THE 21ST SUMMER COURSE
BEHAVIOR MODELLING SUMMER SCHOOL

REDUCING CARBON EMISSION BY INTRODUCING AUTOMATED DELIVERY SYSTEMS

TEAM 02
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CONTENTS

INTRODUCTION: A

- **Toyosu PP Data 2021**

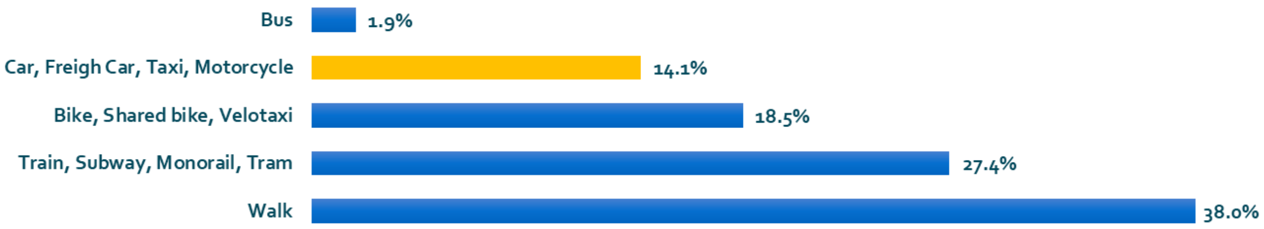
- Private and/or Polluting Modes such as Cars, Freight Cars, Taxis and Motorcycle contribute to approximately 14% of Toyosu's Traffic
- Going out to eat and going for shopping contribute to approximately 26% of Toyosu's Traffic

- Approximately 20% of all trips for shopping and eating are caused by these polluting modes
- Approximately 22% of trips by cars and 32% of trips by motorcycles are for shopping and eating out

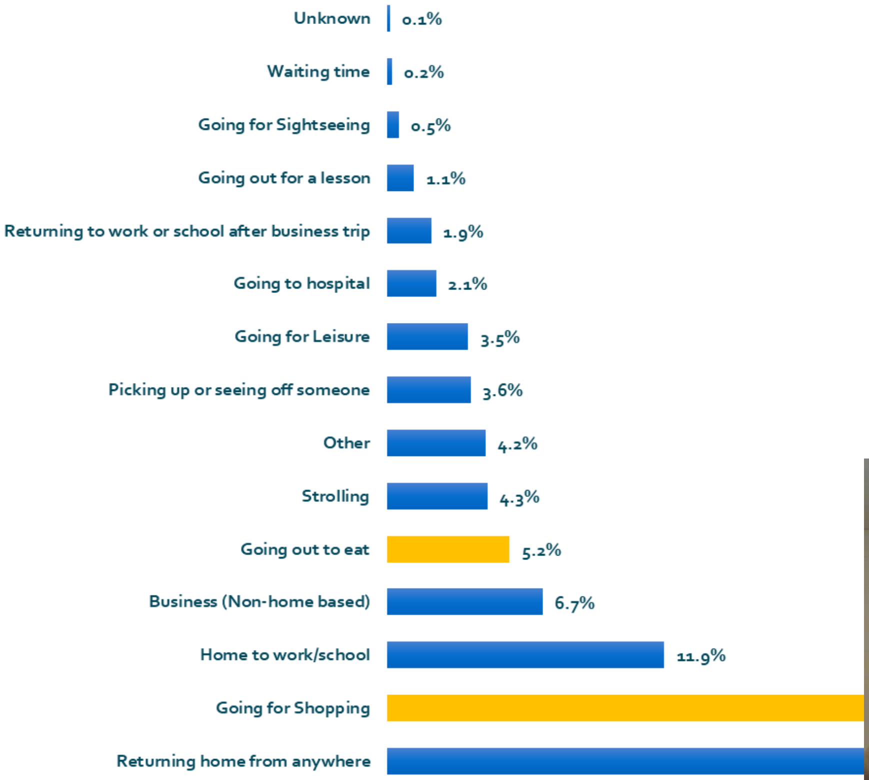
	Car	Freight Car	Taxi	Motorcycle
Going for Shopping (100%=7064)	10.28%	0.04%	0.17%	1.57%
Going out to eat (100%=1760)	9.55%	0.74%	0.85%	1.59%

	Car (100%=3863)	Freight Car (100%=241)	Taxi (100%=236)	Motorcycle (100%=413)
Going for Shopping	18.79%	1.24%	5.08%	26.88%
Going out to eat	4.35%	5.39%	6.36%	6.78%

Mode-Wise Distribution of Sample Population



Purpose-Wise Distribution of Sample Population



INTRODUCTION: B

Car | Motorcycle | Taxi | Freight Cars | Walk | Bike | Sharebike | Train | Subway | Monorail | Tram | Bus

Private | Shared | Other | Non Motorised | Motorised

Polluting | Non Polluting

MODES

Eating Out | Shopping | Sight Seeing | Leisure | Hospital | Strolling | Work | School | Lesson | From work | From Shopping

Buy Commodity | Non Buy Commodity | From Home | To Home

Discretionary | Non Discretion

PURPOSES

METHODOLOGY

Descriptive Analysis

- Understand the share of shopping, eating and delivery trips
- Understand the mode choice for shopping, eating and delivery trips

MNL Modelling

- Understand the factors influencing mode choice behaviour for shopping, eating and delivery trips by Multinomial Logit Modeling (MNL)

Trip Chain Analysis

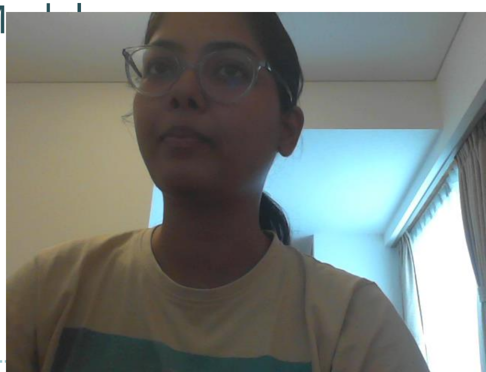
- Understand factors influencing mode choice in trip chains

Studying Alternatives

- Understand feasibility of Automated Delivery Systems (ADS) to reduce Carbon Emission and Traffic

Destination Modelling

- Modelling location of shopping, eating and delivery through Machine Learning (ML) M



DATA DESCRIPTION

Descriptive Analysis

- PP Data: Toyosu 2021
- Sample Size = 33,494

MNL Modelling

- PP Data: Toyosu 2021
- Shopping and Eating Trips
- Sample Size = 2,237

Trip Chain Analysis

- PT Data
- Sample Size = 1,448,714 (trips)
- Sample Size (tours) = 510,222

Studying Alternatives

- Literature Review
- Previous research on ADS

Demand Modelling

- PP Data: Toyosu 2021
- Shopping and Eating Trips
- Sample Size = 2,237

ANALYSIS: MNL

Variable	Description	Specific to Mode	Coefficient	Std. Error	T-stat
IVTT	In-vehicle travel time	Generic	-6.77173***	0.50046	-13.53
TC	Travel cost	Generic	-.00088***	0.00022	-3.96
ET	Egress time	Generic	-11.9997***	1.59509	-7.52
AT	Access time	Rail	-9.55363***	1.42754	-6.69
FEM	Female	Rail	-.46046**	0.20616	-2.23
INC_C	Income	Car	.17024**	0.07489	2.27
INC_B	Income	Bike	-.17962***	0.0564	-3.18
CHILD	Children	Car	.23965*	0.14399	1.66
PVOWN	Pvt. Vehicle ownership	Car	3.00634***	0.15703	19.15
BIOWN	Bicycle ownership	Bike	2.76261***	0.16373	16.87
Peak	Peak hour	car	-.31826**	0.15798	-2.01
C_BIKE	Constant	Bike	-2.92325***	0.31183	-9.37
C_BUS	Constant	Bus	-2.12323***	0.24904	-8.53
C_CAR	Constant	Car	-4.20224***	0.34768	-12.09
C_WALK	Constant	Walk	-0.23228	0.25502	-0.91

N =	2237
Log likelihood of constant only model =	-2620.8
Log likelihood at convergence =	-1854.7
Rho square =	0.30

U(Rail) = - 6.77*IVTT – 0.000088*TC – 11.99*ET – 9.55*AT – 0.46*FEM

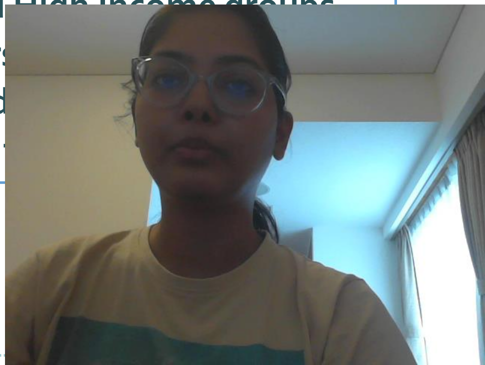
U(Bus) = - 6.77*IVTT – 0.000088*TC – 11.99 *ET -2.12

U(Car) = - 6.77*IVTT – 0.000088*TC – 11.99 *ET + 0.170*INC + 0.23*CHILD + 3*PVOWN – 0.31*PEAK – 4.2

U(Bike) = - 6.77*IVTT – 0.000088*TC – 11.99 *ET + 2.76*BIOWN – 0.179*INC – 2.92

U(Walk) = - 6.77*IVTT – 0.000088*TC – 11.99 *ET – 0.23

- **Females, HH with children and**
  can be the potential consumer
- **Deliveries can be preferred and**
  hours as peak hours have rush



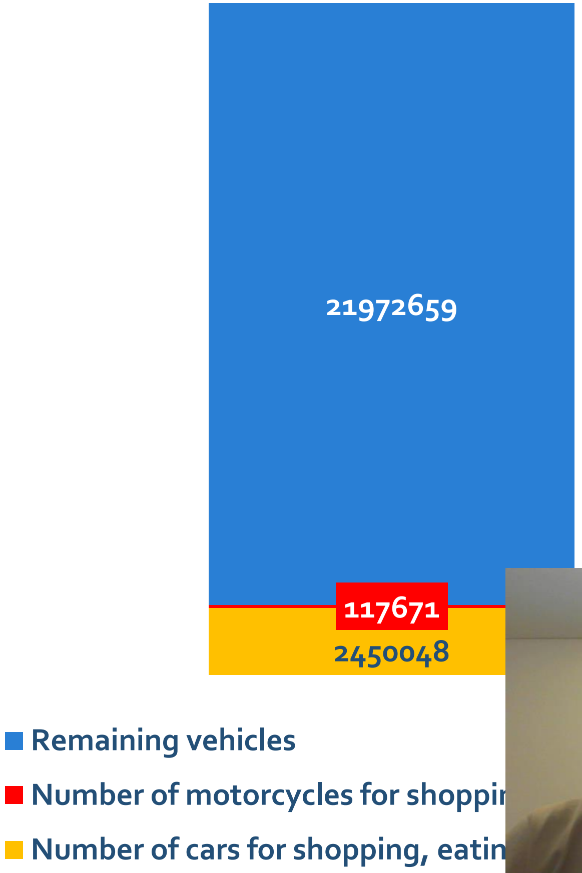
ANALYSIS: TRIP CHAINS

1. It can be observed that among the trips which use cars, 33% of the trips include at least one the purposes among shopping, eating or delivery
    - Number of cars used specifically for shopping, eating or delivery trips = 7,362,447
    - Number of cars used if at least one purpose in the trip chain is shopping, eating or delivery = 2,450,048

3. If even 80% of these trips are reduced, approximately 42,000 passenger car units of traffic can be reduced per day through ADS
    - PCU of Car = 1
    - PCU of Motorcycle = 0.5

4. Considering only cars, of 243,5 tonnes of CO2/day emission can be reduced through ADS
    - Carbon Emission by Cars = 140 gCO2/passenger-km (Hayashiya, 2017)
    - Carbon Emission by Cars = 182-143 gCO2/km
    - Occupancy of Car = 1-1.25 (assumption)
    - Number of cars for shopping, eating or delivery = 2,450,048

Out of the total vehicles in traffic, approximately 10.4% are the motorcycles or cars being used for shopping, eating or delivery



PROPOSAL: AUTOMATED DELIVERY SYSTEMS

Three types (Figliozzi, 2020) of autonomous vehicle are:

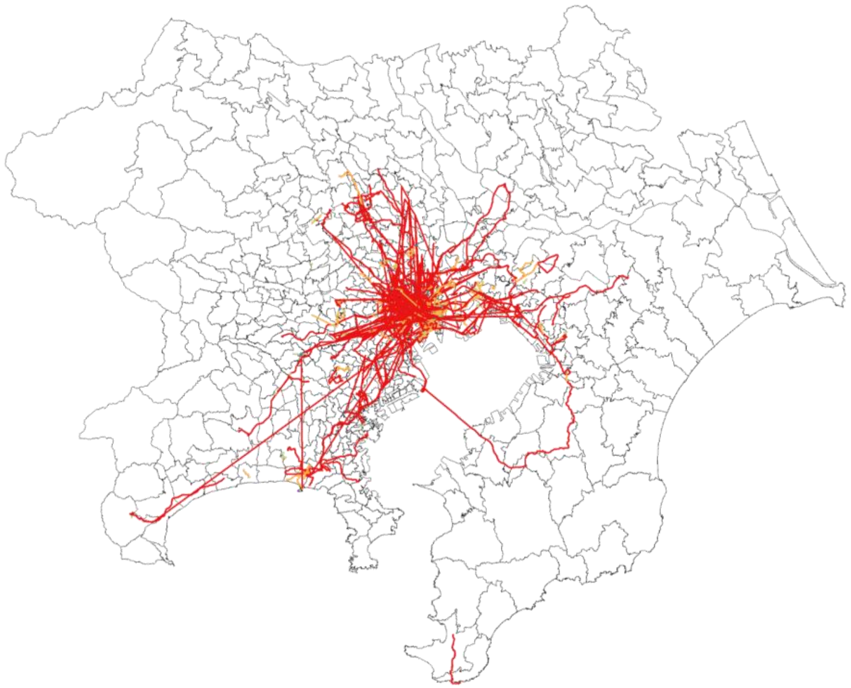
1. Drones or unmanned aerial vehicles (UAVs)
2. Sidewalk autonomous delivery robots (SADRs)
3. Road autonomous delivery robots (RADRs)

- ADR technology for last-mile freight deliveries is a valuable step towards **low-carbon logistics** (Pani et al., 2020)
- Last-mile delivery has received a great deal of attention mainly due to the **enormously growing e-commerce** (Vleeshouwer et al., 2017)) (Kapser and Abdelrahman, 2020)
- Approximately **61.28% population** showed **positive willingness to pay** responses to SADRs, and the urban residents show positive response (Pani et al., 2020)
- **Investment** in technologies that **reduce delivery times** like SADRs is happening (Figliozzi, 2019)
- The amount of time people deem acceptable for delivery times is shortening (Figliozzi, 2019)
- SADRs can also indirectly **reduce the number of on-road vehicle** miles travelled by delivery vans (Figliozzi, 2019)

- Approximately **17%-31% on-road van travel distance reduction** by SADR (Figliozzi, 2019)
- SADRs can **be faster and more cost efficient** than standard delivery vans when customer density increases
- (Figliozzi, 2019)
- ADRs that travel on sidewalks and roads are being tested in several US cities
- Air and ground autonomous vehicles have **high potential to reduce CO_2 emissions** (Figliozzi, 2020)
- Customers highly value the ability to rec
  their choice of **location and time** (Figlio
- Significant increase in e-commerce is als
  current **COVID-19 pandemic** (Figliozzi, 2

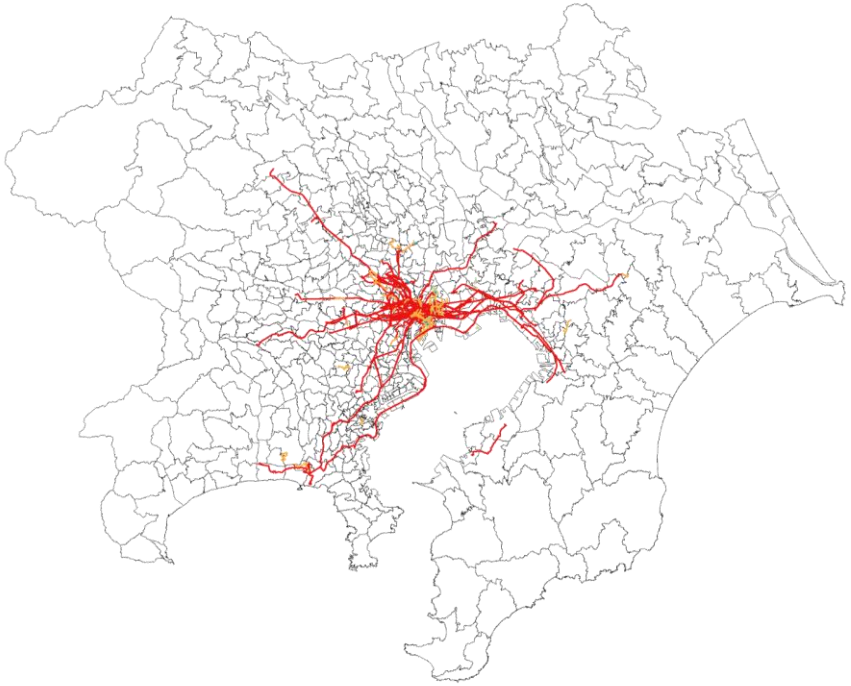
PROPOSAL: FEASIBILITY ANALYSIS: A

Shopping Trips (21.0%)

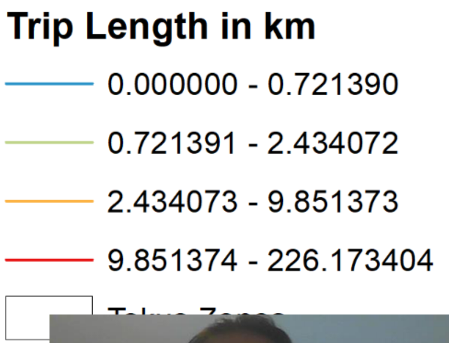


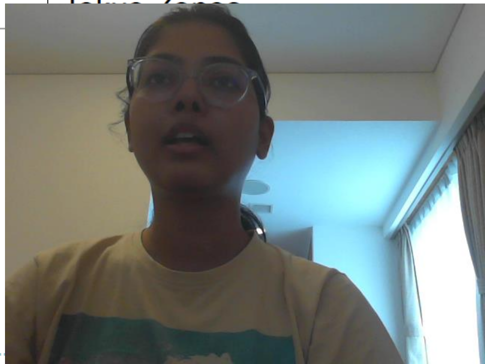
Total Trips = 845
Mean (distance in km) = 10.67
Median (distance in km) = 2.48

Eating Trips (5.2%)



Total Trips = 222
Mean (distance in km) = 9.50
Median (distance in km) = 2.33





PROPOSAL: FEASIBILITY ANALYSIS:

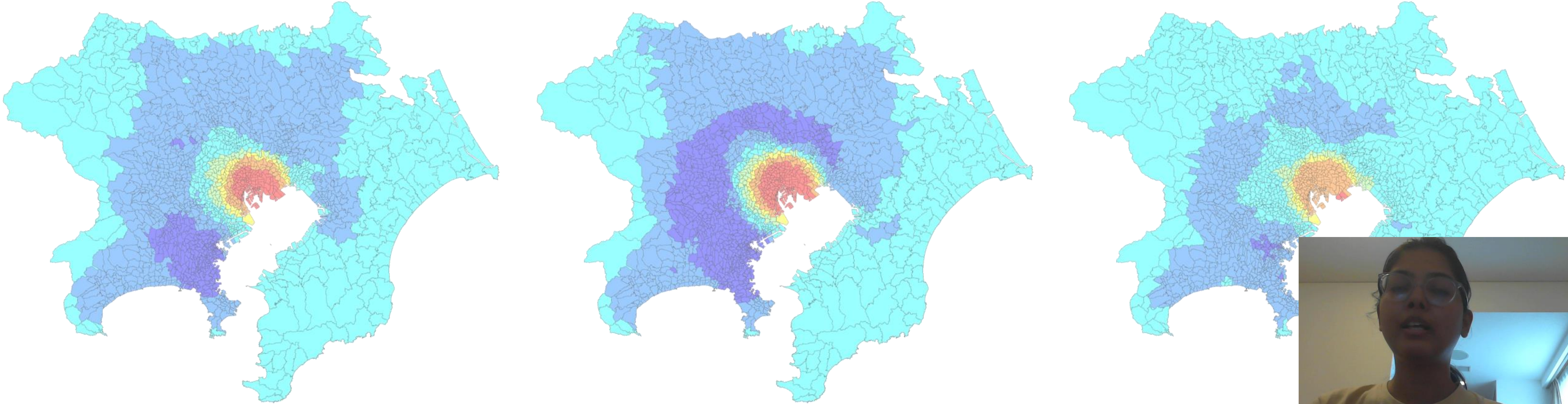
GiZScore

- 12.617690 - 19.900671
- 6.669142 - 12.617689
- 2.987215 - 6.669141
- 0.645001 - 2.987214
- -0.736319 - 0.645000
- -1.433943 - -0.736320
- -2.250437 - -1.433944
- Szpt

N

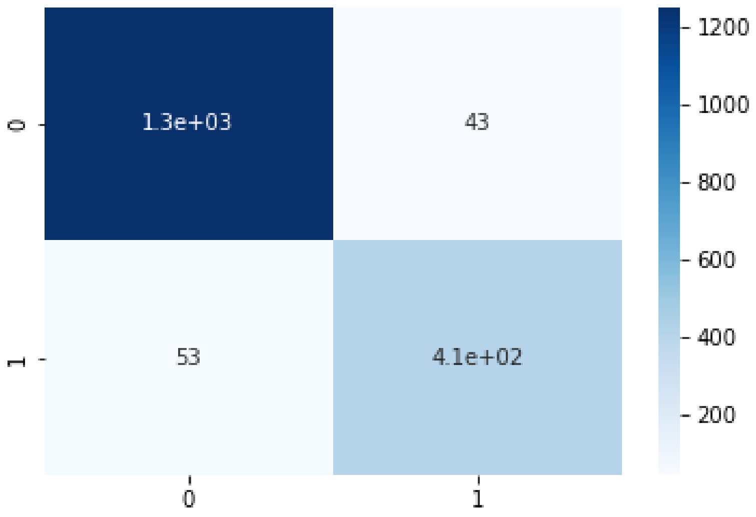
$$z\ score = Getis - Ord\ G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} * x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\dfrac{\left\{ n \sum_{j=1}^{n} w_{i,j} - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right\}}{n-1}}}$$

Shopping and Eating-out Locations | **Work and School Locations** | **Home Locations**

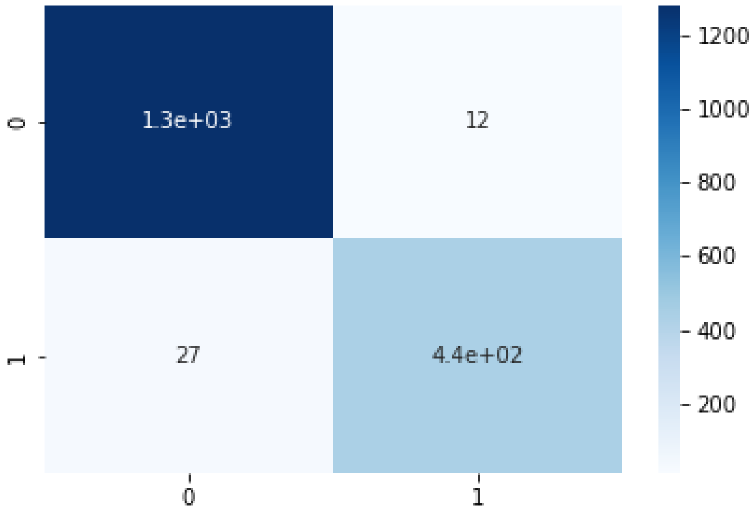


PROPOSAL: DESTINATION CHOICE MODELLING

Modelling the destination of shopping and eating trip (CBD or not). It can be elaborated to predict exact location of such demands with respect to time of the day.



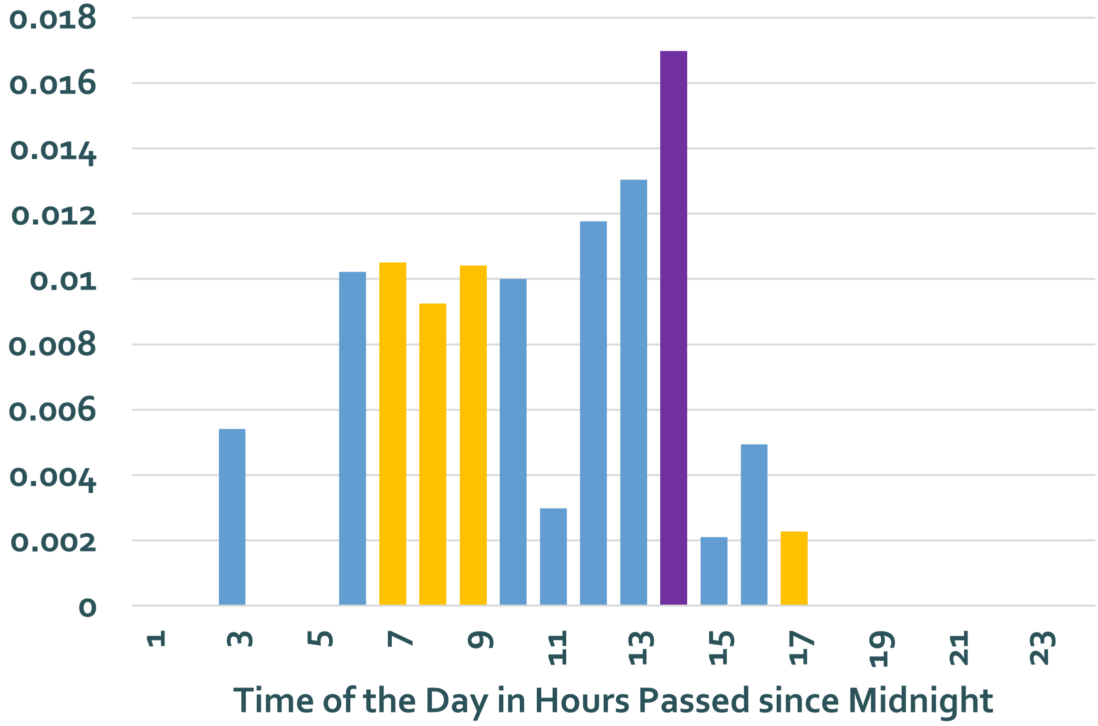
ANN: ACCURACY = 94.54%				
	Precision	Recall	F1-score	Support
0 = not CBD	0.96	0.97	0.96	1296
1 = CBD	0.90	0.89	0.89	462
Accuracy			0.95	1758
Macro Average	0.93	0.93	0.93	1758
Weighted Average	0.95	0.95	0.95	1758



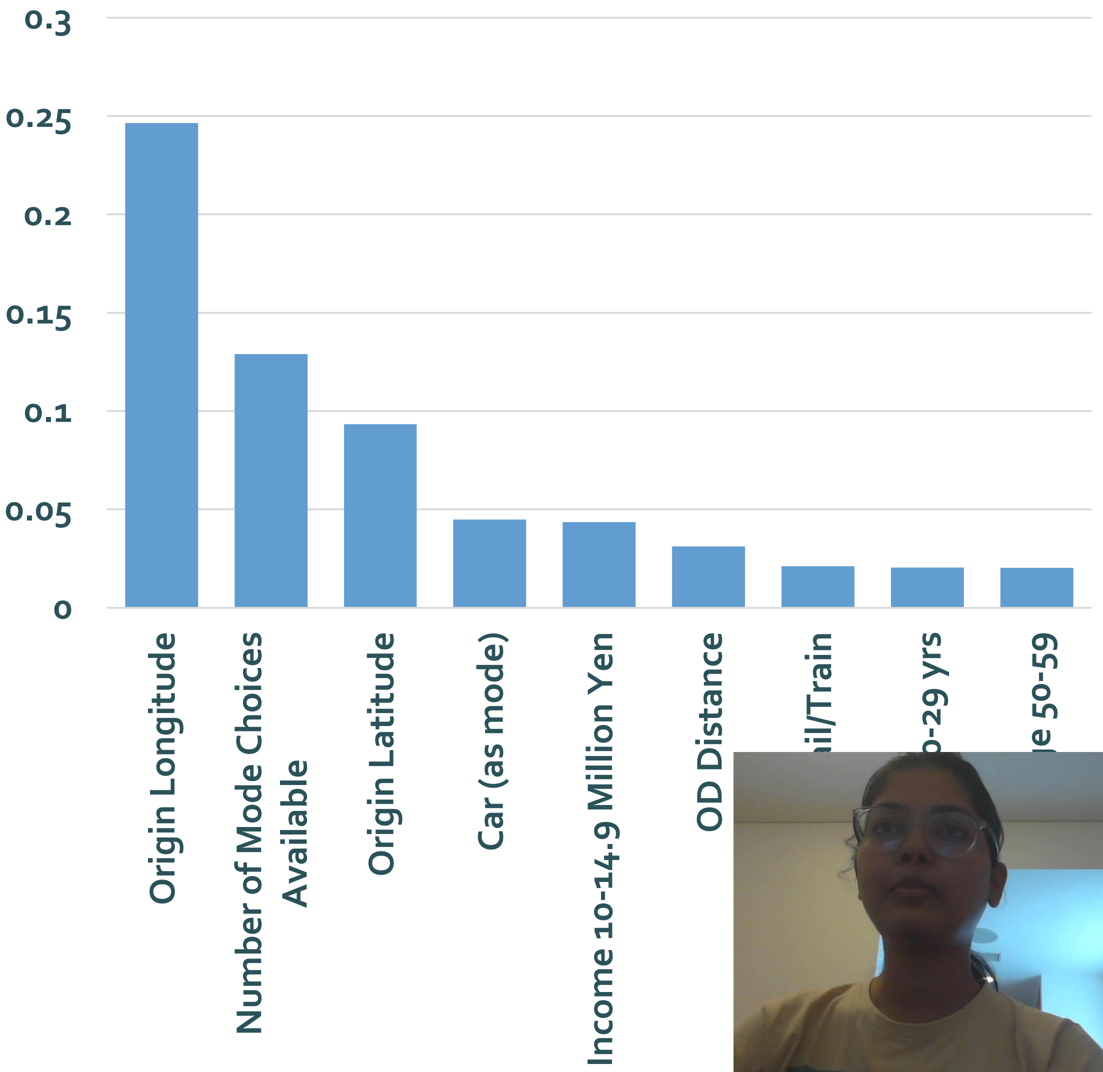
XGB: ACCURACY = 97.78%				
	Precision	Recall	F1-score	Support
0 = not CBD	0.98	0.99	0.99	1296
1 = CBD	0.97	0.94	0.96	
Accuracy			0.98	
Macro Average	0.98	0.97	0.97	
Weighted Average	0.98	0.98	0.98	

PROPOSAL: DESTINATION CHOICE MODELLING

Feature Importance of Departure Times of Cooking and Eating-out Trips



Ten Highest Important Variables to Determine Destination Location



- We can observe that the time of the day influences whether a destination is CBD or not
- Location of origin of trip, number of modes available, car availability, OD distance, and age are a few of the important features of this model

THE WAY FORWARD

User Acceptance

- A study to ensure user acceptance of such system should be done beforehand

National Policies

- Policies related to aerial delivery vehicles must be taken care of

Safety Concerns

- In the case of sidewalk delivery vehicles, pedestrian safety should be taken care of

Parking Infrastructure

- In case of road delivery vehicles, parking facilities should be taken care of

THANKYOU!