Mode Detection, Age Pattern Transition, and its Consequences on Carbon Emissions

Team 5

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BACKGROUND: MODE CHOICE DETERMINANTS

Purpose

Public modes for majority of work trips

Private modes majorly for leisure trips.

Trip start time

Lesser number of **Private mode** users during the working hours.

Walk and bicycle least preferred for late night trips.

Gender

Walk and bicycle more preferred mode by **female.**

Public and private modes more preferred mode by **male.**

Travel time

39.17% & 25.47% of short trips (less than 30 minutes travel) are made **on foot & by Car** respectively.

Above 60% of long trips are made **on train.**

Trip end time

Private mode for late night trips

Walk and bicycle least preferred for late night trips.

Age

Most preferred mode

Children aged less than 15 years - Walk
Working aged people – Public transport
Elderly - Private mode

Objective 1 : Comparing Mode Detection using Traditional and Machine Learning techniques.

Predictor Variables

- Purpose (5 categories)
- Gender (2 categories)
- Age (17 categories)
- Start Time
- End Time
- Travel Time

Target Variable

- Mode (4 categories)

MULTINOMIAL LOGIT MODEL (MNL MODEL)

- The most widely used mathematical form for choice probabilities in behavioural travel demand analyses

Key Strengths:

- The MNL model is simple to perform
- Computationally efficient
- Permits a simple behavioural interpretation of its parameters

Key Weaknesses:

- Independence of Irrelevant Alternatives (IIA) property
- No correlation between error terms (i.i.d. errors)
- Random taste variation can not be represented,

Testing Set: 216224 nos.

Total samples	Actual \ Predicted	Public	Private	Bicycle	Walk
72885	Public	56122	14274	13	2476
63074	Private	13341	29967	459	19307
31675	Bicycle	1671	10431	421	19152
48590	Walk	2510	13640	616	31824

Log-Likelihood: -1464800

McFadden R^2: 0.24345

Likelihood ratio: 942710

Random Forests (RF)

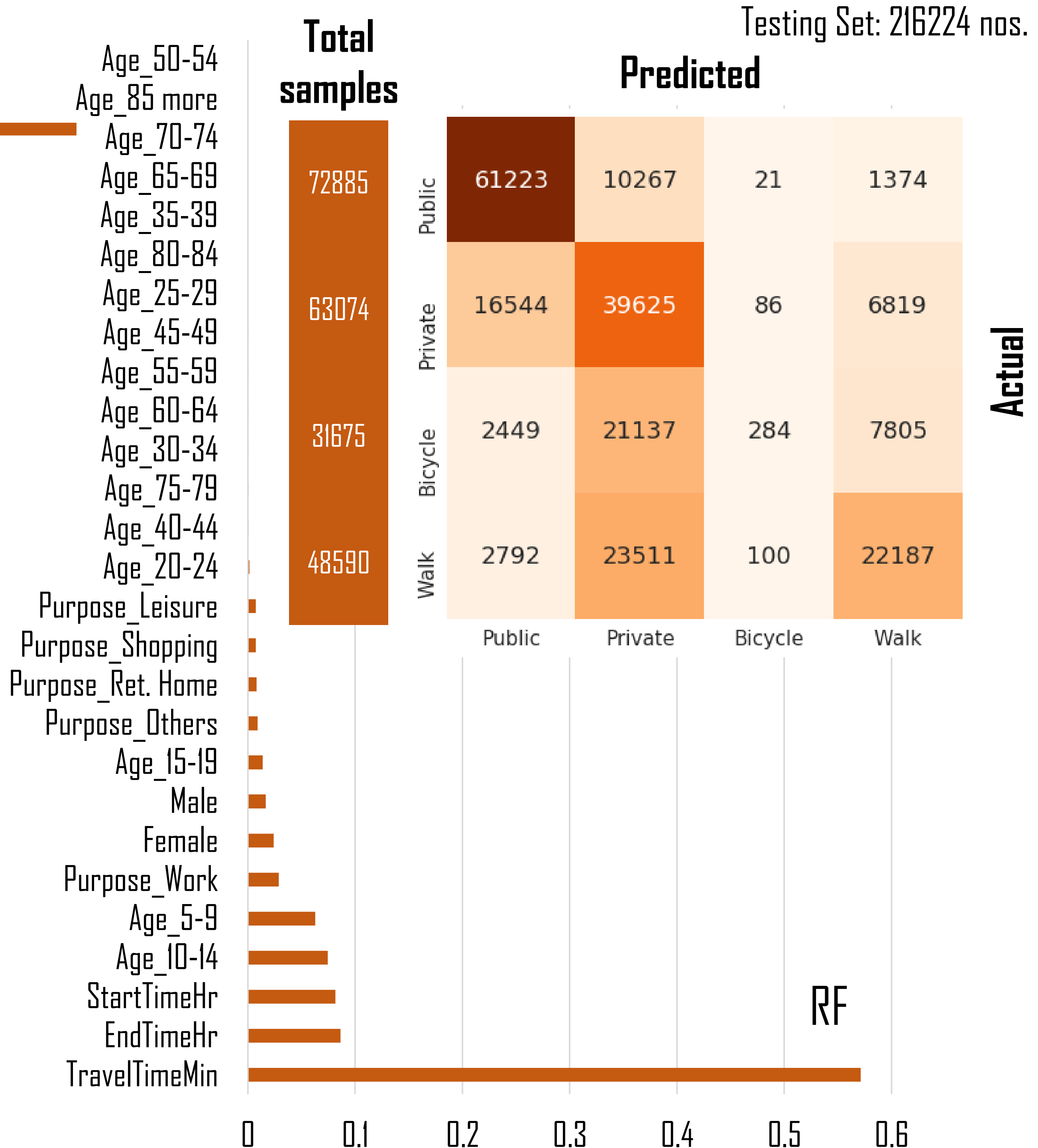
- A decision tree is a decision support tool that uses a tree-like graph or model of decisions.
- RFs train each tree independently, using a random sample of the data.

Key Strengths:

- RF is much easier to tune. Only two hyperparameters (a) depth of trees (6) and (b) number of estimators (25).
- More robust than a single decision tree, and less likely to over fit on the training data.
- Does not require preparation of the input data.
- Works with unscaled data and missing values.
- Provides information on Feature importance.

Key Weaknesses:

- For data including categorical variables with different number of levels, RFs are biased against attributes with more levels.



Extreme Gradient Boosting (XGB)

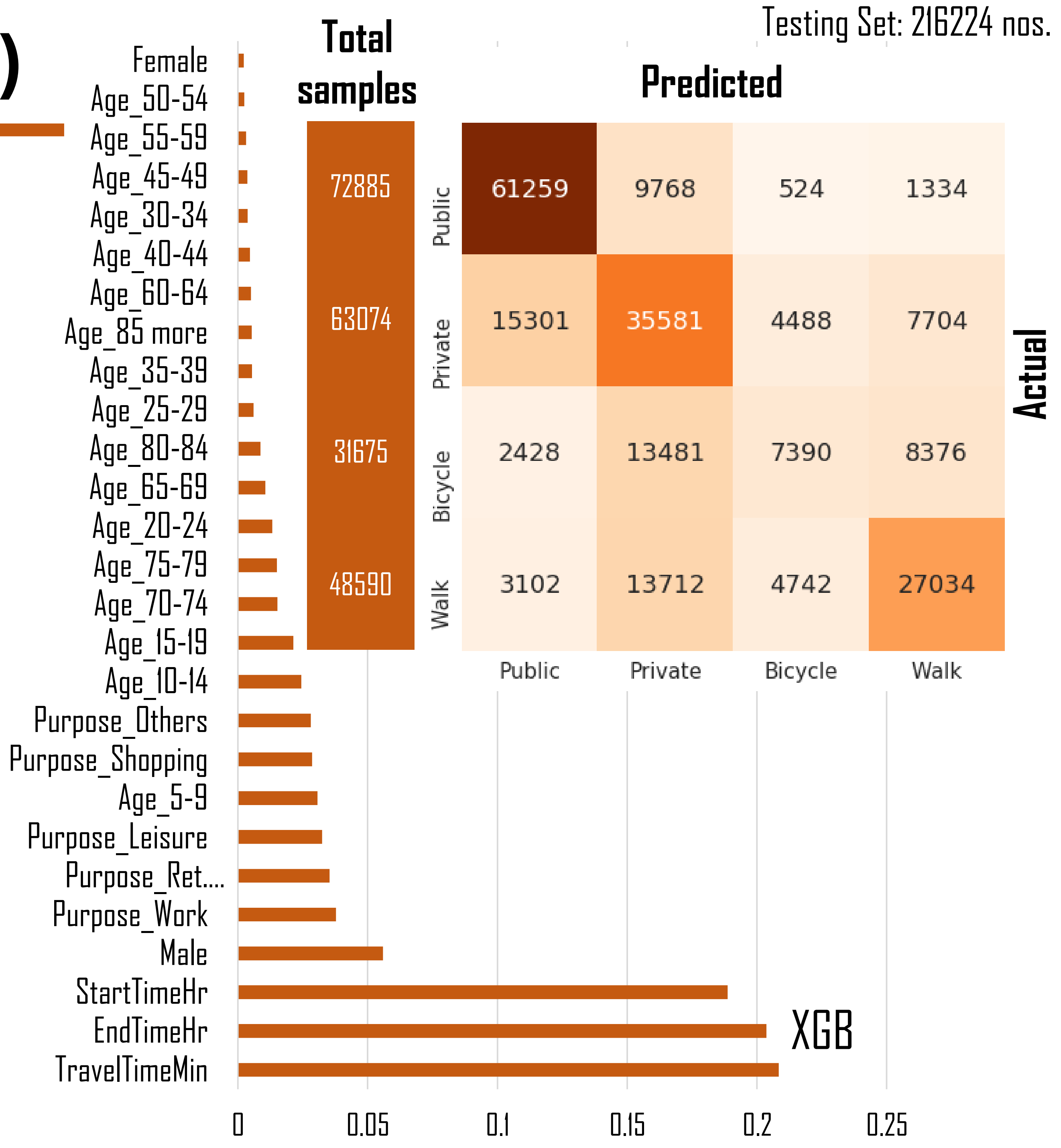
- XGB build trees one at a time, where each new tree helps to correct errors made by previously trained tree.

Key Strength:

- It performs the optimization which makes the use of custom loss functions much easier.
- Boosting focuses on unbalanced datasets by strengthening the impact of the positive class.
- Provides information on Feature importance.

Key Weaknesses:

- Training generally takes longer because of the fact that trees are built sequentially.
- XGB is harder to tune than RF. Three parameters to tune: (a) number of estimators (100), (b) depth of trees (6) and (c) Learning rate (0.1)



Artificial Neural Network (ANN)

- ANN is based on a collection of connected units (nodes) called artificial neurons, which loosely model the neurons in a biological brain.

Key Strengths:

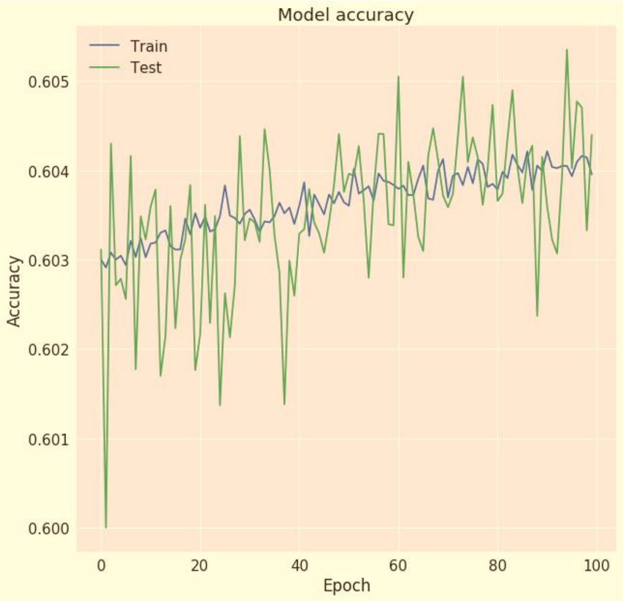
- Ability to learn and model non-linear and complex relationships.
- Efficiently processes large amount of training samples.

Key Weakness:

- Hardware dependence
- Unexplained behavior of the Model.
- Comparatively sub-standard performance in smaller datasets.
- Large number of hyperparameters to tune. (a) No. of Hidden Layers (3), (b) Activation functions(Relu, Relu, Softmax), (c) Loss functions (Cross-entropy), (d) Dropout rate (0.8), (e) Optimizer (Adam), (f) Learning rate (0.01).

Testing Set: 216224 nos.

Total samples	Actual \ Predicted	Public	Private	Bicycle	Walk
72885	Public	61330	8806	931	1818
63074	Private	16111	31927	6182	8854
31675	Bicycle	2507	10987	9137	9044
48590	Walk	3218	11290	5791	28291



Evaluation Metrics

- *Overall Accuracy:* The ratio of a total number of correctly identified pixels to the total number of considered pixels.
- The overall accuracy metrics is influenced by unbalanced and prominent classes.
- *F1-score:* is a harmonic mean of Precision and Recall.
  - Precision is the proportion of positive detections of the classifier which were actually correct,
  - Recall refers to the proportion of actual positives which were detected correctly.
- *Kappa index of Agreement* is used in assessing the performance of different models.
- The Kappa value (k) of model classifier suggests that the classifier is k*100 percent better than random assignment of classes.

PT data

	F1-score			
Classes	MNL	RF	XGB	ANN
Public	0.77	**0.79**	**0.79**	**0.79**
Private	0.46	0.5	**0.52**	0.51
Bicycle	0.03	0.02	0.3	**0.34**
Walk	0.52	0.51	0.58	**0.59**
Ov. Acc.	54.72	57.03	**60.71**	60.44
Kappa	0.368	0.388	**0.451**	0.45

PP data

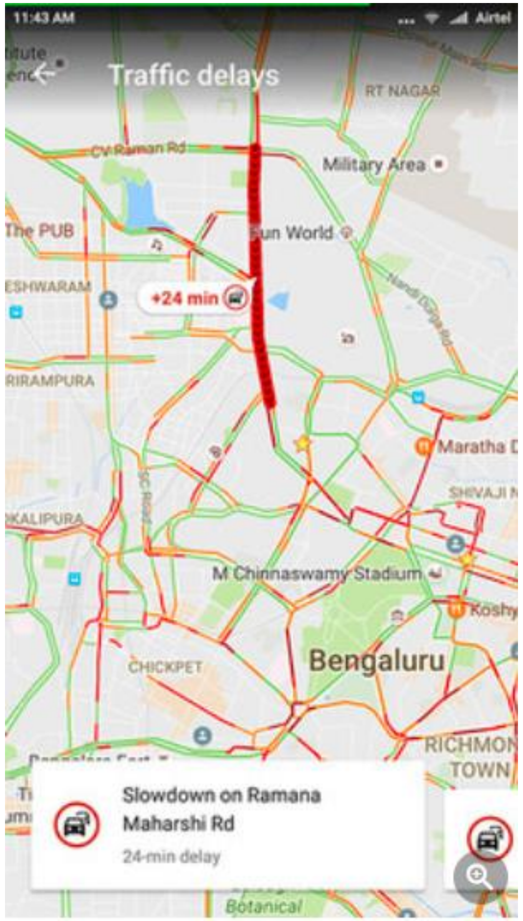
	F1-score			
Classes	MNL	RF	XGB	ANN
Public	0.66	**0.76**	0.72	0.69
Private	0.53	0.63	**0.66**	0.55
Bicycle	0.46	0.52	**0.57**	0.52
Walk	0.49	0.49	**0.51**	0.48
Ov. Acc.	56.09	64.52	**64.75**	58.76
Kappa	0.379	0.491	**0.499**	0.406

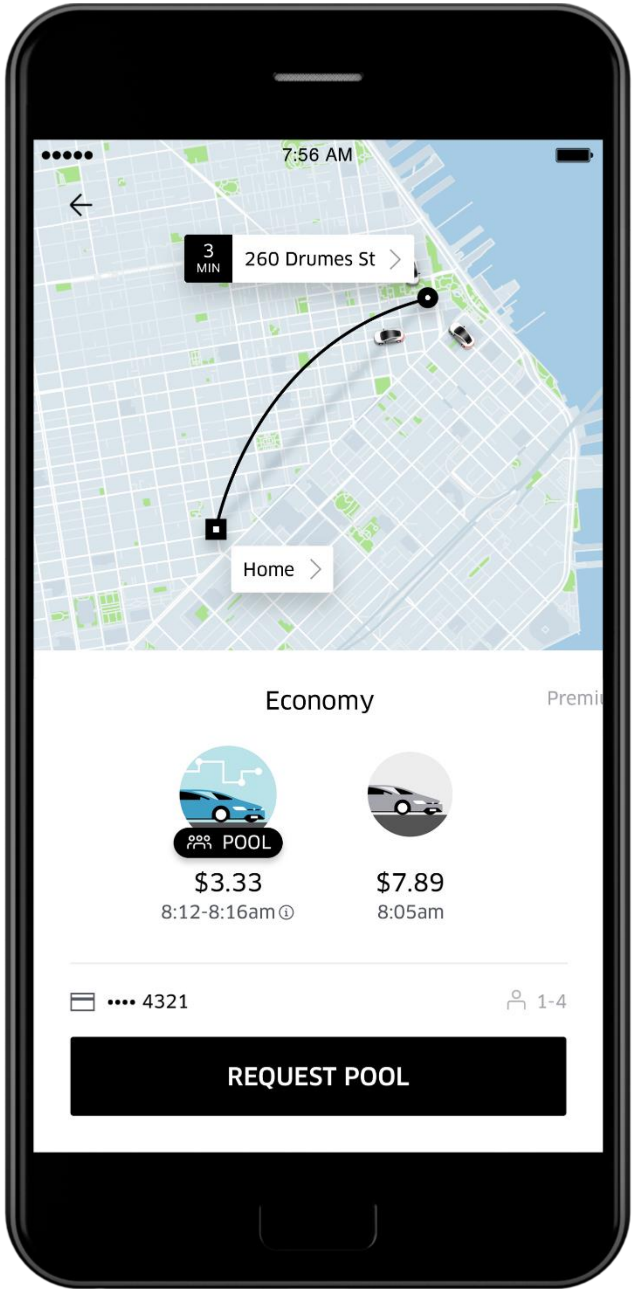
Potential Use Cases

Real-time congestion estimation/pricing : By the use of mode detection models trained on telemetry data from various smartphone applications.

Advertising: Push Notifications influencing future mode choice behavior by cab aggregators based on trained model.

Health: Evaluation of exposure to pollution by estimating the choice of mode.





Objective 2 : Analyzing the Mode Pattern considering the Shifting Age Composition

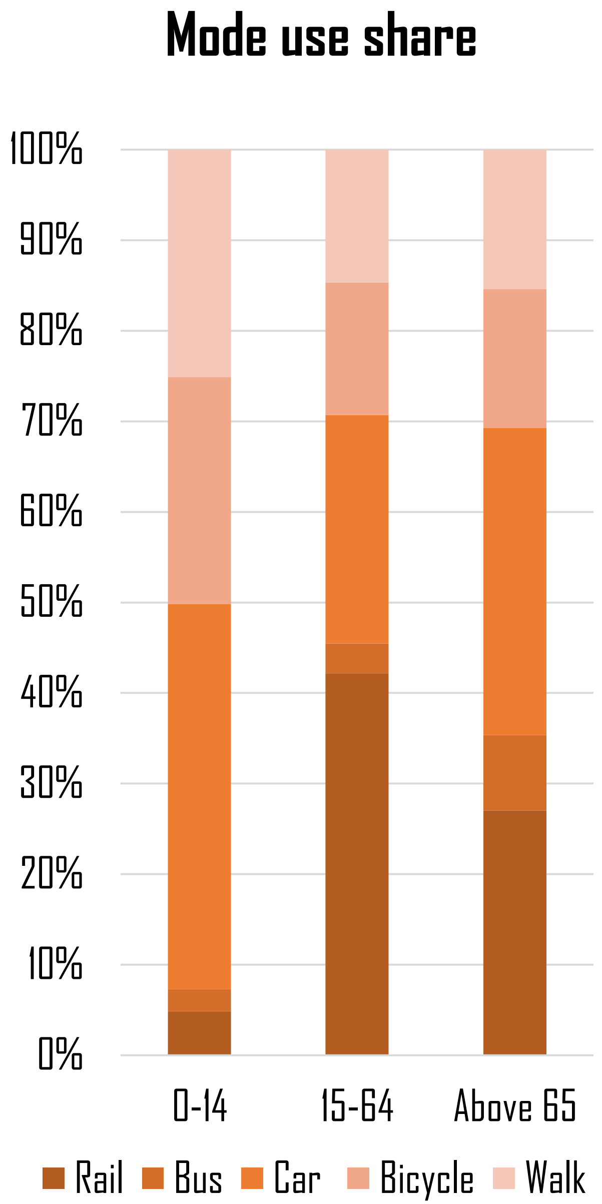
AGE PATTERN AND MODE CHOICE

OBSERVATIONS

Higher share of on-road motorised modes by elderly people

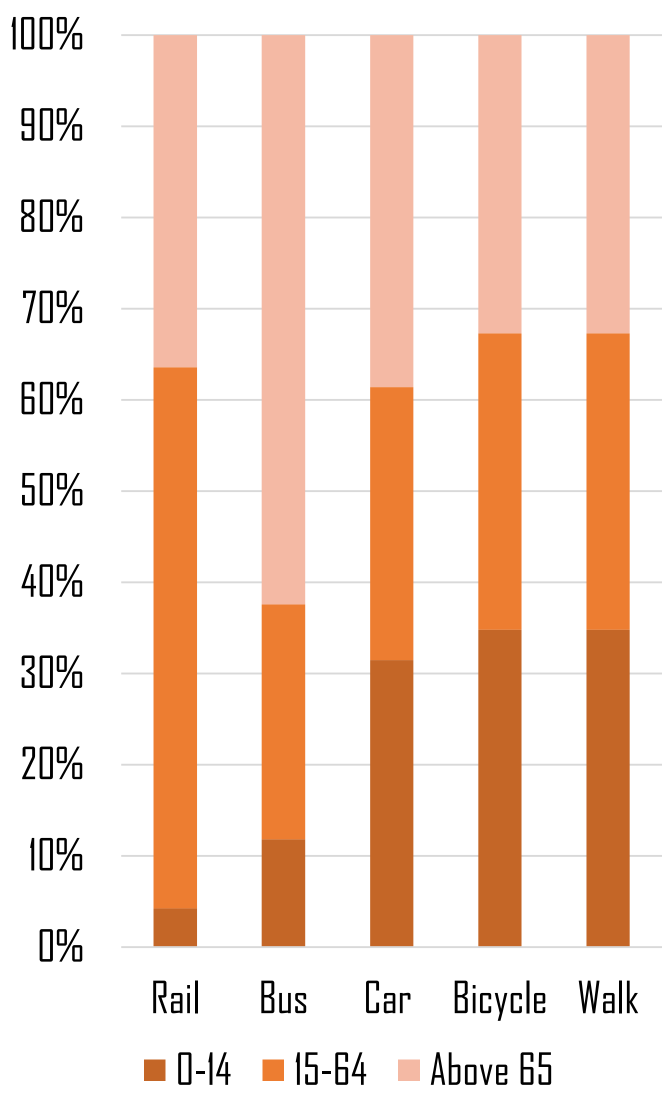
Increasing traffic volume of on-road vehicles
Increasing carbon share by elderly
Comfort and convenience of elderly people

Measures to reduce carbon share by transportation
Measures to ease the travel for elderly

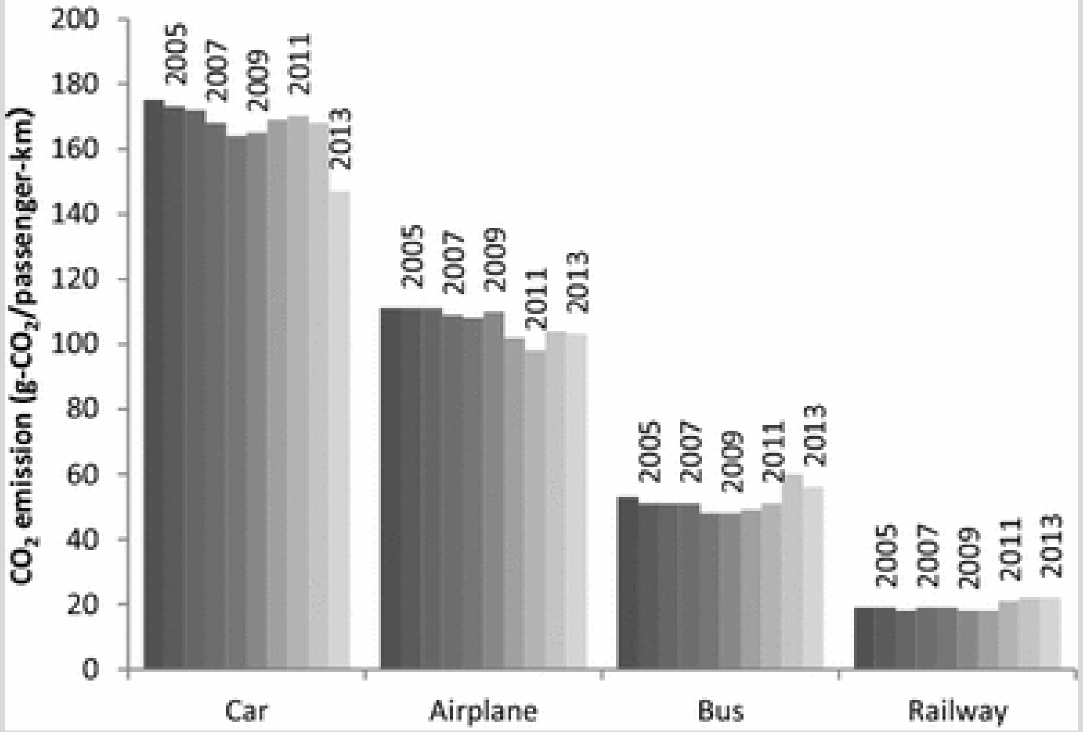


MODE USE AND CHANGING EMISSION LEVEL

Age wise share of different modes

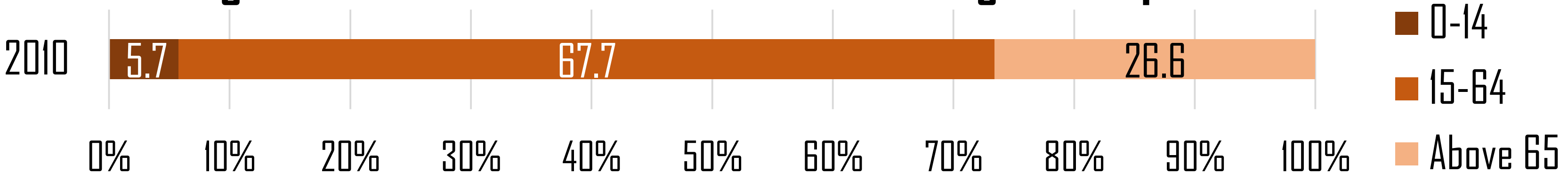


Carbon Emission by Transport Modes

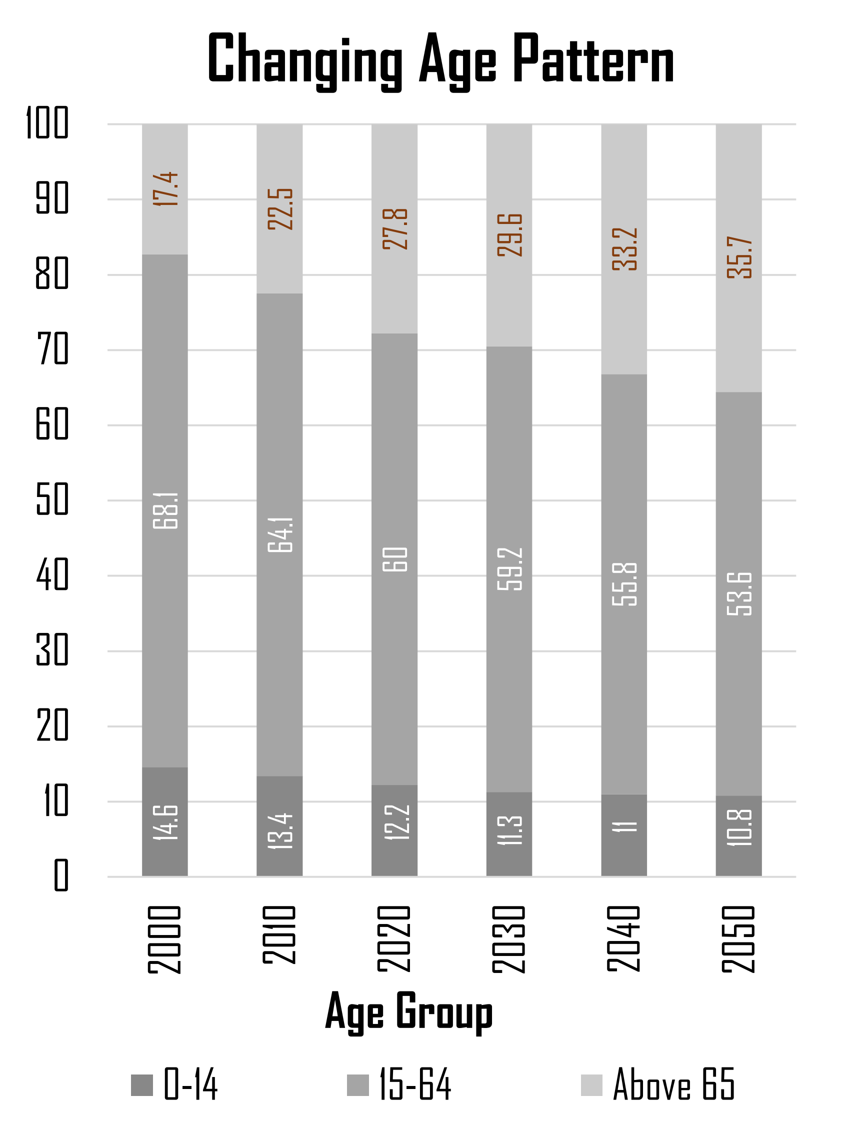


Source: Hayashiya, H. Urban Rail Transit (2017) 3: 183. https://doi.org/10.1007/s40864-017-0070-4

Age-wise Share of Carbon Emission through Transport Modes



CARBON EMISSION THROUGH TRANSPORT MODES



Source: National Institute of Population and Social Security Research

Scenario 1

a. Changing Population trend
b. Same Mode pattern
c. Same Mode based emission per PKM

Scenario 2

a. Changing Population trend
b. Same Mode pattern
c. Changing Mode based emission per PKM (Reference: Decadal average)

Scenario 3

a. Changing Population trend
b. Same Mode pattern
c. Changing emission per PKM in car while emission per PKM in other mode are constant

Scenario 4

a. Changing Population trend
b. Shifting Car users to Public transport (Bus)
c. Changing Mode based Emission per PKM

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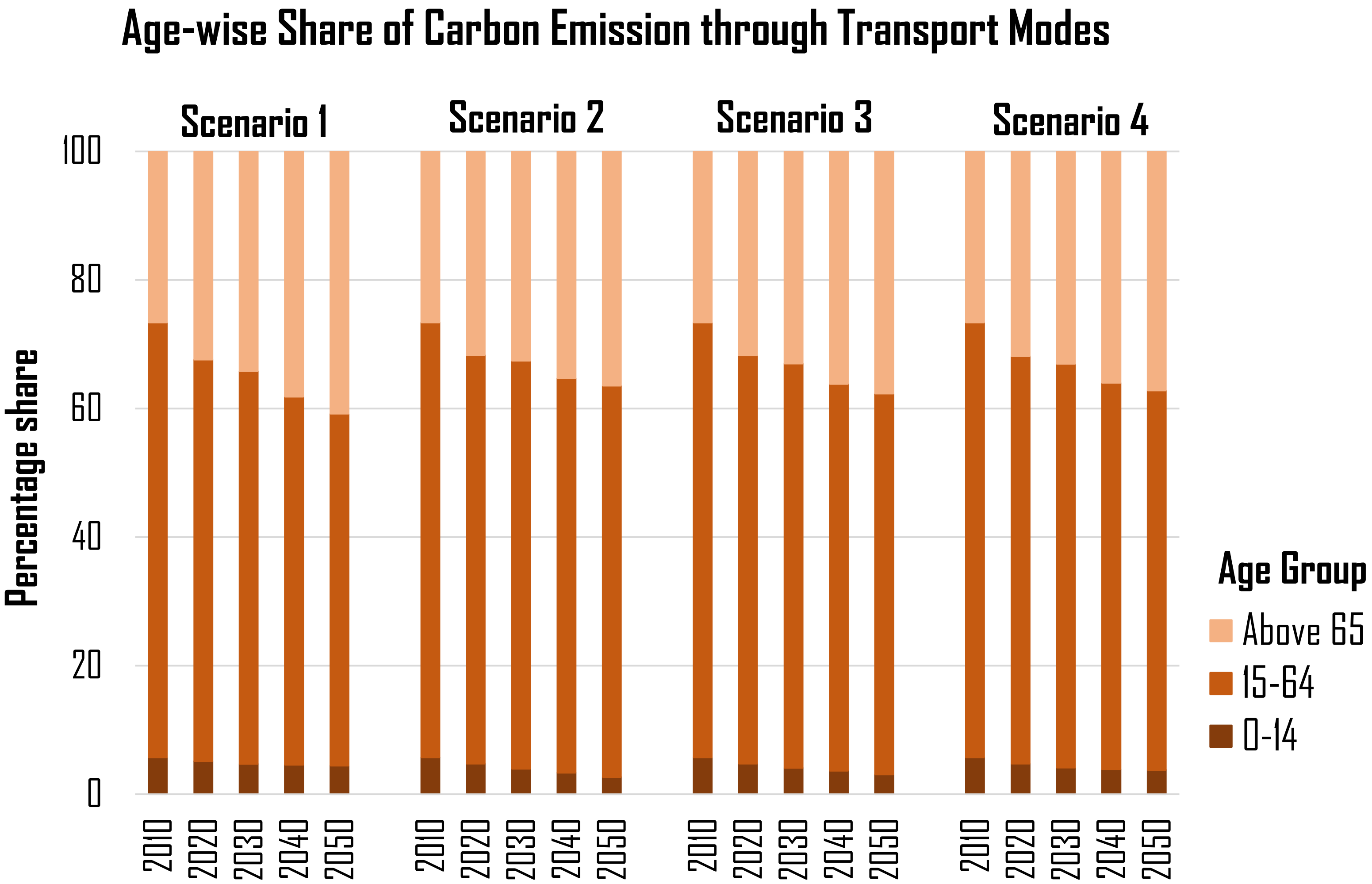


FLEXIBLE TRANSPORT SERVICES FOR EASE OF TRANSPORT FOR ELDERLY PEOPLE

FTS SYSTEMS

Provide flexible transportation service (FTS) for elderly people in the city to access the metro station to improve their mobility.

More detailed study of the

a **Route deviation**
Fixed schedule and direction

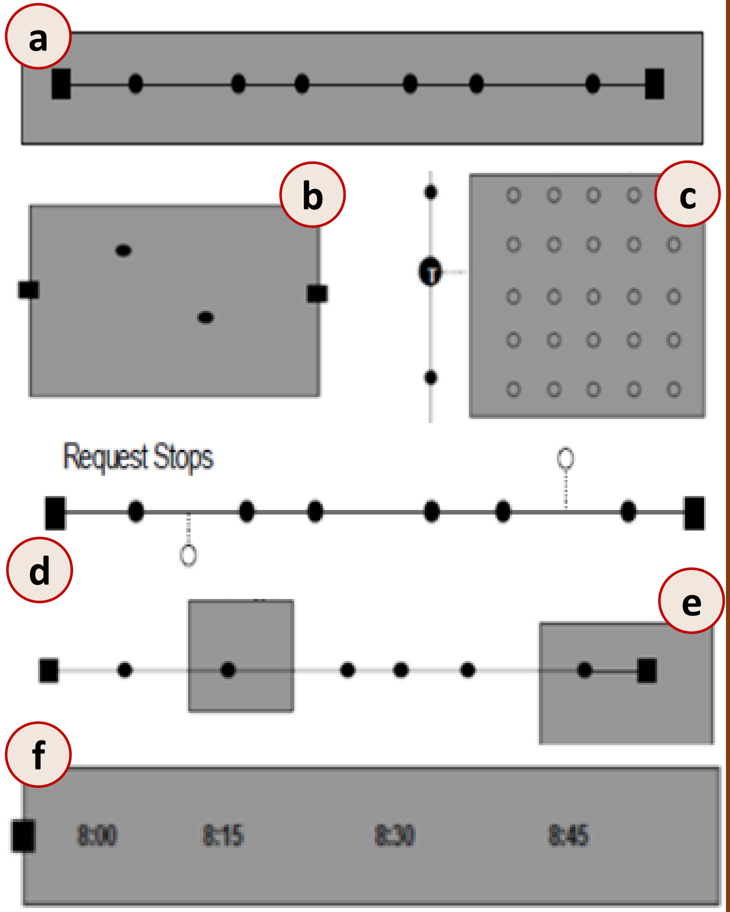
b **Point deviation**
No defined path or schedule, demand responsive and deviates routes between two points

c **Demand responsive connectors**
Fixed route connectors

d **Request stops**
Defined path and schedule

e **Flexible route segments**
Fixed schedule and path

f **Zone route**
One or more end points decided by passengers



Route terminus
Transfer point
Scheduled bus stop
Bus stop served by request only

SCOPE & LIMITATIONS