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Modelling bike-sharing choice in a developing country with a focus on the impacts of air pollution and weather conditions

Weibo Li*, Maria Kamargianni

UCL Energy Institute, University College London,
Central House, 14 Upper Woburn Place, WC1H 0NN, London, UK.

Abstract

Developing countries are facing increasing challenges to make urban mobility sustainable and more specifically to tackle the continuously growing air pollution and congestion caused by rapid increase in car ownership. As part of a broad strategy to achieve sustainable urban mobility, bike-sharing service can help reduce car use, especially in city centre area. There is currently a lack of knowledge in developing countries about the factors affecting bike-sharing choice, hindering policy making to effectively improve existing bike-sharing schemes and launch more schemes. This research investigates the factors affecting bike-sharing choice in China with a particular focus on the impacts of air pollution and weather conditions. Multinomial logit model is used to analyse transport mode choice behaviour based on the short-distance stated preference data collected in the case study city, Taiyuan, which currently operates the most demanded bike-sharing scheme in China. The results confirm the strong and significant impacts of air pollution on bike-sharing usage as well as other exposed alternatives such as walk and electric bike. Thus, it is concluded that tackling air pollution can create a virtuous circle to deliver sustainable urban mobility. The impacts of a number of other factors are also found to be significant (e.g. trip purpose, travel cost, age, income and educational level etc.) and can lead to corresponding policy implications.

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Keywords: Bike-sharing; Air pollution; Weather conditions; Discrete choice model; Mode choice; Stated preference; Developing country

* Corresponding author. Tel.: +44 (0) 75 871 96096.
E-mail address: weibo.li.10@ucl.ac.uk

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1. Introduction

Developing countries are facing increasing challenges to make urban mobility sustainable and more specifically to tackle the continuously growing air pollution and congestion caused by rapid increase in car ownership. As part of a broad strategy to achieve sustainable urban mobility, bike-sharing service can help reduce car use, especially in city centre area. Bike-sharing provides short-term hiring services (i.e. in minutes or hours) for users to access bikes without having to own the mode per se. Many researches have explored the advantages of bike-sharing showing that the key user benefits include: avoiding parking and maintenance troubles, offering more convenient connection to public transport, reducing travel time and costs especially in city centre, improving body health, and opening opportunities for more social and leisure purposes (DeMaio and Gifford, 2004; Jäppinen et al., 2013; Ricci, 2015).

Following the success in Europe and North America (DeMaio, 2009; Shaheen et al., 2010), bike-sharing schemes have recently been introduced in several cities in developing countries. However, although there are many mode choice behaviour studies for developed countries, there is currently a lack of knowledge in developing countries about the factors affecting bike-sharing choice. The current research gap has significantly hindered policy-making to effectively improve existing bike-sharing schemes and launch more schemes. More importantly, findings from developed countries are difficult to be directly applied in developing countries as culture and local/ geographical characteristics are significantly different (Maurer, 2012; Faghih-Imani et al., 2015; Kamargianni, 2015).

As a result, this research is going to investigate the factors affecting mode choice behaviour in China with a focus on bike-sharing and explore policy implications for promoting bike-sharing usage in developing countries. Particular focus will be placed on the impacts of air pollution and weather conditions on mode choices. So far, very limited attention has been put on these factors, and especially air pollution levels. However, they may play important roles in affecting mode choice behaviour in developing countries, which could have more frequent air pollution periods and more volatile temperatures and weathers.

2. Literature review

Existing studies on factors affecting bike-sharing choice will be reviewed in order to reveal any knowledge gaps and to acquire insights on influential factors. Due to the limited amount of literature exclusively on bike-sharing choice, the review will also include studies on cycling choice due to its similar features to bike-sharing.

2.1. Socio-economic characteristics

Age and gender have been studied in many mode choice studies. Younger generations are usually much keener to cycle (Shafizadeh and Niemeier, 1997; Ricci, 2015). However, such strong connection may not always be the case. Rodriguez and Joo (2004) showed that the negative relationship between age and cycling was only significant at 75% confidence level. The similar contradiction can also be seen in gender research. Since females often have more household responsibilities (Baker, 2009), most of the studies found that males could cycle more than females (Rodriguez and Joo, 2004; Moudon et al., 2005; Akar et al., 2013; Ricci, 2015; Wang et al., 2015), while Parkin et al. (2008) further showed more males would cycle for work. On the contrary, Faghih-Imani et al. (2015) showed opposite results by doing case studies in Barcelona and Seville. The research found that the proportion of females to males would positively affect bike-sharing usage in both cities and the result was even more significant in Seville. However, no particular reason was given to explain such finding.

Occupation and economic status may play important roles in determining cycling choice. Xing et al. (2010) showed that travellers with lower income cycled more because those with higher income would value more of their time and thus choose faster modes. Faghih-Imani et al. (2015) found similar conclusions from another perspective that the unemployed usually favoured more cycling. However, some studies found that higher cycling rate could be associated with higher economic status (Parkin et al., 2008; Zahran et al., 2008; Ricci, 2015). Such phenomenon could be explained by the fact that more wealthy people may cycle more for leisure purposes instead of commuting. Additionally, Baltes (1996) found that economic status and unemployment are both insignificant in determining cycling choice, but at the same time he found that students would cycle more which was consistent with the recent findings by Whalen et al. (2013) and Wang et al. (2015) on university students.

Vehicle ownership seems to be a more direct determinant of mode choice. In general, vehicle ownership could decrease the incentive or the need to cycle, either for educational (Rodriguez and Joo, 2004) or work purposes (Parkin et al., 2008). Baltes (1996) reached the same conclusion but he also pointed out that such inverse relationship might be attributed to the collinearity with other factors, i.e. the fact that those who do not own any vehicles and have to cycle could be caused by their disadvantaged income status that make the purchase unaffordable or travel distance is too short to own a vehicle. Nevertheless, the influence of vehicle ownership was shown as insignificant when using a bicycle to access another mode (Martens, 2004; Givoni and Rietveld, 2007).

In addition, some studies also captured other types of socio-economic characteristics for example Moudon et al. (2005) showed that better health status would facilitate cycling and Xing et al. (2010) found that higher educational level could contribute to more cycling activities.

2.2. Trip and mode characteristics

First of all, mode choices could differ by trip purpose. Cycling is preferred for recreational purposes compared to commuting (Moudon et al., 2005; Xing et al., 2010). Faghih-Imani et al. (2015) found that cycling trips occurred more during lunch time and evening/after-work usually for dinner purposes while most of the morning cycle trips were for commuting. Moreover, due to bicycle's weaker mobility compared to motorised vehicles, trip distance is also critical in mode choice decision. There was overwhelming evidence showing the negative relationship between cycling choice and trip distance (Parkin et al., 2008; Zahran et al., 2008; Akar et al., 2013; Faghih-Imani et al., 2015; Wang et al., 2015;). Xing et al. (2010) even argued that perceived trip distance had the largest influence compared to all other variables. Besides purpose and distance, Lin and Yang (2011) also found evidence that lowering trip cost could attract more people to choose bike-sharing via an optimal design study for bike-sharing scheme.

Many researches have specifically studied the impacts of different attributes associated with bike-sharing (e.g. riding duration, comfort level etc.) and also characteristics of alternative modes (e.g. car speed, parking availability, public transport cost, service frequency etc.) to evaluate mode choice decisions (Kamargianni and Polydoropoulou, 2013; Whalen et al., 2013; Faghih-Imani et al., 2015; etc.). Again, conclusions more or less differ across studies due to different sample characteristics and different mode attributes considered.

2.3. Built and natural environment characteristics

Cycling facilities have attracted the most attention in the previous literature. Many studies have discovered the importance of more cycle lanes and bike-sharing stations for promoting the use of cycling or bike-sharing in terms of reduced travel time, increased safety and convenience (Akar and Clifton, 2009; Larsen and El-Geneidy, 2011; Daito and Chen, 2013; Hankey et al., 2012; Kamargianni and Polydoropoulou, 2013; Deenihan and Caulfield, 2015; Kamargianni, 2015; Maness et al., 2015; Wang et al., 2015). However, there were also a few papers that found an insignificant relationship between the number of cycling facilities and cycling choice (Rodriguez and Joo, 2004; Moudon et al., 2005; Xing et al., 2010).

Hilliness is another possibly significant factor in determining cycling choice. Waldman (1977), Rietveld and Daniel (2004) and Parkin et al. (2008) showed that steeper roads would significantly discourage the choice of bicycle. However, this conclusion was not supported by Moudon et al. (2005), as the authors did not find any significant effects of road slope on cycling choice. Additionally, Motoaki and Daziano (2015) argued that the impacts of road hilliness heavily depend on the fitness of cyclist.

Further, some other influential built environment factors such as population density in community, the existence of university campus and number of parks etc. have been studied in a number of researches (DeMaio and Gifford, 2004; Rodriguez and Joo, 2004; Barnes and Krizek, 2005; Moudon et al., 2005; Parkin et al., 2008; Maurer, 2012; Whalen et al., 2013).

Weather conditions (i.e. temperature and weather) are the most commonly explored natural environment factors. A few researches have modelled the impacts of weather conditions on cycling choice. Daito and Chen (2013) and Kamargianni (2015) incorporated different weather conditions (e.g. sunny, rain or snow) in their mode choice models; Parkin et al. (2008), Saneinejad et al. (2012) and Motoaki and Daziano (2015) further considered temperature impacts. In general, these studies held close conclusions that more adverse weather conditions and temperatures would discourage travellers from cycling.

2.4. Gaps

Although a lot of researches have been conducted on cycling choice, gaps still exist. First, natural environment characteristics (weather conditions and air pollution) are rarely considered in the analysis. Only a few researches have modelled the impacts of weather conditions while there is also a lack in the literature regarding the impacts of air pollution on mode choice. To our knowledge, so far only Zahran et al. (2008) attempted to model the pollution impacts on cycling choice in the United States. Such overlook could be due to the fact that the existing case study cities all belong to developed countries, which do not normally have significant natural environment volatility, (especially significant air pollution levels). However, in order to study bike-sharing choice in developing countries, it is critical to take into account air pollution and weather conditions. Secondly, to our knowledge no mode choice studies involving bike-sharing have been identified for developing countries. The results in developed countries have limited implications to developing countries due to the fact that local characteristics could lead to completely different results, especially given the vast differences in many dimensions between the two worlds. The existing literature have demonstrated tremendous differentiations in results and conclusions even when they were all within developed countries and some studies have directly proved such context-sensitive nature of mode choice study through simultaneously studying multiple cases (Barnes and Krizek, 2005; Tang et al., 2011; Maurer, 2012; Faghih-Imani et al., 2015; Kamargianni, 2015).

3. Case study and data

Stated preference transport mode choice data is collected to study factors that may affect bike-sharing choice. Taiyuan is chosen as the case study city. It is a Chinese city of more than 3 million citizens that currently operates the most demanded bike-sharing scheme in the country (Yuan, 2014; Song, 2015; etc.). Lessons can be learned to identify factors that have caused such a success. The city has sharp air pollution level differences as well as temperature and weather differences. Therefore, it is also an ideal case to study the impacts of natural environment variations on mode choice behaviour. Figure 1 provides a glance of the city's bike-sharing docking stations (yellow spots), which are within approximately every 500m in average.

Figure 1: Bike-sharing stations in downtown area of Taiyuan (http://www.ty7772345.com)

A questionnaire was designed to collect both revealed preference (RP) and stated preference (SP) data at an individual level. The questionnaire consists of six sections:

- Personal socio-economic characteristics;
- Household socio-economic characteristics;
- Trip diary to reveal trip characteristics and mode choice for a single day;
- Attitudes and perceptions towards bike-sharing and car-sharing;
- Retrospective survey to collect past socio-economic characteristics and mode choice data since 2006;
- SP mode choice experiment.

The SP mode choice experiment presents to participants various hypothetical scenarios and seeks to capture their preferred mode under different situations. It is the key step to generate policy implications as SP data can "capture a wider and broader array of preference-driven behaviours" (Louviere et al., 2003; p. 231) than RP data. Each participant had to respond to: 1. two scenarios for short-distance trips (less than 2km), 2. two scenarios for medium-distance trips (2km to 5km), and 3. two scenarios for long-distance trips (more than 5km), since some attribute levels (i.e. travel time and travel cost) vary based on the trip distance. The attributes and their levels were derived according to the literature review, discussions with local experts and pilot survey results (e.g. to produce the levels of travel times and travel costs, the average actual travel times and costs from the pilot survey were used as references). In this paper, we use only the SP for the short-distance trips. The experimental design is presented in Table 1 showing the alternatives, their attributes and their levels. There are six transport mode alternatives: car, electric bike, bus, car-sharing, bike-sharing and walk; each of them possesses a number of attributes. In addition, trip purposes, weather conditions and air pollution levels are associated with each scenario besides mode attributes. In total, sixty different scenarios were generated following orthogonal design.

Table 1: SP experimental design, short-distance trip

Trip purpose: work/education, leisure, shopping.
Weather condition: sunny (-10°, -5°, 0°, 5°, 10°, 20°, 25°, 30°), snow (-10°, -5°, 0°), rain (5°, 10°, 20°, 25°, 30°).
Air pollution level: excellent, good, light pollution, medium pollution, heavy pollution, terrible pollution.

	Car	**Electric bike**	**Bus**	**Car-sharing**	**Bike-sharing**	**Walk**
Travel time	2, 3, 5, 7, 10 min.	5, 6, 7, 9 min.	5, 7, 10, 12, 15min.	2, 3, 5, 7, 10 min.	8, 10, 12min.	10, 15, 20, 25, 30min.
Travel cost	￥1, 1.2, 1.4, 1.6, 1.8.		￥0.5, 1, 1.5, 2, 2.5.	￥0.8, 1, 1.5, 2, 3, 4, 5.	￥0, 0.5, 1.	
Parking space	Easy/hard to find parking					
Parking cost	free, ￥2/h, ￥5/h, ￥8/h.					
Walking time to/from station			5min, 10min, 15min.	5min, 10min, 15min.	2, 5, 10 min.	
Bus Frequency			every 2min, 5min, 10min, 15min.			
Mobile app availability			Yes, no.	Yes, no.	Yes, no.	

For collecting the data, we co-operated with Shanxi Transportation Research Institute, which provided 19 researchers assisting us with the distribution of the questionnaires, the collection of the questionnaires and the incorporation of the data into electronic datasets. The questionnaire was distributed in paper format to 15,000 Taiyuan citizens during summer 2015 after a pilot survey in January 2015. Due to the population size of more than 3 million in the urban area, the challenge of sample representativeness was mitigated by calibrating the sample with Taiyuan census data. First, the sampled individuals proportionally spread over the six districts in the urban area according to the population in each district; and second, the gender distribution of sampled individuals in each district is proportional to the population gender distribution in each district.

In the end, 7,866 questionnaires provided valid responses offering 13,277 SP observations for modelling purposes. The mode choice distribution and the descriptive statistics of the key socio-economic characteristics of the sample are shown in Table 2. Age and occupational status statistics altogether demonstrate that adults with fixed jobs constitute the main group in the sample. In other words, the sample has successfully captured regular commuters whose mode choice behaviours are the mostly concerned in urban planning and policy-making. Half of the sampled individuals have a driving licence; there is a high possession rate of public transport card meaning that most of the sampled individuals can access bus and bike-sharing services "barrier-free". Nearly all respondents state that they are healthy enough to cycle which ensures that bike-sharing can be a feasible choice in a sufficient number of scenarios. There may be a paradox between the two wealth status indicators, house tenure type and household income since the relatively negative skewed income level among Taiyuan citizens should be associated with more rented houses or more mortgaged houses in many situations. However, China as a developing country has adopted planned economy for a long period which means a significant portion of houses that are owned outright might come from free distribution by the public sector in the past. The fact suggests that income level would be a more accurate indicator than house tenure type when accounting for wealth and cost impacts on mode choice.

Table 2: Sample descriptive statistics and mode choice distribution in short distance scenarios

		Descriptive statistics (N=7,866)
Gender	Male	49%
	Female	51%
Age	under 18	9%
	18-25	27%
	26-35	32%
	36-45	21%
	46-59	10%
	60 or above	1%
Marital status	Single	44%
	Married	56%
Educational level	High school or below	26%
	College	31%
	Undergraduate	37%
	Graduate and above	6%
Occupational status	Fixed job	73%
	Student	20%
	Retired	2%
	Self-employed or unemployed	5%
Driving license	Percentage of possession	51%
Public transport card	Percentage of possession	78%
Cycling capability	Health enough to cycle	94%
House tenure type	Owned outright	57%
	Owned with mortgage	15%
	Rented	28%
Household monthly income (after tax)	Under ￥3000	32%
	￥3000 - ￥6000	36%
	￥6000 - ￥9000	17%
	￥9000 - ￥15000	10%
	￥15000 - ￥30000	4%
	Over ￥30000	1%
Household car	Percentage of possession	49%
Household electric bike	Percentage of possession	39%
	Mode choice distribution (N=13,277)	

Walk	Bike-sharing	Electric bike	Bus	Car-sharing	Car
29%	12%	9%	29%	11%	10%

4. Model specification and results

A multinomial logit (MNL) model is developed to study factors affecting mode choice behaviour emphasising particularly on bike-sharing choice. MNL model is based on random utility theory that a choice made by an individual is attributed to his/her perceived utility generated by that choice (Ben-Akiva and Lerman, 1985). The model can show why a particular alternative mode would be chosen rather than bike-sharing or why bike-sharing would be preferred over other alternatives. Such simultaneous comparison between choices of bike-sharing and alternative modes can enrich the insights on impacts of factors and lead to more robust policy implications.

The utility of each of the six alternative modes in short distance scenarios is determined by different factors. In general, the explanatory variables may include mode attributes, trip and natural environment characteristics that were directly evaluated by sample respondents when making mode choice decisions, and also socio-economic characteristics of each individual respondent.

Variable selections are mainly based on the literature review in order to 1. identify which variables should theoretically to be included in the models and 2. choose the most likely relationship (e.g. linear or curvilinear etc.) between an explanatory variable and the utility associated with each mode. For example, it is expected that temperature may have a curvilinear relationship with mode choice such that extreme temperatures (too high or too low) could decrease bike-sharing utility. Nonetheless, only linear relationship was confirmed in earlier researches (e.g. Parkin et al., 2008, Saneinejad et al., 2012) which reached similar conclusions that temperature positively affected cycling choice. Thus, temperature is included in linear form in the MNL model. Age and income were occasionally found to have curvilinear relationships with the utility of cycling choice (e.g. Moudon et al., 2005). However, they are still assigned linear relationships in this research as per the results in most of the literature. The variables used in the mode choice model specification are presented in the Equations 1 to 6 below.

Local facts and characteristics are also taken into account in variable selections. For example, as explained earlier household income is a more accurate indicator than house tenure type when representing wealth status of Taiyuan citizens. Also, some variables are deliberately dropped out. Usage of the smartphone may affect mode choice. Nonetheless, there is a high percentage of smartphone possession in the sample such that it will not demonstrate any significant impacts if being included in the model. The possession of public transport card is highly correlated to both bus and bike-sharing choice in positive direction. However, due to the possibility of reverse causality that the card may only belong to those who have interests in bus and bike-sharing usage, this variable is dropped out from the model. Some researches use GIS to capture the distinctive geographical characteristics around each individual’s home or workplace (e.g. road hilliness, cycle lane availability etc.) to explain mode choice. Nevertheless, such built environment characteristics do not affect this case study since the streets and transport infrastructures across Taiyuan are in general identical in terms of appearance and function; other built environment characteristics such as parking space and bus/bike-sharing station proximity are already captured in the SP mode choice experiment.

Additionally, a number of pilot models are tested to analyse the potential impacts of several categorical variables, such as age groups, income groups and educational level groups. Some clear trends are observed for these variables on mode choice behaviour; however, the impact of each individual subgroup can hardly be statistically significant per se. As a result, the subgroups of each categorical variable are merged into two general groups (i.e. low and high) in order to more explicitly demonstrate their impacts.

Three availability conditions are added in the model: 1. Car is available to households that own a car, 2. Electric bike is available to households that own an electric bike, and 3. Cycling is available to those who are able to cycle given their health condition. The availability conditions will increase model validity by helping explain the circumstances that someone does not choose a particular mode due to the fact that the mode is an unavailable option. Possession of driving licence is not considered as an availability condition since choosing car or car-sharing as travel mode can be made by drivers as well as passengers; possession of public transport card is also excluded as travellers can still access bus or bike-sharing by borrowing others’ cards or paying cash.

$$U_{walk} = \alpha_{walk} + \beta_{com1}*\mathrm{COMMUTE} + \beta_{rain1}*\mathrm{RAIN} + \beta_{tem1}*\mathrm{TEM} + \beta_{pol1}*\mathrm{POLLUTION} + \beta_{walktt}*\mathrm{WALKTT} + \beta_{age1}*\mathrm{AGELOW} \tag{1}$$

$$U_{bikeshare} = \alpha_{bikeshare} + \beta_{com2}*\mathrm{COMMUTE} + \beta_{rain2}*\mathrm{RAIN} + \beta_{snow2}*\mathrm{SNOW} + \beta_{tem2}*\mathrm{TEM} + \beta_{pol2}*\mathrm{POLLUTION} + \beta_{bikesharett}*\mathrm{BIKESHARETT} + \beta_{bikesharetc}*\mathrm{BIKESHARETC} + \beta_{bikesharewt}*\mathrm{BIKESHAREWT} + \beta_{bikeshareapp}*\mathrm{BIKESHAREAPP} + \beta_{male2}*\mathrm{MALE} + \beta_{age2}*\mathrm{AGELOW} + \beta_{inc2}*\mathrm{INCLOW} + \beta_{fix2}*\mathrm{FIXJOB} + \beta_{edu2}*\mathrm{EDULOW} \tag{2}$$

$$U_{ebike} = \alpha_{ebike} + \beta_{com3}*\mathrm{COMMUTE} + \beta_{rain3}*\mathrm{RAIN} + \beta_{snow3}*\mathrm{SNOW} + \beta_{pol3}*\mathrm{POLLUTION} + \beta_{ebikett}*\mathrm{EBIKETT} + \beta_{male3}*\mathrm{MALE} + \beta_{age3}*\mathrm{AGELOW} + \beta_{inc3}*\mathrm{INCLOW} + \beta_{fix3}*\mathrm{FIXJOB} \tag{3}$$

$$U_{bus} = \alpha_{bus} + \beta_{tem4}*\mathrm{TEM} + \beta_{bustt}*\mathrm{BUSTT} + \beta_{bustc}*\mathrm{BUSTC} + \beta_{buswt}*\mathrm{BUSWT} + \beta_{busfre}*\mathrm{BUSFRE} + \beta_{busapp}*\mathrm{BUSAPP} + \beta_{male4}*\mathrm{MALE} + \beta_{age4}*\mathrm{AGELOW} + \beta_{inc4}*\mathrm{INCLOW} + \beta_{fix4}*\mathrm{FIXJOB} \tag{4}$$

$$U_{carshare} = \alpha_{carshare} + \beta_{com5}*\mathrm{COMMUTE} + \beta_{rain5}*\mathrm{RAIN} + \beta_{snow5}*\mathrm{SNOW} + \beta_{tem5}*\mathrm{TEM} + \beta_{pol5}*\mathrm{POLLUTION} + \beta_{carsharett}*\mathrm{CARSHARETT} + \beta_{carsharetc}*\mathrm{CARSHARETC} + \beta_{carsharewt}*\mathrm{CARSHAREWT} + \beta_{carshareapp}*\mathrm{CARSHAREAPP} + \beta_{male5}*\mathrm{MALE} + \beta_{age5}*\mathrm{AGELOW} + \beta_{inc5}*\mathrm{INCLOW} + \beta_{fix5}*\mathrm{FIXJOB} + \beta_{edu5}*\mathrm{EDULOW} \tag{5}$$

$$U_{car} = \alpha_{car} + \beta_{com6}*\mathrm{COMMUTE} + \beta_{rain6}*\mathrm{RAIN} + \beta_{snow6}*\mathrm{SNOW} + \beta_{pol6}*\mathrm{POLLUTION} + \beta_{cartt}*\mathrm{CARTT} + \beta_{cartc}*\mathrm{CARTC} + \beta_{carps}*\mathrm{CARPS} + \beta_{carpc}*\mathrm{CARPC} + \beta_{male6}*\mathrm{MALE} + \beta_{inc6}*\mathrm{INCLOW} + \beta_{fix6}*\mathrm{FIXJOB} \tag{6}$$

Where:
COMMUTE = 1 if trip purpose is work/education, 0 if otherwise;
RAIN = 1 if weather is rainy, 0 if otherwise;
SNOW = 1 if weather is snowy, 0 if otherwise;
TEM = temperature;
POLLUTION = air pollution level (1=excellent air, 2=good air, 3=light pollution, 4=medium pollution, 5=heavy pollution, 6=terrible pollution);
WALKTT = travel time by walk (in min);
BIKESHARETT = travel time by bike-sharing (in min);
BIKESHARETC = travel cost by bike-sharing (in ￥);
BIKESHAREWT = walking time to bike-sharing station (in min);
BIKESHAREAPP = app availability for bike-sharing (1 if available, 0 otherwise);
EBIKETT = travel time by electric bike (in min);
BUSTT = travel time by bus (in min);
BUSTC = travel cost by bus (in ￥);
BUSWT = walking time to bus (in min);
BUSFRE = bus frequency, the waiting time between two buses (in min);
BUSAPP = app availability for bus (1 if available, 0 otherwise);
CARSHARETT = travel time by car-sharing (min);
CARSHARETC = travel cost by car-sharing (￥);
CARSHAREWT = walking time to car-sharing station (min);
CARSHAREAPP = app availability for car-sharing (1 if available, 0 otherwise);
CARTT = travel time by car-sharing (min);
CARTC = travel cost by car-sharing (￥);

CARPS = car parking space (1 if easy to find, 0 if not);
CARPC = car parking cost (￥/h);
MALE = 1 if gender is male, 0 if female;
AGELOW = 1 if age is “under 18” or “18-25” or “26-35”, 0 if “36-45” or “46-59” or “60 or above”;
INCLOW = 1 if household monthly income is “under ￥3000” or “￥3000-￥6000” or “￥6000-￥9000”, 0 if “￥9000-￥15000” or “￥15000-￥30000” or “over ￥30000”;
FIXJOB = 1 if occupation is fixed job, 0 if otherwise;
EDULOW = 1 if educational level is “high school or below” or “college”, 0 if “undergraduate” or “graduate and above”.

Model estimation results are presented in Table 3. Variables with coefficients statistically significant only at 95% confidence interval or higher are labelled. In general, most of the coefficients have the expected signs of impacts on mode choice. The unexpected signs will be interpreted accordingly throughout the text. The results offer rich insights on the impacts of natural environment factors, trip and mode attributes and socio-economic characteristics on bike-sharing as well as other alternative mode choices.

First of all, air pollution level, weather and temperature all have the expected directions of impacts on bike-sharing usage and the impacts are all highly significant at 99% level. An increase in air pollution level will discourage travellers from using bike-sharing due to the concern of health damage. Air pollution has the same impact also on walk and electric bike, which both are more exposed transport modes. However, air pollution is not statistically significant in the electric bike alternative probably due to the fact that the exposure is limited as travel time is significantly low. As expected, air pollution positively affects the choice of car attributed to the protection it can offer. However, the impact is insignificant possibly due to the short trip distance as well. Car-sharing can also protect travellers from air pollution as a private car but it involves an inevitable walking period or even waiting time to access vehicles. Such slight differentiation may explain the opposite pollution impact signs between car and car-sharing, especially in short distance trip in which the walking period may be more weighted than in longer trips. Thus, it is expected to have positive air pollution impact signs on car-sharing in longer distance trips although this needs further research to prove.

The findings regarding the impact of weather conditions are similar to those of earlier studies. Specifically, bad weather (i.e. rain or snow) and low temperature can both decrease the demand for bike-sharing, electric bike and walk; whereas car and car-sharing will be more appealing. In particular, the temperature impacts fit well with the conditions in the case study city, which is extremely cold in winter but not too hot in summer. As such, a warmer day can indeed benefit the choices of more exposed modes. Nonetheless, the most valuable finding by reviewing natural environment impacts comes from the results of car-sharing choice. As already explained, car-sharing is featured by both better protection to the natural environment and an access trip by walking. By comparing the results that car-sharing will be avoided when air pollution level increases and it will however still be chosen in rainy or snowy days, we may conclude that air pollution impacts are more concerned by travellers than weather condition impacts when making mode choice decisions. The finding is also shown by the t-statistics that air pollution impacts are more significant than rain and temperature impacts on car-sharing choice.

Secondly, insights on impacts of trip characteristics and mode attributes are revealed. A commute trip (i.e. work/education) is positively correlated with walk and electric bike use while it is negatively correlated with bike-sharing, car-sharing and car use. Two conclusions can be drawn: 1. in short distance trips, car is less preferred than others; 2. arriving on time is usually a key requirement for a commute trip and therefore door-to-door modes (i.e. walk and electric bike) are more likely to be chosen than shared modes (i.e. bike-sharing and car-sharing) since the latter could involve time uncertainties during vehicle rent/return process. Next, the impacts of mode attributes offer a number of important findings. All the coefficients of bike-sharing attributes have the expected signs. Increases in travel time, walking distance to the docking station and cost will decrease the possibility to choose bike-sharing, whereas smartphone app availability favours bike-sharing choices. However, their impacts appear insignificant when the trip distance is short. Similar insignificances are also found on some attributes associated with car and car-sharing choices, which altogether imply the need for further research including longer trips to reassess the impacts of mode attributes when travel distance varies. Nevertheless, several coefficients do have the impact signs that are opposite to our expectations, such as bus travel time (positive sign), bus walking time to station (positive sign), car share travel time (positive sign), car travel time (positive sign) and car parking space availability (negative sign). The key insight that could be drawn is the fact that Taiyuan citizens may have strong unwillingness to pay for transport activities since the signs imply they will give up a choice when the mode becomes costlier but will not do so when travel time increases. In the end, the unexpected sign of car parking space availability can be explained by the fact that parking regulations are not strict in Taiyuan and drivers often park wherever they want when they do not easily find a designated parking space. Thus, it is not an influential factor to car use in this case.

Finally, the impacts of different socio-economic characteristics vary across transport modes. The younger generation (those under 36 years old) seems to prefer the convenience of car-sharing and bus (positive signs) instead of walk, bike-sharing and electric bike (negative signs). Such result is sharply different to the results in developed countries where younger generations are usually keener to use active transport (e.g. Shafizadeh and Niemeier, 1997; Ricci, 2015; etc.). This may be a special phenomenon in China owing to its one-child policy such that too much care is given to the single child who is, therefore, more likely to develop “comfort or spoiled habits”. It is not only revealed by Chinese young people’s transport mode choices but also widely reflected in other areas such as lack of sports activities (Ye, 2012) etc. Next, males are found to use more bike-sharing than females, which is similar to earlier research results (e.g. Moudon et al., 2005; Akar et al., 2013; etc.). Males also prefer private cars, while females are more likely to choose electric bike, bus or car-sharing. Household income also has explicit impacts on mode choice behaviour. Higher income groups prefer choosing private car even the trip distance is short, whereas lower income groups generally prefer shared, public or active transport. Travellers with fixed jobs will use more privately owned or faster modes such as electric bike, car or car-sharing; they do not like to use bus or bike. At last, educational level is included to test its impacts on shared mode choices which are fresher and more innovative concepts compared to traditional public transport among people in developing countries. The results show that participants with higher education prefer car-sharing. However, educational level does not significantly affect bike-sharing choice. Such difference may be due to the fact that bike-sharing is already available in Taiyuan so that the lower education groups, who may learn and accept new modes more slowly, have already been familiar with bike-sharing as well. However, car-sharing is only a potential option that may be introduced in the future and many respondents firstly know this concept via the questionnaire survey of this research. Therefore, the educational impact of faster learning and more openness to new concept is only significant in affecting car-sharing choice.

In summary, the most important insights based on model results are highlighted below:

- As air pollution levels increase, the possibility of choosing bike-sharing, electric bike, walk, and car-sharing (which involves walking to access the mode) decreases.
- Shared modes (i.e. bike-sharing and car-sharing) are not preferred for commute trips due to the concern of time uncertainty during vehicle rent/return process.
- Negative willingness to pay for transport modes is discovered in this Chinese city case; in order words, travellers are willing to trade travel time for a cheaper transport fare.
- The Younger generation in China do not prefer bike-sharing, walk or electric bike and would rather choose car-sharing or bus for short distance trips. The phenomenon can possibly be explained by their habits of avoiding discomfort.
- Lower income groups prefer bike-sharing and car-sharing.
- Travellers with higher educational levels are more likely to choose newly introduced transport modes perhaps due to their openness to new mobility services.

Table 3: Model estimation results for short distance trips

	Coefficient	t-statistic	Significance
Commute-walk	0.10	1.41	-
Rain-walk	- 1.00	- 9.13	99%
Temperature-walk	0.02	6.07	99%
Air pollution-walk	- 0.25	- 11.05	99%
Travel time-walk	- 0.03	- 3.83	99%
Age (lower half)-walk	- 0.26	- 3.52	99%
Commute-bike share	- 0.35	- 3.06	99%

Rain-bike share	- 1.17	- 6.15	99%
Snow-bike share	- 0.94	- 9.40	99%
Temperature-bike share	0.02	4.15	99%
Air pollution-bike share	- 0.27	- 6.93	99%
Travel time-bike share	- 0.07	- 1.25	-
Travel cost-bike share	- 1.12	- 0.96	-
Walk time-bike share	- 0.04	- 1.97	-
App availability-bike share	0.07	0.71	-
Male-bike share	0.02	0.41	-
Age (lower half)-bike share	- 0.18	- 2.12	95%
Income (lower half)-bike share	0.02	0.19	-
Fixed job-bike share	- 0.08	- 1.11	-
Education (lower half)-bike share	0.01	0.14	-
Commute-ebike	0.15	1.34	-
Rain-ebike	- 0.99	- 6.74	99%
Snow-ebike	- 1.02	- 9.96	99%
Air pollution-ebike	- 0.02	- 0.75	-
Travel time-ebike	- 0.14	- 2.65	99%
Male-ebike	- 0.08	- 1.10	-
Age (lower half)-ebike	- 0.25	- 2.65	99%
Income (lower half)-ebike	0.46	3.71	99%
Fixed job-ebike	0.23	2.55	95%
Temperature-bus	0.01	2.32	95%
Travel time-bus	0.06	3.85	99%
Travel cost-bus	- 0.29	- 3.49	99%
Walk time-bus	0.10	6.34	99%
Frequency-bus	- 0.02	- 2.24	95%
App availability-bus	0.24	2.81	99%
Male-bus	- 0.33	- 7.07	99%
Age (lower half)-bus	0.04	0.48	-
Income (lower half)-bus	0.37	5.41	99%
Fixed job-bus	- 0.23	- 4.24	99%
Commute-car share	- 0.19	- 1.98	95%
Rain-car share	0.13	0.82	-
Snow-car share	0.22	2.10	95%
Temperature-car share	0.01	1.27	-
Air pollution-car share	- 0.08	- 2.47	95%
Travel time-car share	0.03	1.62	-
Travel cost-car share	- 0.27	- 4.62	99%
Walk time-car share	- 0.05	- 2.67	99%
App availability-car share	0.04	0.38	-
Male-car share	- 0.16	- 2.58	99%
Age (lower half)-car share	0.02	0.23	-
Income (lower half)-car share	0.23	2.54	95%
Fixed job-car share	0.14	1.71	-
Education (lower half)-car share	- 0.13	- 2.11	95%
Commute-car	- 0.55	- 5.37	99%
Rain-car	0.35	2.38	95%
Snow-car	0.08	0.80	-
Air pollution-car	0.05	1.51	-

Travel time-car	0.06	1.74	-
Travel cost-car	- 0.06	- 0.19	-
Parking space-car	- 0.08	- 0.98	-
Parking cost-car	- 0.08	- 4.81	99%
Male-car	0.17	2.46	95%
Income (lower half)-car	- 0.23	3.84	99%
Fixed job-car	0.34	- 2.89	99%

5. Conclusions and policy implications

This study investigates the factors affecting mode choice behaviour for short distance trips in China. Taiyuan, a Chinese city with 3 million citizens and the mostly demanded bike-sharing scheme in the country, is chosen as the case study area. A mode choice model using SP data is developed. Mode choices among multiple alternatives are simultaneously modelled by MNL to create more insightful comparisons and produce more robust findings. The impacts of various natural environment factors, trip and mode attributes and socio-economic characteristics on mode choice behaviour are revealed, while the results generate a number of important insights. Based on those key findings, policy implications can be derived accordingly to explore the potential pathways to promote bike-sharing usage in developing countries:

- Tackling air pollution in industrial, service and residential sectors can indirectly help deliver sustainable urban mobility via "multiplier effect[†]". The findings have confirmed the significant negative impacts of air pollution on bike-sharing usage as well as other exposed alternatives such as walk and electric bike. Therefore, a virtuous circle is highly expected; a reduction of air pollution level could considerably encourage the demand for all those low-carbon transport modes and their higher usage rates could further reduce air pollution level, and so on so forth, which generates the "multiplier" effect. New transport mode alternatives such as carpooling and car-sharing could also be introduced in developing countries to serve as practical substitutes to private car and in turn directly reduce air pollution resulted by car-related emissions.
- Improve bike-sharing service standards especially in areas that have high workplace densities (e.g. Central Business District, CBD). Measures can include increasing the number of docking stations or create more flexible bike return rules during peak time to eliminate uncertainties concerned by commuters. For example, portable card scanning machine can be developed to record bike usage data so that bikes can be returned to and assembled by a staff besides returning to the traditional docks on a one-to-one basis; however it should only be a temporary service at certain time and certain locations since labour costs will be involved.
- Maintain bike-sharing price at low levels due to the discovered negative willingness to pay for transport modes among travellers in developing country. For example, any fixed rental cost can be abandoned to avoid discouraging short distance bike-sharing usage.
- Effort on changing young people's transport mode choice behaviour should be a focus since the current young generation may become the main commute group in near future. Policies can involve direct measures such as offering young-person discounts to travellers under certain age criteria, or can be indirect measures such as information campaigns at schools or workplaces to disseminate the benefits of bike-sharing within young generations.
- Utilising the demand potential of lower income groups via designing bespoke policies to allow bike-sharing to become their first transport choice especially for short distance trips. Effort can also involve increasing incentives for higher income groups such as introducing tax schemes on their private car use. However, any pricing related policies must be treated with caution since lower income groups may be the most affected instead of those with more wealth who may still be willing to afford any extra charges.

[†] Multiplier effect is a term used in economics, that an injection of new spending into the circular flow produces an increase in national income greater than the initial amount spent. This is because the injection leads to more income, which creates more spending, and so on.

- Communicate with local residents to provide them with sufficient knowledge on bike-sharing especially when introducing the scheme to a new place.

As this paper is the first attempt to model the factors affecting mode choice behaviour in a developing country, there are a number of future research opportunities to further exploit the results and insights generated at this stage. Firstly, the reliability of mode choice study based on SP data may be limited by the possibility of inconsistent choice behaviours between hypothesised scenarios and reality. As a result, a mode choice model using both the RP and the SP data will be developed in the future. Secondly, the second round of the survey that recruits the same individuals to track their travel behaviour during winter is about to be completed. By having data about the actual travel behaviour during summer and winter, we could use the RP data from the travel diary and compare the actual effects of different temperatures and air pollution levels. Thirdly, more potential explanatory variables can be added to more precisely interpret mode choice behaviour. These may include interaction effects between natural environment factors and different demographic groups, attitudes and perceptions of travellers in developing countries towards different transport modes etc. In these cases, more advanced models such as hybrid choice models should be developed to capture for example the latent effect of attitudes and perceptions. Finally, after having improved models and results as well as different distance scenarios, the effects of different policy combinations can be quantified via simulation to offer more thorough and explicit evidence to policy makers.

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