was employed using the best parameters outlined in Table 3. This process incorporated repeated stratified K-fold cross-validation with 3 repeats and 5 splits and a fixed random state of 42. This optimization improved the model’s accuracy to 82.3% on the 11th run, with a standard deviation of 0.06.

The process involves two phases of hyperparameter optimization. In the first phase, the model undergoes training and hyperparameter tuning using a random search or another tuning method to identify the optimal set of hyperparameters. Once these parameters are recorded, the second phase involves training a new model initialized with the identified hyperparameters. This model is further evaluated using repeated cross-validation to validate its stability and select the best-performing run. This two-phase optimization approach led to a notable 13.4% improvement in accuracy, significantly enhancing the model’s predictive capabilities. Table 5 summarizes these accuracy metrics.

Table 5 Comparison of Model Accuracy before and after Two-Phase Optimization

Initial Accuracy	*Accuracy after two-phase optimization*	*Increase in Accuracy*
77.3%	82.3%	13.4%

In addition to accuracy, precision, recall, and F1-score metrics were evaluated to comprehensively assess the classifier's performance, as depicted in Figure 3. The precision for the 'Female' class is 73%, while for the 'Male' class, it reaches 88%, demonstrating the models' consistency in predicting male samples more accurately. The recall values are 76% for 'Female' and 85% for 'Male,' indicating that the model is more sensitive to identifying male instances correctly.

The F1-score, a harmonic mean of precision and recall, provides a single metric to evaluate the balance between the two. It is particularly useful in imbalanced datasets, where focusing solely on accuracy may mask the model's performance for specific classes. The F1-score of 74% for the 'Female' class and 86% for the 'Male' class indicates that the model performs better for the 'Male' class. By integrating F1-scores with other metrics, the evaluation ensures that the findings are both reliable and interpretable, offering a nuanced understanding of the classifier's performance.

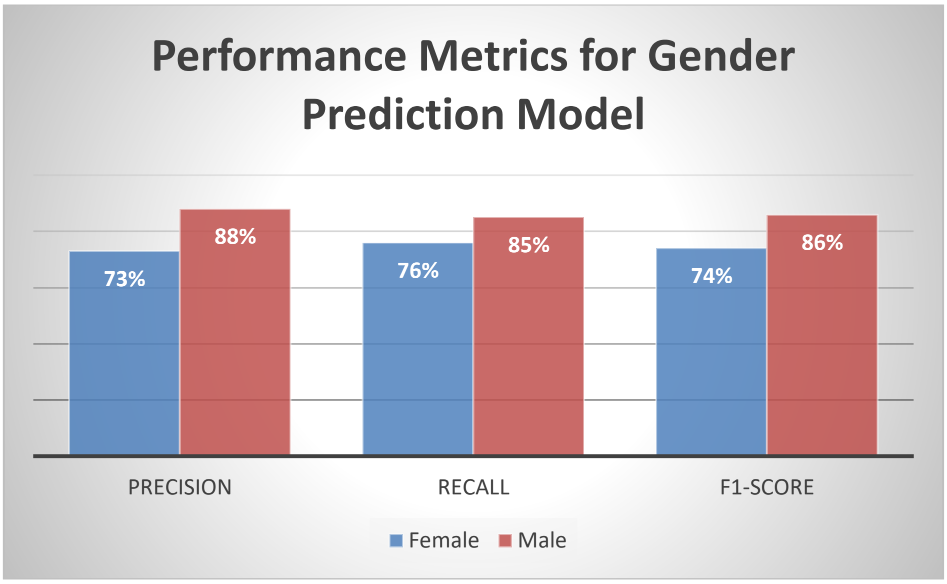


Figure 3 Performance Metrics for the Binary Class XGBoost Gender Prediction Model, Comparing the Results between the 'Female' and 'Male'

4.3 Global-level Interpretation

Figure 4 represents a summary plot for global-level model interpretation for the gender preferences' prediction model. The y-axis represents the input features sorted by their importance, with the most important feature at the top. The x-axis represents SHAP values, which quantify the impact of individual features on the model's output. Each dot represents a single data point (instance) in the dataset. The position and colour of each point indicate the SHAP value and the intensity, respectively, of that particular instance. The negative SHAP values mean that the feature pushes the prediction towards class 0 (Female) and vice versa. Similarly, the red dots represent higher values/intensity of the feature, and blue dots represent lower values.

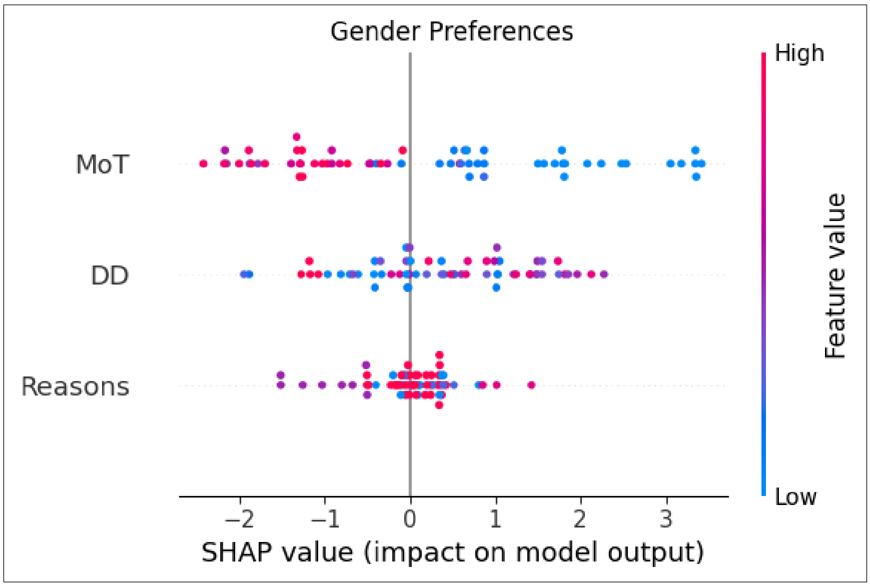


Figure 4 SHAP Summary Plot of Binary Class Gender Prediction Model.

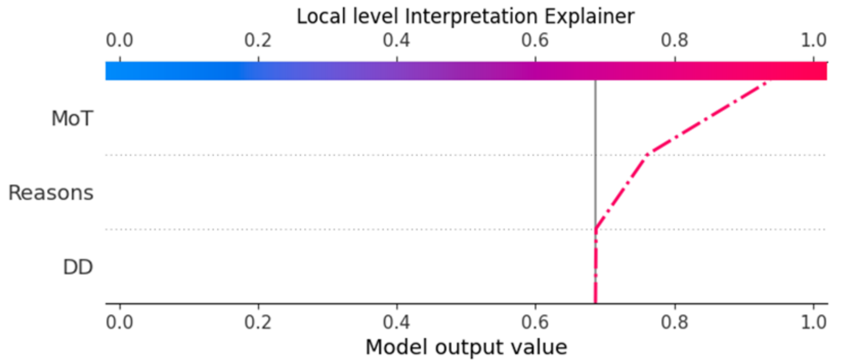
From Figure 4, the following observations can be drawn:

1. For the Travel Mode (MoT), the results indicate a strong gender association with transportation types. Lower MoT classes, such as motorcycles and cars, are predominantly linked to male predictions, as shown by the positive SHAP values in blue. In contrast, higher MoT classes, including public transport and university shuttle services, are more strongly associated with female predictions, indicated by negative SHAP values in red. This suggests that men are more likely to use motorcycles and cars, while women prefer public transport and university shuttle options. A similar observation has been reported in a study of mode choice among college students that the distance does not have a significant effect on the probability of motorcycling/biking and also that males are more likely to bike to campus than females (Zhou et al. 2018).
2. Travel distance (DD) also plays a significant role in the model's predictions. Longer travel distances (higher DD values) correspond with positive SHAP values, pushing the prediction toward males. On the other hand, shorter distances are more likely associated with female predictions, indicated by the negative SHAP values. This finding suggests that men tend to travel longer distances, which may be linked to their mode of transport preferences.
3. The Reasons for choosing a particular mode of transport further distinguish gender preferences. Factors such as cost and time-saving, which have higher SHAP values, tend to align more with male predictions. Conversely, reasons like safety, reliability, and convenience, which are associated with lower SHAP values, are more closely related to female predictions. This highlights that men prioritize cost and time-saving, whereas women focus more on safety and reliability when selecting a travel mode.

4.4 Local-level Interpretation

SHAP decision plots illustrate model predictions by showing the contributions of features across the feature space. The plot is read from bottom to top, following the path to the horizontal colour line. The vertical grey line represents the baseline, which is the average of all the predictions, also known as the *expected* or *base* value. The colour gradient indicates SHAP values, with blue representing the least influential values and red the most significant. In binary classification, SHAP values reflect the difference between predicted log odds and the average log odds, where positive values increase and negative values decrease the log odds.

The decision plot in Figure 5 illustrates the model's prediction for sample 61 in the gender prediction model. With a baseline prediction of 0.783, the model predicts a high probability that the participant is male, which aligns with the true values: [MoT, reasons, DD] = [motorcycle, cost, 1]. The travel mode (MoT) is the most influential feature, with a significant SHAP value of 1.57, followed by the reason for travel with a SHAP value of 0.374. Travel Distance (DD), at only 1 km, has a negligible impact (SHAP value of 0.004), making it a minor factor in the prediction. This confirms that the decision is primarily driven by MoT, then reasons, with DD being the least impactful, leading to an accurate prediction that the participant is male.



Feature Names	SHAP values for sample_IDX = 61
MoT	1.57
Reasons	0.374
DD	0.004

Figure 5 A Scenario for one Data Point; Sample Index = 61 for Gender Preferences' Prediction Model

The SHAP interpretation of various data samples in Figure 6 highlights the model's ability to assess individual feature importance differently for each sample. For instance, in sample (a), the order of feature importance is DD > MoT > Reasons, whereas in sample (c), it shifts to MoT > DD > Reasons. Despite these differences, both samples predict a high probability of male preference. This variation suggests that individual preferences for different features can vary significantly, even among samples classified with the same gender. The observed differences in feature importance across samples (a) to (f) emphasize the model's capacity to treat each instance uniquely, reflecting its nuanced understanding of feature influence on decision-making. While most predictions align with true values, as seen in samples (a) and from (c) to (f), the model does make occasional errors, such as in sample (b), where it incorrectly predicts male instead of the true female label. This analysis highlights the model's varying ability to accurately predict gender based on the given features, with some discrepancies where it misclassifies female samples as male. Furthermore, Table 6 compares the *expected* and *true* values to assess the relative impact of each feature in the decision-making process.

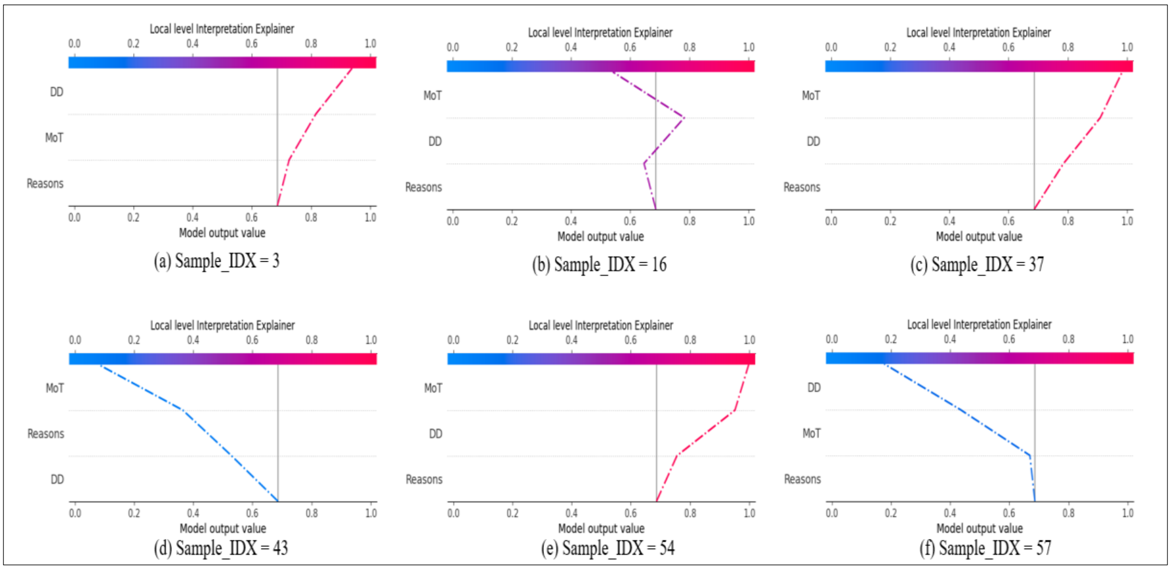


Figure 6 Interpretation of SHAP Values across Sample Indices

Table 6 Model Performance for Local-Level Gender Preferences Using SHAP Values of Each Feature

S. No.	*Sample Index*	*Features names*			*Expected Value*	*True Value*	*Feature importance Rank*
		MoT	Reasons	DD			
(a)	3	0.516	0.192	1.24	M	M	DD > MoT > Reasons
(b)	16	-1.118	-0.181	0.678	M	F	MoT > DD > Reasons
(c)	37	1.86	0.515	1.012	M	M	MoT > DD > Reasons
(d)	43	-1.89	-0.67	-0.67	F	F	MoT > Reasons > DD
(e)	54	3.357	0.345	1.853	M	M	MoT > DD > Reasons
(f)	57	-0.96	-0.078	-1.27	F	F	DD > MoT > Reasons

5. Conclusions

This study demonstrates the potential of machine learning hidden insights, specifically through the use of the XGBoost algorithm, in accurately predicting gender-based travel mode preferences in urban settings. By analysing a dataset of young adults in Karachi, Pakistan, we found that gender plays a significant role in shaping travel behaviour. The model, with an accuracy of 82.3%, successfully predicted gender based on factors such as travel mode, distance, and purpose.

SHAP analysis enhances the interpretability of the model, revealing that travel mode, distance, and purpose/reasons for travel are the key factors influencing gender-based predictions. The global-level analysis indicated that transportation modes like motorcycles and cars are strongly associated with male users, whereas public and shuttle transport options are more likely linked to female users. Locally, SHAP provided a more nuanced view, showing that individual preferences can vary across samples, with travel mode being the most critical factor in most cases. Travel distance and reasons such as cost or safety were influential but varied depending on the specific instance. These findings highlight the importance of considering gender-specific factors in transportation planning and policy-making.

The results emphasise the potential of explainable AI tools like SHAP in understanding model behaviour beyond simple accuracy metrics. SHAP analysis not only deepens the understanding of how certain predictions are made but also improves transparency by uncovering the nuanced patterns in human behaviour. This is particularly relevant in social science research, where trust in machine learning models depends on the ability to interpret outcomes meaningfully and within context.

These findings can be utilised by a range of stakeholders, including urban planners, transport policy makers, gender advocacy groups, and local government authorities. By identifying gender-specific travel needs, targeted interventions such as improving the safety and accessibility of public transport for women or optimising transport networks for cost and time efficiency can be implemented. This contributes to more inclusive, equitable, and user-centred urban mobility systems.

While this study provides valuable insights, it is essential to acknowledge its limitations. The sample size and geographic scope may limit the generalizability of the findings to other urban contexts. Future research could expand the dataset to include a wider range of demographics and geographic locations. Additionally, incorporating additional factors such as socio-economic status, cultural norms, and urban form could provide a more comprehensive understanding of gender-based travel behaviour.

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Conflict of Interest

The authors declare no conflict of interest with any person or organization.