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Incorporating the extended theory of planned behavior in a school travel mode choice model: a case study of Shaoxing, China

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ABSTRACT

Travel to and from school can have social, economic, and environmental implications for students and their parents. Therefore, understanding school travel mode choice behavior is essential to find policy-oriented approaches to optimizing school travel mode share. Recent research suggests that psychological factors of parents play a significant role in school travel mode choice behavior and the Multiple Indicators and Multiple Causes (MIMIC) model has been used to test the effect of psychological constructs on mode choice behavior. However, little research has used a systematic framework of behavioral theory to organize these psychological factors and investigate their internal relationships. This paper proposes an extended theory of planned behavior (ETPB) to delve into the psychological factors caused by the effects of adults' cognition and behavioral habits and explores the factors' relationship paradigm. A theoretical framework of travel mode choice behavior for students in China is constructed. We established the MIMIC model that accommodates latent variables from ETPB. We found that not all the psychological latent variables have significant effects on school travel mode choice behavior, but habit can play an essential role. The results provide theoretical support for demand policies for school travel.

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Introduction

In recent years, children's travel behavior, including active school transport (AST, such as walking and cycling), has attracted the substantial attention of researchers from varying disciplines, such as urban planning, transportation, and public health. Previous studies have shown that those who often walk or cycle to and from school are much more active than those who are driven and have more knowledge regarding their neighborhood environment (Mackett 2013). Research is also reported that AST plays an important role in promoting children's physical activity and has the potential to prevent and reduce childhood obesity (Mendoza et al. 2011). Furthermore, AST can not only contribute to children's physical activity levels but also have positive impacts on children's mental and psychological health (Fusco et al. 2012). In addition, it was estimated that as much as

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10–14% of morning traffic is generated by parents driving their children to school (McDonald et al. 2011). Similar trends have been documented in developing countries. It has also been found that, in Beijing, traffic congestion indices can rise from 3–6 to 6–9 points in the 2 weeks before and after school begins (above 6 means moderate or severe congestion) and the capacity of three-lane roads around schools will drop by 38% under the influence of student shuttle vehicle trips (Shi and Jiang 2014). The problem caused by this traffic congestion on roads near schools may create hazardous conditions for children using non-motorized means and increase emissions from automobiles that will contaminate the air that children breathe in and around their school.

Despite AST's significant health and environmental implications, there has been a decline in AST over the past few decades internationally (Buliung et al. 2011; Witten et al. 2013). For example, in the United States, the rate of AST declined from 47.7% in 1969 to 12.7% in 2009 (McDonald et al. 2011); in Australia, the share of children aged 5–9 who walked to school decreased from 57.7% in 1971 to 25.5% in 2003 (Van der Ploeg et al. 2008).

In order to reverse the declining trend of AST, it is necessary to understand the motives of the mode choice decision in school travel behavior. An emerging literature has explored school travel behavior with a wide range of factors, which have largely focused on five major aspects: (1) built environment including home–school distance, neighborhood walkability, and other urban form elements; (2) social environment related to perceived crime danger, child safety, and neighborhood socioeconomic status; (3) school characteristics referring to a school's size, policies, and location; (4) household characteristics including the number of cars owned, licensed drivers, household income, children's gender and age, and ethnicity; and (5) psychological concepts such as attitudes, preferences, intentions, beliefs, values, and norms. A detailed discussion of factors influencing school travel can be found in a number of systematic reviews (cf. Pont et al. 2009; Wong, Faulkner, and Buliung 2011; Mitra 2013; Larouche et al. 2014; Lu et al. 2014).

According to these reviews, most literature has focused on a subset of alternative modes, while few have been related to a complete coverage of the alternative modes. In China, the electric bike has achieved impressive sales but few studies have taken it into consideration as one of important school travel modes. Figure 1 used data on school-going children aged 6–18 from the 2012 Shaoxing Household Travel Survey. Because there may be more than one adult in a household, it is possible for a non-driving adult to have children in the household use other modes to travel to school. Therefore, a proportion of children are driven to school for each type of commuting mode of adults.

From Figure 1, we can see that the proportion of children being driven to school is higher for adults choosing a car as commuting mode (40%), compared with adults using other commuting modes. Moreover, the figure illustrates that the proportion of household children walking to school is only 30% for adults commuting by car, while the proportion is 52% for adults walking to work and 47% for adults using a bike. It is interesting that the electric bike almost shares the same proportion (25%) as bus users for household children's school travel when adults go to work by electric bike. To our knowledge, this may be the first study involving the electric bike as one of the alternative modes for school travel.

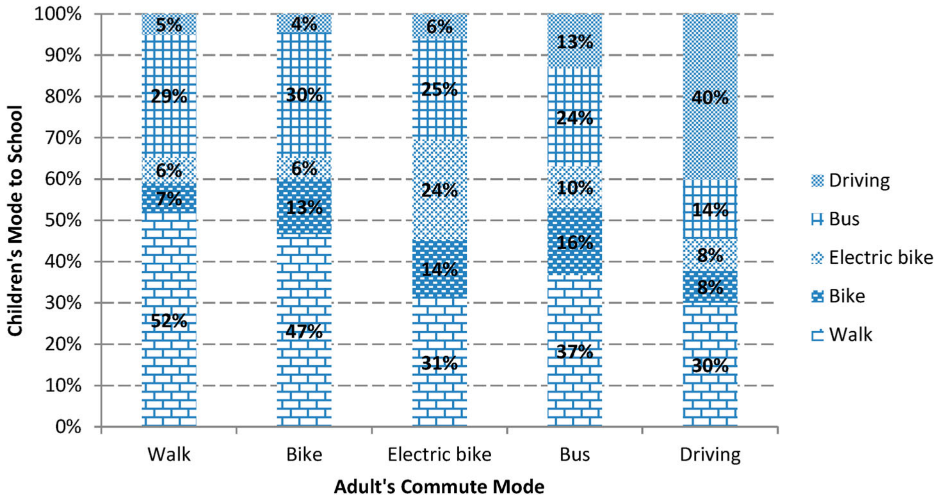

Figure 1. School travel modes by commuting travel modes of household adult.

Despite the explanatory variables or factors mentioned above for modeling school travel varying from study to study, these previous studies highlighted the importance of including adult household members' activities in analyzing children's school travel pattern (Deka 2013; Susilo and Liu 2015). For example, Deka demonstrated through Heckman probit models that children's travel mode to school is influenced by parents' travel mode to work, while the relationship is mostly unidirectional. It was also suggested that future studies should consider the travel pattern of household adults when predicting children's mode to school (Deka 2013). McDonald (2008) examined the influence of parental employment status and work travel time on children's travel to school by using a binary logit model and found that young children (aged 5–14) with mothers who commute to work in the morning are less likely to walk or travel by bike to school, but only walk and bike modes were taken into consideration. Yarlagadda and Srinivasan (2008) used multinomial logit model (MNL) to analyze the influence of parents' employment and work flexibility on children's mode use. He and Giuliano (2015) focused on children aged between 5 and 18 years living in dual-earner households, and bundled together both parent's working arrangements and spatial variables to model by MNL escort-mode decisions about school travel. They found that the parents', especially the mother's, increased working hours and more distant job locations result in an increased likelihood of several alternative escort modes. Other studies have paid attention to the characteristics of parents' influence on how children travel to school (Wen et al. 2007; Faulkner et al. 2010; Yoon, Doudnikoff, and Goulias 2011). All these studies recognized that the travel patterns of children and adults in a household are interrelated, but only a limited literature involved the adults' characteristics of commuting travel patterns comprehensively, such as adults' mode, commuting time, and psychological factors toward modes. Although a growing body of research illuminates the significant effects of a wide range of individual psychological factors on adult travel behavior, such as convenience, attitudes, and perceptions regarding environmental protection (Walker and Li 2007; Zeid 2009), there is a limited literature that has examined how these factors affect children's travel behavior.

In addition, theoretical frameworks from literature reviews regarding active travel in youth and children's trip to school do not appear to have fully integrated psychological factors with built environment and social influences (McMillan 2005; Panter, Jones, and van Sluijs 2008). In addition, some researchers have suggested that prominent psychological constructs such as attitudes, beliefs, and social norms have not been explored sufficiently in school travel research (Sirard and Slater 2008) and previous studies that considered psychological factors may have lacked theoretical grounding or used theories superficially.

The most widely applied model of the cognitive determinants of choosing travel modes is the theory of planned behavior (TPB), which suggests that behavior is most closely determined by an intention to act (Ajzen 1991). Intentions are based on a combination of attitude toward the behavior, subjective norm (SN), and perceived behavioral control (PBC). Intention has a direct effect on behavior and, under some circumstances, the same applies to PBC. The theory recognizes the importance of background factors, such as personality, emotions, education, age, gender, and past experience; although if they affect behavior, it would be via beliefs. The TPBs sufficiency assumption is invalid; in other words, intention may be determined not only by attitude, SN, and PBC but also by more additional variables (Ajzen 2011). In this study, descriptive norm (DN) and habit as additional predictors of intention and behavior in TPB were examined, because the two variables have provided sufficient evidence to satisfy Ajzen's criteria of adding predictors in other behavior domains (Rivis and Sheeran 2003; Gardner 2009; Ajzen 2011). We use the extended theory of planned behavior (ETPB) as a systematic framework of behavioral theory to organize psychological factors of household adults that have significant effects on school travel mode choice behavior and investigate the role of these factors on the process of school mode choice by the Multiple Indicators and Multiple Causes (MIMIC) model.

The purpose of this paper is to gain a deeper understanding of children's school travel behavior by addressing the gaps mentioned above. Specifically, we propose an ETPB to delve into the psychological factors caused by the effects of adults' cognition and behavioral habits and determine their relationship paradigm. The paper is organized as follows: the next section describes the data collection process and data used in the research followed by a section presenting the MIMIC model and the estimation results; the paper ends with a customary section of conclusions.

Data and analysis

Data description

The empirical analysis of this paper was carried out with data from the 2012 Shaoxing Household Travel Survey. The paper-based survey was conducted in October 2012 in Shaoxing, Zhejiang Province, China, with an area of 1191 km^2, a population of 1.03 million, and 128 traffic analysis zones. The data-set from the survey provided household, personal, and travel characteristics for 32,364 individuals from 11,290 households. These individuals of all ages and for various purposes made 70,091 trips including school travel by children and commute travel by adults. The data used for this paper were restricted to those households that had at least one child aged between 6 and 18. Adult workers aged between 18 and 24 who might be students but who also made occasional work trips were excluded. Note that only one adult in a household with children answered the attitudinal questions toward various travel modes. We took five school travel modes into consideration: walk, bike, electric bike, bus, and auto drive. Other modes, such as taxi, were eliminated because they accounted for less than 5% of all school trips. After extensive data cleaning and filtering, the final data-set for this paper included 1873 respondents.

In the final data-set, the proportion of children walking to school was 33%, which is the largest, compared to bike with 11%, electric bike with 17%, bus with 21%, and car with 18%. The greatest difference of school mode share between male and female children is related to electric bike – 14% of male children use electric bike to school compared to 17% of female children. Among adults in the household, about 36% of males drive to work compared to 23% of females, 8% of males walk to work compared to 12% of females, 16% of males use taxi compared to 4% of females, and 30% of males use electric bike compared to 43% of females.

Selection of variables

Since the objective of this paper is to consider household adults' commuting travel patterns in relation to children school travel mode choice, the commuting travel patterns of household adults with children are measured by adults' commuting mode, commuting time, distance from home to workplace, and their attitude towards commuting modes. Other factors that have an impact on children's school travel mode choice behavior are also included in the paper. The independent variables are divided into five groups: (1) household adults' commuting travel pattern; (2) household adults' social demographic; (3) household adults' psychological perception about commute modes; (4) children's social demographic; and (5) children's school travel behavior. All these variables are listed in Table 1.

A number of dummy variables have been included. For example, a dummy variable for household income was introduced with the expectation that children from higher income households would be more likely to go to school by car and less likely to take bus, walk, or cycle. Whether a household has more than one child aged between 6 and 18 was regarded as a dummy variable with the expectation that having more children in a family would increase the likelihood of walking or cycling to school. The number of cars, bikes, and electric bikes in a household were regarded as exogenous variables in models in this paper with the expectation that vehicle type has a positive significant influence on the same school travel mode.

Children's school travel is related to their age and gender, as well as household characteristics. The age of children is constantly reported to have a strong association with the likelihood of AST (McDonald 2008; Johansson et al. 2012), that is, older children are more likely to go to school by active travel modes, such as walk and bike. Children's gender may also affect school travel behavior. Adults in a household are likely to be more concerned about the travel safety of girls (Zwerts et al. 2010).

Distance from home to school is a critical variable that plays an important role in children's school travel mode choice. Previous studies have reported that children are less likely to walk or cycle to school when distance increases (Babey et al. 2009; Emond and Handy 2012).

Attitudes toward three travel modes were accessed by a combination of behavioral beliefs and outcome evaluations. Initially, respondents were solicited to rate the

Table 1. Description of explanatory variables considered in models.

Variable	Description	Mean	Std. Dev.
Adults' commuting travel pattern and perception of modes			
Attitude	Attitude toward travel commute modes (latent variable)	–	–
SN	Subjective norm in TPB (latent variable)	–	–
DN	Description norm (latent variable)	–	–
PBC	Perceived behavioral control in TPB (latent variable)	–	–
Habit	Habit of choosing a mode (latent variable)	–	–
Intention	Intention in TPB (latent variable)	–	–
commute_time	Commute travel time, minute	18.47	12.95
age	Household adults' age	39.83	5.86
edu	Household adults' education level: 1: primary school; 2: junior middle school; 3: senior high school; 4: graduate; 5: postgraduate	2.30	0.82
Adults' social demographic			
male_adult	1: male adult; 0: female adult	0.61	0.49
salary_low	1: monthly salary is less than 2k RMB; 0: otherwise	0.20	0.40
salary_ref[a]	1: more than 2k and less than 3k; 0: otherwise	0.31	0.46
salary_middle	1: more than 3k and less than 5k; 0: otherwise	0.33	0.46
salary_high	1: more than 5k; 0: otherwise	0.18	0.39
fam_num	The number of family's members	2.90	0.98
car_num	The number of household's cars	0.58	0.68
ebike_num	The number of household's electric bikes	1.29	0.82
bike_num	The number of household's bikes	1.09	0.79
Children's social demographic			
male_child	1: male child; 0: otherwise	0.42	0.49
children	1: more than one child in a household; 0: otherwise	0.20	0.40
age_0610	1: Children aged between 6 and 10; 0: otherwise	0.18	0.38
age_1112[a]	1: Children aged between 11 and 12; 0: otherwise	0.47	0.50
age_1314	1: Children aged between 13 and 14; 0: otherwise	0.27	0.44
age_1518	1: Children aged between 15 and 18; 0: otherwise	0.09	0.29
dis_school	Distance between home and school, km	4.80	4.64
Children's school travel choice			
school_walk	1: Children walk to school; 0: Otherwise	0.33	0.47
school_bike	1: Children cycle to school; 0: Otherwise	0.11	0.32
school_ebike	1: Children go to school by electric bike; 0: Otherwise	0.16	0.37
school_bus[a]	1: Children go to school by bus; 0: Otherwise	0.21	0.41
school_car	1: Children is driven to school; 0: Otherwise	0.18	0.39
school_active	1: Children go to school by walk or bike; 0: Otherwise	0.45	0.50

[a]Reference category for independent variables.

consequences of using the three travel modes, creating three different behavioral beliefs on a five-point scale (1 = strongly disagree, 5 = strongly agree), in relation to the extent to which using that particular mode would improve their fitness level, making them feel free and relaxed. Subsequently, the importance of each of the consequences was evaluated on a five-point scale (1 = not at all important to me, 5 = very important to me) to give the outcome evaluations. Before combining the behavioral beliefs and outcome evaluations into measures of attitudes toward the three modes, positive consequences were re-coded to make sure those higher values on all behavioral beliefs indicated a more positive belief. Take attitudes towards electric bike, for example, a principal components analysis identified just one component accounting for 86% of the variance (eigenvalue of 1.72) with a Cronbach's alpha (α) of 0.84, indicating a strong inner consistency.

Two types of social norm were measured by two indicators for both SNs and DNs. For SNs, the items 'My best friends consider using the electric bike/using the bus/using the car to be … ' and 'My family/relative consider using the electric bike/using the bus/using the car to be … ' was assessed on a five-point scale ranging from completely unacceptable to completely acceptable. The items were re-coded so that a high value indicated a stronger SN. Take electric bike, for example, here a principal components analysis identified a single coherent component, accounting for 83% of the variance (eigenvalue of 1.66) with a Cronbach's alpha lower than that for intention ($\alpha = 0.80$) but still indicating a strong internal consistency.

DNs were measured by the items 'My closest friends will themselves use the electric bike/use the bus/use the car' and 'My family/relative will themselves use the electric bike/use the bus/use the car' and rated on a five-point scale from strongly disagree to strongly agree. After re-coding the items, a high value indicated a strong DN. Again, principal components analysis of DNs on electric bike revealed one component accounting for 79% of the variance (eigenvalue = 1.57) with a Cronbach's alpha indicating moderate internal consistency ($\alpha = 0.73$), again in line with expectations for such a belief-based aggregate.

Direct measures of PBC were used, including three items for each mode: (i) 'It's mainly up to me whether I choose the … travel mode or not'; (ii) 'To use the travel mode on my ordinary trip is difficult'; (iii) 'It will make me feel troubled to choose the travel mode'. All three items were evaluated on a five-point scale ranging from strongly disagree to strongly agree. Subsequently, the items were re-coded so that a higher value indicated a higher PBC. These items for electric bike formed one component in a principal components analysis accounting for 66% of the variance (eigenvalue = 1.33) with a Cronbach's alpha (α) of 0.50, indicating reasonable inner consistency. Nunnally and Bernstein (1967) suggest that $\alpha = 0.70$ represents a strong inner consistency, but Cortina (1993) urges researchers to consider the number of items used – a moderate alpha with a small number of items may well represent better internal consistency than a larger alpha with a larger number of items (Rhodes, Plotnikoff, and Spence 2004). Ajzen (2002) suggests that a requirement for high internal consistency for belief-based measures is not necessary, given that it is the aggregate of differing beliefs that forms an attitude. The principal components analysis showing that the aggregated variable forms a unitary component is an important justification for aggregation.

Behavioral intention was assessed separately for different travel modes by way of three items: (i) 'It is likely that I will choose the … travel mode in the future'; (ii) 'I would expect to use the travel mode next time'; and (iii) 'Within the next coming one month I have the intention to use the travel mode'. All items were evaluated on a five-point scale (1 = completely impossible, 5 = completely possible). After re-coding the items, a higher value signified a stronger intention to use that particular travel mode. A principal components analysis identified just one component accounting for 85% of the variance (eigenvalue of 1.71) with a Cronbach's alpha (α) of 0.82, indicating a strong inner consistency.

Habit was measured using a 10-item version of Verplanken and Orbell's Self-Report Habit Index (Verplanken and Orbell 2003). Each item related to 'Choosing the travel mode on the … trip' (e.g. 'Choosing the electric bike on the commute trip is something I do automatically' and 'Choosing the electric bike on the commute trip is something I do without having to consciously remember') was measured on a five-point scale (1 = strongly disagree, 5 = strongly agree; Cronbach's α= 0.90).

The indexes of reliability and validity are shown in Table 2.

Table 2. Measurements of reliability and validity.

Variables	Percentage of one component accounting for the variance	Eigenvalue	Cronbach's alpha (α)	Average variance extracted
Electric bike				
Attitude	86.23	1.72	0.84	0.70
SN	83.18	1.66	0.80	0.67
DN	78.61	1.57	0.73	0.57
PBC	66.31	1.33	0.50	0.50
Habit	72.63	3.63	0.90	0.66
Intention	85.32	1.71	0.82	0.70
Bus				
Attitude	81.28	1.63	0.77	0.60
SN	79.94	1.60	0.75	0.60
DN	74.40	1.49	0.66	0.51
PBC	61.85	1.31	0.46	0.52
Habit	57.45	2.87	0.81	0.56
Intention	83.00	1.66	0.80	0.65
Car				
Attitude	85.85	1.72	0.83	0.63
SN	81.59	1.63	0.77	0.64
DN	76.12	1.52	0.69	0.53
PBC	74.53	1.37	0.54	0.52
Habit	70.09	3.50	0.89	0.63
Intention	81.56	1.63	0.77	0.69

Model and estimation

In order to examine the complicated interrelationships among the TPB's latent variables of adults and children's school travel mode choice with the socioeconomic status variables, an MIMIC model is estimated. In terms of the multivariate regression of indicators on causes, the model implies restrictions of two types: (i) the regression coefficient matrix has a rank of one; and (ii) the residual variance–covariance matrix satisfies a factor analysis model with one common factor. The MIMIC model is in fact a special form of structural equation modeling. The specification of the model is as follows:

$$\boldsymbol{\eta} = \Gamma\mathbf{x} + \zeta, \tag{1}$$

$$\mathbf{y} = \Lambda\boldsymbol{\eta} + \varepsilon, \tag{2}$$

where equation (1) is the structural equation and equation (2) is the measurement equation. The latent variable vector $\boldsymbol{\eta}$ is linearly determined, subject to disturbances ζ, by vector of observable exogenous causes $\mathbf{x}$. The latent variable determines, linearly, subject to disturbance ε, a vector of observable endogenous indicators $\mathbf{y}$. Γ and Λ are matrices of unknown parameters to be estimated. The operational implications of the model appear when we solve for the reduced-form relation connecting the observables:

$$\mathbf{y} = \Lambda(\boldsymbol{\Gamma}x + \boldsymbol{\zeta}) + \boldsymbol{\varepsilon} = \Pi\mathbf{x} + \mathbf{v}, \tag{3}$$

where the reduced-form coefficient matrix is

$$\boldsymbol{\Pi} = \boldsymbol{\Lambda\Gamma} \tag{4}$$

and the reduced-form disturbance vector is

$$\mathbf{v} = \boldsymbol{\Lambda}\zeta + \varepsilon. \tag{5}$$

Estimation of a structural equation latent variable model minimizes the difference between the sample covariance matrix **S**, and the covariance matrix $\boldsymbol{\Sigma}$. The elements of $\boldsymbol{\Sigma}$ are hypothesized to be a function of the parameter vector $\boldsymbol{\theta}$ so that $\boldsymbol{\Sigma} = \boldsymbol{\Sigma}(\theta)$. The parameters are estimated so that the discrepancy between **S** and the implied covariance matrix $\boldsymbol{\Sigma}(\hat{\theta})$ is minimal. The discrepancy function, $F = F(\mathbf{S}, \boldsymbol{\Sigma}(\theta))$, measures the discrepancy between **S** and $\Sigma(\theta)$ evaluated at $\hat{\theta}$. $F_{\min}$ is the minimum value of the discrepancy function and equals zero only if $\mathbf{S} = \Sigma(\hat{\theta})$. An indication of model fit is, therefore, given by the closeness of the $F_{\min}$ to zero. We suppose that the disturbances are all mutually independent. For convenience, all variables are taken to have expectation as zero:

$$E(\zeta\varepsilon') = 0,\ E(\zeta^2) = \sigma^2,\ E(\varepsilon\varepsilon') = \Theta^2, \tag{6}$$

where Θ is the diagonal matrix with θ, the vector of standard deviations of the ε values, displayed on its diagonal. The covariance matrix can be computed by the following equation:

$$\Sigma\ (\hat{\theta}) = E(\mathbf{vv}') = \sigma^2\boldsymbol{\Lambda}\boldsymbol{\Lambda}' + \Theta^2. \tag{7}$$

The multiple indicator part of the MIMIC model is a confirmatory factor analytical model. The multiple cause part of the model is given by:

$$\begin{gathered}\eta_{li} = \gamma_{l1} male\_adult_i + \gamma_{l2} salary\_low_i + \gamma_{l3} salary\_middle_i + \gamma_{l4} salary\_high_i \\ + \gamma_{l5} fam\_num_i + \gamma_{l6} car\_num_i + \gamma_{l7} bike\_num_i + \gamma_{l8} ebike\_num_i + \gamma_{l8} edu_i + \zeta_i \\ l = Attitude,\ SN,\ DN,\ PBC,\ Intention,\ Habit.\end{gathered} \tag{8}$$

Figure 2 illustrates the structure of the MIMIC Model. The structural equation and measurement equation are abbreviated to SE and ME, respectively.

As illustrated in Figure 2, the MIMIC model includes demographic characteristics of travelers, the latent variables that construct the expand TPB and endogenous observed indicators. Specifically this model hypothesizes that the socioeconomic variables influence all latent variables of TPB, which are also explained by indicators from questionnaires for respondents. Figure 3 presents the detailed path analysis diagram, which specifies the hypothesized relationships among the latent factors, where ellipses represent unobservable variables and rectangles represent observable indicators. Dashed arrows represent measurement equations while solid arrows represent the structural equations. The latent variable model describes the relationships between the latent variables and their indicators and causes.

The MIMIC model simultaneously estimates the measurement equations relating each factor to its indicators, and the structural equations specify the relationships among latent factors and between them and socioeconomic status variables. The estimation of the MIMIC model was conducted in STATA. Table 3 summarizes the overall goodness-of-fit statistics.

Most interpreters of the root mean squared error of approximation (RMSEA) test label the fit close if the lower bound of the 90% CI is below 0.05 and label the fit poor if the upper bound is above 0.10. CFI and TLI are two indices such that a value close to 1 indicates a good fit. CFI stands for comparative fit index. TLI stands for the Tucker–Lewis index and is also known as the non-normed fit index. A perfect fit corresponds to a standardized root mean squared residual (SRMR) of 0. A good fit is a small value, considered

Table 3. Goodness-of-fit statistics for MIMIC model.

Adults' perception about mode	Car		Ebike		Bus	
Children's school mode	Active	Car	Active	Ebike	Active	Bus
RMSEA	0.048	0.048	0.044	0.044	0.044	0.044
CFI	0.915	0.915	0.937	0.935	0.899	0.894
TLI	0.881	0.881	0.915	0.913	0.865	0.858
SRMR	0.038	0.039	0.037	0.037	0.034	0.034

by some to be limited to 0.08. Though CFI is 0.894 for adults' perception towards bus when children go to school by electric bike slightly below 0.9, SRMR is below 0.05 and in particular the full 90% confidence interval 0.027–0.030 falls below 0.05, so the overall data fit is considered acceptable; that is, the model cannot reject the hypothesis of the relationships among the latent factors and between them and the demographic variables specified in Figure 2.

Results

Based on the results from the six MIMIC models, we can examine the relationships between the demographic characteristic variables and the latent variables in TPB and within them. Table 4 presents the estimation results. Here we can see that the psychological factors of household adults on different commuting modes, such as Intention, PBC, and Habit, have various impacts on children's school travel mode choice behavior. (We will discuss the influence of adults' latent variables towards commuting modes on school travel modes in the next section.)

Table 4 illustrates that children's gender has a significant impact on children's going to school by electric bike and active mode. In the MIMIC model for children using electric bikes, boys have a significantly negative influence on school travel. That is, girls are more likely to be escorted to school by adults who have a significant habit of using electric bikes. Table 4 also shows that boys are more likely to walk or cycle to school for male children have a positive significant influence on active school mode, which had also been reported by a previous study (McMillan et al. 2006). Compared to Deka's finding that male children are less likely to be driven to school than female children (Deka 2013), our study indicates that children's gender has no significant association with being driven to school.

Most of the age category's variables are significantly associated with school travel mode. For being driven to school, children aged between 6 and 10 have a positive significant influence and those aged more than 13 have a negative impact, which means that younger children are more likely to be driven to school than older children. Children aged 13–14 and 15–18 are less likely to go to school by electric bike. Overall, probably due to safety concerns, younger children are more likely to be escorted to school by car and electric bike and less likely to walk or cycle to school than older children, as previous research has shown.

The distance between a child's home and their school is concerned with whether the school travel mode is motorized or not. For the MIMIC model of school travel by car and bus, the distance from home to school has a significant positive influence on school travel mode choice, and for the active school mode, distance has a negative impact. Because the electric bike has a flexible travel distance, the distance from home to school is not associated with the mode using electric bike.

Table 4. Estimation results.

Adults' latent variables by mode	Car Coefficient (*p* value)	Car *z*	Electric bike Coefficient (*p* value)	Electric bike *z*	Bus Coefficient (*p* value)	Bus *z*
school_car						
PBC	**−0.11**** (0.001)	−3.21				
Habit	**0.30**** (0.000)	7.55				
Intention	0.08	1.75				
male_child	−0.02	−0.88				
age_0610	**0.06**** (0.004)	2.91				
age_1314	**−0.07**** (0.001)	−3.29				
age_1518	**−0.10**** (0.000)	−4.78				
dis_school	**0.28**** (0.000)	14.71				
ch_trip_num	0.03	1.75				
Children	**−0.08**** (0.000)	−3.87				
_cons	−0.03	−0.27				
school_ebike						
PBC			**−0.60**** (0.000)	−4.01		
Habit			**0.30**** (0.000)	4.68		
Intention			**0.47**** (0.000)	3.96		
male_child			**−0.04*** (0.042)	−2.04		
age_0610			0.04	1.72		
age_1314			**−0.12**** (0.000)	−5.05		
age_1518			**−0.09**** (0.000)	−3.80		
dis_school			−0.03	−1.52		
ch_trip_num			**−0.07**** (0.003)	−2.95		
Children			0.00	−0.11		
_cons			**0.67**** (0.000)	4.29		
school_bus						
PBC					**0.17**** (0.000)	4.59
Habit					0.01	0.16
Intention					0.02	0.54
male_child					0.01	0.53
age_0610					**−0.05*** (0.042)	−2.03
age_1314					0.00	−0.18
age_1518					0.01	0.35
dis_school					**0.42**** (0.000)	23.06
ch_trip_num					0.01	0.11
Children					0.01	−0.06
_cons					0.13	1.40
school_active						
PBC	0.06	1.40	**−0.56**** (0.004)	−2.85	−0.01	−0.46
Habit	**−0.12*** (0.014)	−2.90	0.12	1.73	0.05	1.41
Intention	0.04	0.76	**0.43**** (0.004)	2.86	−0.01	−0.40
male_child	**0.05*** (0.014)	2.51	**0.05**** (0.005)	2.78	**0.05*** (0.013)	2.50
age_0610	**−0.05*** (0.026)	−2.25	**−0.05*** (0.020)	−2.32	**−0.05*** (0.019)	−2.34
age_1314	**0.16**** (0.000)	7.95	**0.16**** (0.000)	8.08	**0.16**** (0.000)	7.98
age_1518	**0.14**** (0.000)	6.99	**0.14**** (0.000)	7.03	**0.14**** (0.000)	7.11
dis_school	**−0.53**** (0.000)	−34.39	**−0.53**** (0.000)	−33.63	**−0.54**** (0.000)	−34.65
ch_trip_num	0.01	0.57	0.01	0.28	0.01	0.37
Children	**0.06**** (0.001)	3.27	**0.05*** (0.015)	2.43	**0.06**** (0.002)	3.09
_cons	**1.26**** (0.000)	16.36	**1.36**** (0.000)	8.88	**1.24**** (0.000)	16.73

*$p < .05$; **$p < .01$.

The trip numbers of children in the day when the survey was carried out has only a negative significant relationship with school travel mode by electric bike. That is, children who have more social activities are less likely to travel to school by electric bike, which is often used to escort children by adults.

The dummy variable *children* indicates that more than one child is in a household. This may lead to the likelihood that the school trip made by a child with siblings is an independent travel without an adult companion. Therefore, a child with siblings has a significant negative impact on being driven to school and positive influence on active school mode. Evidence from Table 4 is found that having other school-aged children in a household increases the propensity for walking or cycling and decreases the likelihood of being driven to school. This is in line with the evidence from previous studies (Deka 2013; Susilo and Liu 2015).

Interactions of household adults' latent variables towards school travel mode

The significant interrelationships among the adults' latent factors are summarized in Figures 4–6, which show the standardized coefficients (with *z*-statistics in parentheses) between latent factors in the path analysis diagram. (Note that * indicates $p < .05$ and ** indicates $p < .01$.]

We can see from the three figures that the MIMIC models with the ETPB account for 77–89% of the variance of intention to use the three travel modes, which is consistent with Bamberg et al.'s previous findings (Bamberg, Ajzen, and Schmidt 2003). In their research, the models with the introduction of habit accounted for 77% and 80% of the variance in intention to choose the bus and car. Although there are distinctions between the two pieces of research, such as in travel modes and latent factors, the amount of the expanded variance in the intention to choose between modes to some extent implies that the ETPB can be fitted with the commute mode choice in the city of Shaoxing.

In the three MIMIC models, SNs and DNs have a significant impact on attitude at the individual 0.1% level, which indicates that the commuter's fondness for a particular commute mode is affected by social expectation. Except for the model of car, PBC has a significant positive effect on attitude toward using electric bike and bus, that is, the commuter's self-confidence plays an important role in taking the bus or driving an electric bike. In the three MIMIC models, SNs and DNs have a significant positive influence on adults' intentions toward commuting modes directly and on children's school travel behavior indirectly, as shown in Table 5.

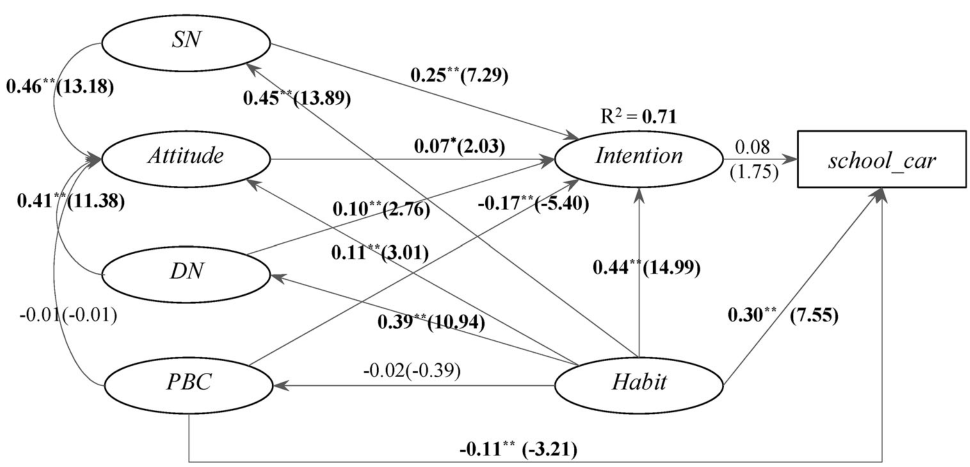

Figure 4. Standardized coefficients for adults' TPB variables of car on driving to school.

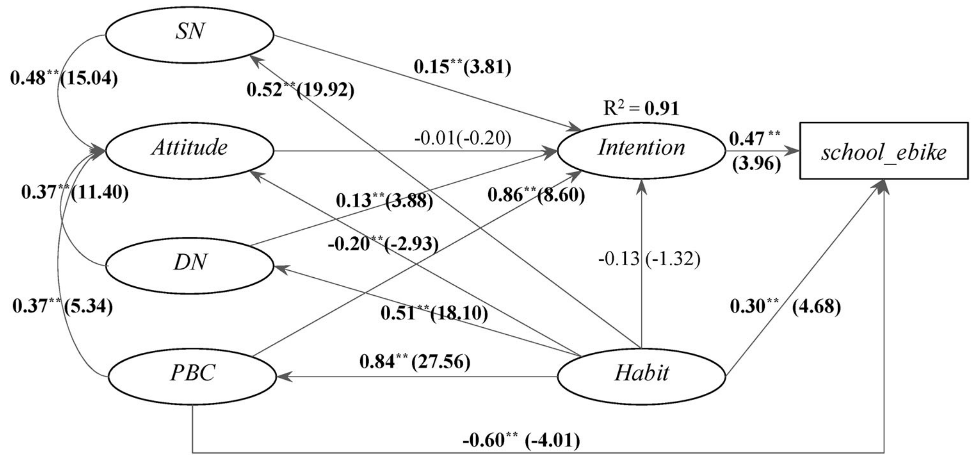

Figure 5. Standardized coefficients for adults' TPB variables on go to school by electric bike.

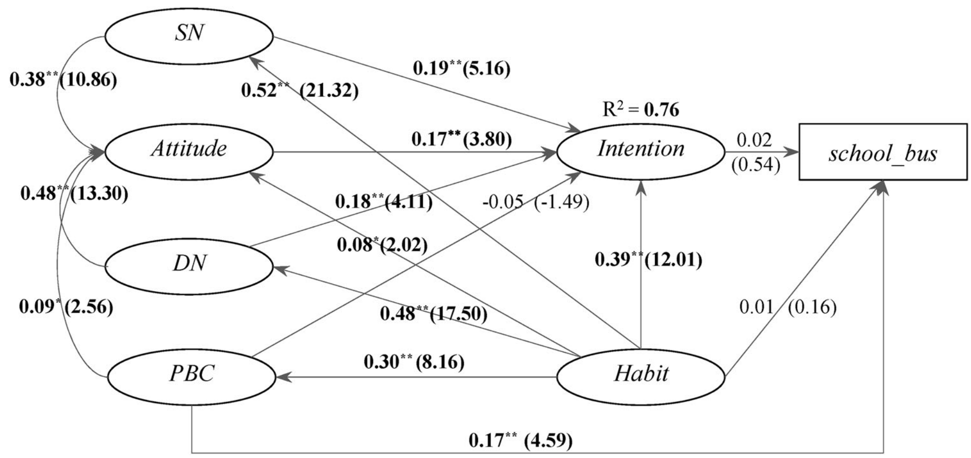

Figure 6. Standardized coefficients for adults' TPB variables on go to school by bus.

Table 5. Indirect effect of latent variables on children's school travel behavior.

Children's school travel mode	Car (*z*, *p* value)	Electric bike (*z*, *p* value)	Bus (*z*, *p* value)
SN	**0.011**(7.85, 0.000)**	**0.029**(3.64, 0.000)**	**0.03**(6.68, 0.000)**
DN	**0.005**(3.54, 0.000)**	**0.029**(3.75, 0.000)**	**0.02**(5.64, 0.000)**
Attitude	**0.003*(2.03, 0.048)**	−0.03(0.85)	**0.02**(3.77, 0.000)**

$^*p < .05$; $^{**}p < .01$.

Habit has a significant positive effect on all the other latent variables of TPB in the MIMIC model for bus, which indicates that bus is the residents' traditional commuter mode and the other predictors of TPB – including attitude, SN, DN, PBC, and intention – may be driven by habit of taking the bus. In the MIMIC model for electric bike, habit has a significant positive impact on PBC that refers to people's perception of the ease or difficulty of performing the behavior. Therefore, those who are accustomed to drive an electric bike may believe that this is a kind of convenient transport vehicle that is easy to use. It is interesting that habit has a significant negative effect on PBC in the model for car. The phenomenon that drivers in the city always encounter traffic congestion may explain the relationship between habit and PBC.

PBC is significantly associated with children's school travel behavior in all three MIMIC models, but the latent variable that refers to PBC in TPB has a negative effect on children's school travel with car and electric bike and a positive effect on bus. This may result from household adults' perception of feeling relaxed when escorting their children to school by bus compared to driving a car or electric bike by themselves and always having to pay attention to the traffic conditions along the way. Habit has almost the same positive significant impact on children being driven or using electric bike to school. That implies that car and electric bike, as the most common motorized travel modes used by residents in China, have also become the common escorting vehicles for taking children to school. Intention using electric bike refers to the proximal determinant of adults' commuting travel behavior, which is the only latent variable that has a significant positive influence on children's school travel behavior. The relationship shows that electric bike plays an important role in both adults' commuting travel behavior and children's school travel in this city in China.

Indirect effect of adults' demographics on children's school travel behavior

The coefficients of the indirect effect of adults' demographics on children's school travel behavior are show in Table 6.

Since a number studies have reported that women often show greater concerns about traffic and street safety for themselves, Hsu and Saphores (2014) hypothesized and demonstrated that mothers usually have greater concerns about letting their children walk or cycle to school, which in turn affects their children's school travel mode. Furthermore, they concluded that the effect of mothers' car use on children's travel mode shares is more apparent than a father's effect (Susilo and Liu 2015). But on the contrary with those previous studies, our finding is that male adults are positively and significantly related to children's school travel mode on car indirectly and have negative impacts on children

Table 6. Indirect effect of adults' demographics on children's school travel behavior.

	school_car		school_ebike		school_bus	
Adults' demographics	Coef. (*p* value)	*z*	Coef. (*p* value)	*z*	Coef. (*p* value)	*z*
male_adult	**0.030**** (0.000)	4.400	**−0.026*** (0.027)	−2.210	−0.008	−1.340
salary_low	0.006	0.740	0.024	1.590	−0.004	−0.610
salary_middle	**0.022**** (0.002)	2.960	0.001	0.060	0.006	0.940
salary_high	**0.067**** (0.000)	6.410	**−0.040*** (0.013)	−2.490	0.010	1.130
fam_num	−0.004	−1.180	0.004	0.820	0.001	0.380
car_num	**0.131**** (0.000)	15.100	**−0.040**** (0.000)	−4.380	**−0.021**** (0.000)	−3.650
ebike_num	**−0.011**** (0.007)	−2.630	**0.043**** (0.000)	4.430	0.001	0.010
bike_num	−0.002	−0.450	**−0.018**** (0.009)	−2.600	**0.007*** (0.025)	2.240
commute_time	0.001	0.730	−0.001	−2.090	0.001	1.020
trip_num	0.005	1.780	**0.013*** (0.014)	2.450	−0.003	−1.340
edu	**0.016**** (0.000)	3.770	−0.003	−0.490	**−0.010*** (0.022)	−2.300
age	**−0.002**** (0.004)	−2.860	0.001	0.800	0.001	0.570

*$p < .05$; **$p < .01$.

being driven to school by electric bike and active modes indirectly, which indicates that male adults are more likely to drive their children to school and less likely to escort children to school by electric bike or active modes. This phenomenon, which is clearly opposite to that of developed countries' experiences, may result from the large share of electric bikes in China. In the data-set of this study, almost 37% of respondents choose the electric bike as their commuting mode. And from Figure 5, we also find that the habit for electric bike use plays an important role in adults' perception about commuting modes and children's school travel modes. Table 6 shows that adults with a high monthly salary have a significant positive correlation with driving to school and negative impacts on going to school by electric bike and active modes. Because higher income households have more travel resources and are more likely to live further from work, increasing location constraints promote more private car escort trips – which is in line with the findings of He and Giuliano (2015). The number of electric bikes is positively related to children's school travel with electric bike is in line with our expectation. It is interesting that the number of adults' trips has a positive significant relationship with children driven to school by electric bike, which indicates that those household adults with more activities are more likely to use an electric bike to escort their children. In addition, both adults' education level and age have significant impacts on children being driven to school.

Conclusion

This paper has sought to gain a deeper understanding of children's school travel behavior. It has integrated psychological factors associated with commuting modes and their impact on school travel mode choice behavior with the development and application of an ETPB together with models of the effects of demographic characteristics of participants on these psychological factors. School travel mode choice and commute mode intention of three travel modes in Shaoxing have been examined and can be explained by the predictors of TPB. Moreover, DNs and habits may significantly increase explained variance in intention. In particular, the introduction of habit in our analyses resulted in the biggest incremental increase in explained variance in intention. The paper also constructed MIMIC models to research the relationship between demographic characteristics and the latent factors of the extended TPB. The results showed that the socioeconomic status of household adults had different significant impacts on the latent factors directly and school travel behavior indirectly. We found that not all the psychological latent variables had significant effects on school mode choice behavior, but habit played an essential role in the behavior of choosing car and electric bike as school travel modes.

In order to provide guidance on school travel mode choice, we need to research the factors and processes that form the habit for car and electric bike use, and devise traffic demand strategy accordingly, which may be our future work to study the school travel behavior from the aspect of psychological factors. In addition, the analyses among the latent factors in the extended TPB verify that the theory's suitability in the context of school travel mode choice increases our understanding of the role of DNs and habit in TPB. Based on this understanding and the different demographic statistical characteristics, transportation planners could design a more socially desirable and sustainable set of transportation policies and effective measures for intervention in school travel behavior.