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Research Article

What Motivates Drivers to Comply with Speed Guidance Information at Signalized Intersections?

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This study explored the intrinsic motivation of drivers most likely to accept guidance information at signalized intersections by using a mixed model approach. The proposed approach contains a multiple-indicator multiple-cause model (MIMIC) with a latent class analysis (LCA). The MIMIC model was used to quantify intrinsic motivations according to individual heterogeneity. From a group similarity perspective, the LCA was employed for the latent classification of drivers. The features and possibility of accepting guidance information of each class were also analyzed according to the intrinsic motivation of drivers. Data were collected from the stated preference online surveys, in which the questionnaire was designed according to the diffusion of innovation, in 2015 and 2019 in China. Four subjective perceptions of drivers were identified: the perception of innovating guidance information, the perception of convenience regarding guidance information transmission, the perception of surrounding complexity, and the individual innovation. The estimation results show that age, driving experience, education levels, and familiarity with road network are significant factors of compliance behavior. The proportion of conservatives gradually decreased from 2015 to 2019, while the proportion of early followers and late followers increased through market penetration, familiarity with the Internet of vehicles, and social networks in the same period. This prevalence demonstrates that guidance information at signalized intersections is gradually becoming acceptable in China.

1. Introduction

Technological innovation is changing the world at an increasingly rapid pace. Speed guidance technology is one such innovation. Speed guidance refers to appropriate speed range advisory through computerized systems, which is provided to drivers by means speed guidance devices available in vehicles or on the roads. It is beneficial to improve the complex traffic environment at signalized intersections since unexpected acceleration, deceleration, and braking behaviors of drivers at signalized intersections are more common than on-road sections [1, 2]. Speed guidance algorithms at signalized intersections are developed by simulation or field tests [1, 3, 4]. In most studies, during the verification of the performance of the proposed speed guidance algorithms, it is assumed that the compliance rate is 100%. However, individual heterogeneity exists on whether the guidance information is accepted or not [5]. Moreover, the hypothesis is divergent of reality [6, 7]. Existing studies have shown that the actual speed of vehicles is not strictly following the advisory speed [8, 9].

Many studies have been conducted to explore the influencing factors of the compliance rate of guidance information, perceiving it as an endogenous variable [10]. These factors include individual-related and information-related attributes. The former refers to sociodemographic characteristics [11], familiarity with the road network [11, 12], driving experience through guidance information [6, 13], and psychological factors, such as the perceived uncertainty of travel time [12], trust bestowed on guidance information [12, 14], and willingness to change driving patterns [12, 14]. The latter includes the type of information [12], source of information [15], and locations of variable message sign [16]. However, most studies focus on the factors determining driver's route choice behavior under the provisioning of guidance information [5–11]. There are few studies evaluating driver's compliance behavior with guidance information at signalized intersections. Wang [5] established structural equation model (SEM) based on the technology acceptance model and found that traffic conditions at intersections affect the willingness of the drivers to abide by provided instructions. Tang quantified drivers' response time and acceptance threshold value of receiving speed guidance information at intersections [7]. These studies focus on stable preferences. However, people's perceptions and preferences may vary over time [17].

So far, speed guidance devices are not very popular. One of the critical reasons affecting its diffusion is the uncertainty of the public attitude towards this technology. If their perception of speed guidance devices is vague or even contrary, the public tends to refuse those devices and then, the improvement of traffic efficiency at intersections slows down regardless of the use of supplementary contrivances. Therefore, it is essential to find early adopters, willing to be the first to pay for such devices. Good user experience or feedback can help speed guidance devices penetrate the market faster through the use of social networks. Thus, the specific questions in this research are as follows:

(1) What motivates drivers to comply with speed guidance information at signalized intersections from a perspective of individual heterogeneity?

(2) What are the features of the early users of speed guidance information at signalized intersections?

(3) What are the differences in drivers' perception of speed guidance information at signalized intersections between 2015 and 2019?

The remainder of this study is organized as follows. Section 2 focuses on the design of the questionnaire and data collection. It is then followed by a description of the proposed approach, which contains a multiple-indicator multiple-cause (MIMIC) model and a latent class analysis (LCA). Section 4 presents the results of the proposed approach using the questionnaire data of 2015 and 2019 and the analysis of the change of drivers' attitude towards guidance information at signalized intersections chronologically. Finally, the conclusion and further studies are presented.

2. Behavioral Survey

2.1. Survey Design. Currently, speed guidance devices are not widely available in vehicles or on the roads, and drivers' perceptions of those devices are vague and uncertain. Drivers' perceptions and preferences are expected to evolve with the increase of the market penetration rate of speed guidance devices. As explained in the process of diffusion, the drivers' compliance towards speed guidance information is similar to the adoption behavior of any new product. Considering that the stated preference (SP) survey can provide different traffic scenarios for drivers to make decisions based on their preferences, the SP survey presents an ideal approach to obtain data in this study.

Respondents were asked about the sociodemographic characteristics and their attitude towards guidance information at signalized intersections. Sociodemographic characteristics of the survey include gender, age, driving experience, familiarity with the local road network, education levels, and type of driving behavior exhibited.

In the case of attitude-based statements, they are derived from the diffusion of innovations. Diffusion of innovations is a theory on how to persuade people to accept new concepts or new techniques through media. Everett M. Rogers proposed it in the 1960s. Diffusion is defined as a process whereby innovations spread within a particular community in a unique period through an exclusive channel [17]. Innovations are irrelevant to whether they appear for the first time or are used for the first time, as long as they are considered new by an individual or a group. Hence, speed guidance devices can be regarded as innovative products.

The four significant factors affecting the diffusion of innovation are *innovation*, *channel*, *time,* and *social system* [17]. *Innovation* involves people's cognitions towards innovation, such as comparative advantage, compatibility, complexity, and visibility. *Channel* refers to mass media or interpersonal communication. The *time* has three meanings, either referring to the time when individuals begin to be exposed to innovation, the time-span from initial contact to final decisions of acceptance or refusal by individuals, and percentage change on acceptance of innovation within a group in a given time. The *social system* signifies the social environment, such as social system norms, recognition, and support.

Additionally, existing studies have shown that the *innovation ability of individuals* also affects the time of being exposed to innovations and accepting innovation [17]. Thus, four perceptions (except *time*, as shown in Table 1) are incorporated into the questionnaire to better explore intrinsic personal preference: the perception of innovating guidance information, the perception of convenience regarding guidance information transmission, the perception of surrounding complexity, and the individual innovation. Four perceptions are developed by *innovation*, *channel*, *social system*, and *innovation ability of individuals*, respectively. The individuals' attitude towards guidance information at signalized intersections and the change of attitude are analyzed from the perspective of *time*. Table 1 lists attitudinal statements based on a five-point Likert Scale from "strongly disagree" to "strongly agree" in tandem with notations.

2.2. Data Collection and Description. In recent years, the connected vehicle (CV) market has been rapidly developing in China. The average assembly rate of the technology of CV in new cars in February 2016 was 11.91% in China. This rate had increased by up to 30.2% in the first quarter of 2019. The

Table 1: Attitudinal statements of the survey.

Original		Perception	Notation	Attitudinal statements
Diffusion of innovations	Innovation	Perception of innovating guidance information	Y_1	Guidance information at signalized intersections is a necessary complement to the driving experience, making the travel smoother
			Y_2	It is so easy to accelerate and decelerate based on guidance information at signalized intersections
			Y_3	It is safe to pass intersections based on guidance information
			Y_4	The travel time of individuals will decrease after complying with guidance information at signalized intersections
	Channel	Perception of convenience regarding guidance information transmission	Y_5	I learned about the technology of speed guidance from traditional media (TV, radio, magazines, and newspapers).
			Y_6	I learned about the technology of speed guidance from the new media (WeChat, Weibo, and Internet).
			Y_7	I learned about the technology of speed guidance by talking with my teachers and friends
			Y_8	I learned about the technology of speed guidance by participating in events such as new product press conferences and design exhibitions
	Social system	Perception of surrounding complexity	Y_9	When the volume of cars at signalized intersections is high, I will comply with the guidance information
			Y_{10}	Where there are many conflicts at signalized intersections, I will comply with the guidance information
			Y_{11}	When the weather conditions are adverse (such as snow, fog, and storm), I will comply with the guidance information
	Innovation ability of individuals	Individual innovation	Y_{12}	I trust high technologies, and I am willing to use them
			Y_{13}	I usually pay more attention to novelty than friends around me
			Y_{14}	I like to share my experience and novelty with friends

penetration rate of CV in China was 10% in 2015, and the rate will be up to 30% in 2020.

Drivers who have adequate experience were randomly chosen to complete questionnaires to identify their attitude towards guidance information at signalized intersections in the real world. Questionnaires were sent out by publishing in a specific website (https://www.wjx.cn/) in May 2015 and April 2019, respectively. The collected data are presented in Table 2.

In 2015, 1000 questionnaires were delivered and 940 answers were collected with a response rate of 94%. 69.36% are male drivers; 53.83% of individuals age between 26 and 35 years old; drivers with more than one year driving experience accounted for 89% of the sample; 57.13% of drivers feel that they are familiar with the local road network; 76.81% are individuals who have a bachelor's degree or above; individuals with driving style of conservative are 82.23%, and the rest of the sample are adventurous (the adventurous driver refers to the driver who has frequent adventurous activities in driving, such as fast speed).

In 2019, 1054 valid samples were collected from 1277 questionnaires with an effective response rate of 82.5%. The statistical analysis shows that 70.87% are male drivers; 61.95% of individuals age is between 26 and 35 years old; drivers with more than one year driving experience account for 89% of the sample; almost everyone is familiar with the local road network (the proportion is as high as 99%); more than 84% of drivers have a bachelor's degree or above; the proportion of adventurous drivers is 25.90%, the proportion of conservative drivers is 74.10%.

3. Methodology

3.1. MIMIC Model. In this study, the MIMIC model is employed to quantify subjective perceptions of drivers related to guidance information at signalized intersections. The model is also a preparation work for the LCA by removing inappropriate attitudinal statements from the model.

As shown in Figure 1, there are two components to the MIMIC model: the measurement model and the structural model. X_i and Y_j represent observed variables and can be directly measured. X_i is an explanatory variable that is not changed arbitrarily but still affects the results of the survey. X_i refers to the sociodemographic characteristic, such as gender in this study. Y_j is the observed variable related to an individual's attitude towards guidance information at signalized intersections. η_k represents a latent variable which cannot be directly obtained but can be estimated by observed variables $Y_j (j = 1, 2, 3, \ldots)$. Explicitly, η_k refers to a subjective perception of drivers in this study.

Table 2: Descriptions of the sample (2015 and 2019 data).

Sociodemographic characteristics		2015		2019	
		Frequency	Percentage	Frequency	Percentage
Gender	Male	652	69.36	747	70.87
	Female	288	30.64	307	29.13
Age (years)	18–25	144	15.32	174	16.51
	26–35	506	53.83	653	61.95
	36–45	209	22.23	178	16.89
	46–55	66	7.02	44	4.17
	>55	15	1.60	5	0.47
Driving experience (years)	<1	98	10.43	116	11.01
	1–3	275	29.26	244	23.15
	3–5	300	31.91	358	33.97
	>5	267	28.40	336	31.88
Familiarity with the local road network	Familiar	724	77.02	1041	98.77
	Unfamiliar	216	22.98	13	1.23
Education levels	High school or below	218	23.19	162	15.37
	Have a bachelor's degree	627	66.70	778	73.81
	Graduate or above	95	10.11	114	10.82
Type of driving behavior exhibited	Adventurous	167	17.77	273	25.90
	Conservative	773	82.23	781	74.10

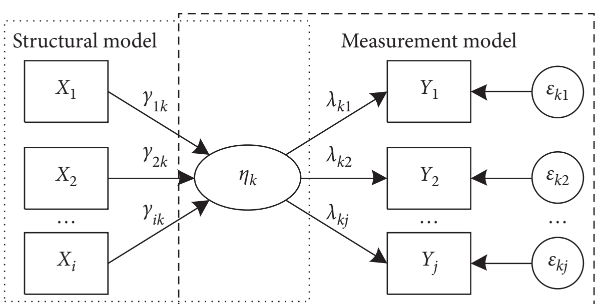

Figure 1: Diagram of the MIMIC model.

Subjective perceptions of drivers affect their attitude towards guidance information at signalized intersections. The measurement model is a multivariate regression model that measures the relationship between observed variables related to individuals' attitudes and subjective perceptions of drivers, and correlation coefficients are calculated by the following equation:

$$Y_j = \lambda_{kj}\eta_k + \varepsilon_{kj}, \quad j = 1, 2, \ldots; k = 1, 2, \ldots, \tag{1}$$

where Y_j is the j^{th} observed variable, η_k is the k^{th} latent variable, λ_{kj} is the correlation coefficient between the observed variable Y_j and the latent variable η_k, and ε_{kj} is the residual error.

Sociodemographic characteristics are associated with latent variables. The structural model measures the causal relationship between subjective perceptions of drivers and sociodemographic attributes in one set of multivariate regression equations, and correlation coefficients are calculated by

$$\eta_k = \sum_{i=1}^{I} \gamma_{ik} X_i + \delta_k, \quad i = 1, 2, \ldots; k = 1, 2, \ldots, \tag{2}$$

where I is the number of sociodemographic attributes; X_i is the i^{th} sociodemographic attribute; γ_{ik} is the correlation coefficient between η_k and X_i; and δ_k is the residual error.

3.2. LCA. Based on the preferred choice of attitudinal statements, a latent variable, as a categorical variable, is identified by the LCA. Once the optimal LCA fits successfully, drivers will be divided into different latent classes.

LCA is the measurement model to explain the relationship between observed variables by a latent class variable, thus maintaining observed variables' local independence [18]. In other words, the probability of choosing a specific option of attitudinal statements is to be illustrated by a latent class variable. A latent class variable is composed of a series of classes. All latent classes are discrete and mutually exclusive. The latent classes in this study are developed based on the diffusion of innovations. It is assumed that there are five latent classes of the sample: innovators, early adopters, early followers, late followers, and conservatives.

Latent class probability and conditional probability are two basic parameters of LCA [19]. Latent class probability involves two crucial aspects: the number of latent classes and the probability of the latent class. LCA determines the number of latent classes, the probability of the latent class refers to the proportion of the population in each latent class to the total sample, and the sum of proportions equals 1. Conditional probability refers to the choice probability of an individual belonging to a particular latent class concerning a specific option of the observed variable.

3.3. Model of Drivers' Compliance Behavior to Guidance Information at Signalized Intersections. The model of drivers' compliance behavior to guidance information at signalized intersections is established, as shown in Figure 2. Based on the MIMIC model and LCA, the features of perceptions in

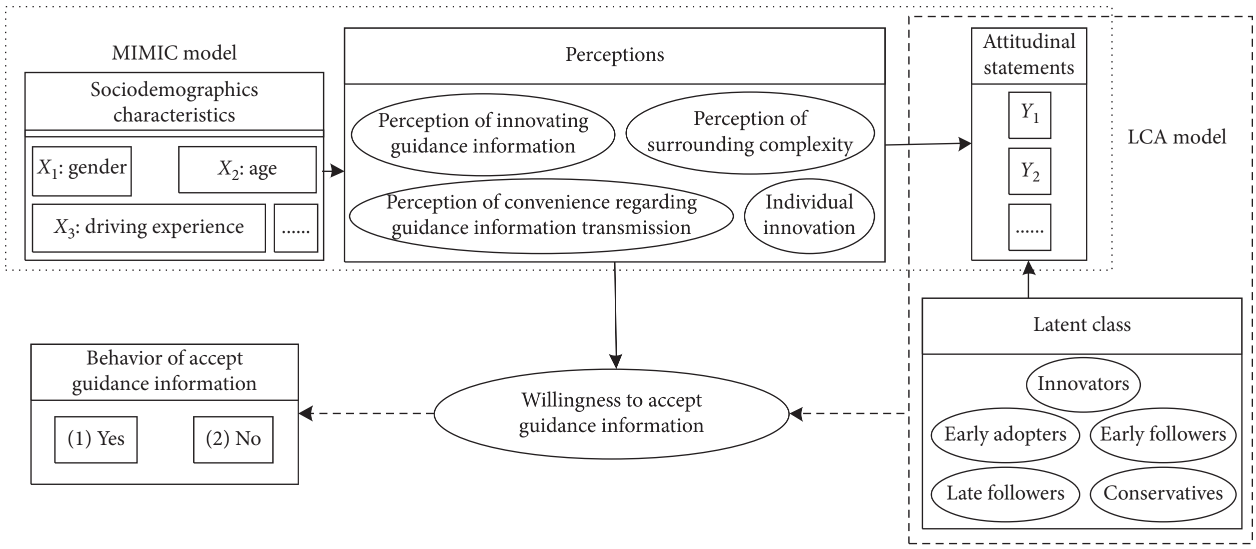

Figure 2: The model framework of drivers' compliance behavior to guidance information at signalized intersections.

potential class are extracted, and the probabilities of accepting guidance information are analyzed.

In the measurement model of the MIMIC, four subjective perceptions of drivers are identified, including the perception of innovating guidance information, the perception of convenience regarding guidance information transmission, the perception of surrounding complexity, and the individual innovation. Moreover, attitudinal statements can measure these four perceptions. In the structural MIMIC model, the hypotheses are made that sociodemographic characteristics have significant impacts on latent perceptions, and data collected will subsequently verify them. An individual's sociodemographic characteristics include gender, age, driving experience, familiarity with the local road network, education levels, and type of driving behavior exhibited.

Attitudinal statements are considered as the latent class variable's indicators. LCA will verify the hypothesis of five latent classes, and the probability of latent class will be calculated.

Based on these two models, features of different latent classes are extracted. To some extent, the perceptions can reflect the willingness and possibility of individuals to accept guidance information at signalized intersections. The chronological proportion change of the latent class is also analyzed to explore the change of attitude towards guidance information at signalized intersections.

4. Estimation Results and Discussion

Mplus Version 7 is a flexible modeling program that provides researchers with a wide choice of models and algorithms to analyze data, especially the data that comes from various heterogeneous populations [17]. Therefore, it is applied to establish the proposed approach in this study. This section will present a detailed analysis of survey data of 2019, and a brief analysis of data in 2015 is also presented. The change in drivers' attitude towards guidance information at signalized intersections is also investigated.

4.1. Analysis of MIMIC Model. The analysis of the MIMIC model can be divided into three steps: *reliability and validity analyses*, *model fit,* and *hypothesis testing*. *Reliability and validity analyses* are conducted to test the rationality of questionnaire design and the existence of latent variables. If the results do not meet the requirements, the erroneous conclusions regarding the reliability and magnitude of the relationship between latent variables are drawn [20]. The *model fit* is to illustrate the rationality of the model structure. If the results show the model is inappropriate, the model needs to be reconstructed. *Hypothesis testing* is a test of hypotheses in the process of model building.

4.1.1. Reliability and Validity Analysis. In order to improve the reliability of the model, the validity analysis of reliability, convergence, and discriminant is carried out using survey data of the year 2015 and 2019. The results of 2015 and 2019 data are analyzed in Table 3.

The estimated parameters of each perception should be greater than 0.5. As shown in Table 3, all estimated parameters are at an acceptable range.

The composite reliability (CR) refers to the consistency of indicators of each perception, and CR is recommended to be larger than 0.7 [21]. As shown in Table 3, CRs are also at an acceptable range, and it shows that observed variables of each perception have a good consistency.

The average variance extraction (AVE) represents the average explanatory capability of each perception to its indicators [21], and AVE should be higher than 0.36. All convergence validities of the model meet the requirements in Table 3, and 0.359 is acceptable for 2019 data [22]. Discriminant validity is an index to measure the distinction between perceptions [21]. If the value of discriminant validity is substantial, it shows that the correlation between perceptions is small, and perceptions should be reserved. On the contrary, it is necessary to merge the observed variables to test the reliability and validity of the model again. Table 3

Table 3: Validity analysis of reliability, convergence, and discriminant (2015 and 2019 data).

Year	Perceptions	Estimated parameters		Composite reliability	Convergence validity	Discriminant validity			
				CR	AVE	Perception of innovating guidance information	Perception of convenience regarding guidance information transmission	Perception of surrounding complexity	Individual innovation
2015	Perception of innovating guidance information	Y_1	0.672	0.725	0.571	0.756			
		Y_2	0.721						
		Y_3	0.831						
		Y_4	0.683						
	Perception of convenience regarding guidance information transmission	Y_5	0.618	0.791	0.562	0.149	0.750		
		Y_6	0.800						
		Y_7	0.815						
		Y_8	0.738						
	Perception of surrounding complexity	Y_9	0.695	0.774	0.509	0.712	0.328	0.713	
		Y_{10}	0.718						
		Y_{11}	0.731						
	Individual innovation	Y_{12}	0.676	0.774	0.509	0.745	0.381	0.702	0.713
		Y_{13}	0.693						
		Y_{14}	0.749						
2019	Perception of innovating guidance information	Y_1	0.720	0.722	0.399	0.632			
		Y_2	0.576						
		Y_3	0.704						
		Y_4	0.504						
	Perception of convenience regarding guidance information transmission	Y_5	0.601	0.736	0.412	0.602	0.642		
		Y_6	0.725						
		Y_7	0.615						
		Y_8	0.620						
	Perception of surrounding complexity	Y_9	0.586	0.623	0.359	0.622	0.563	0.599	
		Y_{10}	0.695						
		Y_{11}	0.501						
	Individual innovation	Y_{12}	0.684	0.699	0.437	0.647	0.408	0.550	0.661
		Y_{13}	0.643						
		Y_{14}	0.655						

The bold diagonal type is the root value of AVE, and the values of the lower triangle are Pearson's correlation of other perceptions.

shows that almost all values on the diagonal are greater than the lower triangle values, that is, the root values of AVE are almost higher than the Pearson correlation coefficient of other perceptions, so there is a discriminant validity between perceptions in the measurement model. Thus, all attitudinal statements and perceptions in the measurement model should be reserved.

4.1.2. Model Fit. The goodness-of-fit indices are used to evaluate the fitness of the model. Seven indices and their recommended values [22, 23] are presented in Table 4. The goodness-of-fit indices of the MIMIC model are consistent with their recommended values, respectively. Thus, data of the year 2015 and 2019 can support both MIMIC models.

4.1.3. Hypothesis Testing. Three indices can help verify hypotheses: *estimated parameters*, *p value*, *and R squared*. *Estimated parameters* are the values of the standardized loading factor, explaining the impact of sociodemographic characteristics on subjective perceptions of drivers. *p value* shows the significance of the causal relationships, and the six hypotheses drawn are also verified. *R square* shows the explanatory capability of sociodemographic characteristics concerning the MIMIC model. The value of 0.19 means that the model has a small explanatory capability, 0.33 shows the model has a moderate explanatory capability, and 0.67 means the model has a tremendous explanatory capability.

The results of model hypotheses using the data of the year 2015 and 2019 are presented in Table 5. Six *R square* values indicate that both MIMIC models have moderate explanatory capabilities for data of the year 2015 and 2019.

According to the results of 2015 and 2019, driving experience and education levels have a positive impact on the perception of innovating guidance information ($p < 0.05$). The longer they drive, the more times they usually use driving navigation, thus increasing trust towards guidance information. The higher the education levels, the deeper the theoretical insight of innovation.

Age harms the perception of convenience regarding guidance information transmission ($p < 0.05$), and older drivers are less likely to have access to information than younger drivers. Education levels have a significant positive effect on the latent variable ($p < 0.001$).

Education levels have a significant positive impact on the perception of surrounding complexity ($p < 0.001$). The higher the education levels, the higher the awareness of risk prevention. When drivers feel danger around themselves at signalized intersections, they are more willing to comply with guidance information.

Moreover, age also harms individual innovation ($p < 0.05$). Driving experience and familiarity with the local road network have a massive impact on individual innovation ($p < 0.05$ and $p < 0.001$, respectively). The duration of driving experience is usually positively related to the familiarity of the road network.

Four perceptions are well measured by the MIMIC model. In other words, these four perceptions are regarded as the characteristics of individuals, which will be used to analyze the features of the latent class.

4.2. Analysis of LCA. Being influenced by surroundings and individuals themselves, the time when individuals start accepting innovation will be different, and the difference will be used to classify individuals. There are similar characteristics of individuals in each class. In the study, the LCA is carried out to classify individuals according to individuals' choice preference for attitudinal statements. Because the number of latent classes is not known in advance, it is necessary to increase the number of latent classes gradually in order to obtain the parameters of each model and its fit indices. Then, the optimal model is determined according to fit indices and practical significance.

There are six indices which are used to evaluate the LCA based on data of the year 2015 and 2019. Existing research pointed out that the smaller the calculated statistics are, the better the model fits [21], such as Akaike information criterion (AIC), Bayesian information criterion (BIC), and sample-size adjusted BIC (aBIC). As shown in Table 6, the model with five classes based on 2015 data is better accepted according to the three indices. Entropy is also used to evaluate the classification accuracy. If the entropy is less than 0.60, it shows that more than 20% of individuals have classification errors; if the value is more than 0.80, it shows that classification accuracy exceeds 90% [24]. The model with three classes based on 2015 data is better because the classification accuracy exceeds 90% (the entropy (0.872) is more extensive than 0.8). Besides, the indices of the Lo–Mendell–Rubin adjusted LRT test (LMR) and bootstrapped likelihood ratio test (BLRT) are used to compare the differences between $k-1$and k class models. If the *p value* of LMR is within the significance range, it shows that the model with k class is better than the model with $k-1$ class. The same applies to the indices of BLRT. The model with three classes based on 2015 data is better because LMR and BLRT are significant. Notably, the evaluations of each index are not consistent. However, considering the classification accuracy and the comparative advantage, drivers of the sample based on 2015 data were consequently divided into three classes, and the individuals of the sample based on 2019 data are classified into two classes.

There are differences in the willingness of individuals and the beginning time to accept innovation. Considering the above factors, Rogers classified people into five categories: innovators, early adopters, early followers, late followers, and conservatives [17]. The innovators are deemed valuable as they discover and explore new things. The early adopters acquire the information from the innovators and make decisions cautiously. The early followers make decisions to follow the early adopters after taking a long time to consider. The late followers are skeptical about the innovation, and they finally accept the innovation due to surrounding influence. The conservatives have a high-risk awareness, and they are very unwilling to change their opinions.

The response characteristics of three latent classes on attitudinal statements are presented in Figures 3(a)–3(d)

Table 4: Goodness-of-fit indices of the MIMIC model (2015 and 2019 data).

Goodness-of-fit indices	Recommended value	2015	2019
Chi-squared (X^2)	The smaller the better	320.475	344.568
Degrees of freedom (Df)	The more significant the better	150	150
Relative chi-squared (X^2/Df)	$1 < X^2/\mathrm{Df} < 3$	2.746	2.300
Comparative Fit Index (CFI)	>0.9	0.980	0.932
Tucker–Lewis Index (TLI)	>0.9	0.964	0.911
Root-mean-squared error of approximation (RMSEA)	<0.08	0.041	0.035
Standardized root-mean-squared residual (SRMR)	<0.08	0.026	0.037

Table 5: Analysis of model hypotheses (2015 and 2019 data).

Perceptions	Sociodemographic characteristics	2015				2019			
		Estimated parameters	p value	R^2	Hypotheses	Estimated parameters	p value	R^2	Hypotheses
Perception of innovating guidance information	Gender	−0.022	0.770	0.364	Not supported	−0.011	0.770	0.340	Not supported
	Age	0.034	0.418		Not supported	0.026	0.538		Not supported
	Driving experience	0.205	0.015		Supported	0.105	0.019		Supported
	Familiarity with the local road network	0.014	0.740		Not supported	0.017	0.650		Not supported
	Education levels	0.141	0.048		Supported	0.08	0.026		Supported
	Type of driving behavior exhibited	0.013	0.740		Not supported	0.015	0.680		Not supported
Perception of convenience regarding guidance information transmission	Gender	0.025	0.672	0.360	Not supported	0.025	0.780	0.330	Not supported
	Age	−0.102	0.019		Supported	−0.103	0.020		Supported
	Driving experience	0.132	0.705		Not supported	0.065	0.679		Not supported
	Familiarity with the local road network	0.024	0.694		Not supported	0.053	0.748		Not supported
	Education levels	0.242	***		Supported	0.189	***		Supported
	Type of driving behavior exhibited	0.047	0.630		Not supported	0.056	0.700		Not supported
Perception of surrounding complexity	Gender	−0.041	0.310	0.381	Not supported	−0.041	0.310	0.390	Not supported
	Age	−0.017	0.721		Not supported	−0.017	0.721		Not supported
	Driving experience	0.010	0.767		Not supported	0.048	0.332		Not supported
	Familiarity with the local road network	0.080	0.813		Not supported	0.064	0.625		Not supported
	Education levels	0.125	***		Supported	0.141	***		Supported
	Type of driving behavior exhibited	−0.027	0.356		Not supported	−0.054	0.164		Not supported
Individual innovation	Gender	−0.06	0.489	0.374	Not supported	−0.02	0.592	0.450	Not supported
	Age	−0.204	0.012		Supported	−0.093	0.033		Supported
	Driving experience	0.156	***		Supported	0.109	0.017		Supported
	Familiarity with the local road network	0.132	***		Supported	0.138	***		Supported
	Education levels	−0.023	0.863		Not supported	−0.002	0.960		Not supported
	Type of driving behavior exhibited	0.035	0.336		Not supported	0.046	0.207		Not supported

*** $p < 0.001$.

Table 6: Goodness-of-fit indices of LCA (2015 and 2019 data).

Year	Number of classes	AIC	BIC	aBIC	Entropy	LMR	BLRT	Latent class probability
2015	Two classes	26153.240	26574.546	26304.574	0.831	***	***	0.45/0.55
	Three classes	25534.297	26168.734	25762.187	0.872	***	***	0.140/0.360/0.500
	Four classes	25161.589	26009.158	25466.036	0.762	0.110	***	0.102/0.250/0.360/0.288
	Five classes	24896.356	25957.056	25277.360	0.760	0.700	***	0.092/0.15/0.183/0.277/0.298
2019	One class	30202.104	30420.360	30280.609	—	—	—	1
	Two classes	23949.668	24351.457	24094.188	0.876	***	***	0.202/0.798
	Three classes	23575.698	24180.861	23793.370	0.790	0.305	***	0.091/0.435/0.474
	Four classes	23454.110	24262.647	23744.933	0.760	0.719	***	0.078/0.411/0.453/0.058

*** $p < 0.001$.

based on survey data of the year 2015, and the conditional probability of "strongly disagree" of all attitudinal statements was calculated. Individuals of three latent classes can be identified as early followers, late followers, and conservatives, respectively.

Early followers accounted for 14% of the total sample (Table 6). According to the choice probability of the "strongly agree" (the mean value was 0.25, see the orange dotted line in Figure 3(d)) and "agree" (the mean value was 0.37, see Figure 3(c)), it was inferred that the attitude of the group towards accepting guidance information at signalized intersections was relatively positive. However, the probability of "neither agree nor disagree" (the mean value was 0.24, see Figure 3(b)) indicated that this group took a wait-and-see attitude towards guidance information at signalized intersections. They could not be classified as innovators because they did not have a high probability of choosing "strongly agree." They were less likely to accept guidance information at the earliest stage of speed guidance device application.

Late followers accounted for 36% of the total sample (Table 6). As shown in Figure 3(d), the probability of "strongly agree" was almost zero (see the blue dotted line). The probability of choosing "agree" was 0.21, and the probability of "neither agree nor disagree" and "disagree" was also high (0.35 and 0.27, respectively). It showed that the attitude of the group towards accepting guidance information at signalized intersections was relatively negative. The group had a skeptical attitude towards guidance information at signalized intersections. It was likely that they would comply with guidance information after most people around them accepted the innovation.

Conservatives accounted for 50% of the total sample (Table 6). The probability of "disagree" and "strongly disagree" were very high (the mean values were 0.34 and 0.40, respectively) for conservatives. The group would like to follow their own driving experience through intersections, thus having a smaller willingness to comply with guidance information at signalized intersections.

Similarly, according to the same principle, the number of latent classes calculated from the data of the year 2019 is also discussed (Table 6), and the choice preference of different classes is presented in Figures 4(a)–4(d). Drivers are classified into two classes: early followers and late followers. They account for 20.2% and 79.8% of the total sample, respectively. Early followers prefer to choose "strongly agree" and "agree" (the mean values are 0.37 and 0.47, respectively) thanof 2015 data. Late followers have the highest probability of choosing "agree" (the mean value is 0.34), and also had a higher probability of choosing "neither agree nor disagree" (the mean value is 0.30).

Diffusion of innovation is a long-term process, and the drivers' acceptance behaviors of guidance information are also changing with market penetration, familiarity with the Internet of vehicles (IOV), and social network. As time goes by, the proportion of early followers has increased from 14% in 2015 to 20.2% in 2019, that of late followers has also risen from 36% in 2015 to 79.8% in 2019, and the number of conservatives has also declined to 0. The four perceptions of individuals in 2019 are higher than that of individuals in 2015, according to the probabilities of all attitudinal statements. Guidance information discussed in the study plays a significant role in IOV, and the development of IOV in China can account for the evident proportional change. IOV has been well understood in the last five years, especially when Internet companies entered the IOV field in 2014. Under the influence of social environment and interpersonal communication, drivers' attitude towards guidance information at signalized intersections gradually changed from unfamiliar at the beginning to slightly favorable.

4.3. Feature Analysis of Latent Classes Based on Two Models. Individuals of each latent class have a particular preference for attitudinal statements, and four perceptions estimated by attitudinal statements can reflect the characteristics of each group. Based on Table 1 and Figures 3 and 4, this section explores features of latent classes identified from its perceptions.

For early followers based on data of 2015, they preferred choosing "strongly agree" and "agree" for multiple attitudinal statements. It could be inferred that the latent class had a strong innovation capability in latent variables (the perception of guidance information innovation, convenience perception of guidance information transmission, perception of surrounding complexity, and individual innovation). For guidance information at signalized intersections, the group could understand its compatibility, complexity, and comparative advantage easily. The compatibility means that guidance information can be compatible with drivers' driving experience (Y_1); the complexity refers to the complexity of guidance information being understood and used

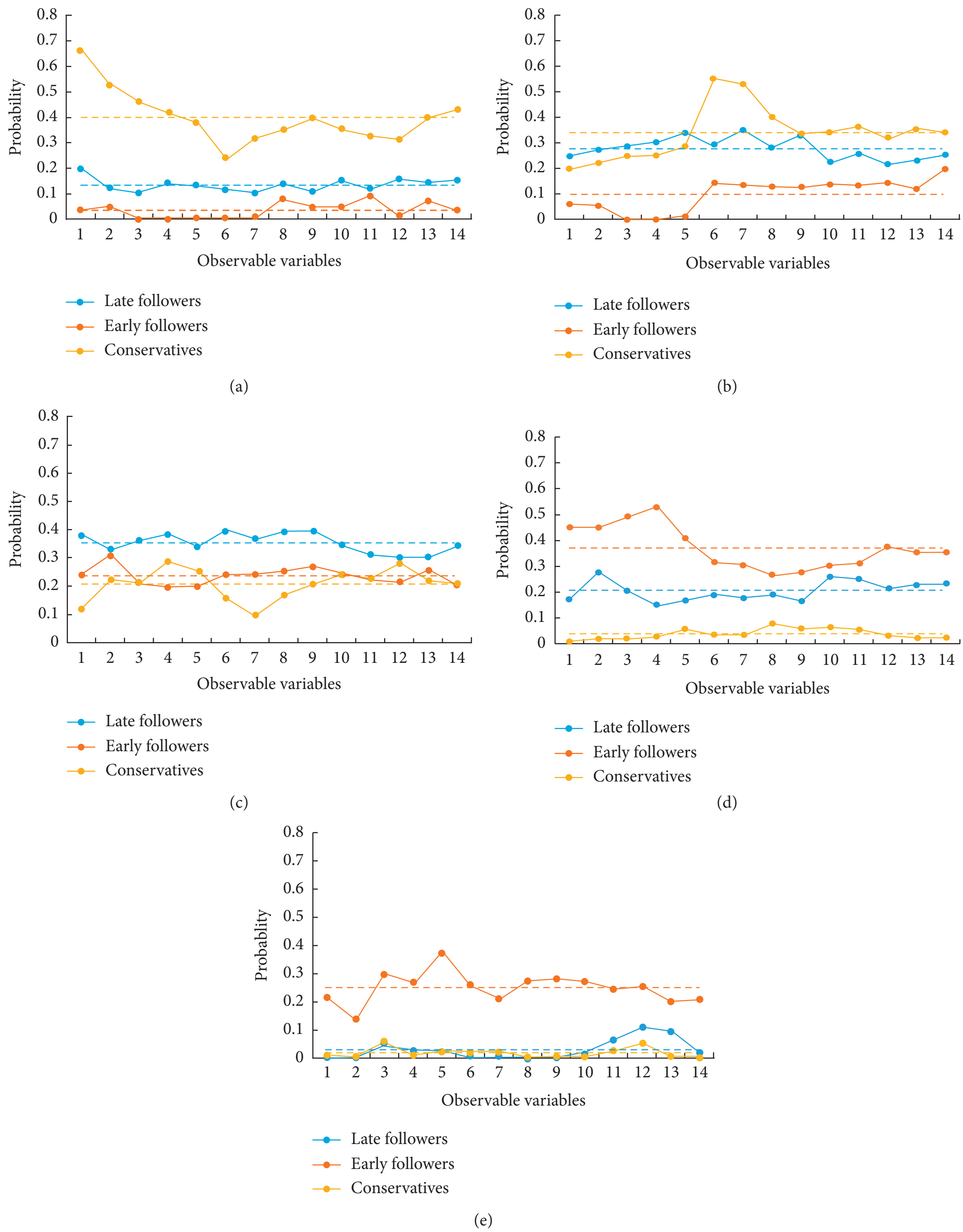

Figure 3: Conditional probability of LCA based on the data of 2015. (a) Strongly disagree. (b) Disagree. (c) Neither agree nor disagree. (d) Agree. (e) Strongly agree.

(Y_2); the comparative advantage indicates that drivers can benefit from accepting guidance information, such as increasing safety (Y_3) and decreasing travel time (Y_4). They believed in science, because most innovations stem from scientific research, and they were more willing to trust and try new technologies (Y_{12}). When they felt the complexity of the traffic environment around them, they were more likely to follow guidance information (Y_9, Y_{10}, and Y_{11}). The

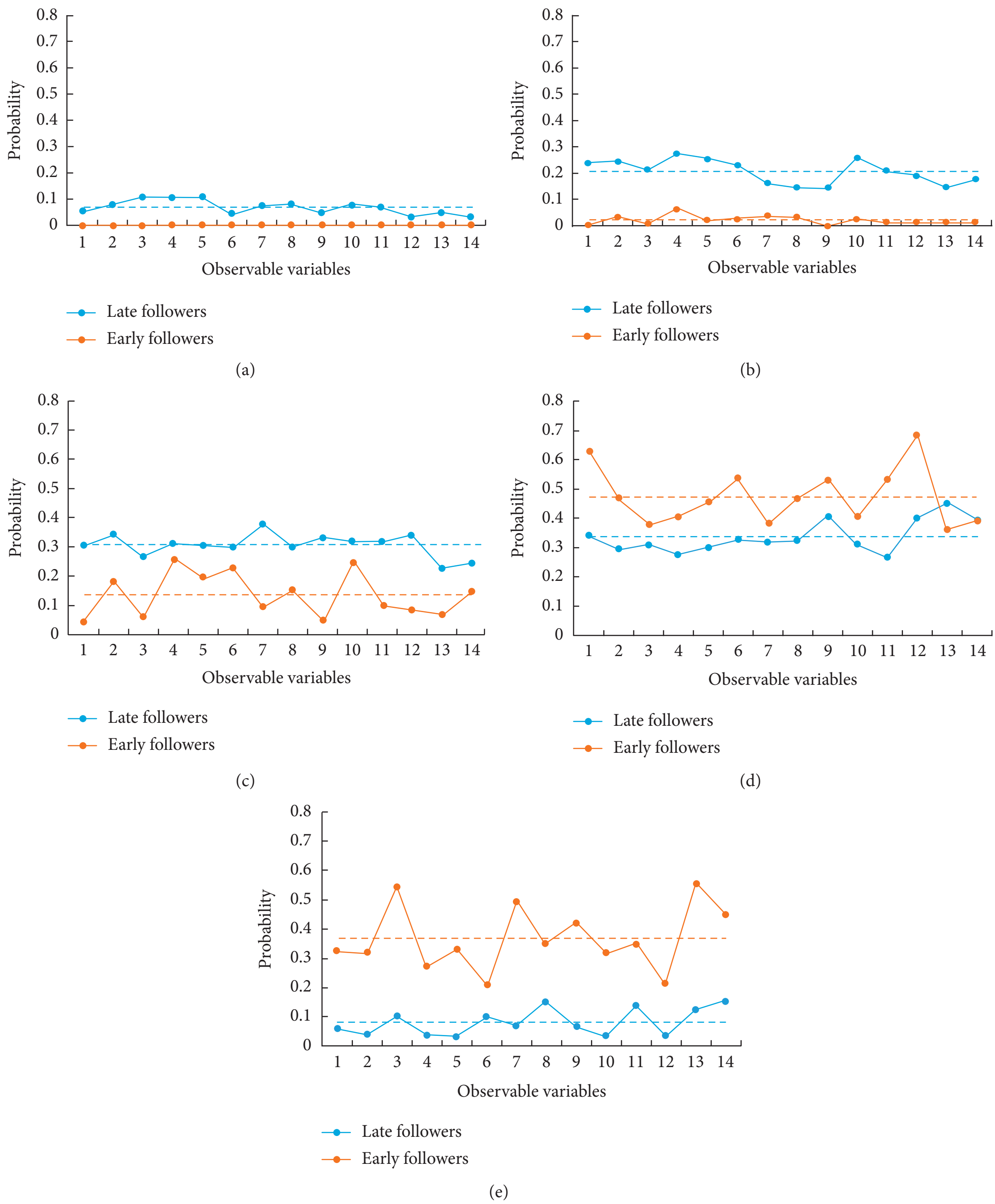

Figure 4: Conditional probability of LCA based on 2019 data. (a) Strongly disagree. (b) Disagree. (c) Neither agree nor disagree. (d) Agree. (e) Strongly agree.

contrivances provoked new ideas (Y_{13}). They could obtain information from multiple channels (Y_5, Y_6, Y_7, and Y_8) and had a willingness to communicate with others (Y_{14}).

For late followers based on data of 2015, they tend to choose "disagree" and "strongly disagree" for each observed variable. The innovation ability of the group in four perceptions was lower than that of early followers. They were more willing to avoid risk and adopted a wait-and-see attitude towards the effect of guidance information at signalized intersections. They were more likely to know the advantages of innovation from the practice of people around them and then accept the innovation. They were also less willing to accept new ideas and got more used to their existing knowledge (such as driving experience).

For conservatives based on data of 2015, they had a higher choice probability to "disagree" and "strongly disagree" in multiple attitudinal statements, and the perceptions to the four potential variables were significantly lower than the other two groups in the same period. The group members had a more conservative or distrustful attitude towards guidance information. However, as technologies gradually penetrated people's daily life in recent years, individuals of the group are slowly turning into late followers or adhering to other latent classes.

The four perceptions of drivers based on data of 2019 are higher than that of drivers using data of 2015. Drivers' understanding of guidance information at signalized intersections in 2019 is higher than that of 2015.

5. Conclusions

This study develops an approach of drivers' compliance behavior to guidance information at signalized intersections based on the diffusion of innovation. The proposed approach explores the features of the latent class by connecting the MIMIC model with LCA and the chronological change of drivers' attitude towards guidance information at signalized intersections. In the MIMIC model, four subjective perceptions of drivers are identified by the measurement model, and the structural model explores the correlation between sociodemographic characteristics of individuals and their perceptions. According to the choice preferences affected by their perceptions, the classification of individuals is performed by the LCA.

The results of data of 2019 show that several factors can affect drivers to comply with guidance information at signalized intersections, such as age, driving experience, education levels, and familiarity with the local road network. Moreover, drivers are divided into two latent classes with a classification accuracy of more than 90%: early followers and late followers. The four perceptions of early followers are higher than those of late followers. The early followers account for 20.8% and have a high probability of complying with traffic guidance information at signalized intersections. The proportion of late followers is up to 79.2%, and most of them are skeptical of the innovation. It is unlikely that late followers would like to accept guidance information at the early stage of speed guidance devices and applications.

The results of data of 2015 show that drivers were classified into three categories: early followers, late followers, and conservatives. They accounted for 14%, 36%, and 50%, respectively. Comparing the results of 2015 with 2019, they demonstrates that the proportion of conservatives has gradually decreased, while the proportion of early followers and late followers has increased with market penetration, familiarity with the Internet of vehicles (IOV), and social network. It can be inferred that most of the drivers had a conservative attitude towards guidance information in 2015, while they have a more open attitude in 2019 and are more willing to accept guidance information at signalized intersections.

Future studies should include the following:

(1) When considering the differences between provinces of China in terms of information transmission mechanisms, economic, and education levels, further studies will be imperative to decipher compliance behavior towards guidance information at signalized intersections.

(2) Also, further research should adopt the second meaning of *time* (i.e., the time-span from initial contact to final decisions of acceptance or refusal by individuals) into account to explore drivers' preference and behavior towards guidance information at signalized intersections when the speed guidance devices are in widespread use.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request (e-mail: xmchen@bjtu.edu.cn).

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Xiaomei Zhang, Xumei Chen, Aihua Fan, and Lei Yu were involved in the study conception and design. Xiaomei Zhang, Xumei Chen, and Aihua Fan collected the data. Xiaomei Zhang, Xumei Chen, and Lei Yu analysed and interpreted the results. Xiaomei Zhang, Xumei Chen, Aihua Fan, and Lei Yu were involved in the draft manuscript preparation. All authors reviewed the results and approved the final version of the manuscript.

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