Dynamics of Mode Use Frequency and the Role of Vehicle Ownership in Urban Ropeway Adoption

UG Project Report submitted in the partial fulfilment for the award of Integrated Dual Degree (B. Tech.- M. Tech.) in Civil Engineering

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THESIS CERTIFICATE

This is to certify that the thesis titled Urban Commercial Vehicle Travel Analysis - Spatial Agglomeration and Demand Modelling, submitted by **Kalyani S. Nair** (Roll No. 21064014), to the Indian Institute of Technology (Banaras Hindu University), Varanasi, in the partial fulfilment for the award of Integrated Dual Degree (B. Tech. – M. Tech.) in Civil Engineering, is a bona fide record of work done by him/her under my/our supervision. It is certified that the statement made by the student in his/her declaration is correct to the best of my/our knowledge.

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DECLARATION BY THE CANDIDATE

I, **Kalyani S Nair**, certify that the work embodied in this thesis is my own bona fide work carried out by me under the supervisions of **Dr. Agnivesh Pani**, from 01-08-2024 to 06-11-2024 at the Department of Civil Engineering, Indian Institute of Technology (BHU), Varanasi. The matter embodied in this thesis has not been submitted for the award of any other degree/diploma. I declare that I have faithfully acknowledged and/or cited to the researchers wherever their works have been utilized in this thesis. I further declare that I have not wilfully copied any other's work, paragraphs, text, data, results, etc., reported in journals, books, magazines, reports dissertation, thesis, etc., or available at websites.

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ABSTRACT

As cities seek sustainable transit solutions, understanding the interplay of different modes become crucial. This study aims to address two key objectives: (1) to examine the interconnectedness of transportation modes through their usage frequencies, employing a Multivariate Ordered Probit Model (MORP); and (2) to investigate the expected use of Aerial Ropeway Transit (ART) based on vehicle ownership using an Ordered Probit Model (OPM). Urban mobility survey data was analysed to find the interdependencies of mode use frequency. Strong influence for age, gender, income, access and service reliability in terms of preference. Older adults are females show greater propensity for Intermediate Public Transport (IPT), due to safety and accessibility concerns. ART appeals to individuals seeking less stressful travel options, but car ownership decreases ART's appeal due to privacy and flexibility. In the MORP model, error correlations have been used to illustrate complementary dynamics among IPT, Public Transport (PT), and ART, while car usage demonstrates very strong substitutive effects across all the modes. These results support the planning of urban transit system by guiding sustainable mode adoption.

TABLE OF CONTENTS

Contents

1. INTRODUCTION

As cities around the world continue to grow, the demand for efficient, reliable and sustainable transportation has never been greater. Congestion and strain on existing transportation infrastructure are the common issues plaguing cities. Cities like London, New York, and Tokyo have made significant investments in advanced public transit systems and policies to reduce car dependency. London has implemented congestion charges (Tang, 2021), New York has expanded its subway, Tokyo has an efficient rail system with smart cards (Sato et al., 2011). Despite efforts, many developing cities still struggle to meet the increasing demands of urban mobility. In cities like Varanasi, these challenges are even more pronounced due to poor infrastructure and unpredictable travel patterns. In the recent past, technological advancements have helped Varanasi become a global destination, resulting in an increased number of pilgrims and tourists. This has also brought forth a number of challenges in the form of management issues, security concerns, socio-cultural conflict, environmental impacts (Das Gupta & Sharma, 2009), and urban development pressures. The dynamic land use changes and space constraints limit the expansion of the road network in the city. To an extent, to address such issues alternative modes of transport such as Arial Ropeway Transit (ART) are also proposed. Understanding how the people make a choice of different transportation modes is considered to be a critical issue in solving the urban mobility problems. The mode choice factors include a myriad of parameters like socio-demographics, accessibility, service reliability and environmental conditions. There is an increasing awareness for these factors to be considered (Tyrinopoulos & Antoniou, 2013). There are two parts to this project: (1) We examine the interconnectedness of different transportation modes by looking into their usage frequencies using Multivariate Ordered Probit Model (MORP); (2) We investigate what is the expected ART use based on vehicle ownership. The study will focus on the underlying patterns and dependencies between different modes of transportation. Through analysis, key factors that influence mode choice behaviour are identified, thus shedding light on insights necessary for transportation planning strategies. Particularly, the results will provide recommendations on promoting adoption of ART, shifting towards a more sustainable mode of transportation, and informing data-driven policy-making.

2. LITERATURE REVIEW

2.1 DRIVERS OF MODE CHOICE

Transportation mode choice behaviour is significantly influenced by a vast number of demographic, psychographic, geographic, and economic factors; therefore, it is imperative to understand the interdependencies between the modes for proper planning. Conceptual frameworks provide the theoretical bases as to why people choose one mode over another. These frameworks include economic, psychological, and sociological orientations such as the Utility Maximization Framework, which assumes that individuals choose modes that help maximize perceived benefits or rewards, and the Theory of Planned Behaviour (Anable, 2005), according to which mode choice is an outcome of attitudes, subjective norms, and actualized control of the intended behaviour. Transportation mode choice depends on socio-economic attributes like age, sex, and income. For instance, poorer individuals are more likely to use public transport, while affluent individuals prefer private transport (Al-Kaderi & Ali, 2024). Additionally, females tend to use transport less frequently than males, with lack of mobility often associated with social or educational constraints. Beyond demographics, the provision and reliability of service are significant because high availability of transport leads to increased usage. Other factors affecting feasibility include environmental conditions, such as weather, and passenger experiences of comfort and safety, which directly impact satisfaction. For example, women above 35 years prefer using the metro for convenience. Perceived risks—whether real or perceived—such as concerns about transport availability or safety, also influence mode choice. During COVID-19, the threat of infection led to reduced public transport use in Pakistan, prompting people to use individual or non-motorized transport modes (Abdullah et al., 2020). Facilitating conditions, which include infrastructure and performance expectancy, are other factors influencing transportation mode choices. Mode use frequency is crucial for transportation mode choice modelling, as it reveals patterns of habitual behaviour and dependencies on certain modes. Analysis of the frequency of different modes can uncover preferences related to accessibility, service reliability, and passenger dissatisfaction (Zhang et al., 2024). High frequency of use indicates perceived satisfaction or a lack of alternatives, while low frequency may highlight barriers such as perceived risks, adverse environmental conditions, or inadequate facilitating conditions. Incorporating mode use frequency into transportation studies enhances understanding of why people choose certain modes, helping optimize services and infrastructure based on actual demand and performance expectations. Ulahannan & Birrell, (2022) and Haryadi et al., (2022) applied Multinomial Logit Models (MNL) to analyse transport mode choice preferences following the pandemic and study student travel mode choice, respectively. MNL is effective for analysing discrete choice data by estimating the probability of choosing a particular mode based on a set of explanatory variables. However, it has limitations, such as assuming that error terms across different modes are independent, which may not always be the case; additionally, it is not suitable for analysing ordered data, like frequency of use. Based on frequency of use, multivariate ordered probit modelling is a more appropriate methodology for analysing the interconnectedness between different transportation modes. This approach can handle ordered data, such as frequency of use, and account for correlations between modes. By estimating the probability of choosing a particular mode based on explanatory variables, multivariate ordered probit modelling captures underlying patterns and dependencies among various modes of transportation. This approach, combined with structural equation modelling techniques, can unravel the dependencies between different modes and key drivers of mode choice.

2.2 VEHICLE OWNERSHIP AND TRANSIT MODE USE

As economies grow, so does the number of people that can afford private vehicles (Vasudevan et al., 2021). There are some downsides to this shift from public to private transport. In the context of upcoming transit modes such as ART, it is crucial to understand the impact of vehicle ownership on expected usage. A significant amount of research suggests that increased private vehicle ownership often correlates with a decline in public transport usage. For instance, as private car ownership rises, public transport patronage tends to decrease, as these modes of transport are often viewed as substitutes (Shaygan et al., 2017). Further it was noted that income growth typically leads to increased car ownership, which negatively impacts public transport demand (Maia et al., 2020). Research indicates that the prevalence of two-wheelers, particularly in Asian cities, often correlates with a decline in public transport usage. noted that in the context of congested urban settings, the high ownership and usage of two-wheelers arise due to the inadequacy of competitive, convenient, and comfortable public transport systems (Mathews & Thadathil, 2023). As income levels rise, individuals may opt for two-wheelers as a more flexible and accessible alternative to public transport, particularly for women and younger demographics who may find two-wheelers more empowering than traditional public transit options (Jindel et al., 2022). It does become necessary to understand the interplay between ownership of different vehicles and their impact on attitude towards public transport as well as future transit modes, so that policy-makers can craft the policies such as to make transit more appealing and encourage shift towards more sustainable mobility system.

3. METHODLOGY

3.1 DATA

The user survey data encompassed of 5 sections (1) socio-demographics such as age, gender, household type, size, and income, vehicle ownership, (2) attitudes toward current public transport, focusing on accessibility and service reliability, (3) perceived risks linked to the upcoming ART, (4) expectations of ART's performance (5) frequency of mode use, including public transport, cars, two-wheelers, non-motorized transport, and expected ART use. All sections except for the first and fifth section, employed a five-point Likert-type scale, ranging from "Strongly Disagree" to "Strongly Agree". For the fifth section, the scale of all modes except for ART use responses was a four-point Likert-type scale assessing frequency with responses as "A few days a year or less," "At least once a month," "1-4 days a week," and "5-7 days a week.". Use responses of ART were also captured on a four-point Likert-type scale. These included "No, I will NOT shift", "Yes, I will shift for a FEW trips", "Yes, I will shift for MOST trips", and "I will use ART for ALL my trips". Data collection was conducted between December 2023 and February 2024. Responses collected were 3,261. A confidence level of 95%, a 2% margin of error, population proportion of 0.5 and a sample proportion of 50% were selected. This led to the resultant sample size being 2,398.

3.2 ANALYTICAL FRAMEWORK AND PROCEDURES

3.2.1 MODE USE FREQUENCY ANALYSIS

3.2.1.1 SEM: CONFIRMATORY FACTOR ANALYSIS

Structural Equation Modelling (SEM) is an advanced statistical technique that combines Confirmatory Factor Analysis (CFA) with structural models to analyse multiple variable relationships simultaneously. Using interdependent variables to be rated together, SEM enables such variables to be analysed since it uses CFA in establishing latent constructs based on the degree of how highly a set of variables co-varies. The use of multi-item scales in SEM reduces random measurement error, making the outcomes more reliable and valid. For instance, in CFA, shared variance through correlations among observed variables can be estimated to make an inference about latent factors. In CFA, the factor loadings represent the relationships between observed variables and latent factors similar to regression coefficients. The model fit is evaluated based on a comparison of the observed covariance matrix with the model-implied covariance matrix. The general form of CFA is as given by equation (4.18), mentioned below

$$\boldsymbol{x} = \boldsymbol{\Lambda\xi} + \boldsymbol{\delta}, \tag{4.18}$$

In the above formula $\boldsymbol{x}$ represents the observed variables, $\boldsymbol{\xi}$ is a vector of latent constructs, $\boldsymbol{\delta}$ is a vector of measurement errors, and $\boldsymbol{\Lambda}$ is a matrix of coefficients or factor loadings that connect latent and observed variables (Lee & Song, 2010). Measurement errors are not influenced by latent factors and are also unrelated to each other. Measurement errors form the part of the observed variables that are not explained by the latent factors. The population variance-covariance matrix for the observed variables, denoted as $\boldsymbol{\Sigma}$ is decomposed of three components (Mueller & Hancock, 2015) ;Loadings in the matrix $\boldsymbol{\Lambda}$, $\boldsymbol{\Phi}$ the covariance of the latent factors i.e. of matrix $\boldsymbol{\xi}$ and $\boldsymbol{\Theta}$ the covariance matrix for $\boldsymbol{\delta}$**,** residuals. The model implied variance/covariance matrix of observed variables is given by equation (4.19) mentioned below:

$$\boldsymbol{\Sigma}(\theta) = \boldsymbol{\Lambda\Phi}\Lambda' + \boldsymbol{\Theta}, \tag{4.19}$$

If the CFA model is correctly defined with precise parameter values, the population variances and covariances matrix of $\boldsymbol{x}$ (denoted as $\boldsymbol{\Sigma}$) will be exactly replicated. However, since model parameters are usually unknown, so is the population matrix $\boldsymbol{\Sigma}$. Therefore, parameters must be estimated to approximate the observed covariance matrix of $\boldsymbol{x}$.

3.2.1.2 MULTIVARIATE ORDERED PROBIT MODEL

The frequency of mode use for the six distinct modes: Car Use, IPT Use, MTW Use, NMT Use, PT Use, Expected ART Use are modelled using a Multivariate ordered probit model. The dependent variables are discrete and ordered with four ordinal groups that are same for all modes except ART. Correlations among ordinal groups that are interrelated but not mutually exclusive are accounted for in this model. It is also hypothesized that the error terms for all six of them are correlated as illustrated in fig 4.1. Socio-demographics and latent variables obtained from CFA are used as the explanatory variables. The model estimates the latent propensity for mode choice categories, which are expressed in the form of functions of covariates and transformed into observed outcomes based on thresholds. Latent propensities are modelled using an ordered probit framework (Gkartzonikas & Dimitriou, 2023).

q (q= 1, 2,..., Q) and i (i= 1, 2,.., I) are used to denote survey participants and ordered response choice categories respectively. The total number of mode choice categories denoted by I are 6 (Car Use, IPT Use, MTW Use, NMT Use, PT Use, Expected ART Use). The latent propensity functions for q individual showing mode use frequencies for varied i is given by the following Eq. (3.20) (Gkartzonikas & Dimitriou, 2023; Greene & Hensher, 2010).

$$y_{qi}^{*} = \beta_i' x_{qi} + \varepsilon_{qi}, y_{qi} = \begin{cases} 0, \text{ ify } y_{qi}^{*} \leq \theta_i^1 \\ 1, \text{ if } \theta_i^1 < y_{qi}^{*} \leq \theta_i^2 \\ 2, \text{ if } \theta_i^2 < y_{qi}^{*} \leq \theta_i^3 \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ K, \text{ ify } y_{qi}^{*} > \theta_i^{K-1} \end{cases} \tag{3.20}$$

The error terms in traditional ordered probit models are assumed to not have any correlations across establishments. However, multivariate ordered probit model allow correlation in the terms across ordered response categories i for each individual q. In a multivariate ordered probit model, error correlation terms between *i* mode choice decisions are used for investigating whether different mode choices are “substitutive” or “promotive”.

3.2.2 VEHICLE OWNERSHIP ANALYSIS

3.2.2.1 ORDERED PROBIT MODEL

Ordered Probit Model (OPM) is a statistical method used for analysis when the dependent variable is ordinal. In this study, the OPM is applied to analyse the influence of vehicle ownership on the expected use of Aerial Ropeway Transit (ART), where the dependent variable is the likelihood of individuals shifting to ART. The dependent variable here being expected use of ART is ordered with four ordinal groups as mentioned in the previous section.

In an Ordered Probit Model, the latent variable $Y*$ is modelled as a linear combination of independent variables:

$$Y *= X\beta + \epsilon \tag{3.21}$$

$Y*$ is the unobserved latent variable, X is a vector of independent variables (e.g., car ownership, MTW ownership, cycle ownership), β is a vector of coefficients corresponding to each independent variable, and ϵ is an error term assumed to follow a standard normal distribution. The coefficients β represent the impact of each independent variable on the latent inclination to adopt ART. In an Ordered Probit Model, interpreting the coefficients requires an understanding of their influence on the probability of the ordered outcomes rather than the actual outcomes themselves. A positive coefficient implies that as the predictor variable increases, so does the likelihood of falling into a higher category of ART adoption likelihood. A negative coefficient suggests that higher values of the predictor variable are associated with a decreased likelihood of moving to higher categories of ART adoption.

4. RESULTS AND DISCUSSION

The table 4.1 consists of the results of CFA, the factor loadings represent the strength of connections between the latent constructs and the observed variables. All the factor loading are statistically significant ($p<0.0001$) and greater than 0.5 implying that the relationships are strong, and that the observed variables effectively capture the latent constructs.

Table 4.1 Confirmatory Factor Analysis Results

Factor	Survey items	Standardized factor loading	S.E.	Two-tailed *p*-value
Accessibility and Service Reliability Concerns	PT Stops Difficult to Reach	0.863	0.006	0.000
	PT No Direct Services	0.939	0.004	0.000
	PT Information Unavailable	0.880	0.006	0.000
	PT Service Runs Late	0.989	0.004	0.000
	PT Waiting Time Too Long	0.855	0.006	0.000
	PT Journey Time Too Long	0.906	0.005	0.000
Environmental Conditions and Passenger Experience Concerns	PT Crowded	0.829	0.006	0.000
	PT Weather Issues	0.962	0.004	0.000
	PT Vehicle Experience Noise Air	0.832	0.006	0.000
	PT Vehicles hard to Climb	0.972	0.004	0.000
	PT Cleanliness Dirty	0.879	0.005	0.000
Perceived Risk and Service Concerns	May Not Be Safe Old People and Children	0.804	0.009	0.000
	Equipment failures	0.918	0.012	0.000
	Heights and Luggage	0.820	0.009	0.000
	Too Slow Unlike Metro HSR	0.707	0.01	0.000
Facilitating Conditions and Performance Expectancy	ART is Compatible with my Existing Travel Needs	0.878	0.016	0.000
	I Think ART Could be Useful for my Daily Life	0.965	0.018	0.000
	Using ART could increase my travel satisfaction	0.993	0.022	0.000

Independent Variables	Car Use		IPT Use		MTW Use		NMT Use		PT Use		Expected ART Use	
	Coef	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
Age (Base: Age < 18 years)												
Age: 19-45 Years	0.204***	3.581	0.161**	2.727	-0.322***	-5.396	-0.201***	-3.495	0.208***	3.641	0.147	1.552
Age: 46-60 Years	0.081	1.214	0.508***	7.403	-0.464***	-6.363	-0.235**	-3.260	0.110	1.531	0.272*	2.418
Age: Above 60 Years	-0.263***	-3.396	0.861***	10.738	-0.698***	-7.464	-0.121	-1.446	0.076	0.950	0.258’	1.808
Gender (Base: Gender= Female)												
Gender: Male	0.091*	2.060	-0.387***	-8.804	0.543***	11.401	-0.021	-0.442	-0.474***	-10.169	-0.218**	-2.939
Income (Base: Income < 1 Lakh INR)												
Income: 1 Lakh-3 Lakh (INR)	0.556***	3.814	-0.530***	-3.982	-0.454**	-3.046	0.349**	3.085	0.449***	3.330	-0.179	-0.871
Income: 3 Lakh-5 Lakh (INR)	0.267*	2.202	-0.310**	-3.037	0.353***	3.441	-0.227*	-2.295	-0.081	-0.705	-0.163	-0.917
Income: 5 Lakh-10 Lakh (INR)	0.727***	6.749	-0.543***	-6.228	0.264**	2.934	-0.229**	-2.645	-0.213*	-2.087	-0.422**	-2.594
Income: > 10 Lakh (INR)	1.436***	13.293	-0.815***	-9.342	-0.429***	-4.588	-0.352***	-3.943	0.108	1.076	-0.256	-1.524
Accessibility and Service Reliability Concerns	-0.068	-1.585	0.102*	2.169	0.074	1.620	0.077	1.585	-0.213***	-4.882	-0.006	-0.092
Environmental Conditions and Passenger Experience Concerns	0.138*	2.502	-0.002	-0.034	0.197**	3.252	0.033	0.505	-0.277***	-4.901	-0.103	-1.173
Perceived Risk and Service Concerns	0.219***	7.146	0.320***	9.043	-0.589***	-16.609	-0.223***	-7.267	0.474***	15.472	0.045	0.894
Facilitating Conditions and Performance Expectancy	-0.501***	-20.925	0.184***	7.268	0.112***	4.008	0.024	0.925	0.256***	10.807	5.472***	36.482

Significance codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

Table 4.2 Estimation of results of Multivariate Ordered Probit Model

The table 4.2 shows the results of MORP, offering insights into the influence of exogenous variables on mode use frequency. The statistical significance of most exogenous variables at a 99% confidence level sheds light on their importance. A detailed interpretation of the influence of each variable is provided in the following sub-section.

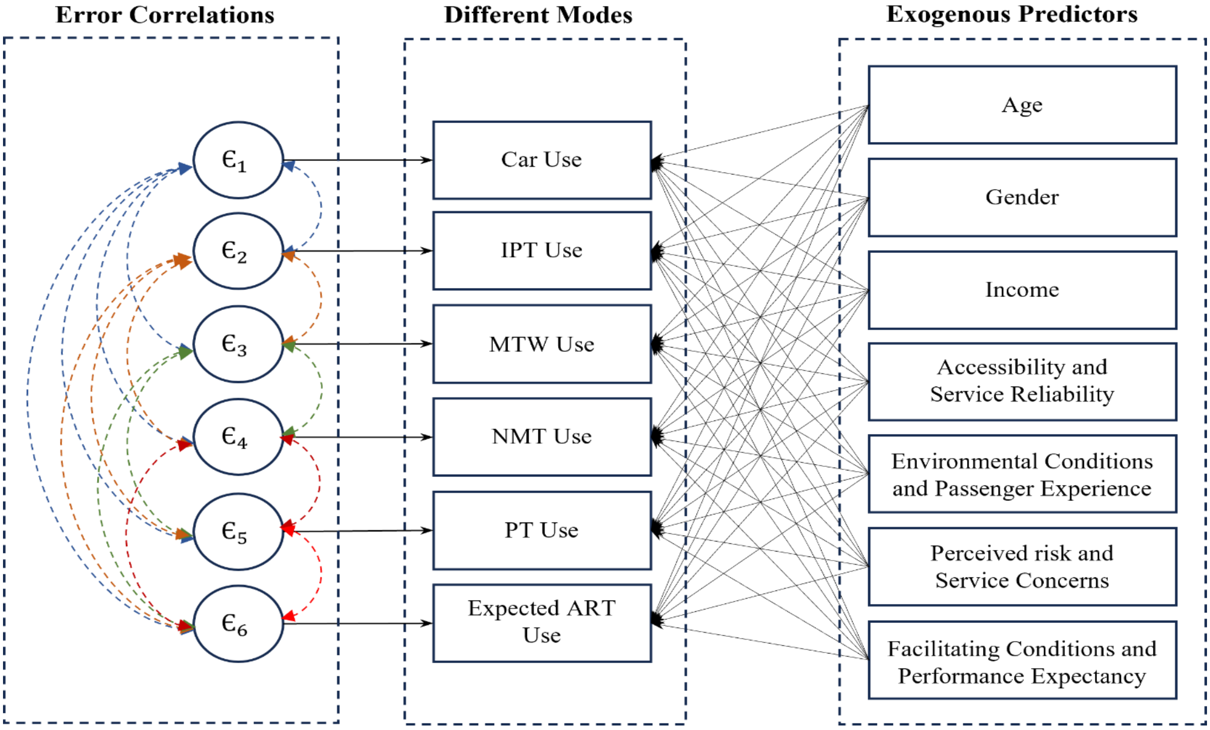

Figure 4.1 Mode Frequency Modelling Framework as Multivariate Ordered Response System

Table 4.3 Results of Ordered Probit model based on vehicle ownership

Independent Variables	**Expected ART Use** *Coef*
VEHICLE OWNERSHIP	
CAR OWNING	***-0.9964***
MOTORISED TWO-WHEELER OWNING	***-0.3740***

CYCLE OWNING	***-0.4443***

4.1 INFLUENCE OF EXOGENOUS VARIABLES

4.1.1 AGE

As people age, they show a greater preference for Intermediate Public Transport (IPT), with people over 60 showing highest inclination (coef. = 0.861, $p < 0.001$). the greater last mile accessibility could be the possible reason for this. Older people show a lower preference for Motorised Two-Wheelers, with 60+ showing least preference (coef. = -0.698, $p < 0.001$). Young people (19-45) are more inclined to use Public Transport (PT), the inclination decreases with age. ART becomes more significant for those aged 46-60 and over 60. This could be a mirroring of their preference towards IPT as both offer similar safety and convenience.

4.1.2 GENDER

Females show a higher preference for PT and IPT as compared to their male counterparts. This could be attributed to the fact that women prioritise safety, accessibility and cost-effectiveness while choosing a transport mode. There could be more driving factors such as cultural norms, limited access to personal vehicles and childcare responsibilities. Men show a strong inclination towards car usage, which can be explained by factors such as autonomy and perceived status. In line with this, it is observed that women view ART as a safer and affordable option in crowded areas.

4.1.3 INCOME

Individuals falling within higher income brackets show a strong preference for car usage (> 10 Lakh INR, coef. = 1.436, $p < 0.001$). PT shows a mixed trend: sharp decline in usage for 3-5 and 5-10 Lakh INR brackets, interestingly, the highest income bracket uptick in usage.

ART use does not necessarily imply sizable impacts, except a decline is evident in the 5-10 Lakh bracket. Generalised higher income levels lead to increased car use while possibly reducing IPT and PT dependence.

4.1.4 ACCESSIBILITY AND SERVICE RELIABILITY CONCERNS

A latent variable, based on questionnaire responses, captures respondents' perceptions of public transport. Analysis shows that higher accessibility and reliability concerns were positively associated with greater IPT use (coef. = 0.102, $p < 0.05$), whereas for PT use, a negative and highly significant coefficient (coef. = -0.213, $p < 0.001$) indicated that people with such concerns are less likely to choose PT. IPT seems to be a compromise between PT in safety and convenience for users and access for transport users. Interestingly, the very small coefficient for expected ART use indicates that these concerns probably do not play as much of a role in determining the predicted use of ART, and there is need for additional work into factors that influence mode choice preferences, which includes socio-economic considerations.

4.1.5 ENVIRONMENT AND PASSENGER EXPERIENCE

The positive and statistically significant coefficient for Car Use (coef. = 0.138, $p < 0.05$) and MTW Use (coef. = 0.197, $p < 0.01$) indicates that unfavourable environmental conditions and bad passenger experience with public transport push people to car and MTW use. On the other hand, a negative and highly significant coefficient for PT Use (coef. = -0.277, $p < 0.001$) indicates that people have less chance of using PT when the environmental conditions are adverse. The coefficients for IPT Use and NMT Use are not statistically significant, these modes are less influenced by environmental and experiential factors. The coefficient for expected ART use is also insignificant, as is for IPT, as both share similar characteristics concerning environmental concerns and passenger experiences.

4.1.6 PERCEIVED RISKS

Individuals expressing higher risk concerns for ART are more inclined to safer modes such as Car Use, PT Use, and IPT Use, as indicated by positive and statistically significant correlations (Car: coef. = 0.219, $p < 0.001$; PT: coef. = 0.474, $p < 0.001$; IPT: coef. = 0.320, $p < 0.001$). While there is a positive correlation with Expected ART Use, this does not reach statistical significance, suggesting that people's anticipation of using ART may not be affected highly by perceived risks and service concerns, most probably because they do not have an experience with it.

4.1.7 PERFORMANCE EXPECTANCY

Inverse relationship between positive attitudes towards ART and the likelihood of Car Use (coef. = -0.501, $p < 0.001$). While this may seem counterintuitive, it seems as though individuals holding favourable attitudes towards ART seek an experience that is more satisfying than driving in high demand conditions, which is stressful. Positive correlations with IPT Use (coef. = 0.184, $p < 0.001$) and PT Use (coef. = 0.256, $p < 0.001$) suggest that both alternatives are viewed as less stressful commuting modes than car use. The strong correlation with expected ART use (coef. = 5.472, $p < 0.001$) could be driven by time and environmental benefits expected through the scheme.

4.2 INFLUENCE OF VEHICLE OWNERSHIP

Results of the Ordered Probit Model are tabulated in table 4.3. It provides insights on the influence of vehicle ownership on expected use of ART. Car ownership suggests the least inclination to shift to ART (coef. = -0.9964), this can be attributed to the fact that personal cars afford so many advantages in convenience, privacy, and flexibility that the ART cannot match. The advantages of car ownership are realized through its frequent usage, coupled with a significant investment in ownership. MTW owners also show less inclination towards a shift to ART (coef. = -0.3740). It could be the autonomy that MTW provides to owners that makes ART less appealing. Cycle owners also show less inclination towards shifting to ART (coef. = -0.4443), cycle owners likely value their autonomy and the health benefits associated with cycling. Factors such a cost-savings, especially for shorter trips where ART may not provide comparable advantages.

4.3 ERROR CORRELATIONS

The correlation matrix in table 4.4 displays significant linkages between transportation modes in the MORP model. A positive correlation is indicative of a complementary relationship where people tend to use one mode more when also using another. Negative correlations point to a substitutive relationship whereby frequent use of one particular mode lowers the probability of using another mode. Car Use has strong substitutive effects on all the other modes, the highest negative correlations appearing against MTW Use (coef. = -0.383, $p<0.001$) and IPT Use (coef. = -0.410, $p<0.001$). The other negative correlations appear with Car Use and Expected ART Use because these modes share some of PT and IPT characteristics. While IPT and PT have complementary dynamics, particularly between PT and ART adoption, with $p<0.001$, IPT affects ART with no significant statistics. Public modes IPT, PT, and ART have negatively correlated values with private modes Car, MTW, and NMT, showing that there is a substitutive relationship across categories. Surprisingly, NMT correlates well positively with ART ($p<0.05$), which may be explained by the physical demands of NMT and possibly the desire for more convenient alternatives like ART.

Table 4.4 Correlation in Unobserved Propensities across the Choice Dimension

	Car Use	IPT Use	MTW Use	NMT Use	PT Use	Intended ART
Car Use	1	**-0.410*** ** | (-17.601)	**-0.383*** ** | (-13.992)	**-0.230*** ** | (-8.473)	**-0.181*** ** | (-7.144)	**-0.139*** ** | (-3.391)
IPT Use	**-0.410*** ** | (-17.601)	1	**-0.410*** ** | (-17.336)	**-0.184*** ** | (-6.639)	**0.045'** | (1.949)	0.017 | (0.379)
MTW Use	**-0.383*** ** | (-13.992)	**-0.410*** ** | (-17.336)	1	**0.268*** ** | (10.609)	**-0.556*** ** | (-19.531)	-0.072 | (-1.574)
NMT Use	**-0.230*** ** | (-8.473)	**-0.184*** ** | (-6.639)	**0.268*** ** | (10.609)	1	**-0.181*** ** | (-6.274)	**0.105* ** | (2.052)
PT Use	**-0.181*** ** | (-7.144)	**0.045'** | (1.949)	**-0.556*** ** | (-19.531)	**-0.181*** ** | (-6.274)	1	**0.236*** ** | (5.819)
Shift to ART	**-0.139*** ** | (-3.391)	0.017 | (0.379)	-0.072 | (-1.574)	**0.105* ** | (2.052)	**0.236*** ** | (5.819)	1

Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1, (t-statistic in parentheses)

5. CONCLUSION AND FUTURE WORK

The MORP framework allowed the study of intricate relationships in mode use frequency. The analysis highlights the key influencers like age and gender. It was observed that older individuals are more inclined towards IPT and ART. Women are observed to show higher preference to IPT and PT, owing to safety concerns and cultural perceptions, while men prefer MTW and cars, policies should consider factors like safety, accessibility, and societal norms that influence these choices. In general, higher income has a positive relation with car usage. Perceived risks and service concerns also play a role, driving respondents towards IPT and private modes. Analysing the error correlations give us insights into the dynamics of mode choice, substitutive and complementary effects. Car use shows a strong negative correlation with other modes, this highlights the need for policy intervention in this direction (car restrictions, congestion pricing (Tang, 2021)) to pave way for more sustainable transit adoption. Analysis on vehicle ownership also suggested that people who owned cars, MTWs and cycles show less inclination towards ART. However, by strategic policy-making we may be able to encourage ART adoption among these individuals. This can be done by targeting specific circumstances and needs. For instance, cycle owners may be more open to using ART for longer trips or when the terrain is challenging or not suitable for cycling. By addressing the situational factors policy-makers can enhance the attractiveness of ART and encourage it as a complement to active and motorised transport for a better integrated urban mobility system. The future scope of the project includes considering additional variables.

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