CHANGES IN TRAVEL BEHAVIOUR DURING THE COVID-19 PANDEMIC

TEAM 04
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METHODOLOGY

Descriptive Analysis

- Graphs
- Maps

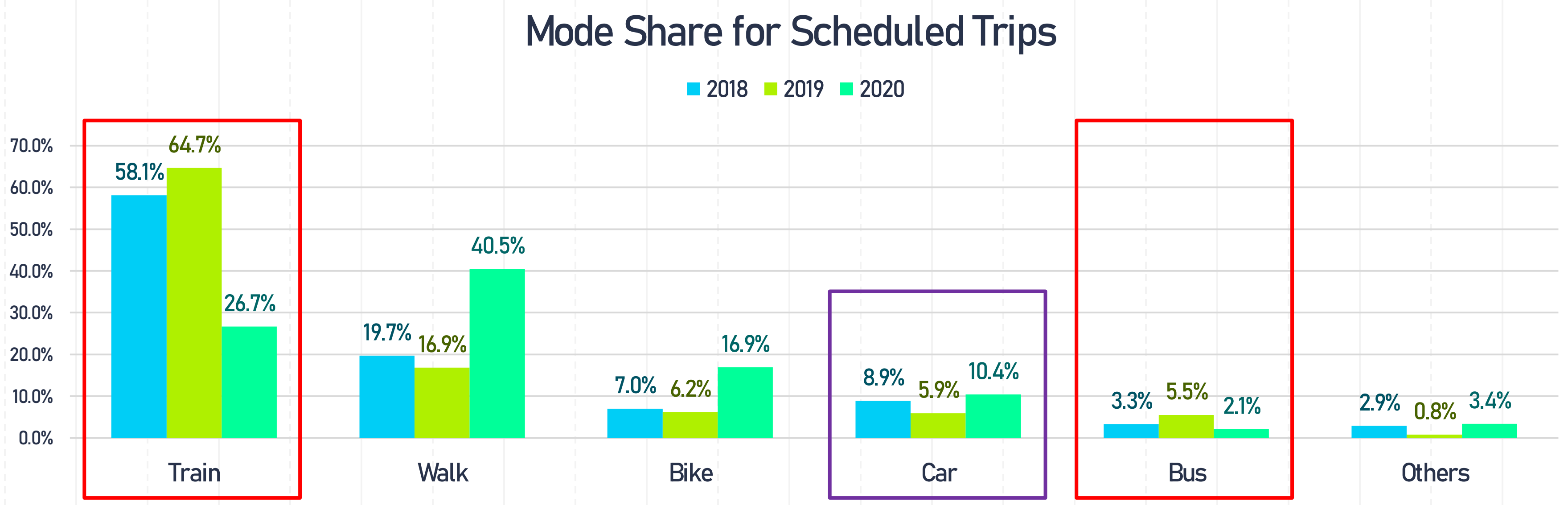
Multinomial Logit

- Significant determinants of mode choice
- Sensitivity Analysis

Machine Learning

- Variables selected through MNL
- ANN, Random Forest, XGB

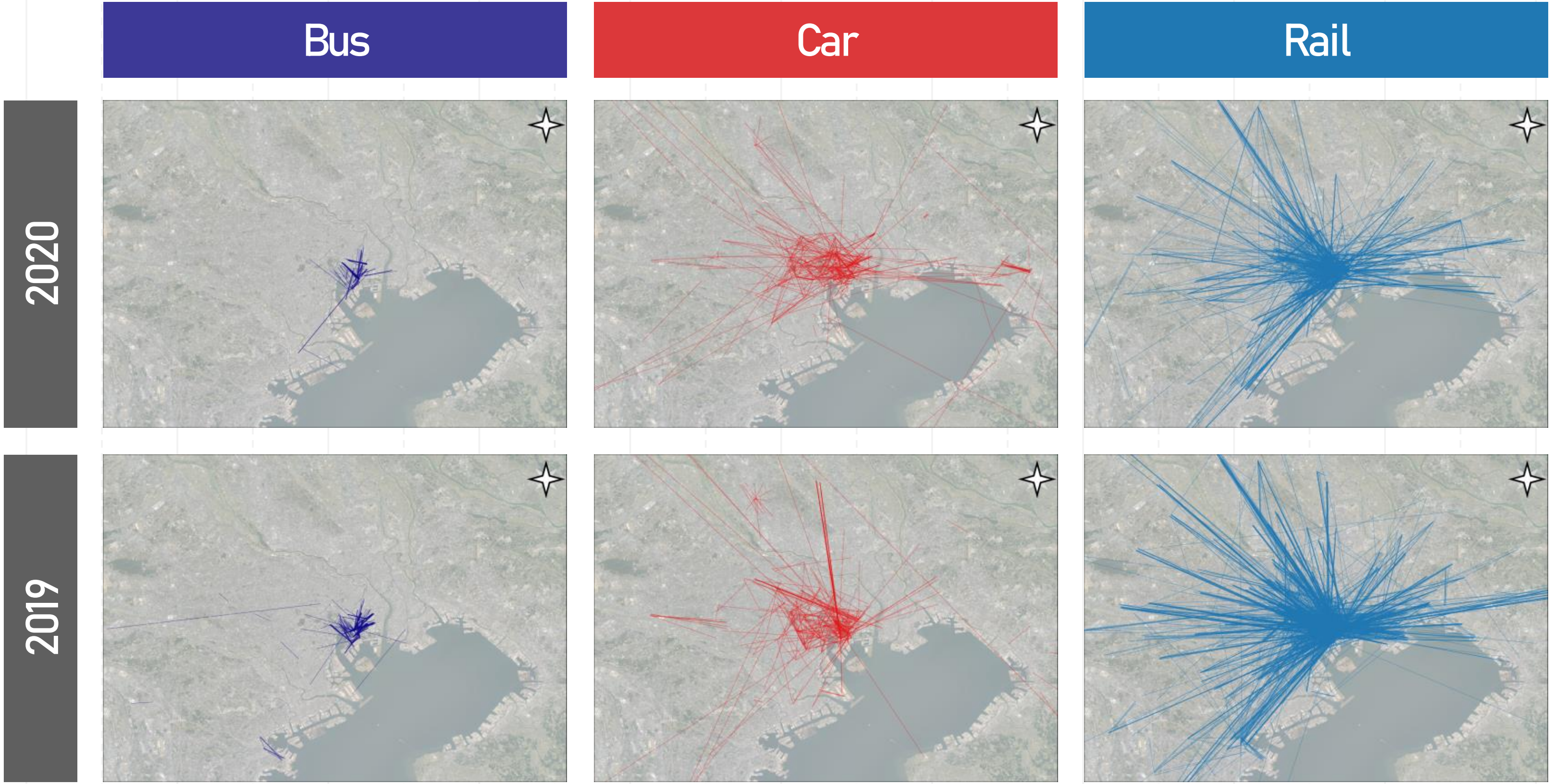
DESCRIPTIVE ANALYSIS



Inferences

- Use of public transport has decreased, and that of private transport has increased in 2020 due to the effect of COVID-19

DESCRIPTIVE ANALYSIS



ANALYSIS: MNL (2019)

Explanatory variables	Co-efficient	t-statistics
In-vehicle travel time	-.03950***	-18.37
Access time	-.07589***	-11.51
Egress time	-.06767***	-9.95
Number of transfers	-.40493***	-3.97
Departure time Car Bus	 -1.00699*** 1.26001***	 -7.37 6.64
OD Distance Car Bike Bus	 -.03571*** .33544*** -.10638**	 -4.16 -11.45 -2.09
Constant Walk Bus Train Car	 1.48730*** 2.01397*** 1.88212*** -.69619***	 20.71 8.58 10.96 -6.11

Goodness of fit statistics	
LL (at convergence)	-2708.91595
LL (constants only model)	-3652.66450
Rho-square	0.26

Note: *** → Significance at 1% level

Sample Size: 5261, Cali. = 85%, Vali. = 15%

Train	282.47	5.69	11.53	8.00	26.31
Bike	5.55	7.66	28.12	2.00	3.67
Walk	10.40	40.83	162.88	2.59	17.30
Bus	7.28	3.39	10.46	33.55	2.32
Car	50.07	11.10	38.00	6.79	11.04
	Train	Bike	Walk	Bus	Car

Prediction Accuracy = 0.630

ANALYSIS: MNL (2020)

Explanatory variables	Co-efficient	t-statistics
In-vehicle travel time	-.03132***	-17.90
Access time	-.05723***	-7.23
Egress time	-.07137***	-8.69
Number of transfers	-.15154	-1.26
Departure time		
Car	-.92148***	-7.83
Bus	.86494***	3.60
OD Distance		
Car	-.01963**	-2.40
Bike	-.25350***	-12.18
Bus	-.34364***	-6.39
Constant		
Walk	.97645***	14.66
Bus	.76312***	2.73
Train	.73832***	4.03
Car	-.55806***	-6.24

Goodness of fit statistics	
LL (at convergence)	-3089.17180
LL (constants only model)	-3656.31847
Rho-square	0.16

Note: ***, ** → Significance at 1%, 5% level

Sample Size: 3959, Cali. = 85%, Vali. = 15%

	Train	Bike	Walk	Bus	Car
Train	158.5	9.5	14.9	2.1	40.1
Bike	15.5	29.5	62.9	11.9	18.1
Walk	14.3	30.2	71.2	4.2	16.2
Bus	11.0	7.4	12.0	11.8	4.8
Car	6.5	9.6	20.3	0.5	11.1

Prediction Accuracy = 0.474

ANALYSIS: ML

2019 Scheduled: Sample Size = 5261, Train = 85%, Test = 15% | 2020 Scheduled: Sample Size = 3959, Train = 85%, Test = 15%

2019

ANN

Accuracy: 0.767

	Bike	Bus	Car	Walk	Rail
Bike	230	1	5	8	0
Bus	51	10	4	1	0
Car	22	0	28	2	0
Walk	23	1	1	331	0
Rail	30	0	2	39	1

XGB

Accuracy: 0.816

	Bike	Bus	Car	Walk	Rail
Bike	235	4	4	14	7
Bus	27	24	4	4	2
Car	0	1	29	9	1
Walk	1	2	9	342	3
Rail	11	6	8	28	15

RF

Accuracy: 0.815

	Bike	Bus	Car	Walk	Rail
Bike	232	11	6	10	5
Bus	31	20	3	5	2
Car	2	0	31	7	0
Walk	1	2	7	342	5
Rail	13	6	5	25	19

2020

ANN

Accuracy: 0.725

	Bike	Bus	Car	Walk	Rail
Bike	165	4	0	0	21
Bus	57	22	0	0	15
Car	0	0	13	6	0
Walk	0	0	4	203	0
Rail	28	9	0	0	47

XGB

Accuracy: 0.725

	Bike	Bus	Car	Walk	Rail
Bike	165	13	3	9	6
Bus	36	59	3	1	4
Car	2	2	12	4	2
Walk	3	3	1	169	12
Rail	25	2	3	29	26

RF

Accuracy: 0.705

	Bike	Bus	Car	Walk	Rail
Bike	161	14	1	9	11
Bus	39	52	3	1	8
Car	3	1	11	4	3
Walk	7	2	0	166	13
Rail	25	4	2	25	29

SENSITIVITY ANALYSIS

Elasticity Effects of Transportation System Attributes on Mode Shares				
Attribute	Bus		Train	
	2019	2020	2019	2020
Travel time				
Car	0.03	0.05	0	0
Bus	-0.34	-0.35		
Train			-0.11	-0.15
Access time				
Bus	-0.21	-0.41		
Train			-0.13	-0.15

Inferences

- The demand of bus is sensitive to travel time of car
- The demand of train is not sensitive to travel time of car
- The demand of Buses and Trains is sensitive to their respective travel and access times

CONCLUSIONS

- Share of public transport has declined in 2020
- Average distance travelled increases from buses to cars to trains
- Significant variables influencing the mode choice are In Vehicle Travel Time, Access Time, Egress Time, Number of Transfers, Departure Time, OD Distance
- ML shows better prediction accuracy
- Demand of bus can be increased by increasing the travel time of car and decreasing the travel time of bus

POLICY INTERVENTIONS

- Case studies show that people are more likely to travel through buses than trains during pandemic
- People find it hard to maintain social distancing in underground closed spaces in train

Increase Accessibility of Buses

- Improve the last mile connectivity of buses

Reallocation of Road Spaces to Buses

- Dedicated bus lanes

THANKYOU!

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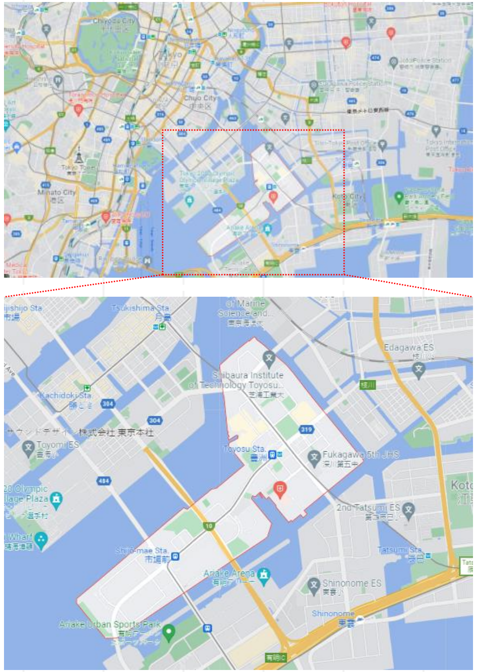
8. Share of consumers in Japan owning a car as of June 2019, Statista, https://www.statista.com/statistics/1027885/japan-share-car-ownership/

APPENDIX

1 INTRODUCTION

Introduction and Elementary Objectives

INTRODUCTION



TOYOSU

Profile

- Created on reclaimed land in 1937.
- Proximity to central Tokyo makes it valuable for real estate development.
- Was preparing for the 2020 Summer Olympics in Tokyo
- The Toyosu Market (Toyosu Shijō) is a wholesale market for seafood, fruits and vegetables.
- Toyosu MiCHi no Eki will be the first Urban Roadside Station in Japan.

Requirements

- Development of efficient transportation system to cater the needs of the businesses
- The emergence of COVID-19 Pandemic has created several hurdles in development, and has caused several behavioural changes among people

Sources:
- https://www.google.com/maps/place/Toyosu,+Koto+City,+Tokyo+135-0061,+Japan/@35.6509201,139.7858718,14.43z/data=!4m5!3m4!1s0x6018899921571b99:0x6b11b36766253d26!8m2!3d35.6545886!4d139.7965201
- https://www.shimz.co.jp/toyosu/index2.html

DATA CHARACTERISTICS

PP Data > Toyosu > Trip Data (2018, 2019 and 2020)

- Purpose of Trip
- Departure and Arrival Time
- Trip Duration
- Main and First Transportation Mode
- Subsequent Transportation Modes
- OD Direct Distance
- Longitude and Latitude of OD
- Shikucode of OD
- If alternatives are available for: Car, Train, Walk, Bike and Bus
- Travel Time, Fare/Cost, Distance, Access Time, Egress Time for available modes

ELEMENTARY AIM AND OBJECTIVES

AIM

- To understand the impact of COVID-19 Pandemic on mode choice behaviour of people

OBJECTIVES

- Do a preliminary analysis of data to understand trip patterns
- Do modelling through MNL and ANN to understand which factors influence the mode choices
- Refine variable choices on the basis of MNL model and then do a prediction through ANN
- Understand the differences between trip patterns of scheduled and non-scheduled trips
- Understand the effect of COVID-19 pandemic on behavioural changes
- Derive suitable policy interventions based on sensitivity analysis

2 METHODOLOGY

Detailed Methodology and Assumptions

METHODOLOGY

Preliminary Analysis
(On Raw Data)

- Inferences through graphs
- Re-classification of data

Initial Analysis
(On Re-Classified Data)

- Inferences through graphs and maps
- Modelling through MNL and ANN
- Modification of classes and independent variables

Final Analysis
(On Modified Data)

- Modelling through MNL and ANN
- Final inferences through modelling results

Policy Interventions
(By Overall Inferences)

- Overall conclusions and Inferences
- Possible scenarios
- SWOT analysis
- Policy Interventions

LIMITATIONS

- Socio-Economic characteristics and built environment characteristics have not been considered
- Influence of Perception of safety on mode choice have not been considered

ASSUMPTIONS

All trips are independent

- The characteristics of any one trip do not depend on, or affect, any other trip

Each day of departure is an independent, uniform and normal day

- Trips on any one day do not depend on, or affect, trips on any other day
- Trips on each day have uniform characteristics
- Each of these uniform days are normal or weekdays, holidays or weekly off days are not considered

If a route is available for walk then it is available for bike as well

Buses require no trip change

Cars, Walk and Bikes Require no Trip Change

Cycling Speed is assumed as 22kmph

Cost of travelling through car is considered as 25 yen per km, plus 150 yen in fees

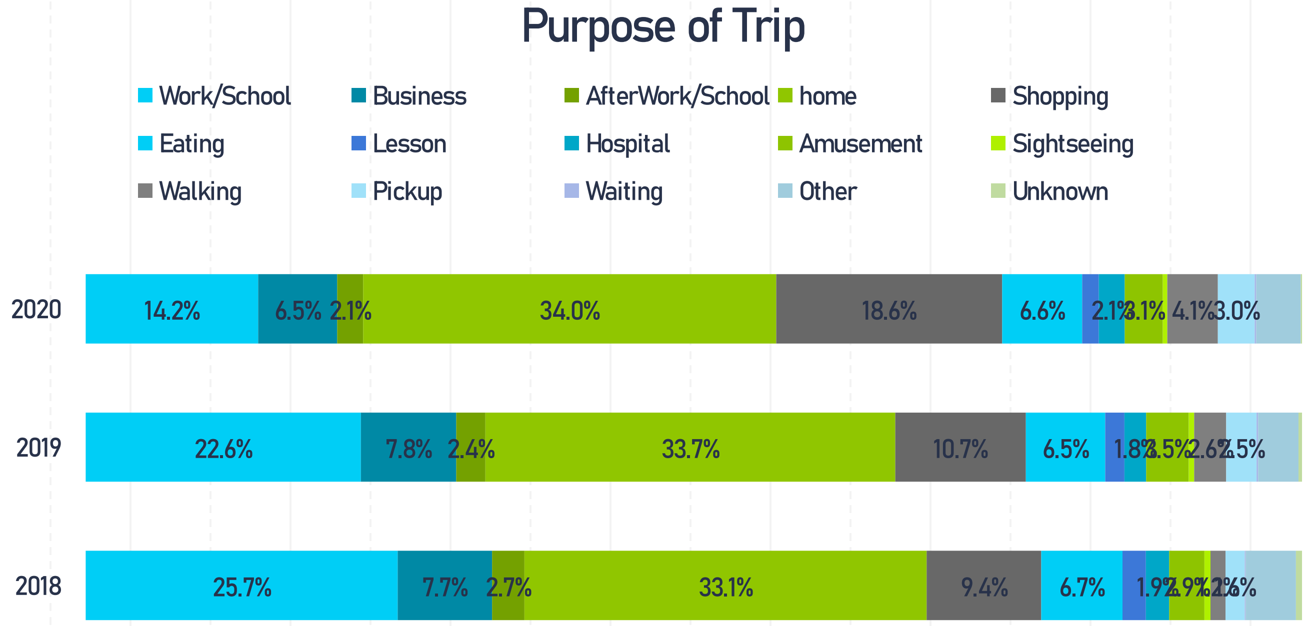
3 ANALYSIS

Detailed Analysis and Inferences

2.A PRELIMINARY ANALYSIS

(On Raw Data)

TRIP CHARACTERISTICS

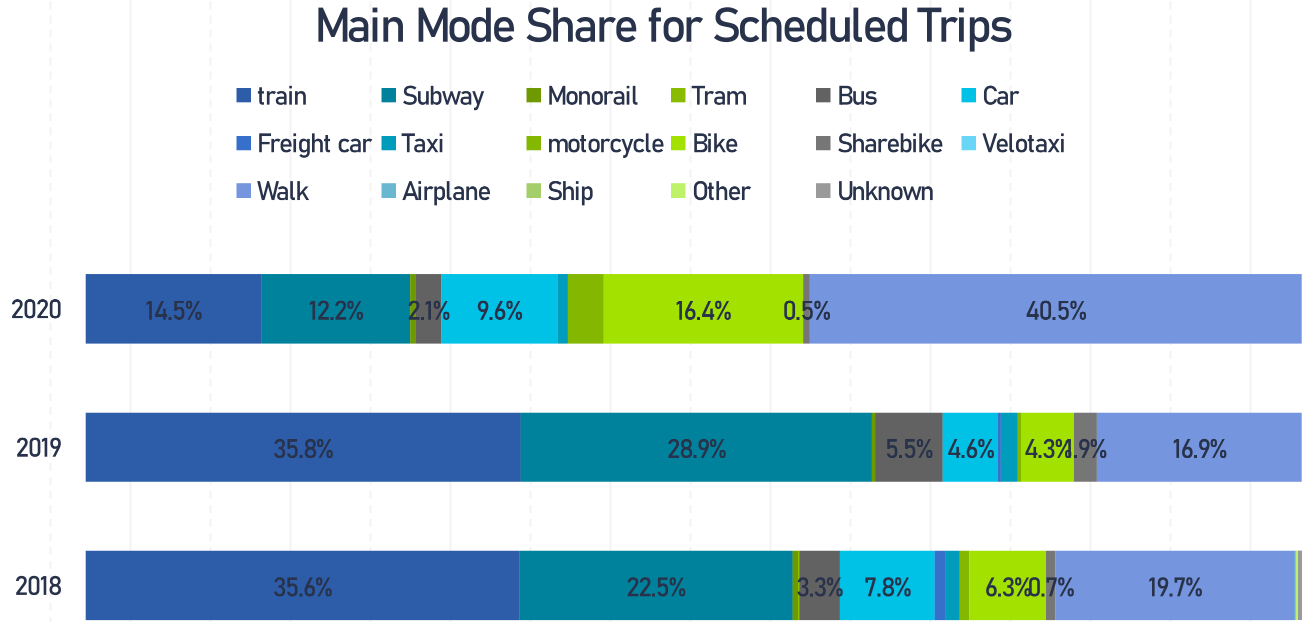


- Trips to work and schools have reduced in 2020 due to COVID-19 Pandemic
- Consequently the share to trips to shopping has increased
- The share of back to home trips has remained uniform, and its value has remained around 33%
- This suggests that on an average people still take two trips in a tour before reaching home

RECLASSIFIED TRIP PURPOSES

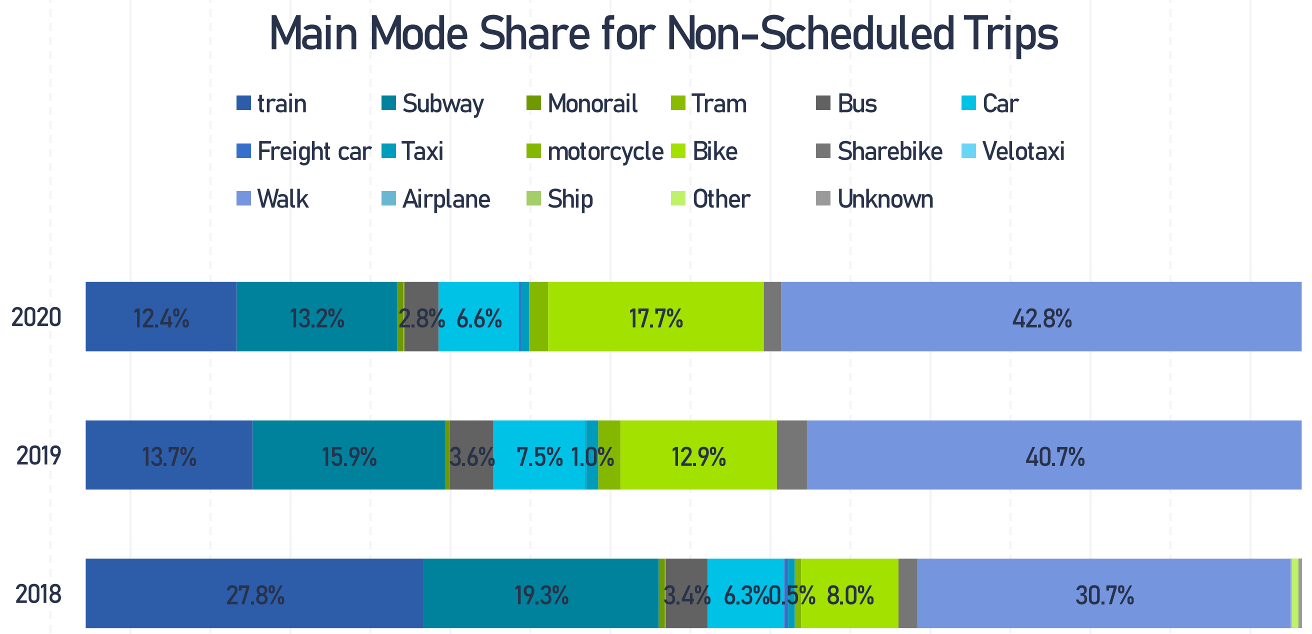
Scheduled	Unscheduled	Home	Other
Work/School	Shopping	After Work/School	Pickup
Working/Business	Eating	Home	Waiting
Lesson	Amusement		Other
	Sightseeing		Unknown
			Hospital
			Walking/Strolling

TRIP CHARACTERISTICS



- Respectively much lesser people are using public transport for scheduled trips in 2020 due to COVID-19 Pandemic
- Consequently the share of people walking has increased
- The number of people using private cars and bikes has increased subsequently in 2020

TRIP CHARACTERISTICS



- As data from 2019 includes entries from initial months of 2020, the effect of COVOD_19 Pandemic can be seen in the use of public transport for non scheduled trips
- The increase in the use of private vehicles such cars and bikes can be observed here as well

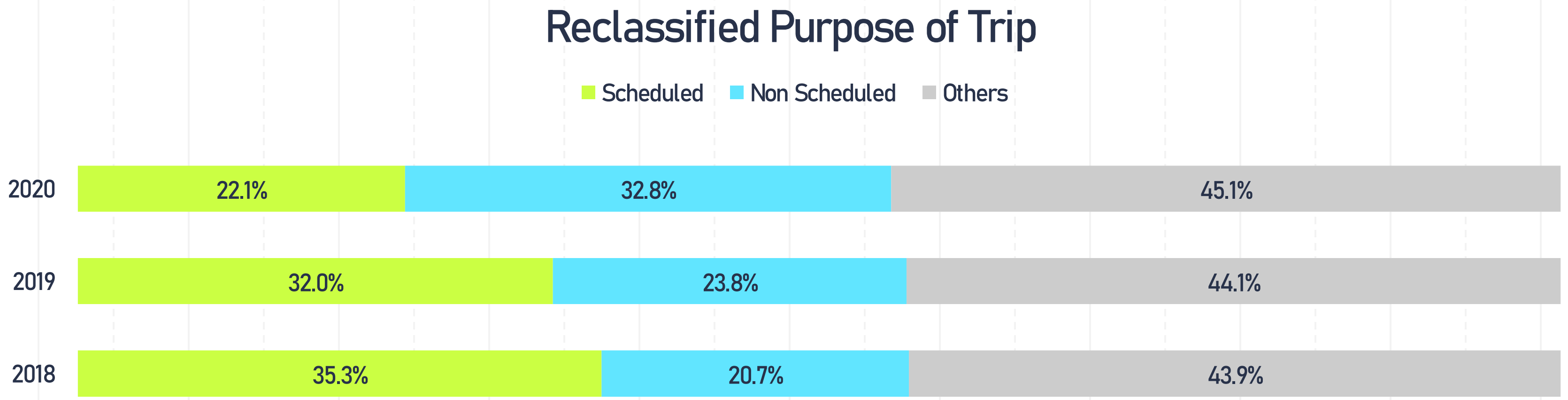
RECLASSIFIED MODES

Train	Bus	Walk	Bike	Car
Train	Shopping	Walk	Bike	Car
Subway			Sharebike	

Other

- Monorail, Tram, Freight Car, Taxi, Motorcycle, Velotaxi, Walk, Airplane, Ship, Other, Unknown

TRIP CHARACTERISTICS



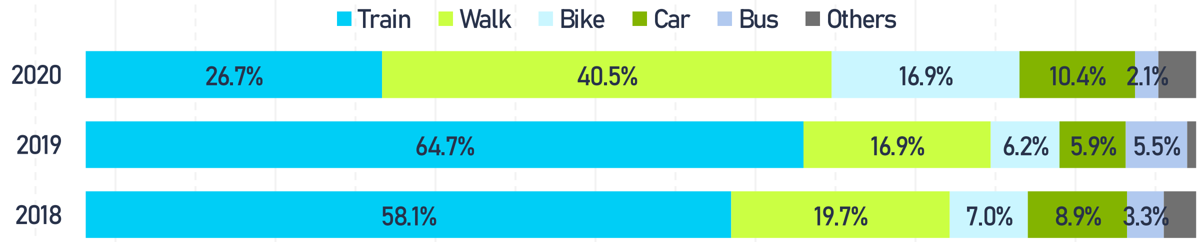
- Scheduled trips have decreased
- People have stopped visiting to offices and schools but they are still taking trips for leisure, shopping, strolling etc.

2.B INITIAL ANALYSIS

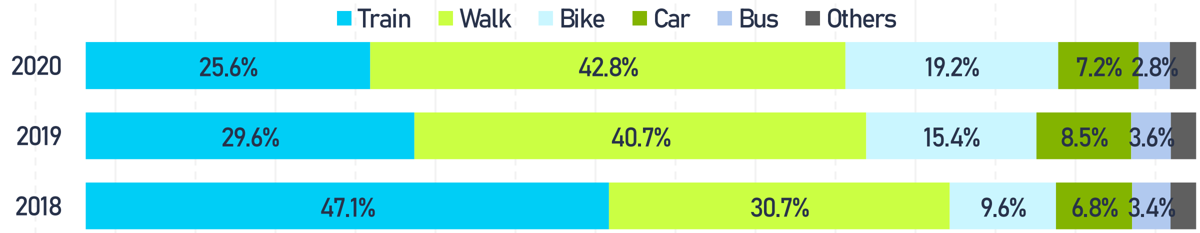
(On Re-Classified Data)

TRIP CHARACTERISTICS: MODES

Revised Main Mode Share for Scheduled Trips



Revised Main Mode Share for Non-Scheduled Trips



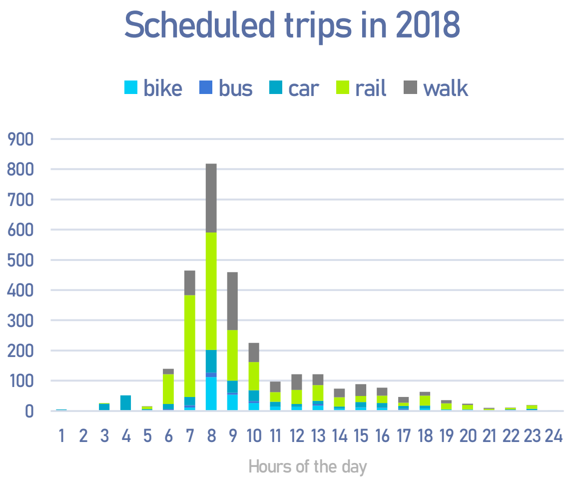
Inferences

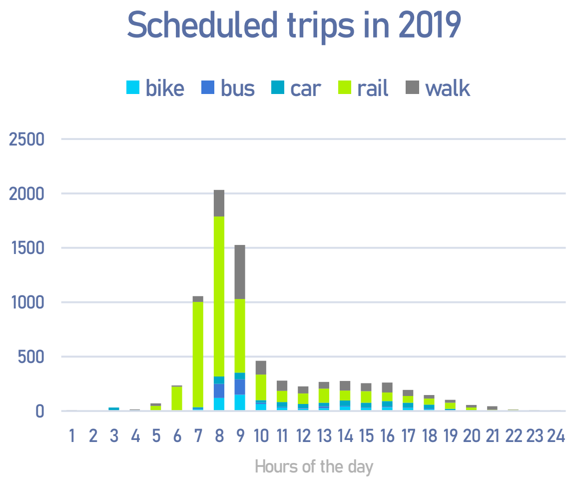
- The share of people using public transport has been decreasing due to safety issues because the decrease can be observed both in scheduled and non scheduled trips

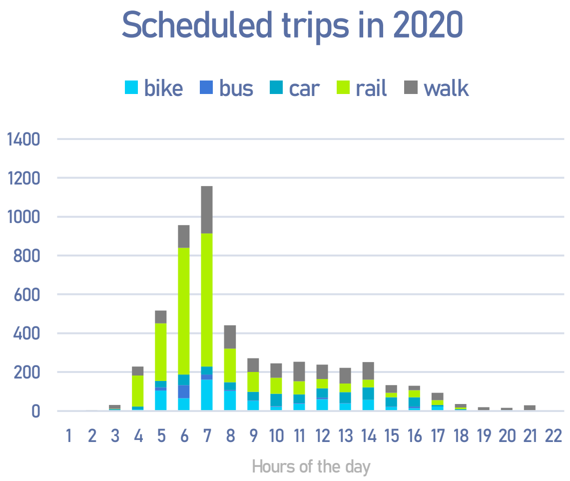
Requirements

- The safety of public transport must be increased
- Consequences of increase in private transportation modes must be considered for future developments

TRIP CHARACTERISTICS: ST

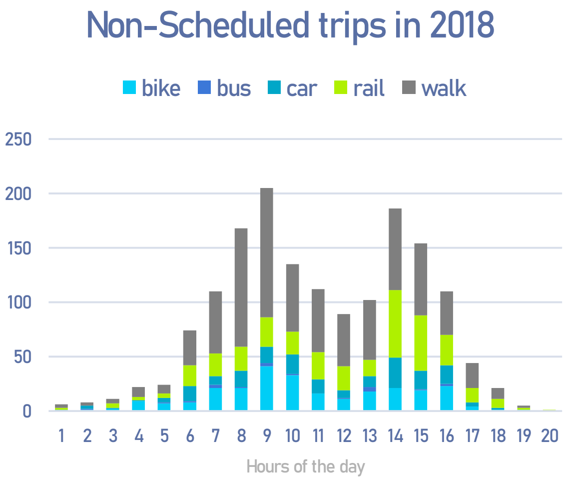


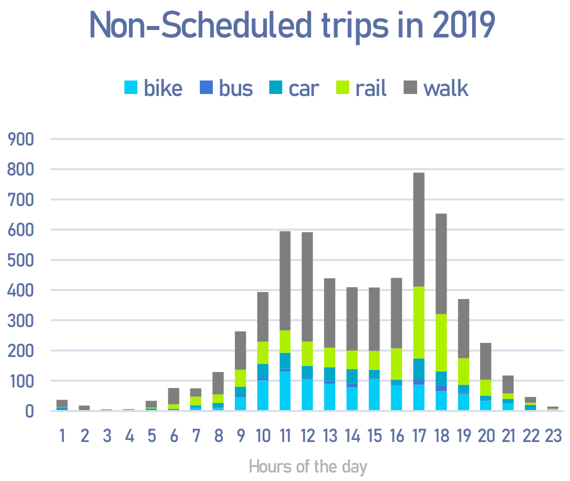


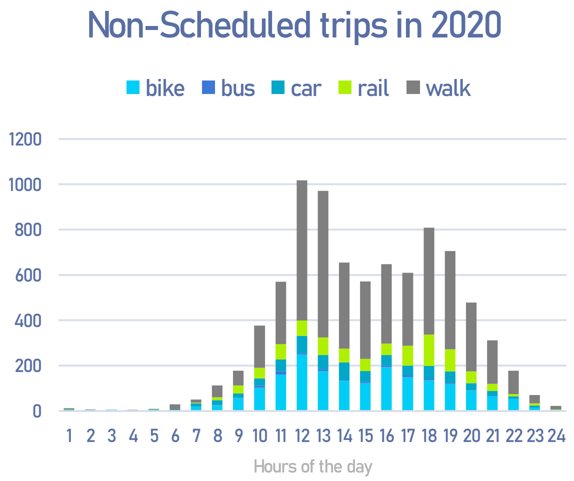


- Scheduled trips have a peak travel time from 07:00am to 11:00am in the morning
- Only one peak is observed for scheduled trips
- Major share of scheduled trips are done by trains
- Use of bike has increased in 2020

TRIP CHARACTERISTICS: NON-ST

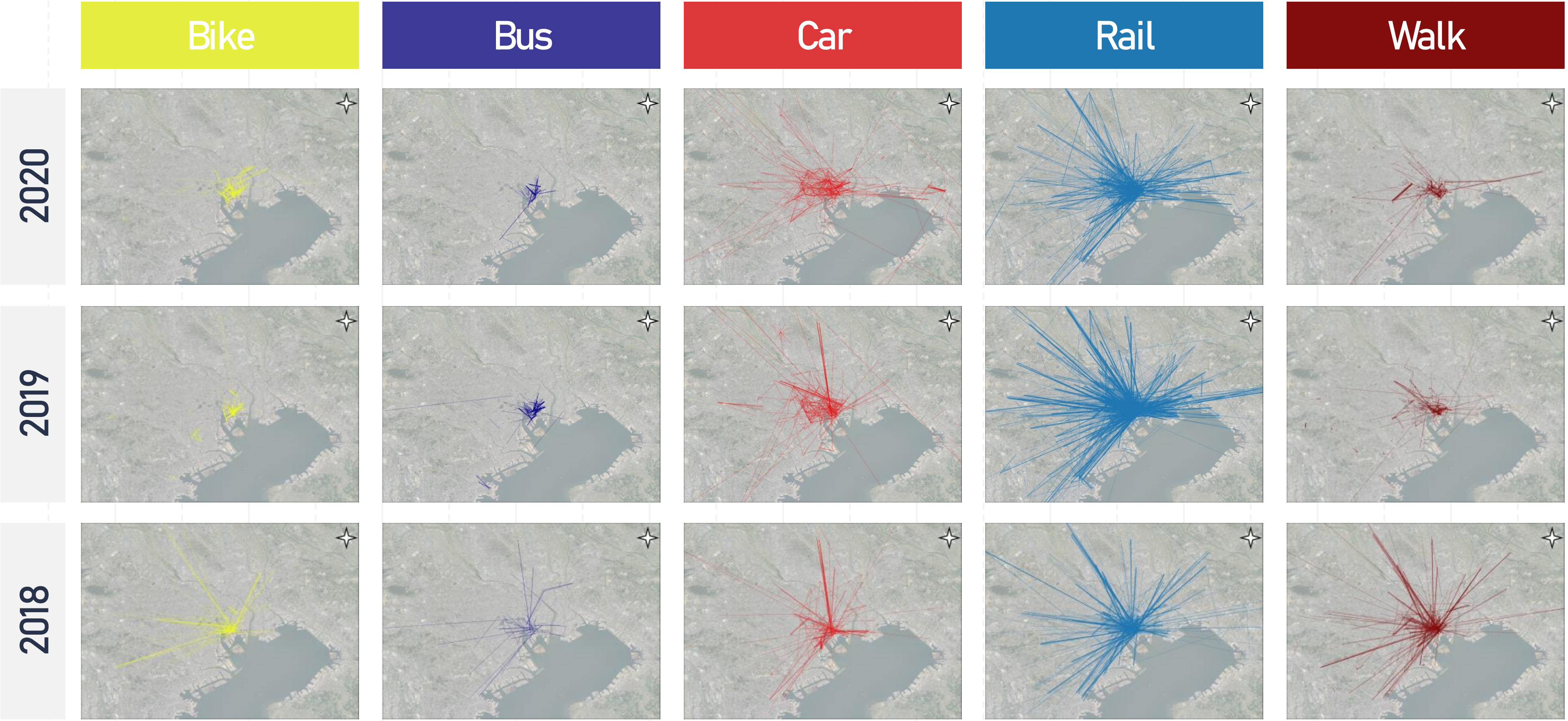




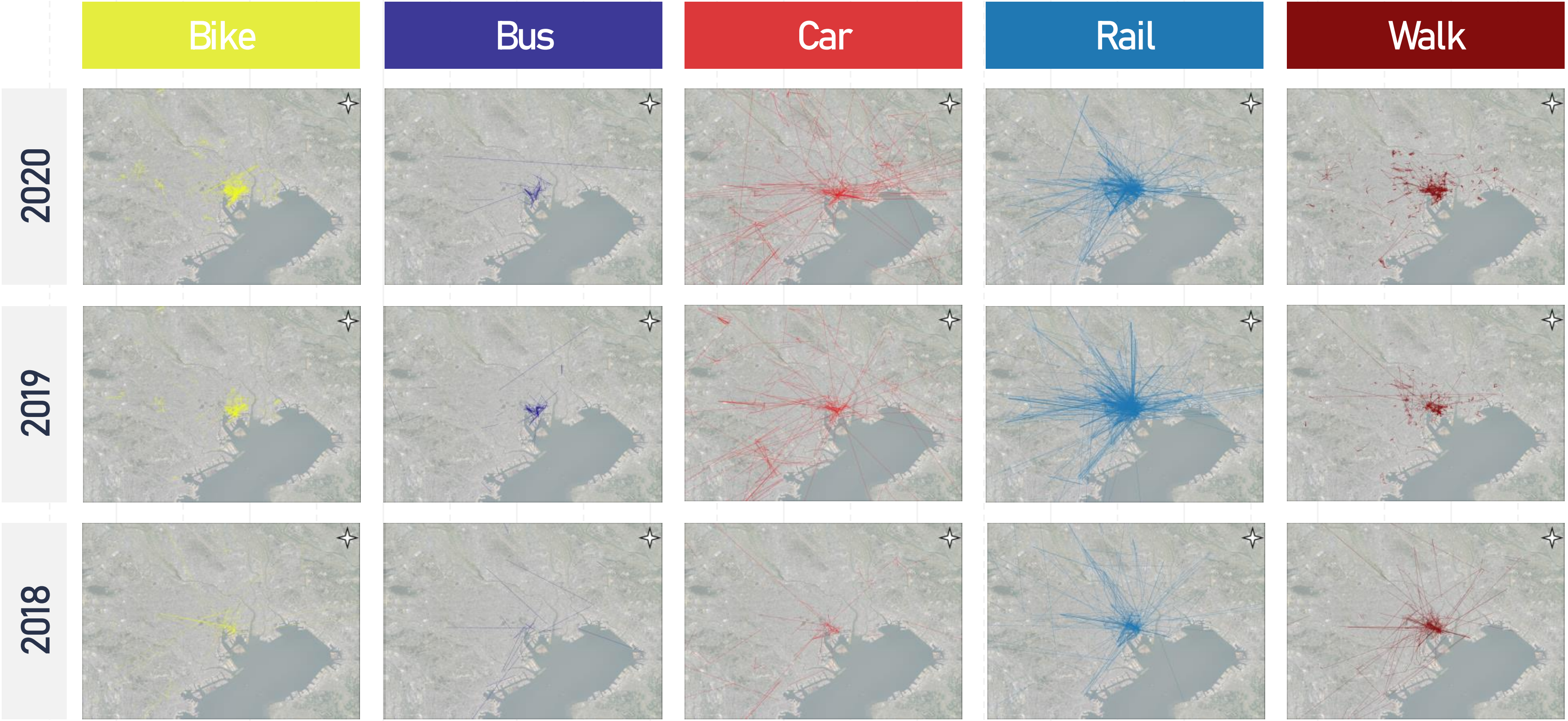


- Non-scheduled trips have a peak travel time from 07:00am to 11:00am in the morning and 13:00pm to 17:00pm in the evening
- Two peaks are observed for non-scheduled trips
- Major share of non-scheduled trips are done by bikes or by walk
- Use of rail has decreased in 2020

TRIP CHARACTERISTICS: ST



TRIP CHARACTERISTICS: NON-ST



INITIAL CHOICE OF VARIABLES

	Main Mode Choice	Departure Time	Departure Time Classified	Number of Mode Changes	OD Direct Distance	Distance Category	Availability	Time	Fare/Cost	Number of Transfers	Access Time	Egress Time
	Y	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
MNL												
ANN												

MNL

The data was converted into multiple line format and each choice was regarded as a separate entity, with the probability of the chosen choice as 1

ANN

- The data was used for training without classifying the departure time and OD distances
- Since the mode characteristics of only the available choice is given, the characteristics were not considered

ANN

2018

Scheduled — Accuracy Score: 0.565

	Bike	Bus	Car	Walk	Rail
Bike	11	0	0	27	29
Bus	1	0	0	0	13
Car	8	0	13	17	34
Walk	21	0	1	91	70
Rail	34	0	0	1	229

Non-Scheduled — Accuracy Score: 0.528

	Bike	Bus	Car	Walk	Rail
Bike	11	0	1	28	6
Bus	1	0	0	1	0
Car	9	0	0	25	5
Walk	27	0	1	107	31
Rail	24	0	0	3	38

2019

Scheduled — Accuracy Score: 0.760

	Bike	Bus	Car	Walk	Rail
Bike	72	0	0	37	15
Bus	36	0	0	0	33
Car	51	0	9	15	46
Walk	49	0	0	261	17
Rail	58	0	5	0	809

Non-Scheduled — Accuracy Score: 0.700

	Bike	Bus	Car	Walk	Rail
Bike	71	0	3	135	13
Bus	4	0	0	0	10
Car	32	0	6	38	50
Walk	40	0	0	564	19
Rail	22	0	1	0	219

2020

Scheduled — Accuracy Score: 0.777

	Bike	Bus	Walk	Rail
Bike	83	0	38	32
Bus	4	0	1	20
Walk	35	0	195	27
Rail	37	0	6	451

Non-Scheduled — Accuracy Score: 0.697

	Bike	Bus	Walk	Rail
Bike	117	0	302	9
Bus	13	0	0	5
Walk	75	0	1061	10
Rail	63	0	5	139

MNL

	2018	2019	2020
Scheduled	Rho square =	Rho square = 0.14	Rho square = 0.23
Non-Scheduled	Rho square =	Rho square =	Rho square =

2.C

FINAL ANALYSIS

(On Modified Data)

SAMPLE SELECTION

Selection of Columns

- On the basis of availability and uniformity of data
- On the basis of variables which showed significant results

Selection of Rows

- Removal of error values

CHOICE OF VARIABLES

IVTT	Continuous	In vehicle travel time (minutes)
AT	Continuous	Access time (minutes)
ET	Continuous	Egress time (minutes)
NT	Discrete	Number of transfers (numbers)
DT1	Categorical	Departure time (1=Peak hour=1700to1900 and 0700to0900, 0=Off peak=other)
DIST1	Continuous	OD Distance (straight line distance between Origin and Destination, km)
TC	Continuous	Travel cost
Mode	Categorical	Bike=1, Bus=2, Car=3, Walk=4, Rail=5

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LL (at convergence)	-2708.91595
LL (constants only model)	-3652.66450
Rho-square	0.26
Note: *** → Significance at 1% level	

Inferences

- Cost of trip is not an significant variable in scheduled trips
- Egress time is not a significant variable in scheduled trips

Utility

U(TRAIN)= -0.0395* IVTT -0.40493*NT -0.07589*AT -0.06767*ET +1.88212

U(BIKE)= -0.0395* IVTT -0.40493*NT -0.07589*AT -0.06767*ET -0.33544*DIST

U(Walk)= -0.0395* IVTT -0.40493*NT -0.07589*AT -0.06767*ET +1.4873

U(BUS)= -0.0395* IVTT -0.40493*NT -0.07589*AT -0.06767*ET +1.26001*DT -0.10638+DIST +2.01397

U(CAR)= -0.0395* IVTT -0.40493*NT -0.07589*AT -0.06767*ET -1.00699*DT -0.03571+DIST -0.69619

ANALYSIS: MNL (2020)

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Rho-square	0.16

Note: ***, ** → Significance at 1%, 5% level

Inferences

- Perception of safety could be an important factor, influence of which which is not reflected in the model

Utility

U(WALK)= -.03132*IVTT-.07137*ET-.05723*AT1+.97645-.15154*NT

U(BIKE)= -.03132*IVTT-.07137*ET-.05723*AT1-.25350*DIST1-.15154*NT

U(BUS)= -.03132*IVTT-.07137*ET-.05723*AT1-.34364*DIST1+.76312+.86494*DT1-.15154*NT

U(TRAIN)= -.03132*IVTT-.07137*ET-.05723*AT1+.73832-.15154*NT

U(CAR)= -.03132*IVTT-.07137*ET-.05723*AT1-.15154*NT-.92148*DT1-.01963*DIST1-.55806

MNL

D:\pythonbehavioral\hyperlink_mnl_docs

CASE STUDIES 4

Past Experiences and Curent Scenario

CASE STUDIES

Changes in transport behaviour during the Covid-19 crisis

- Covid19 may cause permanent change in travel choice behavior and government must prepare for that
- People do not want to travel through public transport and its demand has considerably decreased
- Previous crises have spurred long-term shifts in transport preferences when supported by other factors
- Governments can influence which transport behaviours are more permanent after the crisis
- Infrastructure investments can be crucial for building trust in public and active transport
- Pricing and regulatory policies can help incentivise less energy-intensive transport behaviours when the crisis ends
- Public behaviour change campaigns can work under the right conditions
- Trust in government can esure that demand for public transport increases again
- Direct stimulus which can have positive economic spill over effects: spending in public transport creates more economic benefits
- .issues of public health post pandemic can be tacked by using sustainable modes such as bikes or share-bikes, which produce long term positive economic development, by reducing congestion and maintaining health

Source: https://www.iea.org/articles/changes-in-transport-behaviour-during-the-covid-19-crisis

Beyond the immediate crisis: The SARS-CoV-2 pandemic and public transport strategy

- People prefer buses over trains as they find it difficult to maintain social distances in underground spaces
- While the actual risk of infection is one thing, perceived risk and behavior is quite another. Fear-induced public transport avoidance decreases over time.
- With respect to modal choice, public transport may continue to suffer.
- Trust reinstating behaviour must be promoted to ensure rebound to pre-pandemic transportation patterns
- Unemployment and digitalization may however restrict the rebound to pre-pandemic pattern, particularly in the area of work and education
- While use of bike may increase, the use of car may remain constant in Germany. However the use of public transport will surely decrease.
- Expansion of Public Transport makes urban mobility more accessible and sustainable
- Capacity must be increased to ensure social distancing in public transport
- Expanding public transport can function as direct and city-specific economic stimuli.
- Multi-modal integration can help public transport to generate customer loyalty by keeping them within their own public-transport centric ecosystem/app even in volatile times.
- Incentives for using public transport is helpful
- Data analytics and AI tools, furthermore, can help generating systematic and near-real-time information about occupancy, travel flows and system bottlenecks.

Source: https://mobilityinstitute.com/wp-content/uploads/2020/04/Beyond-the-immediate-crisis-The-SARS-CoV-2-pandemic-and-public-transport-strategy_mib_v1.03.pdf

CASE STUDIES

Transport policymaking that accounts for COVID-19 and future public health threats: A PASS approach

- Public transport firms receive more subsidies in the USA and Europe than in Japan
- PASS approach is proposed for systematically designing policies that address concerns during COVID-19 and future pandemics, it was initially named by the present author after a review of railway transport policy measures by The Ministry of Land, Infrastructure, Transport and Tourism of Japan (2020)
- PROTECT employees and users by wearing masks, washing hands, installing antiseptic solution dispensers, and monitoring the body temperature of employees. AVOID trip making, SHIFT departure time for commuting, STOP making unnecessary or non-urgent trips
- P. Prepare–Protect–Provide: prepare well for pandemics, preparations before a pandemic starts in a country/region, and preparations before the pandemic starts in a city/town of the country/region, provide public goods and services that cannot be provided by individuals or firms
- A: Avoid–Adjust: . Avoidance allows transport users to keep away from the virus and transport operators to prevent transport users from being infected when using transport services, transport users need to adjust their activities and schedules as well as trip timings to reduce opportunities of being infected or transmitting virus to others
- S: Shift–Share: people who have to make trips need to shift their modes to reduce their infection risk, Sharing of information and resources is critical to collective decisions and actions, because such sharing can fill knowledge gaps and further enhance the feasibility and transparency of collective decisions and actions
- S: Substitute–Stop : When the pandemic becomes more serious, people must substitute or stop activities involving trips

Source: https://www.sciencedirect.com/science/article/pii/S0967070X20306181

Mass transit ridership didn't snap back after the 2003 SARS outbreaks

- The peak of the epidemic in Taipei and Hong Kong lasted about a month, but ridership lagged significantly for half a year
- Planning and transportation experts say that a number of habits acquired by both passengers and agencies had serious staying power after the SARS outbreak
- The measures city governments implemented to attract riders back to mass transit, some of them quite expensive, also persisted. More intensive cleaning regimens were implemented, better ventilation was installed, and trains were run more frequently to ensure they weren't overcrowded.
- Riders may eventually fully return to transit, especially after congestion and parking gets bad in central cities again, but that could take years, system may not exist till then.
- Public transit is an essential service that must be provided if their most economically productive cities are to remain functional
- Subsidies are a way to ensure they are functional

Source: https://citymonitor.ai/transport/mass-transit/transit-ridership-didnt-snap-back-after-the-2003-sars-outbreaks

SWOC: POLICY INTERVENTIONS

Goal	Policy	Strengths	Weaknesses	Opportunities	Challenges
1. Accommodate to use of private modes ✗	a. Develop infrastructure wrt Private Modes	High vehicle ownership rate	Increase in use of motorcycles and cars will increase pollution, congestions and more accidents	Increase in use of bike improves air quality, decreases congestion, and improves public health	Modification of Infrastructure required
2. Shift back to public transport ✓	a. Increasing Safety wrt COVID-19 b. Dis-incentivise Private Modes c. Increase speed of Buses d. Increase connectivity of public transport	Existence of efficient public transportation system	On-going pandemic, subsequent waves	Pandemic may end soon, helps in boosting/maintainin g overall long-term economy	Re-developing trust among people

MORE EXPLANATIONS

Cost does not affect mode choice for scheduled trips in Toyosu

- Majority of scheduled trips are through trains, and for offices and schools, the fare is either reimbursed or discounted

The demand of train is not sensitive to travel time of car

- In practical usage, with respect to last mile connectivity, cars are more similar to buses, and not similar to trains

The use of bikes has also increased

- But since the bikes are not used for long distance travelling, and they are sustainable modes, our focus is on decreasing the use of cars

The share of train has also decreased

- But since studies show that people still prefer buses than trains in pandemic, the focus is on buses
- Since the average distances covered by buses is significantly low, there is an opportunity to increase its connectivity

THE WAY FORWARD

Accumulation of more detailed data related to age and gender of respondents is required for achieving better results

Details like occupancy play a vital role in deciding the demand of public vehicles and thus corresponding study must be carried out

Technological interventions like real time access to occupancy data can be a decisive factor for mode choice

Social campaigns have proved to be effective in making the public consider certain modal choices

The perceived risk and actual risk in using public vehicles with respect to COVID-19 must be studied

END