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RESEARCH PAPER

Empirical Study on the Influence of Learning Ability to Individual Travel Behavior

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Abstract: Learning ability is a primary symbol, which distinguishes humanity from other creatures and plays an important role in travel decision-making. To explore the major effects of learning ability on travelers' characteristics, the paper first divides the influence on travel decision-making into static and dynamic factors based on the functions of individual travel behavior factors and analyzes the effects on travelers' characteristics from the aspects of learning ability. Subsequently, qualitative analysis of travel behaviors is conducted. Then, the paper proposes structural equation model (SEM) of individuals' travel behavior analysis .With the daily travel data derived from Binhai New Area, Tianjin, model estimation, evaluation, and modification are demonstrated. Finally, explanations of the results are presented, which indicate that there is a strong effect of learning ability on travel behavior.

Key Words: learning ability; travel behavior; SEM (structural equation model); empirical study

1 Introduction

Urban traffic is the link between urban social and economic activities. With the rapid development of economy and the speedup of urbanization, traffic congestion has been a problem to many cities, and the traditional Four-Step method is no longer able to solve traffic problems effectively[1].

To understand the residents' travel rule and predict traffic demands, it is important to make a research on individual travel behavior and establish the travel models. From the analysis of the source of individual travel demand-activity, activity-based method[2–4] attempts to solve the contradiction between supply and demand and balance the distribution of total travelers from space and time. The method is able to cover the shortcomings of traditional methods. Travelers' behaviors based on activities have been researched a lot from econometrics. Golob made the review and summery about the application of structure equation model (SEM) in the study of traffic behavior in Ref. [5]. Lu and Pas[6] established the SEM and made an empirical study about the relationship among individual socio-economic characteristics, time of various activities of a family, and travel behavior. Kuppam and Pendyala[7] revealed the relationship among the Demographic characteristics, activity participation, and travel behavior by three SEMs by the survey data from Washington. The previous researches mainly focused on the relationship between individual characteristic and travel activity and seldom on the influence of human's unique learning ability.

This paper concentrates on the influence of individual learning ability on traveler's behavior with the consideration of individual socio-economic characteristics, and then develops the activity-based SEM of individual travel. The model is verified by the daily travel data derived from Binhai New Area, Tianjin. The evaluation and explanation are documented at the last section, which reveals the learning ability's influence on individual travel rules to some extent.

2 Influencing factor analysis of individual travel behavior

Individual day-to-day travel choice is an adaptive process to various environment factors (such as on-road time and fee, road conditions, weather, land use, and so on) but a one-time activity. The process also can be regarded as a feedback learning process in which the traveler makes the conclusion and evaluation to the travel experience, continuously learns and modifies the travel behavior, and shapes his/her travel characteristic and habit.

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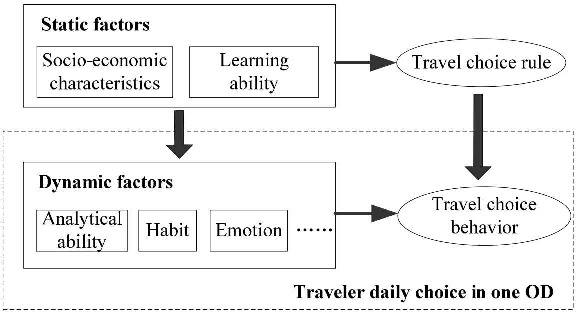

Fig. 1 Dynamic and static factors influencing individual travel behavior and their relationship

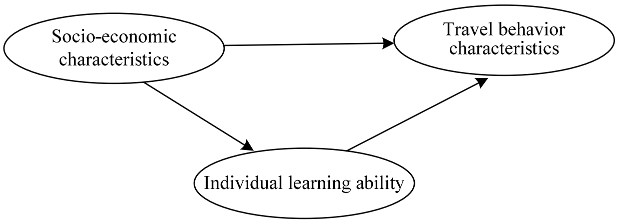

Fig. 2 Relationship among influence factors

From the whole process of feedback learning, considering the influence scope to individual decision-making, it is acceptable to divide the inner factor (ignoring the influence from outside) influencing individual travel behavior into static and dynamic factors (Fig. 1).

Static factors include individual socio-economic characteristics and the learning ability to travel experience. Socio-economic characteristics are individual social attributes that influence traveler's decision-making, such as age, income, children, and vehicle sums in the family, and so on. Learning ability usually means the ability that gets the knowledge and skills from experience in cognitive physiology, and the authors define it as the ability that adapts and modifies travel choice behavior from travel experiences in the study of transportation. Both travel experience accumulation and habit formation have direct relation with individual learning ability. The factors influencing individual learning ability involve age, gender, education, income, and so on. Static factors usually shape the rule of individual travel choice.

Dynamic factors are some uncertain factors of travelers in one phase of travel decision-making. Experience, habit, analytical ability, emotion, etc. can be regarded as dynamic factors. These factors are different from the proceeding of traveler's daily choice in the day-to-day feedback learning process. Dynamic factors determine one specific travel choice behavior.

Static factors influencing the formation of dynamic factors of individual daily travel choice have indirect effect, which cannot be ignored on travelers' behavior. Dynamic factors, which determine travelers' specific decision-making, are the direct factor on travel choice. It can be considered that static factors normally influence travelers' long time choice pattern, and dynamic factors determine travelers' choice in one trip. Travelers with similar static factors may not have the same choices in one trip for the difference of dynamic factors, but for a long term there must be some relations and rules in statistics sense.

3 Learning ability in individual travel behavior

Travelers adapt to the environment gradually, act and make decisions under the interactions both between individuals and environment and among individuals themselves. In fact, individuals gather the perceived travel experiences by travel activities. Pre-experiences provide references for the decision-making of this time, and their influences are the changing of decision (e.g. departure time, travel route, mode, etc.) for the travel utility optimum. The effect of learning is to help travelers to make the travel choice with the changing of travel environment. Learning ability, which makes an association and expansion according to available experience and knowledge, distinguishes humanity different from other creature behaviors and common reflex. Thus, the analysis only covers travelers' socio-economic characteristics is absolutely not enough.

Travelers make their choices by learning the pre-experiences and the perceived experience when facing a new OD pair. Although the specific choices are different, travelers with similar learning abilities often obey some common rules in the whole adapting process. The common rules are the reflection of learning ability, which is based on individual socio-economic characteristics.

Learning ability has important influence on travelers' experience accumulation and habit formation. Obviously, travelers with worse learning ability gather experience slowly, are not sensitive to the environment variance, and their choices are more similar or more random, vice versa. Both experience accumulation and habit formation are important to individual travel behavior. Therefore, the study on travelers' learning ability, in brief, is significant to travel planning and travelers' decision-making behavior.

4 SEM of traveler behavior

According to the above analysis, the authors reveal the complex relationship among individual socio-economic characteristics, learning ability, and travel behavior. The model, which reflects the effects of travelers' behavior, can be formulated through the method of SEM. First, assuming that:

(1) Travelers' socio-economic characteristics have direct influence on their learning ability; (2) Travelers' socio-economic characteristics have direct influence on their travel behavior characteristics; (3) Travelers' learning ability have direct influence on their travel behavior characteristics. These relations are illustrated in Fig. 2.

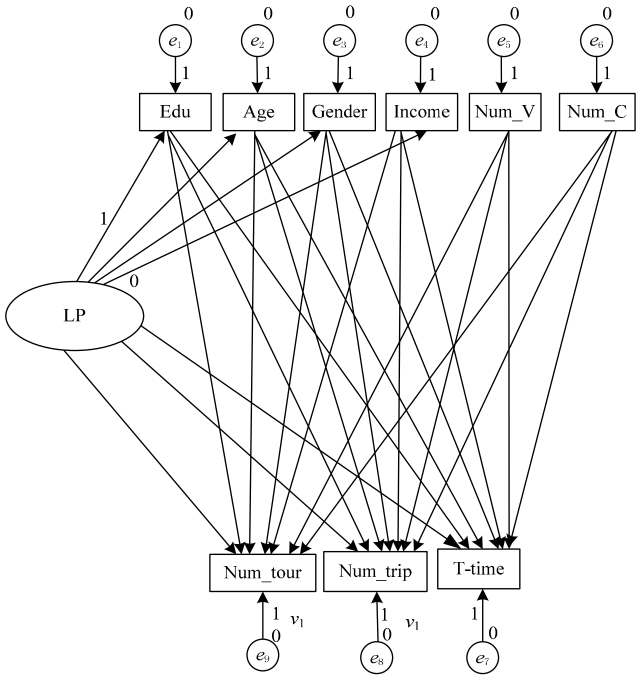

Fig. 3 Path analysis of the assumed models

Individual socio-economic characteristics contains: age (Age), gender (Gender), income (Income), education (Edu), children sum of family (Num_C), and vehicle sum of family (Num_V). As learning ability (LB) is an unobservable variable, only age, gender, education, and income are chosen as the indexes in this paper. Individual travel behavior characteristics are reflected by the travel times of one day (Num_trip), trip-chain sum (Num_tour), and the total on-road time (T_time).

Developing the model with the path analysis method is not only helpful to understand the relationship among variables but also can transfer the path graphs to the model equations directly (Fig. 3).

From the path analysis, the SEM of corresponding travel behavior can be described as the following two equations by matrix. One is the measurement equation and the other is structure equation:

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} \lambda_{11} \\ \lambda_{12} \\ \lambda_{13} \\ \lambda_{14} \end{pmatrix} \xi + \begin{pmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \end{pmatrix}$$

$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} & \beta_{25} & \beta_{26} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} & \beta_{35} & \beta_{36} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{pmatrix} + \begin{pmatrix} \tau_{11} \\ \tau_{12} \\ \tau_{13} \end{pmatrix} \xi + \begin{pmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \end{pmatrix}$$

where,

x_1, x_2, x_3, x_4, x_5, x_6—travelers' education, age, gender, income, children sum of a family, and vehicle sum of a family, respectively;

y_1, y_2, y_3—travel times of one day, trip-chain sum, and the total on-road time;

ξ—individual learning ability;

δ—error term of measurement equation;

ζ—residual term of structure equation.

5 Model fitting

The estimation of SEM is based on the covariance structure of variables. By the decomposition of the covariance structure, the relations of variables can be verified indirectly. The application of SEM requires a number of sample data, which is usually not lower than 200. In this paper, the residents daily travel data of Binhai New Area in Tianjin is used, and it contains individual socio-economic characteristics and daily travel records. The sample size is 281, and the maximum likelihood is used. After modifying and fitting of several times, the results are obtained and listed as below:

χ^2=57.845, DF=12, χ^2/DF=4.82, SRMR=0.064, RMSEA=0.117, CFI=0.942, NFI=0.931.

χ^2 is the value of chi-square test; DF is the degree of freedom; SRMR is the standardized root mean residuals; RMSEA is the root mean square of error approximate; CFI is the compared fitting index; NFI is the normed fitting index. To the model test of ML and GLS, Hu and Bentler[8,9] recommended to use SRMR and combine with one of the following indexes: TLI, BL89, RNI (or CFI), Gamma Hat, Mc, and RMSEA. The cut off values are TLI, BL89, RNI (or CFI), and Gamma Hat is 0.95. Mc is 0.9; SRMR is 0.08; RMSEA is 0.06. Meanwhile, Bentler and Bonett[10] suggested that NFI should not be lower than 0.9.

The maximum likelihood of SEM assumes that every variable should obey normal distribution. Under the condition of the same degree of freedom, the smaller the χ^2 is, the lower the mutual excluding possibility of the model and the data[11] is. The approximation of the distribution of χ^2, as a kind of asymptotic distribution, is better with bigger sample size, but too big sample size will cause the refusal of the model for big χ^2. Thus, χ^2 is not an ideal index. The model is acceptable when χ2/DF is less than 2[12].

The results of the above fitting test are that χ^2/DF>2, CFI<0.95, and RMSEA>0.06. All of these show that the fitting between the model and the data is not as good as expected, and the modification of the model is necessary.

6 Model evaluation and modification

The fitting results indicate that the above model is not satisfying. However, the relationships of the measurement variables and structure variables can be confirmed as correct. Analyzing the fitting indexes carefully, it can be found that

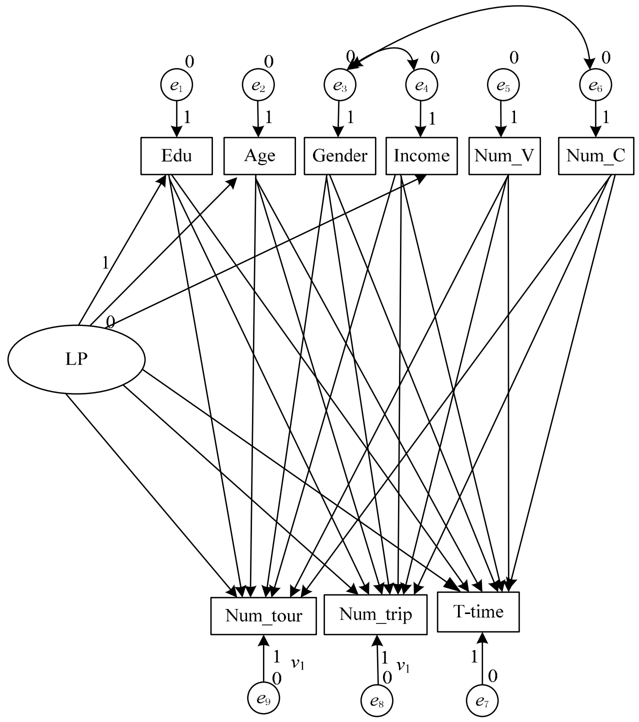

Fig. 4 Path analysis of the modified model

there is some strong relativity of the measuring variables errors of gender and income and of gender and children sum. For improvement, the correlations between e_3 and e_4, e_3 and e_6 are increased. In addition, from the parameter estimate results, the index of gender can be deleted because it makes smaller impacts to learning than other indexes. To modify the model according to the above two reasons, a new path analysis of the model can be obtained (Fig. 4).

The results show that χ^2 of the whole fitting model is 28.998 and the degree of freedom is 11. χ^2 decreases to 28.998 from 57.845 after sacrificing one degree of freedom. The fitting indexes of the modified model are listed as below:

χ^2=28.998, DF=11, χ^2/DF=2.64, SRMR=0.042, RMSEA=0.076, CFI=0.977, NFI=0.965.

The results indicate some improvement in the model fitting. Although RMSEA>0.06, and χ^2/DF>2.0, the results are close to the standard. Compared with the previous model, the values of the SRMR, CFI, and NFI all get certain improvements. It means to some extent that the fitting between the model and the data is better and the modified model is acceptable. In fact, there is no unique index determining whether the fitting of SEM is completely good or not, and it is hard to get a model satisfying all the fitting indexes. Thus, the modified model is acceptable to some extent.

7 Results analysis

After analysis and test, the model of individual travel behavior generally fits the sample data. Hence, some specific meanings of parameters can be explained through the model output. AMOS can produce standard and nonstandard solutions (nonstandard solution like the changing scope of variables or intermediate variables with the changing of independent variables). Table shows the impact effects of variables. Direct effect reflects the direct influence from cause variables to outcome variables; indirect effect means that the cause variables making an influence on outcome variables by one or more intermediate variables; total effect is the sum of direct and indirect effects.

Table Impact effects of variables (non-standard resolution)

		LP	Gender	Num_C	Num_V	Income	Age	Edu
Income	Total	1.675	0	0	0	0	0	0
	Direct	1.675	0	0	0	0	0	0
	Indirect	0	0	0	0	0	0	0
Age	Total	−0.351	0	0	0	0	0	0
	Direct	−0.351	0	0	0	0	0	0
	Indirect	0	0	0	0	0	0	0
Edu	Total	1.000	0	0	0	0	0	0
	Direct	1.000	0	0	0	0	0	0
	Indirect	0	0	0	0	0	0	0
Num_tour	Total	−0.468	0.189	0.285	−0.026	0.162	−0.504	0.420
	Direct	−1.337	0.189	0.285	−0.026	0.162	−0.504	0.420
	Indirect	0.869	0	0	0	0	0	0
Num_trip	Total	−1.053	0.301	0.241	0.231	0.383	−1.140	1.009
	Direct	−3.104	0.301	0.241	0.231	0.383	−1.140	1.009
	Indirect	2.051	0	0	0	0	0	0
T-time	Total	−0.204	0.046	−0.114	0.007	0.137	−0.431	0.271
	Direct	−0.857	0.046	−0.114	0.007	0.137	−0.431	0.271
	Indirect	0.653	0	0	0	0	0	0

According to the impact effect, a global analysis is conducted on the residents travel behavior of Binhai New Area in Tianjin to reveal the influence level, the direction, and the mechanism.

(1) The relationship between individual characteristics and learning ability

The top two factors influencing the learning ability are the traveler's income and their education and age makes the smallest contribution. The learning ability declines with the decrease of age. Gender can be ignored for the little influence on the learning ability. The parameters are satisfied with the common sense and basic rules.

(2) The relationship between individual characteristics and travel behavior

Age makes significant impact on travel times, which means that the old residents have less travel frequency, and they usually prefer indoor activities or stay in the residential area. Female is more prone to travel than male. The group with high income has more travel frequency, which connects with more social activities to some extent. Families with vehicles have more travel times for the convenience. The results also show that the group with higher education also has more travel times. A seemingly unreasonable result is that the resident with children under 6 years old is prone to travel. Actually, it is still acceptable for the possible reason that children in many young families are taken care by their grandfathers or grandmothers due to the Chinese tradition, and the youth are often go outside.

To the number of trip-chains, it can be found that families with children have more family-based activities and more trip-chains, which is in accordance with Lu's research[6]. The vehicle sum and age has negative effect on the number of trip-chains, while the income and education has positive effect.

(3) The relationship between learning ability and travel behavior

Learning ability makes direct impact on travel times, the number of trip-chains, and travel time. Meanwhile, it makes influence on individual behavior indirectly by individual characteristics. From the overall view of the influence, the on-road time, travel times, and the number of trip-chains decrease with the improvement of learning ability and the accumulation of experiences. The reason of the phenomenon may have relations with the development of transportation of Binhai New Area these years. As a national development zone with large scale construction, the urban planning and infrastructure has gradually been mature and promoted, and the facilities around the residential areas, such as supermarkets, restaurants, bookstores, hospitals, etc., have been completed step-by-step. The reason that causes the reduction of residents' travel time and the number of trip-chains may be the lack of residents' travel for short distance in the survey data.

8 Conclusions

To reveal the rules of travelers' choices, this paper analyzes the static and dynamic influence factors of individual travel behavior and clarifies the indispensable role of learning ability in travel choice. Through the use of the survey data from Binhai New Area in Tianjin, the related Structural Equation Model is established. The modified individual travel behavior model with rational fitting indexes to some extent is useful to understand travelers' behavior rules deeply and provides us with the evidence in transportation management policy making. For the incompleteness of the survey data, the indexes are relatively simple and the fitting results are still not fully satisfying. The key points of our further study will be the travelers' behavior under information broadcasting and the travel choice model based on the feedback leaning mechanism.

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