Article
Exploring the Macro Economic and Transport Influencing Factors of Urban Public Transport Mode Share: A Bayesian Structural Equation Model Approach

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Abstract: The public transportation priority strategy is a significant way to alleviate urban traffic congestion, and the urban public transport mode share (UPTMS) is a crucial indicator to measure the performance of public transportation priority strategies. To explore the influence factors of UPTMS, this study hypothesized that UPTMS is influenced by factors such as population, economy, road operation performance, public transport infrastructure, and private transport facilities, and tested the hypotheses using structural equation modeling (SEM) and Bayesian structural equation modeling (BSEM) based on urban macro economic and transport data in Guangzhou and Beijing, China. The results showed that, in the case of a small sample, BSEM is more adept at examining the correlation between the UPTMS and its influencing factors than SEM; in the Guangzhou and Beijing models, public transport infrastructure has the greatest positive and most significant impact on the UPTMS, and road operation performance has the greatest negative and most significant impact. Moreover, road operation performance is significantly improved by public transport infrastructure, while private transport facilities have a significant negative influence on road operation performance.

Keywords: urban traffic congestion; public transport mode share; Bayesian structure equation model; urban macroeconomic factors; urban macro transport factors

1. Introduction
Urban traffic congestion and environmental pollution issues are getting worse in China as urbanization picks up speed [1–3]. Many studies verify that improving the urban public transport mode share (UPTMS), which refers to the proportion of public transportation in urban travel modes, is an important means to alleviate traffic congestion and air pollution [4–6]. Therefore, exploring the influence mechanism can provide a reference for improving the UPTMS, relieve the pressure of urban traffic, and reduce air pollution.

Several studies have found that some micro-level factors of travellers’ feelings are determinants of urban public transportation choice behaviour. Yan and Li [7] discovered a correlation between public transportation distribution rate and four features, including safety, convenience, comfort, and cost. Augustus, et al. [8] found that travellers’ attitudes towards overcrowding is a significant feature influencing their choice of travel mode. Another study showed that low bus fares do not have a great influence on improving the UPTMS, while good public transport services can increase the UPTMS [9]. Although these studies are of great significance for formulating targeted public transportation management measures, they do not take into account the macro-level factors of cities.
Some researchers have also pointed out that some macro-level factors of cities are influencing factors of UPTMS. A study using the traffic data of Taiwan, China, found that social, economic, land use, and private transport facilities are important factors that have a significant influence on the utilization rate of urban public transportation [10]. Moreover, using the traffic data of Sweden, Holmgren identified that the demand for local public transportation is heavily influenced by economy and car ownership [11]. Scholl et al. found a relationship between the ownership of the new public transport mode, the net car, and the share of urban public transport [12]. Shojaeian et al. discovered the effect of public transportation characteristics, such as bus and subway fares, on the public transportation share [13]. These studies contribute towards understanding and determining the development direction of urban public transport. However, few researchers have systematically analyzed the relationship between the urban macro-economic and transport factors of public transport mode share. A study in Colombia identified the main determinants of macroeconomic factors and public transport factors on market shares for public transport services; however, they ignored the macro private transport factor.

This study attempts to systematically analyze the macro-economic and transport factors that affect the public transport mode share based on urban macro-level data. However, urban macro-level data are more difficult to obtain than personal data. Generally, only the city’s annual statistics can be found, and the sample size is usually limited. Therefore, a high-quality factor analysis method that is suitable for small sample conditions is the key to obtaining accurate results. Structural equation models (SEM) can be used to explore the relationship between travel mode choice behavior and its influencing factors [14–16]. SEM often uses the least-squares and the maximum likelihood method to estimate the model parameters, and it depends on the progressive distribution of the sample covariance matrix. Therefore, it is difficult to obtain better results under small sample conditions with SEM. Bayesian estimation is less dependent on progressive distribution, so that better results can be obtained under small sample conditions [17]. At the same time, studies have shown that the structural equation model with Bayesian estimation (Bayesian structural equation model, BSEM) has better parameter estimation results than traditional SEM towards small samples [18].

The purpose of this study was to investigate the effects of urban macroeconomic and transportation factors on UPTMS based on urban macro-level data. Therefore, finding validated factor analysis methods applicable to the small sample case to identify the important influencing factors affecting UPTMS is the research question that was addressed in this study. The contributions of this study can be summarized by the following two aspects: (1) the validity of BSEM for macroscopic influence factor analysis of UC under small sample conditions was verified; and (2) the important influencing factors affecting UC were clarified, and corresponding improvement measures were proposed.

This study was based on the urban macro-level data of Guangzhou and Beijing, and a BSEM was conducted to analyze the impact of urban macroeconomic and transport factors such as population, economy, public transport infrastructure, private transport facilities, and road operation performance on public transport mode share. The findings can be used to guide the construction of urban public transportation.

The remainder of the paper is arranged as follows: the methods used are described in Section 2. Section 3 presents the case study’s comprehensive results and analysis. Section 4 provides conclusions and recommendations for further work.

2. Materials and Methods

2.1. Bayesian Structural Equation Model

An improved structure equation model (SEM), the Bayesian structure equation model (BSEM) [19], was employed for factors analysis of urban public transport mode share in this study.
First, SEM is a confirmatory factor analysis model that builds a model using substantive prior knowledge, including a measurement model and a structural model. The measurement model is employed to identify the link between latent variables and observable data. Let \( y = (y_1, y_2, \ldots, y_p)^T \) represents a \( p \times 1 \) vector of observed variables, and \( \omega = (\omega_1, \omega_2, \ldots, \omega_q)^T \) represents a \( q \times 1 \) vector of latent variables associated to \( y \). The measurement model can be expressed as the following equation measurement equation:

\[
y = \Lambda \omega + \epsilon
\]

where \( \Lambda \) is a \( p \times q \) factor loading matrix, \( \epsilon \) is a \( p \times 1 \) random measurement errors vector, \( \epsilon \) is distributed as \( N[0, \Psi_\epsilon] \). \( N[0, \Psi_\epsilon] \) represent a normal distribution with the mean of 0 and the variance of \( \Psi_\epsilon \), and \( \Psi_\epsilon \) is a diagonal matrix. Let \( \omega = (\eta^T, \xi^T)^T \), where \( \eta \) and \( \xi \) are \( q_1 \times 1 \) and \( q_2 \times 1 \) \( (q_2 = q - q_1) \) vectors respectively contain the outcome and explanatory latent variables in \( \omega \).

The structural model depicts the correlation between the result and the explanatory latent variables. The relationship between \( \eta = (\eta_1, \eta_2, \ldots, \eta_{q_1})^T \) and \( \xi = (\xi_1, \xi_2, \ldots, \xi_{q_2})^T \) are defined by the following structural equation:

\[
\eta = P\eta + \Gamma \xi + \delta
\]

where \( P \) and \( \Gamma \) are matrices of unknown coefficients, \( \delta \) is a residual error distributed as \( N[0, \Psi_\delta] \), \( \Psi_\delta \) is also a diagonal matrix, and \( \epsilon \) and \( \delta \) are independent. It is assumed that \( \xi \) is distributed as \( N[0, \Phi] \).

The BSEM is a Bayesian approach to estimating SEM. BSEM begins by including priors for cross-factor loadings and residual correlations. The posterior distributions of parameters and latent variables may then be calculated using a large enough number of data generated using efficient Markov Chain Monte Carlo (MCMC) techniques. Eventually, simulated observations may be used to determine the means and quantiles of this posterior distribution [20].

Use \( Y = (y_1, \ldots, y_n) \) to represent the observed dataset, \( \Omega = (\omega_1, \ldots, \omega_n) \) to represent the latent matrix, \( \theta \) is the structural parameter vector containing unknown elements such as \( \Lambda, \Phi \) and \( \Psi_\epsilon \). In BSEM, the concept of data enhancement is used for posterior simulation, the latent matrix \( \Omega \) is regarded as missing data, and it is used to increase the observation data. The MCMC algorithm is used to sample a large number of \( (\theta, \Omega) \) from \( [\theta, \Omega | Y] \) by Gibbs sampling [20]. More specifically, with the current values \( \Omega^j, \Psi^j, \Lambda^j \) and \( \Phi^j \), the specific operations in the \( (j+1) \) iteration are as follows:

1. Generate \( \Omega^{j+1} \) from \( p(\Omega | \Psi^j, \Lambda^j, \Phi^j, Y) \).
2. Generate \( \Psi^{j+1} \) from \( p(\Psi | \Omega^{j+1}, \Lambda^j, \Phi^j, Y) \).
3. Generate \( \Lambda^{j+1} \) from \( p(\Lambda | \Omega^{j+1}, \Psi^j, \Phi^j, Y) \).
4. Generate \( \Phi^{j+1} \) from \( p(\Phi | \Omega^{j+1}, \Psi^j, \Lambda^{j+1}, Y) \).

Before sampling, the prior distributions of \( \Lambda, \Phi \) and \( \Psi_\epsilon \) need to be given. If the data and model fit well, the desired posterior distribution can be obtained when the sample converges. Use \( \{ \theta^{(t)}, \Omega^{(t)} \} : t = 1, \ldots, T^* \) to represent the sample drawn by Gibbs sampling. The following equations yield the Bayesian estimate of \( \theta \) as well as the standard error estimate:

\[
\hat{\theta} = T^* - 1 \sum_{t=1}^{T^*} \theta^{(t)}
\]

\[
Var(\theta | Y) = (T^* - 1) \sum_{t=1}^{T^*} (\theta^{(t)} - \hat{\theta})(\theta^{(t)} - \hat{\theta})^T
\]
Use $\omega_i$ to represent the latent variables vector of any individual observed variables vector $y_i$, the posterior mean $\hat{\omega}_i$ and the matrix of posterior covariance $\hat{\text{Var}}(\omega_i | Y)$ can be obtained by the following equations:

$$\hat{\omega}_i = T^* - 1 \sum_{t=1}^{T^*} \omega_i^{(t)}$$  \hspace{1cm} (5)

$$\hat{\text{Var}}(\omega_i | Y) = (T^* - 1) \sum_{t=1}^{T^*} \left( \omega_i^{(t)} - \hat{\omega}_i^{(t)} \right) \left( \omega_i^{(t)} - \hat{\omega}_i^{(t)} \right)^T$$  \hspace{1cm} (6)

2.2. Theoretical Model

The theoretical model is the basis of BSEM analysis, and the establishment of theoretical models requires a wealth of background knowledge. Some studies have shown that the urban public transport mode share (UPTMS) is affected by many urban macroeconomic and transport factors [21,22]. One study analyzed people’s travel choice behaviour in southeast Asia and found that the social population of the region has a certain relationship with the choice of residents’ travel mode [23]. A study based on traffic data of Heilongjiang, China, discovered that economic factors, such as GDP and tertiary industry share rate, have an impact on the UPTMS [24]. A study carried in Shanghai, China, pointed out that the UPTMS is affected by the rail network and other public transport infrastructures [25]. A study in Sweden proposed that private transport facilities, such as private car ownership, have a significant impact on UPTMS [11]. In addition, a number of studies have found that increasing the share of public transportation can help alleviate traffic congestion [26,27]. Some studies believe that congested road conditions will also promote the transfer of travellers from private car traffic to public transportation [28,29]. According to previous research on the UPTMS, population, economy, public transport infrastructure, private transport facilities, and road operation performance were selected to construct the theoretical model. The structure of the theoretical model which analyzed the macroeconomic and transport factors of UPTMS is shown in Figure 1. The theoretical model in this study makes the following 12 assumptions:

H1. The UPTMS is significantly affected by the population development of cities.

H2. The UPTMS is significantly affected by the economic development of cities.

H3. The UPTMS is significantly affected by the development of urban public transport infrastructure.

H4. The UPTMS is significantly affected by the development of urban private transport facilities.

H5. The UPTMS is significantly affected by the urban road operation performance.

H6. The operation of roads is significantly affected by the growth of infrastructure for public transportation.

H7. The operation of roads is significantly affected by the development of private transport facilities.

H8. The public transport infrastructure development is significantly affected by the population situation.

H9. There is a certain mutual influence between the economic situation and the growth of infrastructure for public transportation.

H10. The development of private transport facilities is significantly affected by the population situation.

H11. There is a certain mutual influence between the economic situation and the development of private transport facilities.

H12. There is a certain mutual influence between population and economic conditions.
3. Case Study

3.1. Data Preparation

Data used in this study were collected from the Annual Traffic Development Report published by Guangzhou Traffic Planning Research Institute and Beijing Traffic Development Research Institute. Guangzhou and Beijing are representative cities in the south and north of China, respectively. In 2021, Guangzhou has a population of 18,810,600 and a GDP of 2823.20 billion yuan, Beijing has a population of 2,189,095 and a GDP of 4026.96 billion yuan. To a certain extent, Guangzhou and Beijing are templates for urban development in the south and north of China, so they were chosen as experimental subjects in this study. The Guangzhou dataset contains urban and transportation development data of 11 administrative districts in Guangzhou from 2000 to 2018. The Beijing dataset contains urban and transportation development data of 16 administrative districts in Beijing from 2005 to 2016. Both datasets contain 13 indicators, such as the proportion of the conventional public, transportation proportion of railway transportation, and the average speed of highways. The detailed indicators are shown in Table 1.

Table 1. The observational indices corresponding to each potential variable.

<table>
<thead>
<tr>
<th>Latent Variables</th>
<th>Observed Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public transport mode share</td>
<td>$\xi_0$ Conventional public transport mode share</td>
</tr>
<tr>
<td></td>
<td>Railway transportation mode share</td>
</tr>
<tr>
<td>Population</td>
<td>$\xi_1$ Permanent population</td>
</tr>
<tr>
<td></td>
<td>Registered population</td>
</tr>
<tr>
<td>Economy</td>
<td>$\xi_2$ GDP of the primary industry</td>
</tr>
<tr>
<td></td>
<td>GDP of the secondary industry</td>
</tr>
<tr>
<td></td>
<td>GDP of the tertiary industry</td>
</tr>
<tr>
<td>Public transport infrastructure</td>
<td>$\xi_3$ Urban railway mileage</td>
</tr>
<tr>
<td></td>
<td>Urban bus ownership</td>
</tr>
<tr>
<td>Private transport infrastructure</td>
<td>$\xi_4$ Urban private motor vehicle ownership</td>
</tr>
<tr>
<td></td>
<td>Urban private car ownership</td>
</tr>
<tr>
<td>Road operation performance</td>
<td>$\xi_5$ The average speed of highways and expressways</td>
</tr>
<tr>
<td></td>
<td>The average speed of main and secondary roads</td>
</tr>
</tbody>
</table>

As Table 1 shows, six latent variables are considered in this study, among which the urban public transport mode share (UPTMS) is represented by $\xi_0$, and population, economy, public transport infrastructure, private transport facilities and road operation performance...
are, respectively, represented by $\xi_1, \cdots, \xi_5$. The 13 corresponding observed variables of latent variables are represented by $y_1, \cdots, y_{13}$.

3.2. Model Parameter Estimation and Evaluation

According to the above theoretical model, the measurement equation of SEM is:

$$y_i = \Lambda \omega_i + \epsilon_i, i = 1, \cdots, 13$$

where $\omega_i = (\xi_{i0}, \xi_{i1}, \xi_{i2}, \xi_{i3}, \xi_{i4}, \xi_{i5})$, The distribution of $\epsilon_i$ is $N[0, \Psi_\epsilon]$, and

$$\Lambda^T = \begin{bmatrix}
1 & \lambda_{1,2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & \lambda_{2,4} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & \lambda_{3,6} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

The structural equation is:

$$\xi_0 = \gamma_1 \xi_1 + \gamma_2 \xi_2 + \gamma_3 \xi_3 + \gamma_4 \xi_4 + \gamma_5 \xi_5 + \delta, \delta = 1, \cdots, 5$$

Here, $(\xi_1, \xi_2, \xi_3, \xi_4, \xi_5)^T$ and $\delta$ are respectively distributed as $N[0, \Phi]$ and $N[0, \Psi_\delta]$.

The Bayesian estimation of SEM is then performed. Use $\Psi_{ik}, \Psi_{\delta k}, \Lambda^T$, to represent the k-th diagonal elements of $\Psi_\epsilon, \Psi_\delta, \Lambda^T$ and the k-th row of $\Psi_\delta$ respectively. The following conjugate distributions are selected as the pre-empirc distributions of $(\Lambda, \Psi_\epsilon)$ and $\Omega$:

$\Phi^{-1} \overset{D}{=} W_5[10, 10], \Psi_{ik}^{-1} \overset{D}{=} Gamma[6, 10], \Psi_{\delta k}^{-1} \overset{D}{=} Gamma[6, 10], \Lambda_k \overset{D}{=} N[0.8, 4, 1], \Psi_{\delta k} \overset{D}{=} N[0.8, 4, 1], \Phi \overset{D}{=} N[0.8, 1], \Omega \overset{D}{=} N[0.5, 1], \Psi \overset{D}{=} N[0.5, 1], I$ is the identity matrix of the corresponding dimension.

After determining the prior distribution of the above SEM and related parameters, the urban macro traffic datasets of Guangzhou and Beijing are analyzed by Openbugs. The parametric trajectory diagram and autocorrelation graph of $\gamma_5$ in Guangzhou and Beijing in a randomly selected replication are presented in Figure 2 to reveal the convergence. It can be seen from these plots that the Openbugs program iterated 8000 times and converged in 4000 iterations. In this study, 4000 observations were collected after convergence to yield estimates and their standard errors.

![Parametric trajectory diagram and autocorrelation graph of $\gamma_5$ in Guangzhou (a) and Beijing (b) model.](a) (b)
3.3. Results and Discussion

Table 2 provides the results of the Guangzhou and Beijing BSEM. The results verified the validity of using BSEM to explore the macroscopic factors of UPTMS under small sample conditions, and the BSEM is an effective tool for conducting the analysis of macroscopic influences of UPTMS. Overall, the parameter estimation results of the BSEM in Guangzhou and Beijing are highly similar. Among the direct influence factors of the UPTMS, the most influential determinant is the growth of infrastructure for public transportation, followed by the road operation performance. The slight differences are that the influence of economic situation on UPTMS is significant in Beijing BSEM, but it is not significant in Guangzhou BSEM. The private transport facilities in Beijing BSEM do not have a significant impact on the UPTMS, but have a significant impact on Guangzhou BSEM. At the same time, the road operation performance in the two models is significantly affected by public transport infrastructure and private transport facilities. Both public transport infrastructure and private transport facilities are significantly affected by population and economic conditions.

Table 2. Estimation of coefficients of correlation between potential variables in Guangzhou and Beijing BSEMs.

<table>
<thead>
<tr>
<th></th>
<th>Guangzhou-BSEM</th>
<th>Beijing-BSEM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean 95% Lower</td>
<td>Mean 95% Lower</td>
</tr>
<tr>
<td></td>
<td>Bound 95% Upper</td>
<td>Bound 95% Upper</td>
</tr>
<tr>
<td>Public transport mode share</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H1 Population</td>
<td>0.13 0.01 1.12</td>
<td>0.12 0.01 1.06</td>
</tr>
<tr>
<td>H2 Economic</td>
<td>0.06 −0.09 1.03</td>
<td>0.10 0.00 1.01</td>
</tr>
<tr>
<td>H3 Public transport infrastructure</td>
<td>0.23 0.11 1.25</td>
<td>0.29 0.13 1.33</td>
</tr>
<tr>
<td>H4 Private transport facilities</td>
<td>−0.11 −0.98 −0.01</td>
<td>−0.09 −0.98 0.01</td>
</tr>
<tr>
<td>H5 Road operation performance</td>
<td>−0.17 −1.05 −0.05</td>
<td>−0.15 −1.09 −0.06</td>
</tr>
<tr>
<td>H6 Public transport infrastructure</td>
<td>0.19 0.07 1.19</td>
<td>0.17 0.07 1.19</td>
</tr>
<tr>
<td>H7 Private transport facilities</td>
<td>−0.12 −1.02 −0.03</td>
<td>−0.15 −1.11 −0.07</td>
</tr>
<tr>
<td>H8 Public transport infrastructure</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H9 Population</td>
<td>0.21 0.17 1.16</td>
<td>0.19 0.12 1.26</td>
</tr>
<tr>
<td>H10 Private transport facilities</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H11 Economic</td>
<td>0.15 0.02 1.15</td>
<td>0.16 0.08 1.15</td>
</tr>
<tr>
<td>H12 Population and economic</td>
<td>0.36 0.16 1.39</td>
<td>0.41 0.19 1.57</td>
</tr>
</tbody>
</table>

Note: “95% Lower bound” and “95% Upper bound” are the lower and upper limits of the 95% confidence interval of the estimated value. If the interval does not contain 0, it means that the estimated value reaches the 0.05 significant level.

The results further reveal that road operation performances have a significant negative influence on the UPTMS (Guangzhou, Mean = −0.17, Beijing, Mean = −0.15), indicating that the better the road operation performance, the smaller the proportion of travellers who travel by public transport. These results are similar to the research of Yang [30] on travel mode choice in Dalian, China. Yang found that the number of travellers who choose public transportation in the congested state is significantly higher than that in the smooth state. When motor vehicles can achieve a good speed on the urban road, the time cost advantage of public transportation reduces. Additionally, private traffic is generally more comfortable than public transport. Thus, in the case of good road operation performance, travellers will be more inclined to private transport travel. Accordingly, reducing the time cost of public transportation and enhancing its comfort are crucial steps to raising the UPTMS.

The growth of infrastructure for public transportation has the greatest positive impact on the UPTMS (Guangzhou, Mean = 0.23, Beijing, Mean = 0.29), suggesting that the UPTMS rises as public transportation infrastructure investment becomes more comprehensive. This is compatible with the findings of the study about the influence analysis of infrastructure for
non-motorized and public transportation on travel patterns in Indian cities, which suggests that the UPTMS is steadily increasing due to the ongoing expansion and upgrading of public transportation infrastructure [31]. The reason why public transport infrastructure has the greatest positive impact on UPTMS may be that longer subway mileage, more bus lines, more convenient public transportation travel, and lower cost of public transportation travel will result in the greater probability that travellers choose public transportation.

The findings also demonstrate that the road operation performance is significantly improved by public transportation infrastructure (Guangzhou, Mean = 0.19, Beijing, Mean = 0.17), connoting that the construction of public transport infrastructure has a good promotion effect on the operation of urban roads, and can effectively alleviate urban traffic congestion. Therefore, increasing the scale of public transport infrastructure and improving the public transportation network are effective measures to increase the UPTMS.

In the Guangzhou BSEM, the growth of private transport facilities significantly harms the UPTMS (Mean = −0.11), demonstrating that the improvement of private transport facilities will hinder the increase in the UPTMS. This might be explained by the fact that better private transport facilities and higher travel comfort level of private transportation will lead to fewer travellers choosing public transportation to travel. The results also reveal that the significant impact of private transport facilities on the UPTMS is less than other significant direct influencing factors in the Guangzhou BSEM. In the Beijing BSEM, the impact of private transport facilities on the UPTMS is not significant (Beijing, Mean = −0.09). The possible explanations for these results are that when the number of private transport facilities on the road reaches a certain limit, road operation performance will decrease (Guangzhou, Mean = −0.12, Beijing, Mean = −0.15), and it will further cause traffic congestion and prolong the travel time of travellers, resulting in the transfer of travellers to public transportation. The private transport facilities indirectly affect the UPTMS mainly through the impact on road operation conditions. It also shows that travel time and travel comfort are important criteria for travellers to choose their travel mode [32]. Hence, in addition to restricting the development of private transport facilities (cars limited, limited purchase), improving the public transport travel experience (reduce travel time, improve travel comfort) is also an important way to guide passengers to transfer to public transport.

The population situation has a significant positive impact on the UPTMS (Guangzhou, Mean = 0.13, Beijing, Mean = 0.12), revealing that population growth will increase the UPTMS. The possible reason is that the rapid development of the urban population will lead to the rapid growth of private transport facilities. When the growth rate of urban private transport facilities does not match the construction speed of road facilities, traffic congestion can easily ensue. At this time, the travel time cost of private travel mode increases, and as the travel comfort reduces, travellers will be more willing to choose the public transport mode with a lower travel time cost [33]. Population conditions have a significant positive impact on private transport facilities (Guangzhou Mean = 0.18, Beijing, Mean = 0.16) and public transport infrastructure (Guangzhou, Mean = 0.21, Beijing, Mean = 0.19). Greater than that of private transportation facilities is the influence of public transportation infrastructure, suggesting that population growth contributes more to the development of public transport than private transport, possibly because public transport can better meet the transport needs of population growth than private transport. Hence, vigorously developing public transport infrastructure is one of the most important means to alleviate the traffic pressure caused by population growth [34].

In the Beijing BSEM, the economic situation has a favourable and considerable effect on the UPTMS (Beijing, Mean = 0.10), denoting that the development of Beijing’s urban economy is crucial to the growth of public transportation. Nonetheless, the economic situation of the Beijing BSEM has the smallest positive effect on the development of public transportation compared with other significant influencing factors. In the Guangzhou BSEM, the impact of economic development on the UPTMS is not significant (Guangzhou, Mean = 0.06), which shows that the direct impact of urban economic development on public
transport is low. It can be seen from the results that the urban economic development has a significant correlation with urban public transport infrastructure and private transport facilities, and the correlation with public transport infrastructure (Guangzhou, Mean = 0.15 *, Beijing, Mean = 0.16) is greater than private transport facilities (Guangzhou, Mean = 0.11 *, Beijing, Mean = 0.15). These results indicate that the development of the urban economy and the construction of urban public transport facilities have a greater mutual promotion, and the development of the urban economy mainly affects the UPTMS indirectly through affecting the construction of public transport facilities. Therefore, in the process of rapid urban economic development, the government’s economy is inclined to the construction of public transport infrastructure, which will help increase the UPTMS. Meanwhile, the growth of public transport infrastructure will further promote economic development [35].

4. Conclusions

This study used a validated factor analysis approach (Bayesian structural equation model, BSEM) under small sample conditions to analyze the macroeconomic and transport influences on urban public transport mode share (UPTMS) based on macro transport statistics for Guangzhou and Beijing. One of the important conclusions from this research is that, in the case of a small sample, the Bayesian structure equation model can obtain good results on the analysis of the relationship between the UPTMS and factors including population, economy, public transport infrastructure, private transport facilities, and road operation performance.

This study identified that, among the influence factors of the UPTMS, public transport infrastructure is the greatest positive factor, and road operation performance is the largest negative factor. The economic situation and the private transport facilities are less influential. Additionally, the public transport infrastructure and private transport facilities have a significant correlation with population and economic conditions. The analysis of the results shows that, in the process of urban population and economic growth, the vigorous development of public transport infrastructure can help relieve the traffic pressure caused by population growth, and it also plays an important role in promoting the city’s economy. At the same time, the travel experience of travellers is an important criterion for their travel behaviour choice.

Based on the above results, in urban planning and management, this study recommends that urban transport planning departments and management departments could increase the UPTMS by further improving public transport infrastructure and the public transport travel experience. Furthermore, this study proves the feasibility of BSEM for UPTMS macroscopic factor analysis under small sample conditions and provides theoretical and methodological references for other similar studies.

There may be some possible limitations in this study. First, the experimental data in this study come from representative cities in China, and have a certain guiding significance for the development of other cities in China. Due to the differences in culture and development levels between countries, the findings may not be generalizable to other countries. Therefore, future studies can use the methodology and framework of this study to explore the macro-influencing factors of UPTMS based on data from other countries. Second, the sample size of this study is small due to the unpublished data of the experimental cities before 2000, and future studies should use as many samples as possible to study the influence of macro factors on UPTMS. Lastly, the impact of traveller characteristics on the UPTMS was not accounted for in this study. In future research, the comprehensive urban macro data and traveller’s attribute data can be considered to study the influencing factors of UPTMS.

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