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Revealing Commute Choice Factors: A SEM Analysis of Public Transport and Active Modes in Hyderabad, India

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Abstract

While extensive research has explored factors influencing mode choices and first/last mile connectivity, few studies have delved into the underlying hierarchy of decision-making processes. Understanding this hierarchy, which illustrates causal relationships, is crucial for modelling travel decisions, as trip structure depends on choice behaviour and vice versa. Traditional mode choice models often neglect these underlying causal relationships, necessitating the development of new models. By incorporating mediating effects of trip chaining and mode choice, alongside traditional factors, a more holistic understanding of mode choice behaviour is achieved. This study develops hierarchical relationships between trip chaining and mode choice in Hyderabad, India using Structural Equation Modelling method due to its inherent strength in handling latent causal relationships. SEM analysis provides total effects of socio-demographic variables on mode choices and trip chain types through these causal relationships. Findings reveals that for non-work trips, the decision-making process is simultaneous, regardless of the mode chosen. In contrast, for work trips, the decision-making process is simultaneous for active and public modes, but the choice of mode precedes trip chaining for private modes. Furthermore, this study learns from those who own private vehicles but use active/public transport by choice and extracts the factors indeed had motivated their choice. Confirmatory factor analysis is employed to validate the identified factors. Identified factors, coupled with the understanding of decision-making hierarchy, offer valuable insights for shaping policies that can maximize the potential of active and public transport modes.

Keywords: Active travel modes; Hierarchy of travel decisions; Public transport; Structural Equation Modelling; Trip chains.

1. Introduction

In today's rapidly globalizing world, countries are increasingly prioritizing sustainability, particularly in the transportation sector, to achieve United Nations Sustainable Development Goals (SDG) #9.1 and #11.2 (United Nations 2015). Mass rapid transport systems such as the metro rail are considered as a means to achieving SDG goals. Governments around the world are investing in transport infrastructure, replacing predominantly fossil fuel-based systems with environmentally efficient ones like metros and electric buses. However, many new metro and bus rapid transport systems record consistently low occupancy levels apparently due to inadequate first/last-mile connectivity (Kåresdotter et al. 2022; Rahman et al. 2022)). Active modes of transport can provide the first and last leg connectivity in any trip made by public transport. A well-planned system with a high level of integration between modes could potentially contribute to sustainability objectives by improving access resulting in a truly multimodal commuting experience.

Numerous studies have examined mode choice, with a particular focus on active modes and public transport. Many of these studies consider factors such as commuter preferences, socio-economic and travel characteristics, to understand how individuals make rational decisions (Arasan et al. 1998; Ashalatha et al. 2012; Buehler 2011; Santos et al. 2013). Some others seek to explain the factors that affected the choices made by individuals as revealed by the data see for example (Rahman and Balijepalli 2016). In addition, many studies have investigated first, and last-mile connectivity using active modes and explored different built environment factors, land use, and neighbourhood design that can affect walking/cycling accessibility to public transport stations (Gupta et al., 2022).

The main research question is thus whether improving accessibility to/from the public transport stations is adequate to encourage people to choose public transport, or is there any underlying behavioural aspect that systematically influences the travel mode choice? The decision of choosing a travel mode is inherently complex as travel behaviour significantly affects the structuring of a trip leading to the formation of trip chains. As people often travel to access various spatially distributed locations, they form trip chains loading more activities per trip to minimize travel times. Individuals select a mode that offers flexible stop-making behaviour. This underscores the importance of incorporating the decision-making process into mode choice modelling in addressing the present-day complexity. Therefore, the interdependency between travel mode and the structure of trip highlights the importance of examining decision hierarchy (causal relationship) between trip chaining and mode choice.

Studying mode choice decisions and promoting active modes as first and last mile connectivity using factors e.g. socio-demographic, travel or built environment characteristics alone may not provide a comprehensive understanding of the travel behaviour. While Discrete Choice Models can capture correlations between mode choices and trip chains, they may not explicitly model causal relationships. Choosing a mode is not solely determined by the factors but the underlying behavioural aspects plays a significant role. The decision-making process of trip makers in selecting a mode entails human approximations that are not accurately captured by them. These underlying causalities are better modelled using SEMs. SEMs offer insights into both factors (in terms of total effects) and underlying behavioural aspects, enhancing the understanding of mode choice. However, combining SEM analysis with discrete choice techniques allows for the determination of modal share more effectively. This sequential approach harnesses the strengths of both SEM (understanding latent behaviour) and discrete choice modelling (estimating mode-specific probabilities), providing a more in-depth analysis.

Moreover, in the literature, it is clearly stated that there is a significant difference in available modes and the choice decisions between developed and developing countries. Commonly, it would be challenging to apply the findings and strategies from studies conducted in developed countries to developing countries because of the vast variation in their spatial attributes, such as population density, geographical spread, in addition to the differences in socio-economic circumstances (Mirzaei et al. 2021). Thus, incorporating the decision-making process along with the effect of socio-demographic characteristics will help to comprehend the travel behaviour and mode choices of individuals.

In this research, Structural Equation Modelling (SEM) is used to test the directional causality between the two key mediating variables viz., trip chaining and mode choice, and then to analyse the influence of exogenous (data) variables on the endogenous (decision) variables through the causal relationship (total effects) to identify the influencing factors that drive the choices. The main aim of this research is to promote the use of active modes and increase the public transport ridership as a step towards sustainability and the particular objectives of the present paper are as follows:

- To analyse the hierarchy of travel decisions involving mode choice and trip chaining behaviour; and
- To identify the factors affecting the choice of active modes and public transportation given the knowledge of the hierarchy of decision making.

This paper has seven sections, including this section. The literature review is presented in section 2. Section 3 introduces the principles of SEM and describes the methodological steps involved. Data collection, trip chaining typology and the mode choices are described in section 4. Section 5 gives the model specification and results. Driving factors of active modes or public transport usage are analysed in section 6. Section 7 has model validation and practical application. Section 8 concludes the paper.

2. Literature review

2.1 Mode choice modelling

In the realm of travel behaviour research, the selection of travel modes has gained the greatest attention. Modelling and predicting mode choices are closely intertwined with the formulation of transportation policies, travel demand management strategies and congestion reduction. Many studies have investigated the mode choice decisions and various influencing variables that drives the mode choice. A predominant approach in mode choice modelling is based on the concept of random utility maximization, derived from econometric theory. Followed by this, several logit and probit models such as multinomial logit and probit models, nested logit models etc., are developed and applied in mode choice modelling. Please refer (Ben-Akiva and Lerman 1985) for detailed description of these models. Later, models based on Artificial intelligence techniques like ANN, fuzzy logic, decision trees are developed.

In India, many researchers have developed mode choice models based on principles of utility maximization. Arasan et al., (1998); Ashalatha et al., (2012) studied the mode choice behaviour of commuters in Indian scenario using the multinomial logit models. Few studies employed ANN and fuzzy techniques to model the mode choice behaviour and made a comparative analysis involving the multinomial logit (MNL), nested logit (NL), and generalized nested logit (GNL) models (Chalumuri et al. 2009; Minal and Chalumuri 2014; Pulugurta et al. 2013; Rajalakshmi 2013; Rao et al. 1998; Srivastava and RaviSekhar 2018). These studies found out that artificial intelligence techniques are much superior to MNL, NL and GNL in prediction. Arasan et al., (1998) studied the mode choice of travellers who have access to own vehicle but in their analysis, they ignored the underlying decision-making process.

Several studies have analyzed the influence of socio-demographic variables(Arasan et al. 1998; Minal and Chalumuri 2014; Srivastava and RaviSekhar 2018; Xie et al. 2007). Some studies focused on travel times and travel cost as they play a significant role in determining the mode of transportation. Longer access and egress times can lead to discomfort and inconvenience during travel, leading to individuals being less likely to opt for public transportation. People preferred to walk or cycle if the distance to and from the public transport stations is less (Givoni and Rietveld 2007). Zhao and Li, (2017) investigated the determinants of 'people's choice of cycling as a transfer mode and found that travel distance is the most influential variable, followed by age and income. This is because distance is related to the built environment; and land use and density largely determine how far the activity locations are in relation to the residential area. (Rastogi & Rao, 2003) studied the access trip characteristics of commuters accessing transit stations in Mumbai, to identify the policies that can improve utility of active modes and public transport. Table 1 summarises a few studies that are reviewed.

Factors related to safety and security have also been investigated for increasing patronage and the uptake of active mobility to access public transport stations (Mandhani et al. 2021). Equally important are studies that explore mobility and infrastructure (Bivina et al. 2019). These aspects significantly impact the accessibility of metro stations, making the metro a preferred option when access is improved and aligns with sustainability goals. Zhao et al., (2022) explore the last mile problem by using public bicycles as a feeder mode and concluded that integration of metro and public bicycle significantly reduces the travel time. Zuo et al., (2020) investigated the first and last-mile solution via bicycles to improve public transport accessibility and found that public transport access distance by bicycles increased by three times compared to walking.

A significant body of literature exists on the factors influencing public transport and active modes, as well as strategies for their integration. However, it's worth noting that travel decisions and behaviour have a notable impact on mode choice, besides socio-demographic characteristics. This is reflected in choosing a mode for a particular trip chain pattern and vice-versa. Thus, incorporating behavioural aspect in the analysis gives a better understanding of the travel mode decisions.

2.2 Interrelationship between trip chaining and mode choice

To understand the travel behaviour patterns and to help framing sustainable transport policies, it is essential to understand the interplay between trip chaining and mode choice along with the driving factors. This question is rarely addressed in the literature, more so in a developing country like India, where travel behaviour is significantly different to that in developed countries. This is because of the possible switching between different modes available making the travel behaviour unique (Subbarao et al. 2020). (Yang et al. 2016) investigated the variations in travel choices between weekdays and holidays through Nested logit model. They found that during weekdays, the sequence of trip chains precedes the decision regarding mode choice, whereas on holidays, the mode choice decision comes before the trip chaining process. On a similar note, (Hensher and Reyes 2000) utilized the Nested logit model to explore the interdependency between trip chaining and the utilization of public transportation. Their analysis revealed that trip chaining impedes the adoption of public transportation.

(Ye et al. 2007) examined the hierarchical connection between complex trip patterns and mode choice behaviours and explored the causality direction. Employing a recursive bivariate probit model and a simultaneous equation model, they analysed the Swiss data pertaining to work and non-work tour samples. Their findings revealed that the pattern of trips significantly influences mode choice behaviours for both work and non-work tours. Similarly, (Xianyu 2013) investigated the interdependencies between trip chaining and mode choice for home-based work trips, utilizing a co-evolutionary approach alongside multinomial logit models. They observed that activity-travel patterns were initially established, followed by the mode choice decision corresponding to the selected pattern.

Previously, several modelling approaches like multinomial and nested logit models (Dissanayake and Morikawa 2002; Hensher and Reyes 2000; Strathman et al. 1994; Yang et al. 2016) and recursive simultaneous bi-variate probit models (Ye et al. 2007) were developed to analyse the decision hierarchy between trip-chaining and mode choice behaviour. But the logit models do not capture the decision hierarchy fully because they do not provide parameters for directly measuring the causal effect. As an alternative to logit modes, SEM is adopted in behavioural research where latent variables can be incorporated in the model to understand the hierarchical decisions and investigate the causal relationships between variables. SEM formulations make it possible to capture bidirectional causality that may exist in the complex relationships between trip-chaining and mode choice.

(Islam and Habib 2012) investigated the hierarchical relationship between mode choice and trip chaining for work and non-work tours separately during weekdays and weekends (only non-work tours were considered during weekends) using SEMs. They found that the trip chaining and mode choice decisions were simultaneous and remained consistent across weekdays for weekday work tours. For non-work tours, mode choice decision precedes trip chaining during weekdays; on weekends, the hierarchical decision is the other way around. (Hadiuzzaman et al. 2019) investigated empirical relationships between trip chain type and mode choice for Dhaka city, Bangladesh. They found out that both the decisions are simultaneous. (Subbarao et al. 2020) investigated the interdependencies between mode choice and trip chaining for Mumbai, India on weekdays and weekends. Their results showed that mode choice decisions precede trip-chaining decisions for weekdays, and these decisions are simultaneous for weekend trips.

Past studies on the interdependency of trip chaining and mode choice behaviour explored their relation by considering work and non-work trips during weekdays and weekends. In this study, we examine the interplay between trip chaining decisions and mode choices by considering public/active and private modes separately for work and non-work trips. Furthermore, this study learns from those who own private vehicles but use active/public transport by choice and extracts the factors indeed had motivated their choice. Most of the previous literature focus heavily on the factors affecting active mobility or public transport and how to increase their usage. But through this work, we identify the driving factors, which provides better ways to frame policies and plans towards transit-oriented development integrated with active mobility. This will encourage the uptake of active mobility in the short run and ensures a mode shift in the long run.

3 Methodology

This study uses SEM to analyse the hierarchical relationship between the mode choice and trip chaining decisions. SEM has become a promising technique because of its ability to handle and analyse many endogenous/exogenous variables and latent relationships among the variables. A typical SEM has two components – structural model and a measurement model (See Joreskog (1970), for details). The structural model indicates the relationship between exogenous variables and the underlying latent variables along with the causal effects, whereas the measurement model represents the relationship between latent variables and endogenous (decision) variables. Generic equations for structural model Equation 1 (expanded form as Equation (2)) and measurement model Equation 3 (expanded form as Equation (4)) are indicated below:

$$\eta = \beta\eta + \Gamma X + \zeta \quad (1)$$

$$\begin{bmatrix}\eta_1\\ \eta_2\\ \cdot\\ \cdot\\ \eta_m\end{bmatrix} = \begin{bmatrix}0 & \beta_{12} & \cdot & \cdot & \beta_{1m}\\ \beta_{21} & 0 & \cdot & \cdot & \beta_{2m}\\ \cdot & \cdot & \cdot & \cdot & \cdot\\ \cdot & \cdot & \cdot & \cdot & \cdot\\ \beta_{m1} & \beta_{m2} & \cdot & \cdot & 0\end{bmatrix} \times \begin{bmatrix}\eta_1\\ \eta_2\\ \cdot\\ \cdot\\ \eta_m\end{bmatrix} + \begin{bmatrix}\gamma_{11} & \gamma_{12} & \cdot & \cdot & \gamma_{1n}\\ \gamma_{21} & \gamma_{22} & \cdot & \cdot & \gamma_{2n}\\ \cdot & \cdot & \cdot & \cdot & \cdot\\ \cdot & \cdot & \cdot & \cdot & \cdot\\ \gamma_{m1} & \gamma_{m2} & \cdot & \cdot & \gamma_{mn}\end{bmatrix} \times \begin{bmatrix}x_1\\ x_2\\ \cdot\\ \cdot\\ x_n\end{bmatrix} + \begin{bmatrix}\zeta_1\\ \zeta_2\\ \cdot\\ \cdot\\ \zeta_m\end{bmatrix} \quad (2)$$

$$Y = \Lambda\eta + \varepsilon \qquad (3)$$

$$\begin{bmatrix}y_1\\ y_2\\ \cdot\\ \cdot\\ y_p\end{bmatrix} = \begin{bmatrix}\lambda_{11} & \lambda_{12} & \cdot & \cdot & \lambda_{1m}\\ \lambda_{21} & \lambda_{22} & \cdot & \cdot & \lambda_{2m}\\ \cdot & \cdot & \cdot & \cdot & \cdot\\ \cdot & \cdot & \cdot & \cdot & \cdot\\ \lambda_{p1} & \lambda_{p2} & \cdot & \cdot & \lambda_{pm}\end{bmatrix} \times \begin{bmatrix}\eta_1\\ \eta_2\\ \cdot\\ \cdot\\ \eta_m\end{bmatrix} + \begin{bmatrix}\varepsilon_1\\ \varepsilon_2\\ \cdot\\ \cdot\\ \varepsilon_p\end{bmatrix} \quad (4)$$

where, X – n × 1 vector of exogenous (x) variables

Y – p × 1 vector of endogenous (y) variables

η – m × 1 vector of latent variables

β – m × m coefficient matrix of latent variables

Γ – m × n coefficient matrix of exogenous (x) variables

ζ – n × 1 vector of errors associated with η

Λ – p × m coefficient matrix of endogenous (y) variables on η

ε – p × 1 vector of measurement errors

Equation (1) gives the structural relationship between latent and exogenous variables of the model and equation (2) specifies the measurement equations between underlying latent and endogenous variables of the model. In this study, LISREL software was used for the analysis which uses maximum-likelihood method, and the best-fit model was selected. This study employs Root Mean Squared Error of Approximation (RMSEA), Standardised Root Mean Squared Residual (SRMR), and Comparative Fitness Index (CFI) to validate the models. According to (Steiger 1990) a value of below 0.10 indicates a good fit, 0.08 or less is reasonable and values below 0.05 indicate a very good fit for RMSEA. SRMR value of less than 0.10 indicates a good fit of the data in SEM models (Vandenberg and Lance 2000). (Bentler 1990) recommended the values of CFI lie between 0-1.0, with higher values indicating better fit.

The model's decision variables remain same across all hypothesis tests, while exogenous variables are chosen on trial basis, with only statistically significant variables are considered. A *t-statistic* value of 1.64 (Two-tail 90 percent confidence interval) is used as a critical value. Figure 1 shows the modelling framework adopted for this study. Structural equations are employed to uncover the directional causality and account for the mediation effect, thereby comprehensively examining the influence of observed exogenous variables on endogenous variables related to mode choice behaviour. Furthermore, a confirmatory factor analysis is conducted to validate the hypothesized factors specifically among individuals who own private vehicles but opt for public transport. By integrating the identified factors with the underlying causality between trip chaining and mode choice behaviour, a comprehensive understanding of the factors driving the usage of public and active transportation modes is achieved. This research contributes to the existing literature by offering valuable insights into the complex dynamics of mode choice behaviour, providing a robust framework for policymakers and transportation planners to enhance the utilization of sustainable modes of transportation. The study's contribution lies in its examination of the specific factors influencing mode choice behaviour among vehicle owners who choose public transport, filling a gap in the literature and offering practical implications for promoting sustainable transportation options.

4 Study area

4.1 Site selection and data collection

Hyderabad, India has been chosen to test a series of hypotheses (See Section 5 later) involving the hierarchy of travel decisions benefitting from the rich database from the Comprehensive Transportation Study conducted by the Hyderabad Metropolitan Development Authority (HMDA). The study area is divided into four subareas: Erstwhile MCH (Municipal Corporation of Hyderabad), rest of GHMC (Greater Hyderabad Municipal Corporation), Secunderabad cantonment and Osmania University connecting three metro rail lines as shown in Figure 2.

From a total of 461 zones, 175 were selected as they are within an arbitrarily decided 1.5 km of the metro rail corridor representing the catchment area. As this distance is considered an acceptable distance for walking and cycling in metropolitan regions in India (Gupta et al. 2022), the zones within this radius of the metro corridor are considered.

Home Interview Survey collected individual and travel characteristics from a total of 6066 households within the selected area. After cleaning/removing incomplete data records, a total of 9910 trips were included. Chi-square tests at 95% confidence interval are performed on the data set to assess the sample representativeness. Resulting P-value is 0.089 against 0.05 critical value indicating that there is no significant difference between sample and the population. A Cronbach's alpha value of 0.842 shows that the data is reliable. Descriptive analysis of socio-economic characteristics of the respondents is presented in Figure 3, which shows that the majority of commuters were middle-aged (26-35 years) and school-going (<18 years), with two-thirds of them being male. About 20% of the total respondents were graduates and 50% of the total respondents were employed. Around 70% of the trips were work and educational trips. Average household size was found to be 4.21 and the average household monthly income was rupees (Rs.) 13,700. Average number of earners per household was 1.38, indicating that the majority of households have only one person earning income. 50% of the households own a vehicle with 33% of residents holding a driving license.

4.2 Trip chain typology

Several past studies defined a trip chain as the one that starts and ends at home with one or more intermediate stops (Primerano et al. 2008), (Valiquette and Morency 2010). A similar definition is adopted in this study too. Trip chains are broadly classified into simple and complex trip chains based on the number of stops within a chain. They are classified further based on the presence of work stop or not. Simple work (non-work) chain is the one that starts and ends at home with only one work (non-work) stop. If there is more than one work (non-work) stop or a combination of both work and non-work stops, then it is considered as a complex trip chain. A complex trip has work or non-work stops in their morning or evening commute other than the primary stop. Table 2 gives the detailed typology used. It is observed that nearly 94% of the trips are simple work or non-work trips and the rest are complex trip chains. In terms of purpose, work trips constitute about 80% whereas the remaining 20% are for non-work. Out of this 80% work trips, 41% of the trips are education trips and the rest are work trips.

4.3 Mode choice classification

Available modes are classified into six categories – walking and cycling are taken together as a single category of active modes, 2-wheelers/motorcycles (2W), 3-wheelers/taxis/hired cars are taken under one category as taxi based on their similar properties (Subbarao et al. 2020), personal cars are labelled as cars, and public transport which includes bus and suburban rail (MMTS). The mode share is shown in Figure 4. 2W has the highest mode share of 27% followed by active modes (26%) and public transport (27%) including bus and suburban rail.

5 Model development and analysis of results

5.1 Model specification

The hierarchical (causal) relationship between trip chaining and mode choice decision is investigated using SEM in LISREL software. In order to do this, appropriate hypotheses were framed, and the path diagrams were created. The following four alternative hypotheses representing the causal structure between mode choice and trip chaining were tested:

Null hypothesis:

H_0: No correlation or decision precedence exists between trip chaining and mode choice.

Alternative Hypotheses:

H_1: Trip chaining and mode choice are correlated

H_2: Trip chain precedes mode choice decision

H_3: Mode choice precedes trip chain decision

H_4: Both decisions are simultaneous

Two models each were developed - one for active/public transport modes and the other for private modes. These two models were analysed for work and non-work purposes, thus making up four models altogether. The data set was prepared in SPSS and then imported into LISREL software. Path diagrams were drawn and the corresponding correlation along with *t-values* were worked out. Initial model was developed without correlations among exogenous variables. But the results were not significant with RMSEA value more than 0.05 (model = 0.2331). Models were then modified by adding necessary correlations between exogenous variables incrementally and the decision hierarchy was investigated.

In the analysis, trip chaining (tchain) and mode choice (tmode) behaviour decisions are the latent variables. Exogenous variables are identified based on the previous works and the prevailing conditions in developing countries. After that, significant variables are taken into account for the analysis. Table 3 lists the variables in the model. Types of trip chains and mode choices are the endogenous variables. For all models, latent and endogenous variables remain identical but exogenous variables are selected on a trial basis. The generalised path diagram is shown in Figure 5.

Four separate models were developed in all for work and non-work trips for private transport users and public and active mode users. Model 1 is developed for work trips (Simple Work - SW and Complex work - CW) by public (bus/MMTS) and active modes, while Model 2 has work trips by private modes (2W, taxi and cars). Model 3 is developed for non-work trips (Simple non-work - SNW and Complex non-work - CNW) by public/ active modes, while Model 4 is for non-work trips by private modes. LISREL software gives path coefficients along with *t-values* and total effects. Total effects are the sum of direct and indirect effects of exogenous variables on the decision variables through the mediation variables which are of interest to us. These total effects are useful in understanding how the household, individual and travel characteristics affect the decision of choosing a trip chain type and mode choice.

5.2 Modelling results

Model 1: Work trips by public and active modes

Initially, to investigate the decision precedence between trip chain and mode choice, the first hypothesis (H1) tested for error correlation between the two. It is found that these are highly correlated with a t-statistic value of 20.00 (>1.64 for 90% confidence level). So, in the next step, decision precedence is tested by connecting the paths from trip chain to mode choice (H2) and mode choice to trip chain (H3) respectively. It is found that both paths are significant but neither can be preferred over the other. Thus, in the next step, both decisions are assumed to be simultaneous. The paths are found to be significant (t-statistic = 3.15 and -3.70 respectively) and the model fit is reasonable (RMSEA = 0.0265, SRMR = 0.0586, CFI = 0.889). The decision is bi-directional i.e., workers decide on their mode and trip simultaneously without any hierarchy. Trip chaining complexity acts as an impediment to the public transport and active mode users to make multiple stops as they are constrained by the fixed routes, schedules, and travel times respectively. Thus, the decision to choose a public mode or trip chain will be made according to the availability of public transport at the time of departure and the travel time.

Table 4 provides the total effects of exogenous variables on endogenous variables. It can be observed that income levels have a significant effect on the trip chaining and mode choice behaviour. An increase in income levels has a negative impact on usage of bus/MMTS. Age positively impacts public transport usage because aged people are more concerned about safety/comfort, than using their own vehicle. At the same time, young age people prefer active modes. Travel time shows a negative impact on the public and active mode usage as people try to reduce their travel time by using faster modes of transport. On the other hand, with the increase in travel cost people are willing to use public transport. This is perhaps due to high fuel prices. People try to reduce the cost of travel expenditure by using public modes rather than own vehicles. Vehicle availability has a negative impact on active modes. This is because people tend to use a motor vehicle than active modes. Also, with an increase in vehicle ownership, people are likely to take complex trips because of the flexibility in making multiple stops.

Model 2: Work trips by private modes

Similar testing method as described earlier is used in this case too. Firstly, the model is tested for error correlation between the two decisions of trip chaining and mode choice. It is found that there is a correlation with a coefficient of 0.66 between them with a t-statistic value of 18.34. Furthermore, the path connecting from trip chain to mode choice and from mode choice to trip chain are found to be significant, simultaneous decision process will be tested in the next step by connecting the paths simultaneously. It is found that the path connecting from trip chain to mode choice is not significant (t-statistic = 0.60), whereas the path coefficient value of -0.29 from mode choice to trip chain with a t-statistic value of -7.86 has been found significant. The model fit is found to be reasonable (RMSEA = 0.0343, SRMR = 0.0552, CFI = 0.886). Thus, the decision is concluded as unidirectional rather than bi-directional for workers using private/hired transport. This is largely due to the vehicle ownership (car or two-wheeler). They already have a mode readily available, so they decide on the trip chain later. Also, owning a vehicle offers more flexibility in performing multiple-stop trips.

Table 5 gives the total effects on endogenous variables. It is observed that higher-income people are more likely to use private vehicles and take complex trips. With the longer travel times, people use their own vehicles as they offer higher speeds. Number of license holders in a household positively impacts the trip chain complexity and are likely to make trips by private vehicle. Time of the day has a negative impact on private vehicle usage. That means they are likely to use private vehicles during non-peak hours to avoid traffic congestion prevalent during peak hours.

Model 3: Non-work trips by public/active modes

Similar to work trips, models are developed for non-work trips. Initially, trip chaining and mode choice are assumed to correlate in their error terms, and the results are significant (t-statistic = 19.81). In the next steps, the path connecting trip chain to mode choice and vice-versa is tested separately. It is found that both the paths are significant. So, the simultaneous decision process is tested by connecting the paths between trip chain and mode choice. Results confirmed the existence of bi-directional decision hierarchy, that is to say, trip chaining and mode choice decisions are made simultaneously without any hierarchy. (t-statistic = 5.06 & -7.18 respectively). The model fit is found to be reasonable (RMSEA = 0.0574, SRMR = 0.0660, CFI = 0.841).

Table 6 gives the total effects of household, individual and travel characteristics effect on the trip chain and mode choice behaviour. In case of non-work trips, household income has a negative effect on active modes. This is because households with higher incomes are less likely to travel by active modes for performing non-work activities. This is also supported by travel times, which has a negative impact on active mode usage. License holders less likely to take public transport for non-work trips rather they prefer active modes for simple non-work activity. With the increase in the number of households, complexity in trip chaining increases because of the household responsibilities shared by the members. Public transport commuters are likely to perform simple trips as complex trips require multiple stops and it may not be possible with public transport because of the fixed routes. Age decreases the complexity in trip chains.

Model 4: Non-work trips by private modes

A similar analysis is performed as earlier for non-work trips by private transport users. It is found that the decision process is simultaneous without any hierarchy. So, the decision hierarchy is not unidirectional. The path coefficient from trip chain to mode choice is -0.94 with a t-statistic value of -29.97, and the path coefficient from mode choice to trip chain is -0.53 with a t-statistic value of -23.63. Model fit is reasonable with RMSEA= 0.0378, SRMR= 0.0531 & CFI= 0.874. These results seem to comply with the findings of (Subbarao et al. 2020), which found that the decision process is simultaneous for weekend trips. As most weekend trips are non-work related, the present results also showed similar findings.

Table 7 gives the total effects of exogenous variables on endogenous variables. It is seen that income has a positive effect on private vehicle usage. With the increased income, people are likely to use 2W for non-work chains. Time of the day has a negative effect on trip chains. People are likely to take simple trip chains during peak hours. For simple non-work chains, people prefer 2W even if the travel times increase. But taxis and cars have a negative impact on travel times meaning they are less likely use these modes for longer trip chains.

Table 8 summarises the model results. It is noted that the decision hierarchy for public/active mode users and private mode users is different for work trips signifying the time constraints that the workers may have, restricting the trip chaining decisions to an extent. Thus, private vehicle commuters tend to choose the mode *before* deciding on trip chaining, whereas public/active transport users plan their trip simultaneously according to the schedules/routes. These results partially agree with the findings of (Islam and Habib 2012; Ye et al. 2007), where they found that the decision process is simultaneous for weekday work trips though non-work trips were not analysed. As the behavioural patterns of public/active mode users and private mode users differ, the analysis needs to be performed separately. For non-work trips, the decision is simultaneous for all transport users. The probable reason is that they do not have any time restrictions for non-work trips, so they can plan the trip according to their convenience.

Knowledge of decision hierarchy (precedence or simultaneity) is necessary for framing transport policies. If the mode choice decision precedes trip chaining, public transport has to compete with the preferred alternative mode (2W/cars). Undoubtedly, 2W/cars offer higher flexibility and convenience in making multiple stops, it thus becomes challenging to attract new riders or to increase patronage by public transport. In contrast, if the decision process is simultaneous, then it is possible to keep the ridership by improving the facilities, information provision, ticketing, and/or schedules/routes.

6 Factors driving the use of active/ public transport and implications to policy

6.1 Factors motivating the use of active/public transport modes by vehicle owning individuals

The proportion of trips by sustainable modes of 53% (public transport 27% + walking/cycling 26%) indicates their strong presence over cars/two-wheelers with a combined share of about 40%. It is interesting to note that among public/active mode users, nearly 60% users own a vehicle (2W or car) but are using public/active modes by choice. This observation could be very useful for promoting sustainable modes of travel if we are able to understand the factors driving their motives. Thus, this section focuses on extracting the factors driving the choice of sustainable modes of transport, building the analysis further from the results shown earlier in Table 8. We have filtered out the datasets seeking active/public mode users for work and non-work purposes separately from which we have extracted further the records of users who own a vehicle. The number of records falling into each such category are shown in Table 9. Percentages shown within the brackets indicate the proportion of users who own a vehicle (2W or car). Before launching statistical analysis on the filtered-out records, let us revisit the results produced earlier (Tables 4,6 for public/active modes of travel) but with a focus on identifying the factors driving the mode choices.

Table 4 earlier shows that household income, vehicle ownership, age, education, and travel characteristics such as cost/time/distance will significantly influence the choice of active/public modes of transport for work trips. In case of non-work trips, in addition to household income and vehicle ownership, travel time/cost/distance have a significant influence, whereas age/education levels do not matter (Table 6). We now extend the analysis further by performing Factor Analysis to confirm the drivers identified. For this purpose, we use the filtered-out datasets as described earlier with the aim of extracting the specific factors driving the mode choices distinguishing the work/non-work trips.

Confirmatory Factor Analysis (CFA), part of the measurement model in SEM, is a statistical procedure which investigates the relationships between a set of observed and latent variables. CFA is theoretically well-grounded and is used to test the existing theory. It hypothesises a prespecified model and then evaluates how well it reproduces the sample covariance matrix of the observed variables. RMSEA and SRMR are the fit indices used for model fit assessment. Figure 6 gives the CFA model for work trips. Model fit values worked out to RMSEA = 0.055 and SRMR = 0.034. These results showed only the highly influential variables in using the public/ active modes for work trips. Travel time and age are the most positively influential driving factors (education is insignificant), whereas marital status and household size negatively impact public/active mode usage. Figure 7 gives the CFA model for non-work trips. RMSEA = 0.070 and SRMR = 0.032 are the obtained model fit values. Travel time and gender have a positive impact (age is insignificant), whereas marital status and chaintype negatively impact public/active mode usage.

Finally, Table 10 summarises the factors influencing the use of active/public modes of transport for work/non-work trips. A number of inferences can be drawn from the results. For work trips, household size and number of earners per household signify the choice of active/public modes of transport despite owning a vehicle. In other words, household structure matters significantly. Time of the day is also very important due to scheduled constraints in addition to the travel costs as the work trips are repetitive by their nature. In contrast, for non-work trips, household structure does not seem to matter at all, whereas gender/age and travel characteristics such as travel time/cost significantly affect the mode choice. In both cases of work/non-work trips, income levels do matter understandably though as they signify the affordability and perhaps even the need for travel. It is interesting to note that the marital status is a significant driving factor which is perhaps linked to the cultural settings in which the use of active/public modes will depend on whether the trip maker is the main earner of a household or not.

6.2 Implications for policies on promoting sustainable modes of transport

Results showed that factors driving the use of sustainable modes of travel are distinct for work and non-work trips. Thus, the strategies to promote them should differ too. Drawing from the inferences earlier, we give below a list of possible strategies to support the uptake of sustainable modes of travel.

Work trips

- Given that the household structure significantly affects the mode choice, attracting younger and elderly persons could significantly improve the uptake of sustainable modes.
- As we have identified, age is a driving factor for choosing active/public modes of travel, thus, running promotional campaigns in schools and also in communities would help. Complementary facilities like bike-sharing programs could significantly influence the attitudes of younger individuals toward walking and cycling. For elderly persons, the strategy could include improving the quality of footpaths, street lighting and cleanliness.
- Travel-related factors, including the time of day and travel time/cost, are crucial determinants for choosing active and public transport modes. Hence, enhancing safety

during travel for all users should be a priority. Additionally, making improvements to public transport that reduce travel times, especially during peak hours (e.g., enhancements to routing, scheduling, ticketing/pricing, and user information), can further promote sustainable modes of transportation.

Non-work trips

- Gender appears to be a significant factor affecting the mode choice; thus, we need to promote the use of active/public modes to targeted users. For instance, approaching women and encouraging them to form cycling and walking groups or clubs. These groups can serve as a source of support, and motivation for women who want to walk or cycle.
- Travel time/distance appear to significantly affect the mode choice; thus, alternative spatial planning of activities could be explored with an intent to promote the use of sustainable modes of travel.
- Trip chain type seems to negatively affect the use of sustainable modes of travel, thus pointing us to the lack of flexibility in using public modes in case of trips with multiple stops. Besides ensuring regularity of services, single ticketing can immensely help travellers with multiple stops along with the awareness campaign on it. This will relieve them of paying as many times, and perhaps could be cheaper for them too.

7 Model validation and practical application

From the results of the SEM, equations were formulated to estimate the latent variables, which are trip chaining behaviour and mode choice behaviour. Equations 5 and 6 focus on trip chaining behaviour, whereas equations 7 and 8 are for mode choice behaviour of work and non-work trips respectively. After the estimation of the latent variables, the utility of each mode is calculated by equations 9 and 10. Subsequently, the probability of mode choice is predicted by equation 11.

$$tchain\_w = (0.88 * hhinc) + (-0.302 * hhsize) + (0.88 * vperhh) + (-0.77 * earnhh) + (0.42 * age) + (0.031 * gender) + (0.88 * educ) - (0.70 * TT) + (0.48 * TC) - (0.29 * TD) - (0.87 * purpose) \quad (5)$$

$$tchain\_nw = (0.67 * hhinc) + (-0.30 * hhsize) + (0.93 * vperhh) + (0.14 * license) + (0.79 * educ) + (0.87 * timeofday) + (0.33 * TT) + (0.46 * TC) - (0.58 * TD) - (0.43 * purpose) \quad (6)$$

$$tmode\_w = (-0.097 * hhinc) - (0.021 * hhsize) - (0.122 * vperhh) - (0.042 * age) + (0.013 * gender) - (0.68 * educ) + (0.09 * timeofday) + (0.90 * TT) - (0.51 * TC) - (0.11 * TD) - (0.21 * purpose) + (0.31 * license) \quad (7)$$

$$tmode\_nw = (0.44 * hhinc) + (0.65 * hhsize) - (0.40 * vperhh) - (0.75 * age) + (0.32 * gender) + (0.11 * educ) + (0.31 * TT) + (0.60 * TC) + (0.14 * TD) - (0.30 * license) \quad (8)$$

$$Utility\ (U_w) = (-0.069 * tchain) - (0.5 * tmode) \quad (9)$$

$$Utility\ (U_{nw}) = (0.73 * tchain) - (0.41 * tmode) \quad (10)$$

$$P_{in} = \frac{e^{u_{in}}}{\sum_{j=1}^{J} u_{ij}} \quad (11)$$

Where, P_{in} – probability of selecting mode ‘n’ by individual ‘i’

u_{in} – utility of mode ‘n’ for individual ‘i’

u_{ij} – total utility of all modes in the choice set for individual ‘i’

The proportion of trips assigned to each mode for both work and non-work trips was then determined. The model estimates that public transportation (buses, MMTS, and metro rail) accounts for 33.9% of the total share, with metro rail contributing 5.4%. According to the Hyderabad Municipal Development Authority (HMDA 2021) report, the share of public transport is 32%, while the Hyderabad Metro Rail (LTMRHL 2023) reports the metro rail share as 4.4%. The error in estimate lies within a 95% confidence interval, with the actual public transportation share expected to be within the error margin of ±1.68% (±1.05% for metro share) of the estimated value thus validating the model.

After validating the model as described, let us now illustrate the use of the model for predicting the modal share on new metro corridors. For instance, the travel time from Miyapur to Ameerpet (red line corridor, 14 km) is 30 minutes by 2W, 38 minutes by car, and 54 minutes by bus during non-peak hours. However, using the metro reduces the travel time to just 24 minutes for the same distance, resulting in an average time savings of 16 minutes. Moreover, the metro ridership along the red line metro corridor constitutes 2.3% of the total metro trips (which is 4.4%), representing approximately 50% of the overall metro ridership. Given the similar traffic conditions on one of the proposed extensions of the red line from Miyapur to Patancheru, the validated model can be applied to estimate the expected metro share. This analysis predicts an initial metro share of approximately 2.3% with a margin of error of ±1.05%. This application demonstrates the model's potential for forecasting modal share on new/existing infrastructure such as metro rail.

Additionally, individuals are more likely to choose modes that allow more stop-making behaviour for complex trip chains. This increased complexity in trip chaining (increased by 19.3%) can lead to peak spreading, as commuters tend to incorporate non-work trips into their morning or evening commutes. In Hyderabad, the extended peak hours have resulted in a 9% increase in overall travel times. This underscores the necessity for capacity adjustments within the existing infrastructure. Ignoring the impact of trip chaining on the expansion of peak periods could further deteriorate travel times, potentially leading to the elimination of non-peak periods, as seen in Delhi, thereby affecting travel speeds.

8 Concluding remarks

Studies on trip chaining and mode choice behaviour are gaining importance as travel behaviour is a fundamental element that has significant implications for transport planning. Mode choice behaviour influences ridership estimates by different mode users, and trip chaining behaviour affects the stop-making. This paper investigates the hierarchical relationship between trip chaining and mode choice behaviour with an intent to understand the interplay between the two, to open up opportunities to promote the use of sustainable modes of transport. A well-integrated system of public transport with active modes potentially contributes to sustainable development and improves the access for all.

This paper hypothesises an underlying structure affecting the travel behaviour and models the covariance between variables using SEM method. This paper examines four different hypotheses considering whether the decision on trip chaining precedes the mode choice for work/non-work purposes separately. Different trip chain patterns and mode choices are identified from the datasets and the analysis is carried out using LISREL software. Results showed that decision hierarchy is *simultaneous* for non-work trips for all users viz., by private and active/public modes. In the case of work trips, however, the outcome is different. For work trips by public/active mode users, the decision process is *simultaneous*, whereas for private vehicle commuters, mode choice drives the trip chaining behaviour indicating a clear precedence.

The main conclusions drawn from this work are summarised as below:

- The decision making between mode choice and trip chaining is simultaneous except in the case of work trips by private modes for which mode choice clearly precedes indicating the hierarchy. This means attracting private vehicle commuters to sustainable modes could be a great challenge. Public transport providers need to develop innovative solutions such as the possibility to productively use their time while on-board, besides offering safe, comfortable journeys. However, non-work trips by private vehicle users can be potentially converted to sustainable modes as the decision making is simultaneous. This will require measures that allow trip chaining such as revising the routing/scheduling of public transport in addition to improving the access to bus stops/train stations.

- The factors driving the use of sustainable modes of transport have been extracted for a subset of users having access to a private mode such as a 2W or car. For work trips, household structure seems to be a big driver in addition to age and travel characteristics such as time/cost. For this group, targeted effort involving young/elderly persons could help the uptake of active/public modes. However, for non-work trips the main factors affecting seem to be the gender and travel characteristics. Thus, targeted effort towards womens' groups could help. Regularity of services during off-peak hours together with through ticketing could immensely help reducing time/cost by public transport.

In a developing country like India, income levels are not too high to afford a own vehicle by all. For the majority, public and active modes are the main commuting modes. So, even a slight improvement in the facilities can lead to generate a big impact. This can be achieved by understanding the travel behaviour of commuters. Without understanding the decision-making processes, the infrastructure provided is likely to be underutilised. Thus, a planned approach through a good understanding of behaviour is essential for achieving sustainability. As the transportation landscape continues to transform, it would be worth analysing the panel data to understand the temporal changes in travel behaviour. This study integrates both active modes and public transport within a single model, as they are sustainable modes of transportation. However, to comprehensively understand the driving factors behind walking and cycling, which are non-motorized modes, it is imperative to develop separate models specifically tailored to these active modes.

Data Availability Statement

Some of the data that support the findings of this study are available from the corresponding author upon reasonable request. This includes raw survey datafiles.

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Author contribution

Author X: conceptualisation; methodology; formal analysis; investigation; writing original draft; funding acquisition. Author Y: conceptualisation; investigation; writing – review & editing; funding acquisition; supervision. Author Z: writing – review & editing; supervision.

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