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Title: The effectiveness of behavioural interventions on residential location choices and commute behaviours: Experimental evidence from China

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The effectiveness of behavioural interventions on residential location choices and commute behaviours: Experimental evidence from China

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We used randomised controlled trials to test the effectiveness of three behavioural interventions, i.e., focalism, social norm, and visualisation, in changing people's housing and commuting preferences. The experiment was conducted online via Credamo, one of the largest online panel data providers in China. We included only renters who needed to commute in the city of Xi'an as participants in the study. Our results show that behavioural interventions significantly increased respondents' willingness to adopt more sustainable commute modes, such as walking or cycling, and reduced the tendency to use private cars. Among the three behavioural interventions, the social norm intervention had the largest and most significant impact. Our findings shed light on the potential of applying behavioural interventions in sustainable urban transport management. More importantly, the results demonstrate the possibility of using behavioural interventions to incorporate sustainable urban development goals into housing decisions.

Keywords: behavioural intervention, nudge, peer pressure, transport management, online panel data, randomised controlled trials

JEL codes: R21, R41, C93

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1. Introduction

Modern urban development brings with it an array of transportation challenges that significantly affect both the environment and the daily lives of people. To address these issues, governments employ a combination of supply-side approaches, such as the expansion of bicycle lanes and subway systems, and demand-side strategies known as transportation demand management (TDM). These TDM strategies, often coupled with behavioural interventions, have shown encouraging results in promoting sustainable urban lifestyles.

Issues related to transportation, like traffic congestion and air pollution, contribute to broader societal challenges, including environmental damage and public health concerns. For instance, the global transportation sector was responsible for 28% of energy consumption and 23% of CO2 emissions in 2014. Increasing reliance on private vehicles leads to urban sprawl and poor land-use efficiency. Moreover, a trend towards driving and less physical activity is associated with higher rates of obesity and cardiovascular diseases. Addressing these transportation issues is thus imperative for society as a whole. Governments tackle these challenges through both supply-side methods, such as creating new cycle lanes and subway stations, and demand-side methods that influence individuals' travel decisions. These demand-side solutions collectively fall under the umbrella of TDM.

TDM tools can be grouped into various categories based on different criteria. For instance, they may be divided into monetary tools, which align with mainstream economic theories and incentivise changes in behaviour through financial rewards like free bus passes or off-peak fare discounts. While effective, these tools often involve ongoing costs and may not

have lasting effects once the incentives are removed. Behavioural TDM tools, derived from psychological research, utilise non-monetary soft interventions to prompt individual changes at a low cost. Beyond categorisation by intervention type, TDM tools can also be classified by their target groups. Some research within TDM is focused on altering the behaviour of specific industries, such as logistics.

Behavioural interventions aimed at the general populace are gaining increased focus in TDM research due to evidence suggesting their effectiveness in reducing private car use and encouraging the use of public transport. Various interventions, including the dissemination of persuasive information, awareness campaigns, and even simple notifications, have been shown to encourage a shift away from private vehicle usage. Given their low expense and substantial impact, these interventions are being adopted globally in the transportation sector.

Behavioural interventions leverage principles of behavioural science to assist individuals in making better decisions while preserving their freedom of choice. The underlying assumption is that unconscious biases often lead to suboptimal decisions. By either utilising these biases or helping individuals to overcome them, behavioural interventions can encourage more favourable outcomes. Although not universally successful, these interventions are still considered cost-effective due to the sheer number of people they can reach and their low deployment costs. These interventions have seen success in a variety of fields. For instance, numerous studies have demonstrated the impact of behavioural interventions on household energy conservation, improving public health, and increasing enrolment in different programs.

Encouraged by these successes, researchers are exploring the application of behavioural interventions within TDM to promote sustainable travel behaviours. These interventions are categorised into several goals: reducing private car usage, promoting public transportation, encouraging active travel such as walking and cycling, and influencing residential choice. The latter is particularly important, as a person's place of residence and work significantly dictates their daily travel behaviour. Studies have shown that nudges encouraging relocation to areas with better public transportation access can effectively alter travel behaviours and are categorised into short-term and long-term programs. Short-term programs directly influence immediate travel choices, whereas long-term programs aim to indirectly impact travel behaviour by influencing factors such as residential location decisions. While long-term interventions may affect fewer individuals initially, they have the potential for more enduring impacts compared to short-term interventions.

Several studies have validated the effectiveness of behavioural interventions in influencing relocation decisions, yet gaps remain in the literature. Notably, existing research predominantly focuses on developed countries, with the efficacy of these interventions in developing countries remaining uncertain. Additionally, while various interventions have proven effective, comparing their relative success is challenging due to varying contexts, environments, and experimental designs across studies.

This study examines the application of Behavioural interventions in TDM, specifically testing the efficacy of three distinct interventions on residential location choices and commuting behaviours in China. It seeks to determine whether these interventions are effective in the unique urban context of China and which intervention is superior. The study's objective is to not only identify effective tools but to discern the most efficient among them. Previous research often examined one intervention at a time, making direct comparisons difficult. This study addresses this by implementing three interventions concurrently for direct comparison.

The paper is organised as follows: Section 2 presents a thorough review of relevant literature. Section 3 outlines the experimental design and execution. The empirical results are detailed in Section 4, and the final section provides a conclusion.

2. Literature Review

Following the Cochrane guidelines (Higgins et al., 2019), this analysis was confined to studies encompassing both behavioural interventions and Transportation Demand Management (TDM), utilizing solely randomized controlled trials (RCTs) and quasi-experiments. The Web of Science database yielded 43 studies. These were further categorized using Michie's behaviour change technique taxonomy (Michie et al., 2013), with the results summarized in Table 1.

The most prevalent intervention – the dissemination of general information – represents a straightforward and efficacious method for influencing individuals' travel decisions. This intervention draws on two behavioural insights. First, individuals' suboptimal choices are often due to a lack of essential information; providing the necessary information can rectify this issue (Sunstein, 2018). For instance, participants in three studies (Franssens et al., 2021; Mir et al., 2016; Lieberoth et al., 2018) received additional data on the advantages of public transport, resulting in a positive shift in their travel behaviours compared to control groups. Second, behavioural scientists assert that unconscious biases influence information processing. Researchers can assist by highlighting these biases. For example, Bhattacharyya et al. (2019) introduced "focalism" – a term denoting the tendency for tangible factors to overshadow more crucial intangible ones in decision-making processes. By informing participants of the "focalism" effect, the study significantly altered travel choices. Information interventions also leveraged other behavioural concepts, such as anchoring and herding effects, all aiming to enhance decision-making by providing targeted information.

Personal travel planning ranks as the second most examined behavioural intervention within TDM. Its essence lies in "directly assisting and motivating individuals to voluntarily modify their travel decisions" (Chatterjee, 2009), involving various behavioural techniques like goal-setting, self-monitoring, and social support. This intervention has proven particularly potent in altering daily commuting habits. Nevertheless, with the experimental designs becoming increasingly stringent, researchers (Semenescu et al., 2020; Rosenfield et al., 2020) have begun to recognize significant discrepancies between participants' self-reported behaviours and passively-collected data.

The feedback intervention has garnered increased focus over the last five years due to technological advancements. Previously deemed impractical due to the high costs of gathering personalized data, the ubiquity of smartphones has since allowed for the economical collection and provision of personalized feedback. Four studies (Lieberoth et al., 2018; Rosenfield et al., 2020; Piwek et al., 2015; Aittasalo et al., 2012) employing this approach have documented substantial positive impacts in diminishing car usage and promoting active travel.

Table 1: Classifications of behavioural interventions in the TDM literature

Behavioural intervention	Number of studies	Description
General information	25	General information intervention means giving more information or making it easier for people to get certain kinds of information. The intervention ranges from a small environmentally friendly label on the bus card to a mixed package of brochure, accessibility information, newsletter, etc.
Complex programme	9	Complex programme means incorporating different behavioural tools (and sometimes monetary incentives) together in the same package. Instead of exploring the effect of certain interventions, the primary aim of these programmes is to maximise the influence.
Personal travel planning	6	Most personal travel planning projects contain two steps: first, the researcher asks participants to think about possible travel changes in the near future. Second, participants write down their plans as detailed as possible and review them in the following days.
Feedback	6	Feedback interventions allow participants to monitor their behaviours, therefore incentivising them to reach specific travel goals. Pedometers, mobile phone apps, and periodic emails are the most commonly used tools.
Training course	3	Training courses provide a range of information and practice opportunities for participants. Those who attended the course may learn specific skills like cycling. These skills can influence their attitudes toward active travel and reduce the accident rate.
Personalised information	3	Personalised information intervention also means giving information to participants, with the only difference being that the information is customised to each participant. This intervention largely depends on mobile phone apps.
Others	3	None of above

The objectives of these behavioural interventions include reducing private car use (see, for example, Luo et al., 2021 and Asensio et al., 2021), promoting public transportation (e.g., Franssens et al., 2021, and Gravert and Collentine, 2021), and encouraging active travel such as walking and cycling (see, for instance, Ahmed et al., 2020, Van de Sompel et al., 2020). Determining the effectiveness of a behavioural intervention is a challenging aspect of these studies. The study design directly influences the effect evaluation. The last decade has witnessed an increase in insignificant results as the experimental method became more rigorous (Bamberg and Rees, 2017, Arnott et al., 2014, Sussman et al., 2020, Villa-Gonzalez et al., 2018). Second, even if different articles tested the same type of intervention, differences in designs among these studies affect their results. For example, to test the effect of the personal travel planning intervention, Kristal and Whillans (2020) used a relatively simple intervention and reported an insignificant result. In contrast, Bamberg and Rees (2017) chose a similar but more user-tailored intervention and reported significant results.

Unlike monetary incentives that hardly last when the incentive is moved, behavioural interventions create a prolonged but dwindling effect (Sunstein, 2018). The central question is how long the effect could last. Existing studies showed the time ranges from weeks to years in different experimental settings. Moreover, the different standards researchers chose to measure the outcome further complexed the problem. Many different measurements (e.g. the self-reported travel distance, the passive GPS record, and the daily travel diary) existed and it was

hard to tell which one was better. Sussman et al. (2020) provided a detailed discussion on this issue.

Researchers are also concerned about the right time to deliver interventions, which is as important as choosing a suitable intervention. Since travel or commute pattern is more like a habit, major life events (e.g., marriage, retirement, and relocation) may provide a "window of opportunity" during which individuals are more self-conscious and sensitive to behaviour change interventions (Larouche et al., 2018, Verplanken and Roy, 2016, Ralph and Brown, 2019, Bamberg, 2013). For example, studies of relocation's influence on travel choices show that the "window of opportunity" to be three months after relocation (Verplanken and Roy, 2016, Haggar et al., 2019, Walker et al., 2015).

Since people's residential choices and workplaces fundamentally determine their travel behaviours in the long term, nudging individuals to a better relocation choice has become an alternative option for TDM. Ideally, once movers receive suitable nudges at the right time, they may move to places with better public transportation facilities and increase the chance of developing environmentally friendly travel habits. Scholars in this field, therefore, are interested in finding effective behavioural interventions and the right time to deliver them. We identified eight behavioural studies in this area, as summarised in Table 2.

Providing information is the most frequently used behavioural intervention. Specifically, six out of the eight studies gave participants in the treatment group additional information. The outcome of these interventions, however, differed due to the local context, the experiment design, and the exact additional information they used.

Bamberg (2006) found that giving participants free travel cards and personal schedule information about public transportation affected their location choices, although Bamberg did not separate the effect of monetary intervention (free travel card) and the behavioural intervention (personal schedule information). Rodriguez et al. (2011) confirmed that accessibility information would change people's location choices in a laboratory setting. Rodriguez and Rogers (2014) and Taniguchi et al. (2014) verified this relationship with university students. However, by separating participants into the 'mover' and 'non-mover' groups, Ralph and Brown (2019) found that the information provision intervention changed students' travel behaviour, but no significant result was reported among the location choices of different groups. Ralph regarded this outcome as evidence showing that, instead of influencing people's location choices, the intervention only changed people's travel behaviour. In 2020, Guo and Peeta (2020) conducted a similar experiment with an interactive online accessibility mapping application. The study showed a 10% decrease in automobile usage and a 10% increase in walking in the treatment group.

There are other behavioural intervention tools used in these studies. Bhattacharyya et al. (2019) adopted two interventions based on the concept of focalism and visualization. The focalism intervention reminded respondents to notice the important but intangible features of housing units; the visualization intervention prompted respondents to imagine their future life. The result indicated both interventions significantly improved people's travel behaviour, but only people in the focalism group significantly reduced their travel time after relocation. Verplanken and Roy (2016) also identified a positive influence of behaviour interventions in promoting environmentally friendly travel habits.

Although the eight experiment studies made considerable progress and provided important information in the last ten years, half of the articles (Ralph and Brown, 2019, Rodriguez et al., 2011, Rodriguez and Rogers, 2014, Taniguchi et al., 2014) used university students in their experiments. Furthermore, all eight studies were carried out in developed countries. The reliability of their conclusions in a broader context is still unclear. Moreover, most of them considered one intervention only, and when multiple interventions were considered, the net effect of each tool was not effectively separated. This study sets out to address these gaps in the literature by conducting field experiments with a wider range of decision-makers in a developing country and by designing and implementing a RCT that can separate the net effect of multiple behavioural interventions.

Table 2: Behavioural Intervention Studies in the TDM Literature

Author	Place	Intervention	Sample	Design	Follow-up period
Bamberg 2006	GER	Bus time info	169	RCT	6 weeks
Bhattacharyya 2019	US	1.Focalism intervention; 2.Visualization intervention	184	RCT	3 months
Guo 2020	US	Personalized accessibility info	282	RCT	3 months
Ralph 2019	US	Transportation guide	561	RCT	3 months
Rodriguez 2011	US	Accessibility info	236	RCT in lab	-
Rodriguez 2014	US	Accessibility info	292	Field experiment	6 months
Taniguchi 2014	Japan	Information brochure; Accessibility info; Persuasive leaflet	69	RCT	5 and 11 months
Verplanken 2016	UK	1.Personal interview; 2.Sustainable goodie bag; 3.Green directory info; 4.Newsletter	521	Field experiment	8 weeks

3. Experiment design and implementation

3.1 Study area

We chose Xi'an, the capital city of Shaanxi province in China, as the study area. The population size of Xi'an is 13 million in 2022. The urban area of Xi'an city is over 700 km^2. By contrast, the Greater London has a population of 8.9 million living in an urban area of 1595 km^2. The location of Xi'an in China is shown in Figure 1.

As the purpose of this study is to test whether behavioural interventions can affect renters' commuting decisions, it is important to choose study areas where people do have choices for commuting. For example, interventions can nudge people to switch to buses and subways only when there are such options available in that city. Until June 2021, Xi'an residents enjoy a subway network of eight lines with 159 stations and 250 km of tracks, radiating out from the centre of the city. Moreover, Xi'an is one of the fifteen "bus city" in China 1. The city has 495 bus lines with an average ticket price of 2 RMB (0.25 GBP) for one-

way trips. The city's temperature ranges from -5 to 30 C. With footpaths and shared bicycles available throughout the city, walking and cycling are viable commute options. Finally, Xi'an does not have any congestion charge or other restrictions limiting the use of private cars (e.g., cars can only be driven on alternative days depending on the last digits of the car registration number). Therefore, Xi'an is chosen because of its range of transportation options.

Another aspect to be factored in is rental affordability, which largely determines how much room renters have for manoeuvrer after prices are considered. In general, the higher the rental prices, the fewer housing options that renters have within their budget. This indirectly restricted their choice of preferred commute modes. We used rental expenditure as a proportion of household income as an indicator and found that Xi'an's value is below average. Therefore, renters in Xi'an have more properties to choose from. The relatively lower commute costs as a proportion of household income also encourage renters to take commute choice seriously.

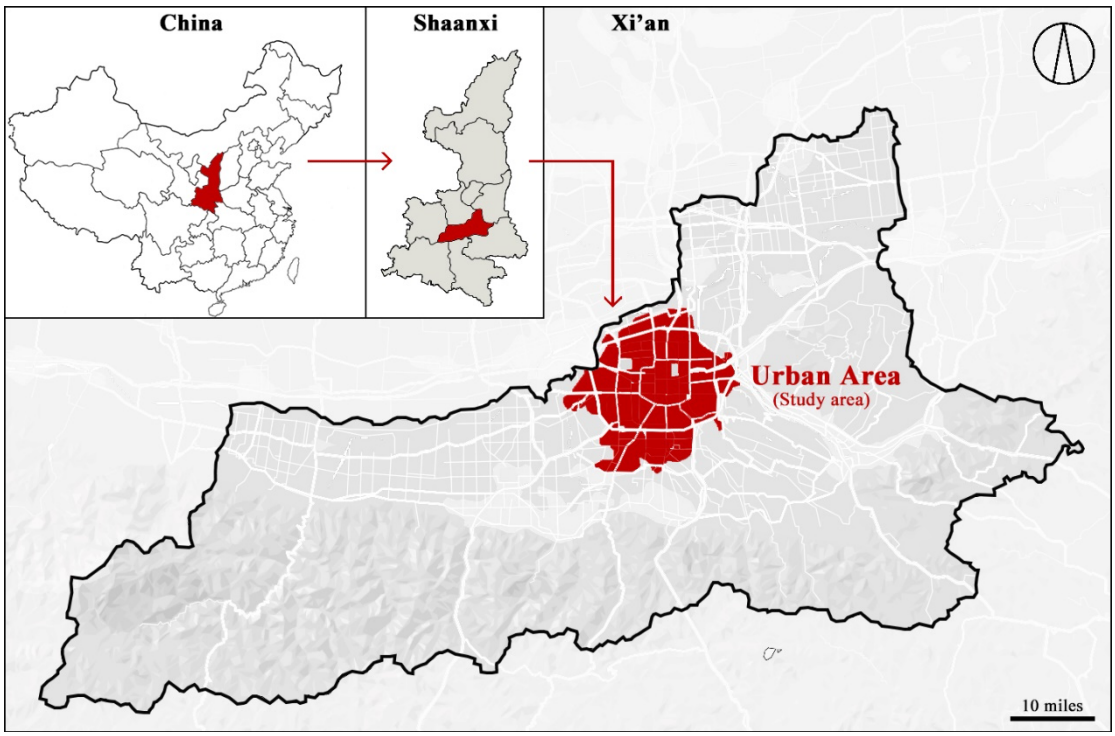

Figure 1: The location of Xi'an city

3.2 Experiment structure

We conducted randomised controlled trials to test the hypotheses. Participants of the experiments were recruited from an online panel data platform in China (www.credamo.co). The questionnaire consists of seven parts of questions (see Figure 2) that covers four groups of information, i.e., background information, life and housing satisfaction, travel and housing preference, and behavioural interventions.

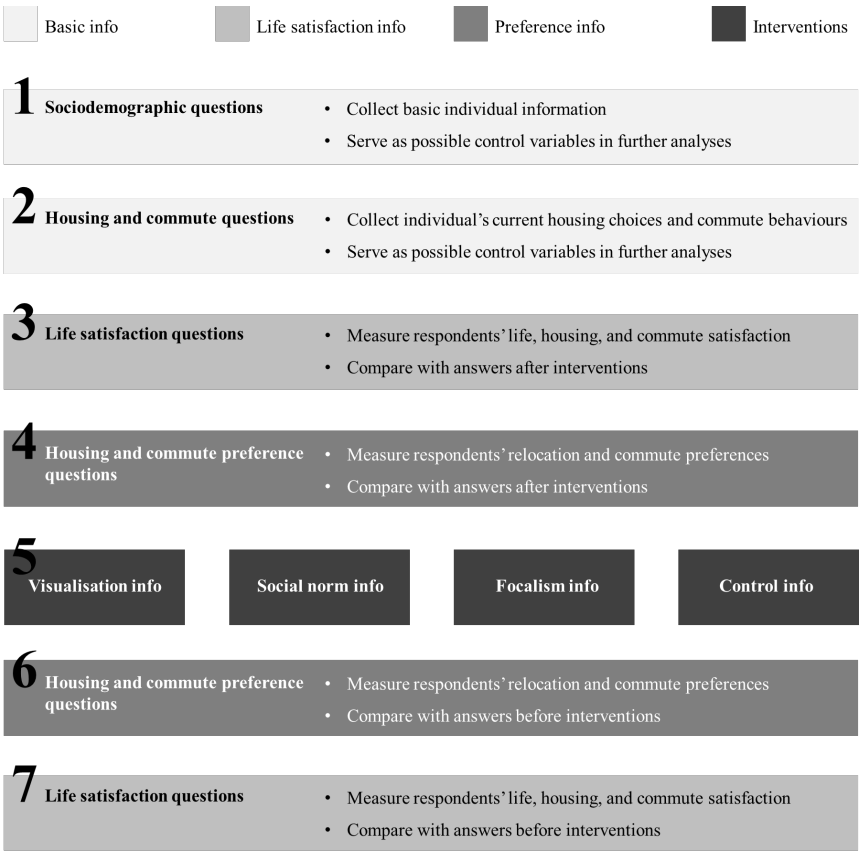

Figure 2: Questionnaire structure

The background information group collects essential sociodemographic information, current housing choices and commute habits. These include gender, age, Education level, Marital status, Number of Children in the household, Annual household income, household size, and whether the household owns a car. We also added an indicator of whether a respondent is a registered resident in the study area, i.e., variable *hukou*[1], according to China's context. These questions are included in the Block 1 in figure 1.

We included ten questions to collect respondents' current housing and commute choices. For the housing part, respondents are asked to provide their house location, size, monthly rent, and total number of residents. For the commute part, respondents need to answer their workplace location, daily commute frequency, monthly travel expenditure, average commute time, and frequently used commute methods. These questions form the Block 2 in Figure 2.

The third block of the questionnaire consists of satisfaction questions. Although environmental protection is important, we should not nudge people to more sustainable residential choices at the expense of their life satisfaction (Bhattacharyya et al. 2019). Measuring life satisfaction levels before and after interventions verify whether this balance has been struck. On the other hand, the interventions should influence people's satisfaction with their current housing and commuting choices. In other words, Block 3 questions were asked again in Block 7 after the intervention, and satisfaction scores were compared to verify the effectiveness of the behavioural interventions indirectly.

[1] *Hukou* is a system of household registration used in China. In most cities, only people with a valid *hukou* have access to certain rights such as education, pension scheme, and homeownership.

To measure respondents' life satisfaction, this dissertation followed the SWLS questions in Pavot and Diener (2009)[1]. We included four questions in random orders in the questionnaire: "*Are you satisfied with your current life?"*, *"Do you agree the following statement: in most circumstances, my current life is similar with my ideal life.*", "*Imagine life as a ladder with 1 to 10 levels where 1 represents your worst life condition while 10 represents your best life condition. Which level do you think you are currently in?*", and "*In general, how do you think your current life is?*"

To measure people's satisfaction with their current housing and commuting choices, we included five questions on housing satisfaction and one question on commuting satisfaction. Five housing questions asked about respondents' satisfaction in the four categories mentioned above (housing quality, community service, transportation accessibility, and social network distance) and overall satisfaction. One transportation question directly asked about respondents' overall satisfaction with their current commute choices. All questions use a scale of 1 to 5, where 1 represents "not satisfied at all" and 5 represents "very satisfied."

We then proceeded to ask questions about housing and commute preferences. We followed previous studies (Bhattacharyya et al., 2019) to subdivide the housing preference questions into four categories: housing quality, community service, transportation accessibility, and social network (see Table 2). Respondents first answer their preferences on four categories with a 1 to 5 scale where 1 means "not important at all" and 5 means "very important." Following the four questions come the preference questions on each factor. All questions in this part use the same 1 to 5 scale as before.

Table 3: Housing preference factors in the questionnaire

Category	Factors	Abbreviation
Housing quality	Size of house	HSize
	Floor of house	HFloor
	Direction of house	HDirection
	Window view of house	HView
	Soundproof quality of wall	HSoundproof
	Have radiator/air conditioner	HRadiator/AC
	Have private kitchen/toilet	HK/T
Community service	Parking lot	CParking
	Greenery/environment quality	CGreen
	Gym facility	CGym
	Property management company service quality	CPMC
	Package delivery service quality	CPackage
	Surrounding shops/restaurants density	CShop
	Surrounding education facility quality	CEdu
	Surrounding hospital quality	CHospital
	Noise level	CNoise
Transportation accessibility	Near subway station	TSubway
	Near bus station	TBus

[1] The original SWLS questions are in English. This dissertation referred to the simplified Chinese version translated by Andrew Wai on 19 August 2019.

Category	Factors	Abbreviation
	Have protected cycle lane	TCycle
	Few road congestion	TRoad
	Near workplace	TWorkplace
	Near supermarket/outlets	TMarket
	Near park/playground	TPark
	Near kindergarden/primary school	TSchool
Social network	Distance to relatives	SRelative
	Distance to friends	SFriend
	Distance to colleague/customer	SColleague
	Relationship with roommates	SRoommate
	Relationship with neighbors	SNeighbor
	Relationship with land lord/real estate agency	SLandlord

To test the short-term effect of interventions on respondents' commute choices, the questionnaire also included four questions on commuting preferences: "*Do you think your daily commuting experience is comfortable?*", "*Do you think you have many alternative commute choices?*", "*Are you satisfied with your current commute time?*", and "*If possible, which commute methods do you prefer – walking, cycling, taking buses, using the subway, driving, or calling a taxi?*"

These two groups of preference questions were asked before and after the interventions, i.e., the Block 4 and Block 6 questions in Figure 2, respectively. Therefore, they are used to measure the changes of respondents' housing and commute preferences before and after interventions.

Finally, in Block 5 we introduced three behavioural interventions: visualisation, social norm, and focalism. Visualisation intervention means providing additional graphic information (e.g., tailored subway maps, cycle lane maps, air pollution and noise maps, personalised accessibility maps, etc.) to participants. The rationality of this intervention lies in people's reliance on heuristics when making location and commute decisions. This phenomenon is prevalent when commuters choose a routine for their workplaces. Therefore, the function of this visualisation intervention is to make participants notice new information which they might ignore before, thus changing their decision-making process.

We provided participants with three maps generated based on the location of their workplaces, which is recorded in their answers to questions in Block 2. An example of these maps is given in Figure 3. These maps show the surrounding bus/subway stations, supermalls, affordable communities, parks, and hospitals. The function of these maps is to make participants aware of useful facilities around their workplaces. Previous studies (Guo and Peeta, 2020) using similar interventions have shown that once participants are more familiar with the area, they might find living near their workplaces is a good choice, therefore changing their location choices and reducing commute time.

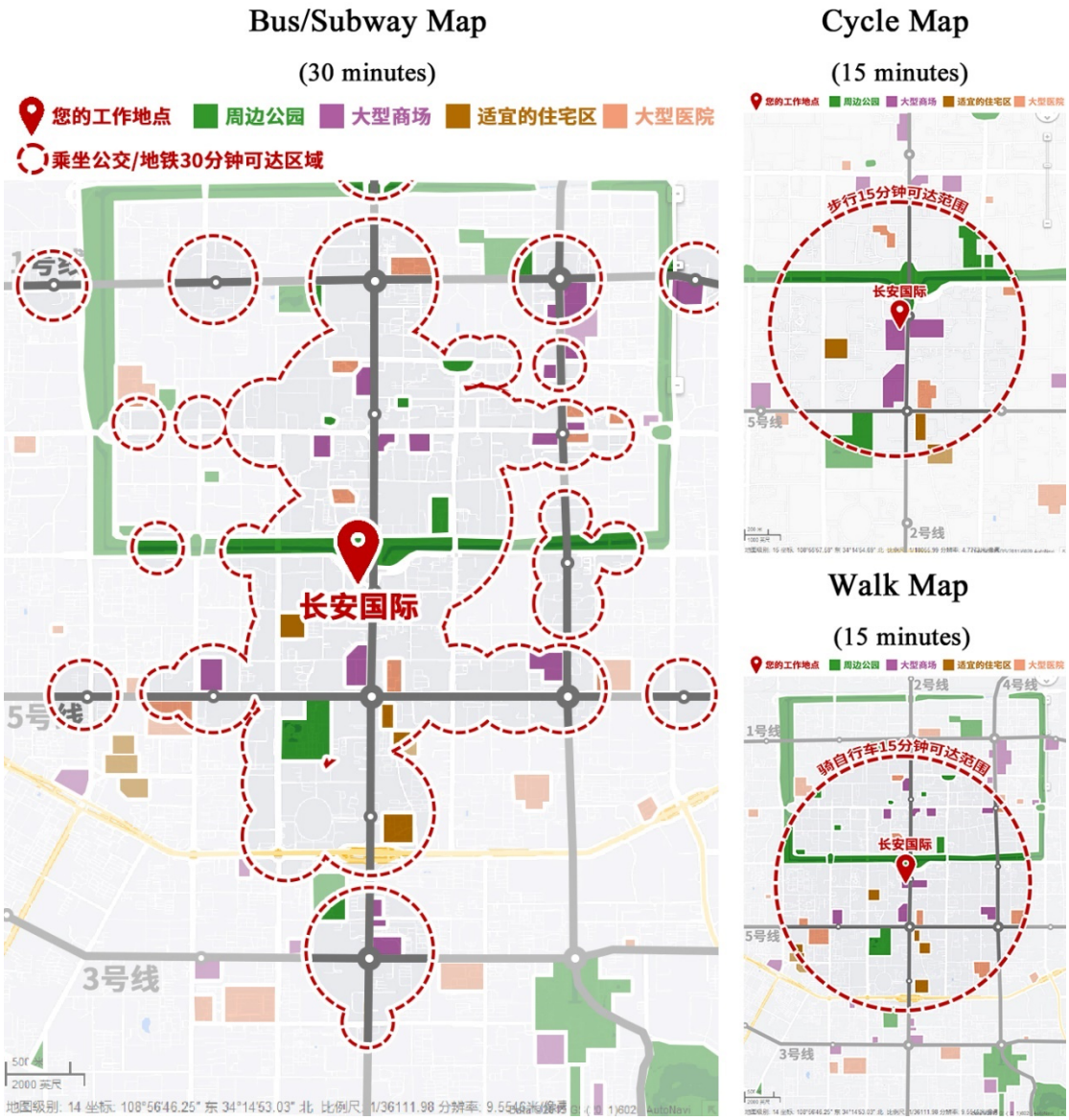

Figure 3: Example of the maps shown in the visualisation intervention

The social norm intervention usually includes certain information describing how reference groups, such as neighbours, friends, or the general public, behave. In the TDM domain, this intervention normally informs people how often other citizens walk and cycle, how many neighbours take public transportation to their workplaces, and other people's passive attitude towards driving. In our experiment, we used a short message introducing the possible benefits of choosing a house with better public transportation (see Appendix 1). Participants need to spend at least 60 seconds reading the message before proceeding to the next question.

The focalism intervention is rarely used in other domains, but it might be a useful tool in TDM studies. The word "focalism" is coined by Wilson et al. (2000) to describe people's tendency to "focus too much on the focal event and fail to consider the consequences of other events that are likely to occur." Bhattacharyya et al. (2019) first brought this concept into TDM studies and extended its definition to explain people's residential choices. They stated that people might "make suboptimal decisions because of their tendency to focus on factors that are observable, tangible, or most salient" and overlook the intangible but important ones.

The content of focalism intervention consists of three parts. In the first part, respondents are asked to state their preferences on different factors when choosing a new house. In the second part, the same factors will appear, with the only difference being that respondents now need to answer the influence of different factors on their life quality. Bhattacharyya et al. (2019) defined the disparity between people's preference scores and life-quality scores for each factor to be the focalism effect. In the third part, the researcher shows this disparity to respondents and introduces the concept of focalism. Ideally, once respondents notice they have an unconscious bias in choosing residential location, they will try to avoid that in the future.

This study adopted the general framework of focalism intervention in Bhattacharyya et al. (2019). Due to the limitation of the online questionnaire platform, this study can not automatically calculate the average score and give participants feedback right after they finish all questions. Therefore, this experiment simplified the second step by telling all respondents that they suffered from focalism (see the text content of this intervention in Appendix 2). By assuming that people who do not have focalism bias would not be affected by this intervention significantly, our results should be a reasonably good estimation of the effect of this intervention.

All respondents will answer questions in all other blocks. Once they reach the Block 5, they will be randomly assigned to one of the three treatment groups or the control group. Respondents in these three treatment groups were set up to read the information for at least 60 seconds before proceeding to the next question. Respondents in the control group were asked to read a message that is not relevant to the study for the duration.

3.3 Data collection

Due to COVID travel constraints in China, we conducted the experiment online at Credamo.co., the largest online panel data platform in China. We conducted two rounds of pilot studies in May 2022 to test the questionnaire and the size of the potential respondents. The experiment data were collected between 7 June and 11 July 2022[1]. We set the filters to exclude university students because they are not representative of the renter population that we are targeting. We also excluded mobile phone users because the maps used in the visualisation intervention cannot be read conveniently on a mobile phone. These measurements significantly reduced the size of eligible respondents, especially when the experiment was conducted in one city. We collected 941 observations within two months. The sample was scrutinised by excluding respondents who answered the questionnaire within 750 seconds, which is the minimum amount of time to complete the questionnaire determined in the pilot study. We also excluded respondents who answered the preference questions within one second. This resulted a final sample of 360 valid observations, of which 85 in the control group, 105 in the focalism group, 100 in the social norm group, and 70 n the visualisation group.

4. Empirical Findings

Table 4 gives descriptive statistics of sociodemographic characteristics for the three treatment groups and the control group. F tests were conducted to check whether the four

[1] Xi'an experienced a COVID outbreak and was in complete lockdown in December 2021. The city did not return to normal until the 24th of January 2022. Since then, the city had several cases, but no more full-scale lockdown and people's daily life went back to normal quickly. Therefore, the data collection process did not get influenced by the pandemic.

groups are comparable. Unfortunately, due to the small sample size, the F test results indicate that the four groups have different Education background and Hukou status. This is mainly due to the lack of respondents without college education in the control group, and the large proportion of non-Hukou residents in the visualisation group. We address this issue by complementing t test with logistic regression, where these sociodemographic variables were included to control for the heterogeneity.

We chose Xi'an as the study area because the city has extensive public transportation networks and ground transportation does not suffer from congestion problems as in other major Chinese cities. It is important that respondents in our experiments are actually able to change commute modes should they decide to do so. Otherwise, it is not possible for their intention and actions to be aligned. As shown in Figure 4, the respondents have a good range of commute modes to choose from, and most of them use more than one method. Buses and private cars are the two most commonly used commute modes. This finding supports our choice of study area for the experiments.

We asked respondents' preference for these commute methods before and after the treatment. The control group answered these questions twice as well, with a 60-second break in between. The responses to commute modes preference questions were classified into two categories: *Car Use* and *Green Commute* (walking, cycling, subway, bus, and taxi). We used the Principal Component Analysis (PCA) method to construct the *Green Commute* preference measurement based on the scores of individual commute modes. The average difference between the control and treatment groups for *Car Use* and *Green Commute* scores is given in Table 5. Positive mean difference values indicate an improvement of preference and vice versa. Therefore, all three behavioural interventions increased respondents' preference for green commute modes and reduced their tendency to drive. However, the Focalism intervention's effect is not statistically significant.

As noted in Table 4, the treatment groups and the control group are not homogeneous in some respects, such as education level and Hukou status. To control for these potential confounding effects, we estimated linear regression models by using *Car Use* and *Green Commute* scores as the dependent variable and behavioural intervention dummy variables as the key independent variables. Specifically,

$$Car\_Use = \beta_0 + \beta_1 Focalism + \beta_2 Social\_Norm + \beta_3 Visualisation + \sum_{i=1}^{k} \alpha_i x_i + \varepsilon \quad (1)$$

$$Green\_Commute = \beta_0 + \beta_1 Focalism + \beta_2 Social\_Norm + \beta_3 Visualisation + \sum_{i=1}^{k} \alpha_i x_i + \varepsilon \quad (2)$$

In equations (1) and (2), $Focalism$, $Social\_Norm$, and $Visualisation$ are dummy variables that equal one for respondents in the corresponding treatment groups and zero otherwise. The control group is omitted from the regression models as the reference group. x_is are control variables included in Table 4 and some additional housing attributes variables, such as the size of apartment currently rented by the respondents and whether the property was sublet. After controlling for personal and housing attributes, the coefficient estimates of the three behavioural interventions are positive in the model for *Green Commute* and negative in the model for *Car Use*.

Table 4: Sociodemographic characteristics of participants among groups

	Control Group (N = 85)	Focalism Group (N = 105)	Social Norm Group (N = 100)	Visualisation Group (N = 70)	Total (N = 360)	*F test statistics*
Gender						
Female	16.88%	17.14%	25.00%	29.49%	21.94%	5.70
Male	83.12%	82.86%	75.00%	70.51%	78.06%	
Age						
Under 27	6.50%	10.48%	10.00%	8.97%	9.17%	19.95
27-29	10.39%	11.43%	14.00%	14.10%	12.50%	
30-32	24.68%	26.67%	31.00%	24.36%	26.94%	
33-35	51.95%	45.71%	37.00%	38.46%	43.06%	
Over 35	6.49%	5.71%	8.00%	14.11%	8.33%	
Education level						
Technical secondary school	0.00%	2.86%	3.00%	1.28%	1.94%	21.79**
Junior college	6.49%	3.81%	12.00%	15.38%	9.17%	
Undergraduate	88.31%	87.62%	76.00%	66.67%	80.00%	
Postgraduate	5.19%	5.71%	9.00%	16.67%	8.89%	
Marital status						
Single	5.19%	8.57%	10.00%	6.41%	7.78%	4.77
Parter	12.99%	13.33%	15.00%	15.38%	14.17%	
Married	81.82%	78.10%	74.00%	78.21%	77.78%	
Divorced	0.00%	0.00%	1.00%	0.00%	0.28%	
Child						
No child	18.18%	22.86%	29.00%	24.36%	23.89%	10.48
1 child	70.13%	70.48%	55.00%	69.23%	65.83%	
2 or more children	11.69%	6.67%	16.00%	6.41%	10.28%	
Annual income						
Under 60,000	2.60%	2.85%	6.00%	8.97%	5.00%	31.17
60,000-89,999	10.39%	13.33%	16.00%	14.10%	13.61%	
90,000-119,999	76.62%	78.10%	65.00%	56.41%	69.44%	
120,000-149,999	5.19%	3.81%	7.00%	12.82%	6.94%	
150,000 or more	5.19%	1.90%	6.00%	7.69%	5.01%	
Hukou						
Not have	22.08%	18.10%	26.00%	60.26%	30.28%	43.91***
Have	77.92%	81.90%	74.00%	39.74%	69.72%	
Car						
Not have	11.69%	18.10%	18.00%	23.08%	17.78%	3.46
Have	88.31%	81.90%	82.00%	76.92%	82.22%	
Number of people living together						
1	10.39%	9.52%	12.00%	8.97%	10.28%	13.77
2	9.09%	12.38%	17.00%	17.95%	14.17%	
3	68.83%	71.43%	56.00%	66.67%	65.56%	
4 or more	11.69%	6.66%	15.00%	6.41%	10.00%	

Note: *, **, and *** denote significance at a 90%, 95%, and 99% level of confidence, respectively

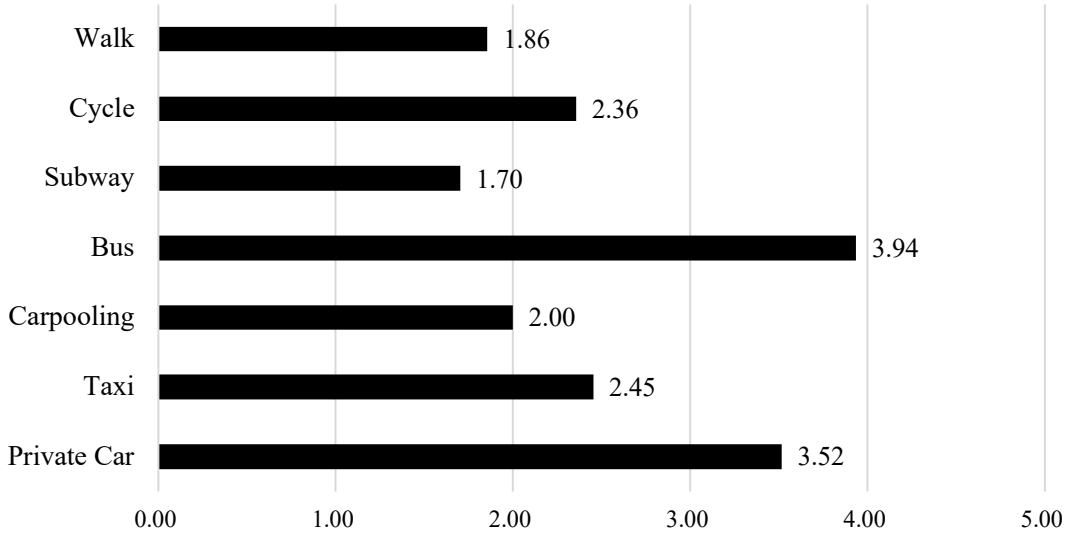

Figure 4: Average score of respondents' frequently used commute methods
Note: scores range from 0 (never) to 5 (very often). This is a multiple choices questions where respondents can select more than one commute methods.

Table 5: T test results

	Mean Difference (Treatment - Control)	**T test results**	
		T statistics	**P-value**
Green commute			
Focalism (N = 105)	0.1169	1.5082	0.1333
Social norm (N = 100)	0.1187	1.7390	0.0839
Visualisation (N = 78)	0.2132	1.8525	0.0666
Car use			
Focalism (N = 105)	-0.0130	-0.5615	0.5752
Social norm (N = 100)	-0.0771	-2.6860	0.0080
Visualisation (N = 78)	-0.0730	-2.1540	0.0336

Table 6: OLS regression results

	Green commute	Car use
Focalism intervention	0.1266	-0.011
Social norm intervention	0.0858	-0.0717**
Visualisation intervention	0.1489	-0.0555
Number of children	-0.1049	0.0811**
Income	0.1180***	-0.023
Household size	0.1659**	-0.0375
Hukou	-0.0335	-0.0282
Education	0.0262	-0.0349
Gender	-0.3182***	-0.011
Married	-0.2383*	-0.0676
Size of property in M^2	0.0006	-0.0027***
Subletting (Yes = 1)	0.1205	-0.1277***
Sample size	360	360
R squared	0.11	0.16
F statistic	3.58	5.32
P-value of F	0.00	0.00

5. Conclusions

This research aims to answer two questions: are the three interventions used in previous studies effective in China's context, and which intervention has a larger influence? We conducted randomised control trials with renters in a Chinese city in June and July 2022. Three behavioural interventions, i.e., focalism, social norm and visualisation were implemented in the experiments. The results show that all three behavioural interventions encourage the use of green commute modes among the respondents. They were also less likely to drive private cars between home and workplace.

This study contributes novel insights to the body of knowledge on behavioral interventions. It suggests that future research should incorporate a more extensive sample size to mitigate the effects of random error. The experiment involved 360 valid samples, with approximately 90 in each intervention group, a sample size that may impact the study's analyses if the standard deviation is extensive. Thus, larger sample groups are recommended for future online questionnaires.

Moreover, the study highlights the necessity for meticulously designed interventions to direct participants' focus effectively. This recommendation stems from the observation that while the study's interventions aimed to influence housing choice considerations towards public transportation, participants showed no significant change in this preference. Interestingly, there was a notable shift in their preference for private kitchens and toilets. This outcome suggests that interventions may not always yield anticipated results but can have unexpected effects in other areas. Therefore, the design of interventions represents a critical facet for subsequent research.

The inclusion of local context is also pivotal. Most existing studies center on cities in developed countries and account for basic sociodemographic data as control variables.

However, this study's results affirm that interventions could manifest divergently across different locales. Influencing factors such as the built environment, housing and commuting policies, and regional culture can shape attitudes and behaviors. For example, whereas car reliance and poor public transport accessibility are prevalent in the US, Chinese cities typically offer the opposite scenario. This disparity molds daily habits, such as commuting preferences. Additionally, in China, where cars symbolize social status, many opt to drive to signify affluence, even when it is not the most practical choice. Therefore, future studies should assimilate more local data to refine the evaluation of interventions' efficacy.

Lastly, the relationship between people's satisfaction and behavioral interventions warrants careful consideration. While this study did not find significant evidence linking interventions to satisfaction levels, preliminary results—coefficients and t-statistics—hint that interventions could potentially diminish satisfaction. Further investigation is necessary to ascertain the precise impact of interventions on life satisfaction and other subjective well-being measures. The overarching aim should be to guide behavior without compromising individual contentment.

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Appendix 1: Social Norm Intervention Text Content

When choosing a new house, people are also choosing their commute options. Once you determine where your home is, you also choose the available bus stations, subway stations, and shared bikes. These transportation facilities will largely determine your future travel choices.

When deciding on travel options, you might choose public transportation because it is beneficial to every citizen, to the city, and to our world. For each individual, taking subway is already faster than driving during peak hours, and active travel alternatives such as walking and cycling can strengthen your body. For the city you live in, more people using public transportation means less urban congestion. For the environment, taking public transportation can effectively reduce carbon emissions and avoid air pollution.

Due to the reasons mentioned above, more and more citizens are putting huge emphasises on public transportation factors when choosing a new home. According to a survey conducted by the city government, renters care more about the location and transportation conditions of a house.

Therefore, when you need to move next time, please think more about the public transportation factors. Choosing a suitable home with accessible bus/subway stations will save you much time, change your travel pattern, and make your personal contribution to the city.

Appendix 2: Focalism Intervention Text Content

You might be a bit out of patience after filling in similar questions twice. But please notice: your answers to the two groups of questions are not the same.

The first question group asked about your personal preferences when choosing a new home, while the second question group asked about each factor's influence on your life quality. People intuitively believe they have given all aspects enough weight when making a decision, but your answers just showed that the factors you emphasise when choosing a house are not exactly factors that influence your life quality most in the future.

Researchers use the word "focalism" to describe this phenomenon. When making decisions, people tend to put more weight on tangible factors and neglect intangible factors. These neglected factors, however, might have a larger influence in the future.

But this phenomenon is not unsolvable. In fact, if you remind yourself of the existence of this phenomenon when making decisions, you can effectively overcome the bias. Therefore, please take some time to think about the factors that really have a huge influence on your life quality.