

# Travel Mode Choice Behavior of Different Income Groups Based on the Value of Time

Jie Feng \*, Xianghong Li

School of Energy Science and Engineering, Henan Polytechnic University, Jiaozuo, Henan, 454003, China

\* Corresponding author: Jie Feng

**Abstract:** The value of travel time (VOT) plays a critical role in transportation project evaluation and policy design. An in-depth analysis of VOT across high-, middle-, and low-income groups provides valuable insights for optimizing transportation policies and infrastructure planning, particularly in alleviating congestion and improving system efficiency. By capturing heterogeneous perceptions of travel time among different income groups, transportation systems can better accommodate diverse user needs and enhance overall social welfare. In this study, a stated preference (SP) survey is designed using an orthogonal experimental approach. Based on the collected SP data from different income groups, a multinomial Logit (MNL) model is developed under the random utility maximization framework to analyze travel mode choice behavior. The value of time for each income group is estimated by examining trade-offs between travel time and cost across alternative modes. The results indicate significant heterogeneity in VOT across income groups. High-income individuals exhibit a stronger preference for time savings and are more willing to pay higher costs for reduced travel time, reflecting a greater emphasis on efficiency. In contrast, middle-income groups tend to balance travel time and cost, while low-income groups show higher cost sensitivity and relatively lower willingness to pay for time savings. These findings provide important implications for differentiated transportation policy design and infrastructure allocation, contributing to improved system efficiency, better demand–supply matching, and more equitable distribution of social resources.

**Keywords:** Traffic Engineering; Travel Time Value; Orthogonal Experiment; Multinomial Logit Model.

## 1. Introduction

The value of travel time (VOT) is a key indicator in transportation research, widely used to evaluate economic efficiency and optimize transportation policies. It plays a crucial role in influencing travelers' behavioral choices as well as the effectiveness of policy-making. In macroscopic transportation models, VOT determines the generalized cost across different population groups, travel purposes, and mode choices, thereby affecting traffic assignment outcomes[2].

According to the existing literature[1], methods for estimating VOT can generally be classified into two categories: direct and indirect approaches. The direct approach estimates VOT based on observed market behavior or survey data, typically using travelers' behavioral information, such as travel time costs and willingness to pay, to infer their valuation of time[11]. For example, individuals' choices among different travel modes and their associated expenditures can reveal their implicit trade-offs between time and cost. In contrast, the indirect approach estimates VOT through the development of economic models, and is commonly used to evaluate the impacts of policies, plans, or transportation systems. This approach is generally based on theoretical modeling or statistical analysis, applying economic principles to assess the effects of time costs on economic outcomes. For instance, cost–benefit analysis models and travel demand models are often employed to indirectly estimate VOT[1].

Existing studies indicate that individuals' travel mode choice is influenced not only by objective conditions but also by latent attitudes and preferences. Vij et al. analyzed the consistency between preferred and actual travel choices, finding that approximately half of travelers do not adopt their preferred mode, with inconsistencies being more pronounced

among public transport users. Their findings further suggest that consistency between preferred and actual modes has a significant impact on travel satisfaction, with travelers using their preferred mode generally reporting higher satisfaction levels, regardless of the specific mode type[12].

In China, research on VOT is predominantly conducted using disaggregate modeling approaches [4]. For example, Xiao Mei et al. employed a multinomial Logit (MNL) model, incorporating travel purpose and transfer conditions as key variables to analyze waiting time value, thereby refining the classification of travel time value [3]. Yu Zhang[7] further improved the travel value estimation model based on disaggregate modeling theory and applied an MNL model to estimate VOT for different population groups in Chengdu.

Internationally, Maria Börjesson synthesized findings from Swedish VOT studies, highlighting recent advances in econometric methods and their implications for understanding the distribution of VOT[6]. Manuel Ojeda Cabral explored passengers' subjective perceptions and preferences regarding the use of recovery time, providing empirical estimates for economic evaluation purposes[5]. Ghadir Pourhashem incorporated subjective factors from the H2020 MoTiV project into VOT estimation, using an MNL model to examine the effects of travel characteristics, emotions, socio-economic attributes, experiential factors, travel activities, and weather conditions[8]. Basil Schmid estimated the value of leisure time (VOL), travel time savings (VTTS), and the allocation of time to travel (VTAT), emphasizing the importance of travel comfort in policy and investment decisions[9]. In addition, Zhong Haotian applied a mixed Logit model to quantify changes in VOT in the context of autonomous vehicles and analyzed their potential impact on commuters' value of travel time (VOTT)[10].

In the field of travel time valuation (VTT), Kováčiková et

al. pointed out that traditional studies have largely focused on time–cost trade-offs under the assumption of a fixed “travel time budget,” which has long supported transportation planning and infrastructure decision-making. However, they argued that such approaches tend to overlook travelers’ subjective perceptions of time value and their relationships with individual needs, preferences, and lifestyles[14]. Their study highlights that VOT is inherently subjective and context-dependent, meaning that the same amount of time may be valued differently across travel situations. Building on the MoTiV framework, they proposed a behavior- and perception-oriented approach to VOT estimation, extending beyond the traditional utility-maximization paradigm and offering a more interdisciplinary perspective.

Overall, these studies not only reveal significant heterogeneity in VOT across income groups, but also provide important implications for the development of differentiated transportation policies and the rational allocation of infrastructure resources, thereby contributing to the optimization of transportation systems and a more equitable distribution of social resources.

## **2. Theoretical Foundations of the Value of Travel Time**

### **2.1. Economic Interpretation of the Value of Travel Time**

In economics, the value of travel time (VOT) refers to the time cost borne by individuals or groups in travel decision-making, as well as its corresponding economic and opportunity costs. This concept not only encompasses the direct time spent during travel, but also includes the opportunity cost associated with foregone alternative activities and related psychological burdens.

Focusing on this core issue, Kenneth A. Small provided a systematic review of the theoretical and empirical literature on the value of travel time, highlighting that individuals’ willingness to pay for travel time savings is closely related to various economic behaviors, including departure time choice, avoidance of travel time unreliability, labor supply decisions, and activity scheduling[13]. His study further emphasizes that VOT exhibits strong context dependence and significant individual heterogeneity. These characteristics make VOT a critical parameter in transportation policy evaluation, public transport pricing, congestion charging, and infrastructure planning.

### **2.2. Characteristics and Determinants of the Value of Travel Time**

The value of travel time (VOT) in transport economics originates from individuals’ trade-offs between time and monetary cost, and is commonly quantified by the marginal rate of time substitution. This concept can be broadly categorized into two types: the resource value of time, which is essential for the economic evaluation of transportation investments, and the behavioral value of time, which focuses on travel behavior analysis and urban congestion management. While the resource value of time has been more widely applied in China, the behavioral value of time remains relatively underexplored and requires further empirical investigation and practical application.

VOT not only reflects the direct time spent during travel, but also incorporates the opportunity cost associated with foregone alternative activities, as well as related

psychological burdens. This dual perspective highlights its economic significance. When individuals make trade-offs between time savings and additional monetary costs, a higher marginal rate of time substitution indicates a greater willingness to pay for travel time savings. Moreover, individuals’ perceived value of travel time varies significantly and is influenced by factors such as income level, lifestyle, occupational constraints, and personal preferences regarding time allocation. Travel-related conditions, including trip purpose, travel distance, transport mode, congestion levels, and travel time reliability, also play a critical role. In addition, psychological factors such as stress and discomfort associated with long-distance travel or congested conditions further shape individuals’ valuation of time.

Empirical evidence further supports the existence of substantial heterogeneity in VOT. Shires and de Jong conducted a meta-analysis of the value of travel time savings (VTTS) across multiple countries, demonstrating that VOT is jointly influenced by income level, travel purpose, transport mode, travel distance, national economic conditions, and methodological approaches (e.g., stated preference versus revealed preference methods)[15]. Their findings also highlight that VTTS plays a central role in cost–benefit analysis and generalized cost modeling, serving as a key parameter for evaluating transportation infrastructure and policy impacts.

Overall, these findings suggest that VOT is not a fixed parameter but a context-dependent and dynamic measure that varies across individuals and travel situations. A systematic understanding of its characteristics and determinants is therefore essential for transportation planning, policy design, and the efficient allocation of transportation resources.

## **3. The Multinomial Logit Model**

At present, the main approaches for estimating the value of travel time (VOT) include the production approach, wage-based approach, cost-based approach, and disaggregate modeling approaches. Among these, disaggregate models place particular emphasis on capturing individual-level heterogeneity and subjective behavioral factors affecting VOT, making them more suitable for practical applications and relatively straightforward to implement. In this study, a disaggregate modeling framework is developed based on stated preference (SP) survey data to reveal travelers’ perceived value of time under different travel purposes.

The multinomial Logit (MNL) model is commonly regarded as a representative discrete choice model within the class of disaggregate models[17]. Disaggregate modeling is a behavioral modeling approach that focuses on heterogeneity across individuals and differences in their decision-making preferences. Such models are typically based on individual-level stated or revealed choices and preferences, rather than aggregated statistical data.

The multinomial Logit model is widely used to analyze the probability distribution of discrete choice alternatives, such as consumers’ purchase decisions or travelers’ mode choice behavior. It is particularly suitable for examining preference heterogeneity across alternatives and quantifying the relative utility associated with each option. In transportation economics, it is commonly applied to analyze travelers’ choices among different transport modes (e.g., car, public transport, walking, etc.), thereby capturing decision-making processes under the joint influence of travel time, cost, and other attributes.

Therefore, the multinomial Logit model belongs to the class of disaggregate models, as it explicitly accounts for individual-level preferences and subjective choice behavior rather than relying on aggregated statistical analysis.

The multinomial Logit (MNL) model is based on the random utility maximization (RUM) theory [7]. For traveler  $n$ , there exists a choice set  $A = \{A_1, A_2, \dots, A_n\}$ , where each element represents a feasible travel alternative. The utility of alternative  $j$  for individual  $n$  is denoted as  $U_{jn}$ . The individual is assumed to choose alternative  $i$  from the choice set  $A_n$  if and only if the utility of alternative  $i$  is greater than that of all other available alternatives, i.e.:

$$U_{in} > U_{jn}, j \neq i, j \in A_n \quad (1)$$

Random utility theory assumes that utility is a random variable. Therefore, the utility function  $U_{in}$  is decomposed into a deterministic component  $V_{in}$  and a stochastic error term  $\varepsilon_{in}$ , and is typically specified in an additive linear form[16].

$$U_{in} = V_{in} + \varepsilon_{in} \quad (2)$$

The deterministic component  $V_{in}$  represents the utility derived from the observed attribute vector  $X_{in}$ , and is typically specified in a linear-in-parameters form as follows:

$$V_{in} = \sum_{k=1}^k \theta_k X_{ink} \quad (3)$$

where  $X_{ink}$  denotes the value of the  $k$ -th observed attribute of alternative  $i$  for individual  $n$ , and  $\theta_k$  represents the parameter to be estimated.

If the stochastic error term  $\varepsilon_{in}$  is assumed to follow an independently and identically distributed (i.i.d.) Gumbel (Type I extreme value) distribution with location parameter 0 and scale parameter 1, the multinomial Logit model can be derived. Under this assumption, the probability that

individual  $n$  chooses alternative  $i$  is given by:

$$P_{iq} = \frac{\exp[V_{in}]}{\sum_{j \in A_n} \exp[V_{jn}]} = \frac{e^{\sum_{k=1}^k \theta_k X_{ink}}}{\sum_{j \in A_n} e^{\sum_{k=1}^k \theta_k X_{jnk}}} \quad (4)$$

The attribute vector  $X_{ink}$  represents the characteristics of each alternative, including alternative-specific dummy variables, alternative-specific constants, and alternative-specific common variables. In general, there are no alternative-specific variables for transportation modes; thus, the explanatory variables typically consist of common variables such as travel time  $t$  and travel cost  $f$ , as well as  $(k-1)$  alternative-specific dummy variables, where the  $k$ -th alternative-specific constant (ASC $_k$ ) is normalized to zero for identification purposes.

Based on this specification, the explanatory variables used in the model are summarized in Table 1.

Based on previous international studies[12], travel time and travel cost are identified as the most important factors influencing travelers' mode choice behavior. Therefore, the deterministic utility function VVV can be specified as follows:

$$V_i = a_i + b_i P_i + c_i T_i \quad (5)$$

In Equation (5),  $a_i$ ,  $b_i$ , and  $c_i$  are parameters to be estimated.  $P_i$  and  $T_i$  denote the cost and travel time associated with the  $i$ -th travel mode or route selected by travelers, respectively.  $n$  represents the number of available travel modes or routes. The value of travel time (VOT) can be expressed as [3]:

$$VOT = \frac{\partial v_i / \partial t_i}{\partial v_i / \partial f_i} = \frac{\partial t_i}{\partial f_i} \quad (6)$$

The estimation of the multinomial Logit model, including the formulation of the maximum likelihood function and the computation of optimal parameter estimates, follows standard procedures described in the relevant literature [4].

**Table 1.** Specification of Attribute Variables

Alternative	Utility	Alternative-specific dummies				Alternative-specific common variables	
		$X_{in1}$	$X_{in2}$	...	$X_{ink}$	Time(min) ( $X_{in4}$ )	Cost(CNY) ( $X_{in5}$ )
Mode 1	$V_{1n}$	1	0	...	0	$X_{1n4}$	$X_{1n5}$
Mode 2	$V_{2n}$	0	1	...	0	$X_{2n4}$	$X_{2n5}$
...	...	...	...	...	...	...	...
Mode $k$	$V_{kn}$	0	0	...	1	$X_{kn4}$	$X_{kn5}$
Parameters		ASC $_1$	ASC $_2$	...	ASC $_3$	$\theta_f$	$\theta_t$

## 4. Data Collection and Processing

The accuracy and reliability of survey data play a crucial role in modeling the value of travel time (VOT), which largely depends on the design of the stated preference (SP) experimental context. In general, sufficient information should be collected from respondents; however, excessively complex questionnaires should be avoided, as survey fatigue may reduce response quality and compromise data accuracy.

To address this issue, an orthogonal experimental design is adopted in this study to construct the SP scenarios. This approach reduces the number of hypothetical choice scenarios

while maintaining statistical efficiency, thereby improving survey manageability.

Orthogonal experimental design is based on the principles of rationality, reliability, constraint satisfaction, and simplicity. It selects a subset of experimental points characterized by "uniform dispersion and balanced comparability" from all possible combinations[18]. In such designs, each level of a factor is systematically combined with levels of other factors to construct experimental scenarios. Statistical Package for the Social Sciences (SPSS), a widely used statistical software for data analysis, is employed to generate the orthogonal design. By using SPSS, complex combinations of multiple factors can be simplified into a

structured experimental design table, enabling efficient arrangement of relevant factors and levels.

In this study, approximately seven travel modes are available in Shanyang District, Jiaozuo City, including walking, bicycle, shared bicycle, shared electric bicycle, public transport, taxi, and private car. Considering the characteristics of walking and cycling, such as zero monetary cost, these two modes are excluded from the experimental design. Therefore, five travel modes are selected for scenario construction: shared bicycle, shared electric bicycle, public transport, taxi, and private car.

For each scenario, the travel time and travel cost of each mode are determined based on average travel time and distance derived from a travel survey of residents in Shanyang District. The detailed scenario settings are presented in Table 2.

**Table 2.** Travel Time and Cost of Different Transport Modes

Mode	Travel time (min)			Cost (CNY)		
	30	60	90	1	1.5	2
Bus	30	60	90	1	1.5	2
Taxi	15	30	45	33	69	105
Private car	18	36	54	18	37	56
Shared e-bike	45	90	135	3	4.5	7.5
Shared bicycle	60	120	180	1	2	3

As shown in Table 2, the SP survey for residents in Shanyang District considers a total of ten experimental factors, including travel time and travel cost for bus, taxi, private car, shared bicycle, and shared electric bicycle. Each factor has three levels. Based on the orthogonal experimental design, a

full combination of 10 factors at 3 levels would generate 27 experimental scenarios[19].

To ensure survey feasibility and reduce respondent burden, the questionnaire was divided into three blocks. Each respondent was required to complete only nine scenarios.

The sample size of the questionnaire is determined using the following formula:

$$n = \frac{Z^2 p(1-p)}{e^2} \tag{7}$$

where n denotes the required sample size, Z is the standard normal deviate corresponding to the selected confidence level, p represents the estimated variability of the population proportion, and e is the acceptable margin of error.

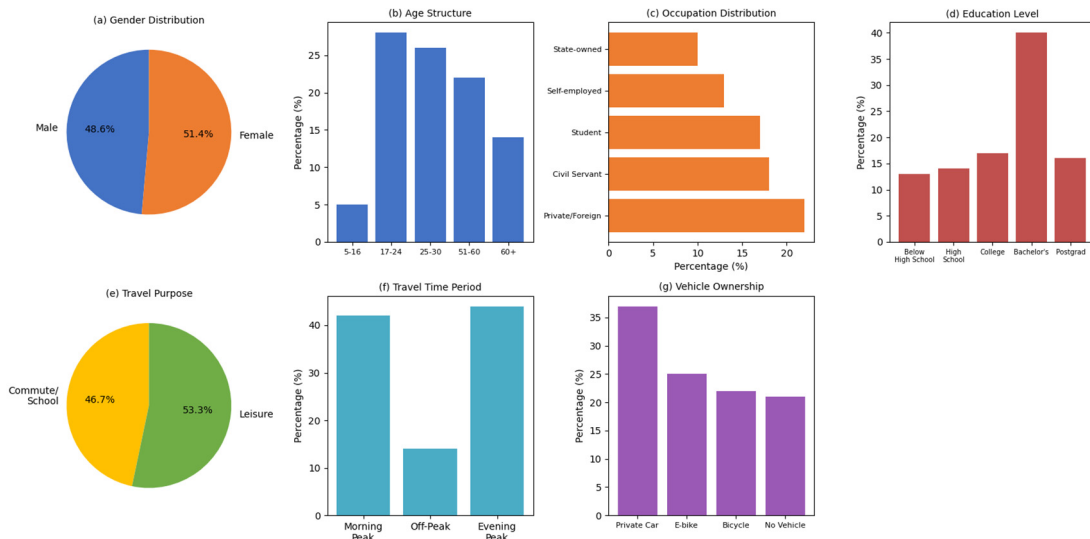
When the population parameter p is unknown, it can be estimated based on prior data or previous survey results. If no prior information is available, p=0.5 is typically adopted. This is because the term p(1-p) reaches its maximum when p=0.5, leading to the most conservative (i.e., largest) sample size estimate and thus avoiding underestimation of sample size.

In this study, a 95% confidence level and a maximum allowable error of 5% were assumed. Under these conditions, the required sample size is approximately 384.

$$n = \frac{Z^2 p(1-p)}{e^2} = \frac{1.96^2 \cdot 0.5(1-0.5)}{0.05^2} \approx 384 \tag{8}$$

A total of 420 questionnaires were collected in this survey. When respondents' stated choices were inconsistent with their individual attributes, the questionnaires were considered invalid and removed. After data cleaning, 405 valid questionnaires were retained for further analysis. In this study, monthly income below 5,000 CNY is defined as low income, 5,001–15,000 CNY as middle income, and 15,000 CNY and above as high income.

The distribution of basic demographic characteristics of the survey sample is shown in Figure 1.



**Figure 1.** Distribution of Travel Characteristics

The survey results show that males account for 48.6% of the sample, while females account for 51.4%, indicating a relatively balanced gender distribution. In terms of age structure, the majority of respondents are concentrated in the 29–50 age group (30.4%), followed by the 17–28 age group (25.2%), suggesting that the sample primarily consists of adult populations.

Regarding occupation, employees in private and foreign-funded enterprises (23.0%) and civil servants (21.7%) represent relatively large proportions, reflecting the

occupational diversity of the respondents. In terms of education level, respondents with a bachelor's degree account for 40.0%, representing the largest educational group in the sample.

With respect to travel behavior, more than one-third of respondents own private cars (37.3%), and most reported travel purposes are non-commuting trips (53.3%). In addition, the income distribution shows that low-income, middle-income, and high-income groups account for 34.7%, 54.0%, and 11.3%, respectively, which is generally consistent with

the overall population structure.

Overall, the survey sample exhibits a balanced distribution in terms of gender, age, occupation, education, and travel purpose, highlighting the heterogeneity and behavioral diversity across different social groups.

## 5. Calculation and Analysis of Value of Travel Time

Based on the data obtained from the above SP survey, the parameters were calibrated using the maximum likelihood estimation (MLE) method. A multinomial Logit model was implemented in Python 3.8. After validation based on the orthogonal experimental design[20], the value of travel time (VOT) for different income groups under different travel modes was estimated.

By comparing the VOT values for the same travel mode across different income groups (Figure 2), the following conclusions are obtained:

**Table 3.** Value of Travel Time for High-Income Group under Different Travel Modes

Mode	$\theta_t$	$\theta_f$	VOT/(¥·h-1)
Bus	-0.057	-0.117	29.0
Taxi	-0.034	-0.050	43.8
Private car	-0.056	-0.115	30.1
Shared e-bike	-0.053	-0.145	20.9
Shared bicycle	-0.087	-0.543	15.6

**Table 4.** Value of Travel Time (VOT) for Middle-Income Group under Different Travel Modes

Mode	$\theta_t$	$\theta_f$	VOT/(¥·h-1)
Bus	-0.047	-0.111	24.7
Taxi	-0.051	-0.106	28.9
Private car	-0.060	-0.135	26.2
Shared e-bike	-0.062	-0.198	18.3
Shared bicycle	-0.061	-0.199	17.6

**Table 5.** Value of Travel Time (VOT) for Low-Income Group under Different Travel Modes

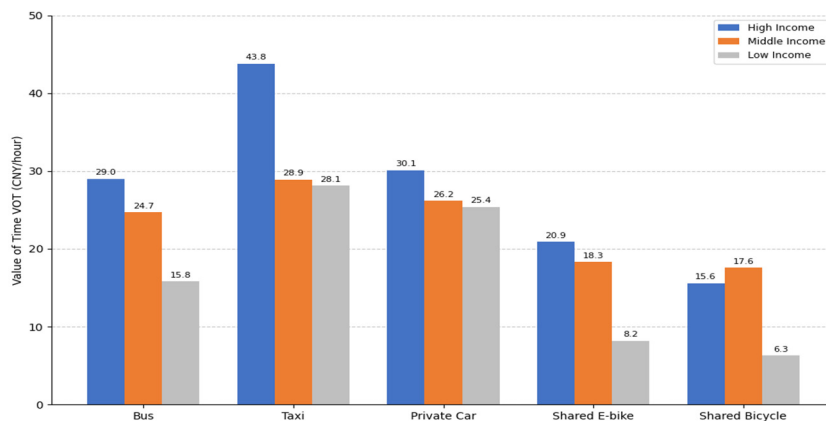
Mode	$\theta_t$	$\theta_f$	VOT/(¥·h-1)
Bus	-0.044	-0.091	15.8
Taxi	-0.038	-0.081	28.1
Private car	-0.023	-0.049	25.4
Shared e-bike	-0.052	-0.222	8.2
Shared bicycle	-0.055	-0.361	6.3

From the perspective of the high-income group, the results indicate that they assign higher values of travel time (VOT) to taxi and private car, with values of 43.8 CNY/h and 30.1 CNY/h, respectively. This suggests that high-income travelers exhibit a stronger preference for travel modes characterized by higher comfort and convenience. The VOT for public transport is slightly lower at 29.0 CNY/h, yet it remains an acceptable option for this group. In contrast, shared bicycle shows the lowest VOT at 15.6 CNY/h, indicating a relatively weak preference among high-income travelers.

For the middle-income group, travel mode choice reflects a balance between time and cost efficiency. Their VOT values for public transport (24.7 CNY/h), taxi (28.9 CNY/h), and private car (26.2 CNY/h) are relatively close, indicating similar perceptions of these modes in terms of time valuation. Meanwhile, shared electric bicycles and shared bicycles are more frequently chosen compared with the high-income group, although their VOT values remain lower, at 18.3 CNY/h and 17.6 CNY/h, respectively.

Low-income travelers show a stronger preference for cost-efficient travel modes. Their VOT values are relatively low for public transport (15.8 CNY/h), private car (25.4 CNY/h), and taxi (28.1 CNY/h). In particular, shared electric bicycles (8.2 CNY/h) and shared bicycles (6.3 CNY/h) exhibit the lowest VOT values, indicating that these modes better satisfy their economic constraints.

Based on the VOT results shown in Figure 2, the factors influencing travel mode choice differ significantly across income groups. High-income travelers tend to prefer taxi and private car due to their higher levels of comfort and convenience. This group generally places greater emphasis on time savings and is more willing to pay additional monetary costs in exchange for faster and more comfortable travel.



**Figure 2.** Value of Travel Time (VOT) across Different Income Levels and Travel Modes

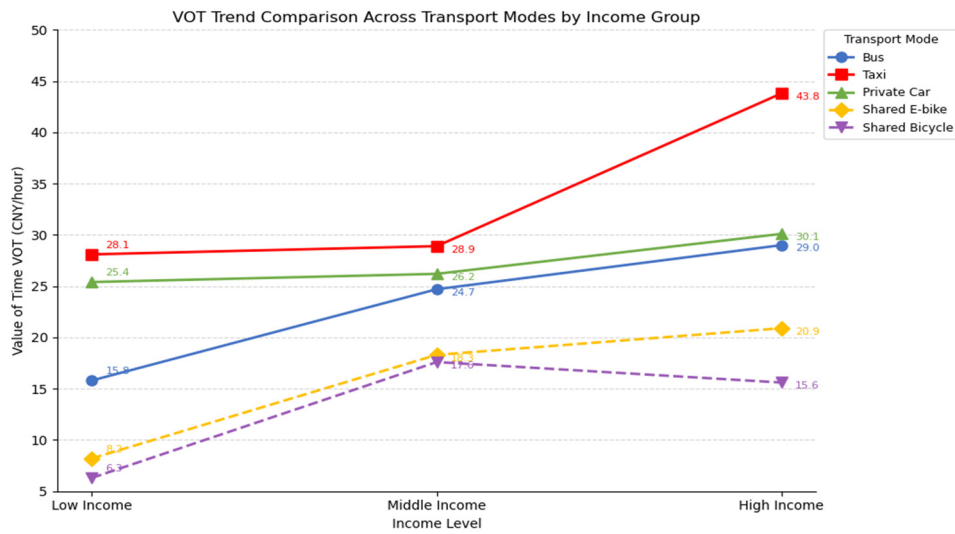
In contrast, the middle-income group tends to seek a balance between public transport and private car use. Their

mode choice is often influenced by a trade-off among travel distance, time, and monetary cost. They are also more willing

to consider shared mobility options, such as carpooling or shared bicycles, to reduce travel costs or mitigate environmental impacts.

On the other hand, low-income travelers are more likely to choose cost-efficient public transport modes, which align

with their financial constraints while satisfying basic mobility needs. Their acceptance of shared mobility services, such as shared bicycles or electric scooters, is relatively lower, which may be attributed to cost sensitivity as well as perceived convenience and accessibility barriers.



**Figure 3.** Comparison of Value of Travel Time (VOT) Trends across Different Income Groups and Travel Modes

As shown in Figure 3, the value of travel time (VOT) for all travel modes exhibits an increasing trend with rising income levels. Among all modes, taxi shows the steepest increase, rising from 28.1 CNY/h for the low-income group to 43.8 CNY/h for the high-income group. This indicates that high-income travelers are highly sensitive to travel efficiency and comfort. In contrast, the VOT curves for shared bicycle and shared electric bicycle are relatively flat, suggesting that the marginal utility of time savings associated with slow mobility modes is less sensitive to income variations.

These results reflect that economic considerations, functional utility, and individual preferences jointly influence travel decision-making across different social groups. Therefore, urban transport planning and service optimization should explicitly account for these heterogeneous needs. For high-income groups, improving the efficiency of taxi and private car systems—such as enhancing traffic flow management and reducing congestion—can further improve overall urban mobility efficiency.

For middle-income travelers, expanding shared mobility services, such as increasing the availability of shared bicycles or improving carpooling systems, may help reduce urban carbon emissions and improve air quality. For low-income groups, enhancing the coverage and frequency of public transport services, as well as reducing fares, can significantly improve accessibility and social inclusion.

Overall, a systematic understanding of income-differentiated VOT patterns enables policymakers and urban planners to develop more intelligent and inclusive transport policies that better serve the diverse mobility needs of urban residents.

## 6. Conclusion

The estimation of the value of travel time (VOT) involves multiple dimensions and influencing factors. By decomposing the VOT across different income groups and travel modes, a more precise understanding of how travelers perceive and value time can be achieved. High-income

travelers tend to place greater emphasis on time savings due to faster-paced lifestyles and higher efficiency requirements, and are therefore more willing to pay higher travel costs to reduce travel time. In contrast, middle-income travelers generally seek a balance between time savings and monetary cost, with their travel decisions jointly influenced by both factors. Low-income travelers are more cost-sensitive and tend to prioritize economic affordability, exhibiting relatively higher elasticity with respect to travel time and a stronger preference for public transport.

Such segmentation not only enhances the understanding of heterogeneous time valuation across income groups but also provides important implications for the development of personalized and optimized transport policies. Through accurate estimation of VOT differences, policymakers can improve transport network design and adjust service provision and infrastructure allocation, thereby maximizing socio-economic benefits while meeting diverse mobility needs. This refined approach contributes to improving overall transport system efficiency and sustainability, as well as enhancing urban development and residents' quality of life.

Taking Shanyang District of Jiaozuo City as a case study, this study designed and distributed SP questionnaires using an orthogonal experimental design to obtain data on travel behavior and preferences. A multinomial Logit model was then established to estimate the VOT for different income groups across travel modes. The results indicate that high-income travelers exhibit a significantly higher valuation of travel time compared with middle- and low-income groups, reflecting their stronger preference for efficiency and willingness to trade monetary cost for time savings. Middle-income travelers demonstrate a trade-off behavior between time and cost, while low-income travelers are more sensitive to cost and show a stronger preference for public transport.

Therefore, travelers' VOT is influenced not only by travel purpose and mode choice, but also by income level and socio-economic conditions. Future research may further explore the specific effects of different travel modes on VOT in greater depth to provide more tailored transport solutions for different

income groups.

Although this study provides insights based on Shanyang District, Jiaozuo City, its geographical limitation may affect the generalizability and transferability of the findings. Future studies should expand the survey scope to multiple regions and cities to enhance the robustness and external validity of the conclusions. Moreover, collecting larger and more diverse datasets will help further refine the understanding of how different travel modes influence VOT.

## References

- [1] Wu, H., Peng, H., Chen, Z., et al. (2019). Estimation of value of travel time based on SP survey and analysis of its influencing factors. *Traffic and Transportation*, 35(6), 9–12.
- [2] He, L., Duan, Z.Y., Qiu, J.D. (2016). Estimation method of value of travel time based on SP survey. *Journal of Jinling Institute of Technology*, 32(2), 30–33.
- [3] Xiao, M., Xu, F.B., Bian, H.Y., et al. (2020). Estimation of waiting time value based on multinomial Logit model. *Journal of Chongqing Jiaotong University (Natural Science Edition)*, 39(10), 24–30.
- [4] Guan, H.Z. (2004). *Discrete Choice Models*. Beijing: China Communications Press, pp. 99–105.
- [5] Ojeda-Cabral M., Shires J., Wardman M. et al. The use of recovery time in timetables: rail passengers' preferences and valuation relative to travel time and delays. *Transportation* 48, 337–368 (2021).
- [6] Maria Börjesson. "Experiences from the Swedish Value of Time study[J]. *Transportation Research Part A: Policy and Practice*, 2014, 59:144-158."
- [7] Zhang, Y. (2022). Study on value of travel time of urban residents based on NL model (Master's thesis). Southwest Jiaotong University, China.
- [8] Pourhashem, G., Georgouli, C., Malichová, E. et al. Factors influencing the perceived value of travel time in European urban areas. *Transportation* 51, 1525–1545 (2024).
- [9] Schmid Basil, Molloy Joseph, Peer Stefanie, et al. "The value of travel time savings and the value of leisure in Zurich: Estimation, decomposition and policy implications[J]. *Transportation Research Part A: Policy and Practice*, 2021, 150:186-215."
- [10] Zhong, H.T., Li, W., Burris, M.W., et al. (2020). Will autonomous vehicles change commuters' value of travel time? *Transportation Research Part D: Transport and Environment*, 83, 1–14.
- [11] Jonas De Vos. Do people travel with their preferred travel mode? Analysing the extent of travel mode dissonance and its effect on travel satisfaction[J]. *Transportation Research Part A: Policy and Practice*, 2018, 117:261-274.
- [12] Akshay Vij, André Carrel, Joan L. Walker. et al. Incorporating the influence of latent modal preferences on travel mode choice behavior[J]. *Transportation Research Part A*, 2013, 54:164-178.
- [13] Kenneth A. Small. Valuation of travel time[J]. *Economics of Transportation*, 2012, 112:2-14.
- [14] Kováčiková, T., Lugano, G., Pourhashem, G. (2018). From Travel Time and Cost Savings to Value of Mobility. *RelStat 2017. Lecture Notes in Networks and Systems*, vol 36. Springer, Cham.
- [15] J.D. Shires, G.C. de Jong. An international meta-analysis of values of travel time savings[J]. *Evaluation and Program Planning*, 2009, 324:315-325.
- [16] Tse, Y. K. A Diagnostic Test for the Multinomial Logit Model. *Journal of Business & Economic Statistics*, 5(2), 283–286.
- [17] Gabriel, S. A., Rosenthal, S. S.. Household Location and Race: Estimates of a Multinomial Logit Model. *The Review of Economics and Statistics*, 71(2), 240–249.
- [18] Derek Bingham, Randy R. Sitter, Boxin Tang, Orthogonal and nearly orthogonal designs for computer experiments, *Biometrika*, Volume 96, Issue 1, March 2009, 51–65.
- [19] Houtman, A. M., & Speed, T. P. Balance in Designed Experiments with Orthogonal Block Structure. *The Annals of Statistics*, 11(4), 1069–1085.
- [20] Z.C.Du, J.G.Yang. et al. Modeling approach of regression orthogonal experiment design for the thermal error compensation of a CNC turning center[J]. *Journal of Materials Processing Technology*, 2002, 129:619-623.